Testing the Monthly Calendar Anomaly of Stock Returns in Pakistan: A Stochastic Dominance Approach

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In this paper, we first examine the presence of monthly calendar anomaly in Pakistan Stock Exchange (PSX) using aggregate and firm-level monthly stock returns. Secondly, we classify the sample firms into low-beta, medium-beta, and high-beta firms to examine the monthly anomaly of stock returns for firms having different level of systematic risk. By considering the stochastic dominance approach (SDA), we employ the simulation based method of Barrett and Donald (2003) to identify the dominant month over the period from January 2000 to December 2017. We find significant evidence of the existence of the January effect in both firm and market stock returns. We also find that the January effect exists more prominently in both low-risk and high-risk firms categorised based on their systematic risk. On the other end of the continuum, for moderately risky firms, there is strong evidence of the presence of the December effect. One of possible explanations of the January effect is the year-end bonus received in the month of January. Such bonuses are generally used to purchase stocks, causing the bullish trend of stock prices in January. However, the evidence of the January anomaly in both low-beta and high-beta portfolios returns is puzzling, suggesting that investors may invest in both low- and high-risk stocks when enthusiastically investing in stock market. The findings of the paper suggest that investors may get abnormal returns by forecasting stock return patterns and designing their investment strategies by taking into account the January and December effects and the level of systematic risk associated with the firms.

JEL Classification: G02, G12, G14

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1. INTRODUCTION

Prior theoretical and empirical studies have documented several calendar anomalies that significantly affect the efficiency of asset markets and the performance of standard asset-pricing models. Among these anomalies, the monthly calendar anomaly is considered one of the well-accepted phenomena and it is observed in several stock markets across the globe. According to Fama and French (1992), stock markets often behave in irrational ways and follow predictable patterns.[1] By examining such patterns

[1]See Lim and Brooks (2011) for a comprehensive survey on market efficiency.

and trends investors try to get abnormal returns, which leads to anomalies. The January anomaly is perhaps the first anomaly of stock returns, which was discovered by Wachtel (1942). In particular, he found the presence of significant January effect in stock markets of the United States. Since then, several studies have documented different months' effects on stock returns.

It is generally believed that market anomalies are very difficult to predict because they appear, sometimes disappear, and then again reappear [Schwert (1991)]. During the last couple of decades, considerable higher and lower stock returns have generally been observed in several markets across the globe. Yet, the empirical literature is inconclusive at best. On the one hand, some researchers are of the view that despite its popularity over the last many decades, the January phenomenon does not exist anymore in developed stock markets. However, it is also evident in the recent literature that the January effect still exists in several emerging markets as these markets are not yet efficient enough [Patel (2016)].

A monthly anomaly is perhaps the most well publicised anomaly discussed in the literature. Further, the monthly calendar anomaly of stock returns is one of the tenacious calendar anomalies especially, in emerging markets. According to Fama (1998), under and overreaction effects exploit the random walk pattern in stock prices. Lim and Brooks (2011) also scrutinise that stock returns show noticeable pattern and violate efficient market hypothesis (hereafter EMH). Hence, market anomalies either cause inefficiency in stock markets or affect the prediction power of the standard asset-pricing models including the standard capital asset pricing model (henceforth CAPM) and the multifactor asset-pricing models like three-factor and newly developed five-factor models of asset pricing.

Market anomalies are of great interest to individual as well as institutional investors. They often do careful examination of stock price instabilities and abnormal profits. Furthermore, they try hard to find opportunities to get abnormal returns, specifically through seasonal anomalies [Darrat, Li, and Chung (2013)]. Wachtel (1942) was the first, who discovered the January anomaly in US stock market. Later on, other researchers including Keim (1983), Annuar (1987) and Haugen and Jorion (1996) have also documented significant evidence on the January effect on stock returns in the USA. One should also note that there are also several studies that have reported significant evidence of the presence of the January anomaly in stock returns for countries other than the USA [e.g., see Lean, Smyth, and Wong (2007)] for Singapore Stock Market and Alagidede (2013) for Egypt, Nigeria, and Zimbabwe Stock Market). Al-Smadi, Almsafir, and Husni (2017) have also discovered that the returns of January month outperform from the rest of calendar months in Malaysian stock market.

Despite numerous studies on the stock return anomalies, we know little regarding the major factors that drive the monthly anomaly. In contrast to EMH, adaptive market hypothesis (AMH) explains the time varying behaviour of well-known calendar anomalies that might prevail in stock markets [Lo (2004)]. Several researchers have given possible reasons in order to sort out such intricacy. For instance, Fama and French (1993) found that the book-to-market value of firms, window-dressing activities by firms, and momentum patterns are the main causes for the monthly calendar anomaly in stock prices. Similarly, Alagidede (2013) claimed that the fundamental reasons of the existence

of the January effect are the tax-loss-selling hypothesis, the liquidity constraint, and the omitted risk factor. Easterday and Sen (2016) have stated that the potential tax-loss sellers are the ones who significantly derive the January anomaly in stock returns rather than the noise traders. On the other hand, Lynch, Puckett, and Yan (2014) attempted to differentiate the tax-loss-selling hypothesis from the risk-shifting window-dressing hypothesis. Their results are consistent with the window-dressing hypothesis. Li and Gong (2015) have showed the January effect in Japan due to relatively high volatility in the month of January. Rogalski and Tinic (1986) have documented that high-beta stocks yield high returns in January as compared to any other month of the year. Furthermore, Banz (1981), Keim (1983) and Rozeff and Kinney (1976) have found that the January effect is mainly due to small cap stocks. Nevertheless, according to Ligon (1997)**,** the January effect is the result of investors' excessive need of liquidity in the month of January. He has also documented that low real interest and high trading volume lead to higher returns in January. Nonetheless, Rozeff and Kinney (1976) have stated that the risk compensation is the main justification of high returns in the month of January.

Researchers have also documented that instead of January, other months of the year yield significant positive stock returns in some countries. For instance, Mouselli and Al Samman (2016) have confirmed the existence of significant and positive returns in May. Gu (2015) has found the June phenomenon for US stock market. There is also evidence that the month of February is dominated in Iran [Ke, *et al.* (2014)], April is outperformed in US stock market [Wang and Frank (2014)], and the month of August is dominated in Macedonian [Angelovska (2014)]. Further, some other studies documented evidence of the presence of December effect in stock markets of Thailand and GCC countries [Ariss, Rezvanian, and Mehdian (2011); Tangjitprom (2011)].

Reviewing the literature we find that relatively limited studies have been done on calendar anomalies in developing and emerging stock markets. Although, evidence from less developed markets significantly helps explain the mystery of anomalies in stock returns. Further, the limited existing studies on developing markets are even not comprehensive and have used statistical tools that may suffer from several caveats.[2] This motivates scholars to test stock returns anomalies in emerging and developing markets by using more sophisticated and robust statistical methods.

Further, when we review the literature on Pakistan we find that although some scholars have tried to explore the monthly calendar anomaly in Pakistan Stock Exchange (PSX), their focus was very limited and have provided inconclusive findings. For instance, Hashmi (2014), Ullah, Ullah, and Ali (2016), Shamshir and Baig (2016)**,** Jebran and Chen (2017), and Shahid and Sattar (2017) have documented the evidence of the presence of the January effect in PSX. In contrast, Iqbal, Kouser, and Azeem (2013), Shahid and Mehmood (2015), Qureshi and Hunjra (2017) have provided evidence of the non-existence of the January anomaly. However, Shahid and Mehmood (2015) have reported that there are the highest positive

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[2]Most of the previous studies, particularly in developing countries, have used OLS, GARCH ARIMA, and ARCH models to test calendar anomalies. The main disadvantage of such techniques is that they follow normal distribution assumption in return distributions. However, the existing studies on Pakistan equity market, for instance, Rashid and Ahmad (2008), have provided evidence that the volatility of stock returns increases with stock returns. Similarly, Khilji and Nabi (1993) have stated that PSX stock returns are leptokurtic and positively skewed. Similarly, Schwert (1991) and Beedles (1979) have also examined that stock returns can be negatively or positively skewed.

returns in March, whereas, significant negative returns are observed in May. Pakistan equity market is an emerging, dynamic, and inefficient market. Thus, it is a highly relevant and interesting case for testing monthly annomalies. Further, there is very limited empirical research on monthly anomalies in PSX, particularly using sophisticated econometric techniques such as stochastic dominance approach. This encourages us to re-examine monthly anomaly in Pakistan equity market.

To fill the above-mentioned gaps, in this paper, we examine monthly calendar anomalies in PSX. We contribute to the existing literature on stock returns anomalies at several levels. First, we explore the monthly calendar anomaly in all listed firms at PSX. Second, we classify the sample firms into low-beta, medium-beta, and high-beta firms to examine monthly anomaly for firms having different level of systematic risk. By doing this, we present first-hand empirical evidence on the monthly anomaly in PSX for firms having different level of systematic risk. Third, and more importantly, unlike most of prior studies, we propose the stochastic dominance (SD) framework to investigate the first, second and, third order of SD. These SD rules are tested by implementing the KS (Kolmogorov-Smirnov) type test of Barrett and Donald (2003) based on SD theory. The main advantage of this test is that it can be useful for examining SD of any-pre-specified order. In addition, it does not require any pre-defined distribution of underlying series. Thus, by applying this test, we present more robust evidence on the presence of monthly calendar anomalies in Pakistan equity market.

We find significant evidence of the existence of the January effect in both firm and market stock returns. We also find that the January effect exists more prominently in both low-risk and high-risk firms categorised based on their systematic risk. On the other end of the spectrum, for moderately risky firms, there is strong evidence of the presence of the December effect. The possible explanation of the January effect is the year-end bonuses received in the month of January. These bonuses are generally used to purchase stocks, causing the bullish trend of stock prices in January. However, the evidence of the January anomaly in both low-beta and high-beta portfolios returns is to some extent puzzling and requires further investigation along these lines. One possible explanation of such finding is that investors invest in both low- and high-risk stocks when enthusiastically investing in stock market, which results in the January effect in both categories of stocks. This finding also provides support for the notion that risk-averse and risk-seeking behaviour simultaneously exists and investors invest in risky stocks with a hope to get higher returns and, at the same time, invest in relatively safe stocks to avoid big losses.

The reminder of the paper is structured as follows. Section 2 first presents the analytical framework and then discusses the empirical methodology and data used in the empirical analysis. Portfolio formulation is also discussed in this section. Section 3 presents the empirical results and their interpretation. Finally, Section 4 presents some concluding remarks and policy implications.

2. EMPIRICAL FRAMEWORK

2.1. Methodology: SD Approach

This study uses the SD approach to test the first three orders of SD. This approach is generally used to test whether one series stochastically dominates the other one at any

specific stochastic order. This paper tests the stochastic dominance of returns of any specific month over other months' returns using the first three SD rules. These rules are the first-order stochastic dominance (hereafter FSD), the second-order stochastic dominance (henceforth SSD), and the third-order stochastic dominance (henceforward TSD).[3]

For an explanation of SD rules, let us assume A and B are the two investment alternatives with stochastic outcome (say "r"). We further assume that this stochastic outcome lies between the range of 0 and 1. We denote the cumulative probability distribution (hereafter CPD) of the outcome of these two investment alternatives by $A(r)$ and $B(r)$, respectively. Regardless of whether investors are risk averse or not, they always attempt to optimise their expected utility of wealth. Therefore, in mathematical expression, asset "a", having CDF: $A_a(w)$ stochastically dominates over asset "b", having CDF: $B_b(w)$ in case of all non-decreasing utility functions by first order only if the following condition holds.

$$[B_b(w) - A_b(w)] \geq 0 \quad \text{for all level of wealth } (w), \text{ with strict inequality}$$
$$\text{for at least one value of wealth } (w_0) \quad \ldots \quad \ldots \quad (1)$$

Given that the risk aversion is considered as the subset of increasing wealth preference feature of the utility function, SSD assumes that a utility function should not only have a positive marginal utility of wealth but also the total utility of wealth should increase at the decreasing rate. In this context, asset "a" stochastically dominates over asset "b" by second order if and only if the following condition is satisfied.

$$\int_{\infty}^{w} [F_b(w) - F_a(w)] du \geq 0 \text{ for all level of wealth } (w), \text{ with strict inequality}$$
$$\text{for at least one value of wealth } (w_0) \quad \ldots \quad (2)$$

The third-order SD (TSD) has an additional assumption that investors are risk averse and have a utility function with a feature of decreasing absolute risk aversion. There are sufficient as well as necessary conditions for the existence of TSD. Specifically, for TSD, the existence of SSD is sufficient condition, while the necessary condition for TSD is that the expected mean value of first asset, say "a" in our case, should be greater than or at least equal to the expected mean of the other asset, say "b" in our case [Hadar and Russell (1969); Levy and Levy (2001); Schmid and Trede (1998)]. Specifically, we define that asset "a" dominates over "b" by third order of SD if and only if we have the following condition.

$$\int_{\infty}^{w} \int_{\infty}^{1} [F_b(w) - F_a(w)] \, du \, dt \geq 0 \quad \text{for all level of wealth } (w), \text{ with a strict}$$
$$\text{inequality for at least one value of wealth } (w_0) \quad \ldots \quad (3)$$

There exist several tests in the econometric literature that can be used to test the stochastic dominance theory. Examples of these tests include DD test, LMW test, and LSW test given by Davidson and Duclos (2000), the KS type test of stochastic dominance, which is proposed by Barrett and Donald (2003) and Linton, Maasoumi, and

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[3]Seyhun (1993) was the first who used the stochastic dominance approach to test the monthly anomaly in NYSE. Later, in order to test the calendar anomaly in Asian countries, Lean, *et al.* (2007) applied the DD test of the stochastic dominance, which is proposed by Davidson and Duclos (2000). However, the orders of stochastic dominance were first proposed by Hadar and Russell (1969).

Whang (2005), and the Improved Bootstrap SD test proposed by Linton, Song, and Whang (2010).

We apply the Kolmogorov-Smirnov (KS) type test of Barrett and Donald (2003).[4] Initially, the KS type test was proposed by McFadden (1989) for FSD. Afterward, Barrett and Donald (2003) proposed the KS type test to test the stochastic dominance of one asset over the other asset. Testing the dominance of one asset over the other in the framework of KS type test is considered superior as compared to running simple OLS regression, ARIMA, or (G)ARCH models. The superiority of this test is mainly attributed to no requirement of any prior knowledge on the distribution of return series. Below we give the brief descriptions of the KS type test. Let $\{A_i\}$, where $i = 1, 2, \dots , N$ be *i.i.d* (identical independent distribution) sample of returns to dominated distribution having the $F_A(x)$ cumulative frequency distribution.

By assuming that the CDFs generally lie between $[0, x]$, where $x > 0$ and are continuous functions between the space $[0, x]$, we define the following rules to explain whether the function $D_A^s(x)$ integrates $F_X(r)$ to any stochastic dominance order $s = i$.

$$D_A^1(\text{x}) = F_A(x) \qquad\qquad \text{For FSD} \quad \dots \quad \dots \quad \dots \quad (4)$$

$$D_A^2(\text{x}) = \int_0^x F_A(u)du = \int_0^x D_A^1(u)du \quad \text{For SSD} \quad \dots \quad \dots \quad \dots \quad (5)$$

$$D_A^3(\text{x}) = \iint_0^x F_A(v)dvdu = \int_0^x D_A^2(u)du \quad \text{For TSD} \quad \dots \quad \dots \quad \dots \quad (6)$$

Similarly, let us suppose $\{B_i\}$, $i =1,2,\dots , N,$ be *i.i.d* sample of returns to non-dominated distribution with CDF of $F_B(x)$. Next, we define the distribution of $D_B^s(x)$ for the function $F_B(x)$ as similar as we have already defined $D_A^s(\text{x})$. Therefore, the test has the following null and alternative hypotheses to test the stochastic dominance order of asset "*A*" over asset "*B*":

$H_0^s: D_A^s(\text{x}) \leq D_B^s(\text{x}) \qquad$ for all x (stock returns)
$H_1^s: D_A^s(\text{x}) > D_B^s(\text{x}) \qquad$ for some x (stock returns)

The null hypothesis is stated that asset "*A*" stochastically dominates over asset "*B*", whereas, the alternative hypothesis implies that distribution *B* stochastically dominates over *A*. The following KS type test statistic is applied to test the null hypothesis, H_0^s.

$$K_s = (\frac{N^2}{2N})^{1/2} \underset{x}{sup} [D_A^{-s}(x) - D_B^{-s}(x)] \qquad \dots \quad \dots \quad \dots \quad \dots \quad (7)$$

This test can be applied for second ($s = 2$) or any higher order ($s > 2$) of stochastic dominance. We obtain the p-values for the underlying null hypothesis through simulation method by estimating the value of suprema of test statistics, K_s [Barrett and Donald (2003)]. Specifically, the following hypothesis could be tested to achieve the objective of our study.

H_0: The underlying target month stochastically dominates over another month at the predefined s^{th} order.

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[4]The KS type test is a nonparametric test, which is suitable for testing the equality of one- and two-dimensional, continuous probability distributions. It is named after Kolmogorov (1933) and Smirnov (1948).

2.2. Data and Portfolio Formulation

Monthly stock prices of all publically listed firms and KSE-100 Index are taken from the official website of PSX. We exclude only those firms from the sample that have trading days less than 6 in one month. The study consists of 18-year period ranging from January 2000 to December 2017. Following, Annuar (1987), Fong, Wong, and Lean (2005) and Tangjitprom (2011), stock returns (SR_{it}) are calculated as follows.

$$SR_{it} = ln(\frac{P_{it}}{P_{it-1}}) \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad (8)$$

where P_{it} denotes stock price of firm *i* at time *t*.

We construct monthly beta (a risk measure) based portfolios of stock returns [Ritter and Chopra (1989)]. Since the risk (beta) associated with the firm may change over time, we calculate the beta for each firm for each month over the sample period. Next, in each month, descending-order ranked firms are categorised as high-beta, medium-beta, and low-beta firms to formulate portfolios based on quartiles. Specifically, top 25 percent firms are considered as high-beta (high-risk) firms, bottom 25 percent firms are classified as low-beta (low-risk) firms, while the middle 50 percent firms are considered as medium-beta (moderately risky) firms.

3. EMPIRICAL RESULTS

We start our empirical analysis by presenting summary statistics. Next, we examine the presence of monthly anomaly using the stock returns of publically listed firms included in our sample. After presenting the evidence on the existence of monthly anomaly in stock returns for full sample, we construct the three beta-based portfolios and examine the presence of monthly anomaly in constructed portfolios' returns. Finally, we present the results on the month effect in overall Pakistan equity market using KSE-100 Index as a proxy for overall stock market performance. We do so, as one of the aims of our study is also to check the presence of monthly anomaly in overall Pakistan equity market.

3.1. Descriptive Statistics

Before testing the presence of monthly anomaly, we present month vice descriptive statistics for all sample firms, beta-based portfolios, and KSE-100 Index returns. Table 1 displays the summary statistics. The table provides several notable stylised facts. Specifically, it displays that most of months' stock returns are positive and show rising trend over the examined period. One can clearly observe from the statistics presented in the table that the mean returns are higher in the month of January (3.832 percent) as compared to the other months of the year. In contrast, October has the lowest stock returns (indeed negative) with the magnitude of –0.065 percent.

These observations are consistent with the results for developed markets. Several existing empirical studies have also documented that the month of January yields high returns, on average, as compared to the other months of the year. Examples of these studies include Agrawal and Tandon (1994), Boudreaux (1995), Gultekin and Gultekin (1983), and Haugen and Jorion (1996). Similarly, the median stock returns (1.359 percent) are also high in January as compared to any other month of the year. Looking at the value of standard deviation presented in the table, we observe that the estimated value

of standard deviation of returns for the month of January is 23.887 percent, which is high as compared to that of other months. Thus, the table provides evidence that in January, not only the stock returns are high but also there is more variation in stock returns. This observation is consistent with the standard finance theory which states that higher expected returns are always associated with higher risks. Some other researchers have also confirmed the high-risk-high-return relationship [Ghysels, Santa-Clara, and Valkanov (2005)]. The statistics also suggest that the stock returns may not be normally distributed. Specifically, we observe that returns are negatively skewed in 4 out of 12 months. In sum, skewness and kurtosis values suggest non-normality in stock returns over the examined period, which motivates us to apply the stochastic dominance approach to test monthly anomaly in Pakistan equity market.

Table 1

Summary Statistics of All Listed Firms

Months	Jan-uary	Feb-ruary	March	April	May	June	July	August	Septem-ber	Octo-ber	Novem-ber	Decem-ber
Mean	3.832	2.418	-1.366	2.668	-0.641	-0.976	0.624	-1.550	0.319	-0.065	0.803	2.717
Median	1.359	-0.077	-0.581	0.662	-0.293	-0.654	0.218	-0.606	-1.338	-0.247	0.008	1.356
Standard Deviation	23.887	18.960	18.117	19.092	19.017	18.312	16.586	17.309	17.737	17.212	17.157	21.530
Kurtosis	26.430	109.063	30.017	21.579	18.457	20.207	34.510	76.302	48.850	19.150	27.285	18.486
Skewness	-0.052	5.397	0.911	-0.268	0.729	0.783	0.574	-3.084	2.310	-0.095	1.484	0.315
No. of Observation	5455	5288	5395	5680	5555	5581	5560	5030	5438	5502	4411	5249

Table 2 presents average returns and standard deviation of KSE-100 Index and beta-based portfolio returns. We divide the table into four panels. The first panel is labelled as "Low-Beta Portfolio", the second is named as "Medium-Beta Portfolio", the third panel is labelled as "High-Beta Portfolio" and the final panel is denoted as "Market Portfolio". We find that high-beta portfolio, low-beta portfolio, and market portfolio, on average, yield higher returns in the month of January, having values of 9.466 percent, 4.625 percent, and 1.161 percent, respectively. Based on this preliminary evidence we can say that the stock returns of high-beta portfolio, low-beta portfolio, and market portfolio may outperform in January as compared to the non-January months. In contrast,

Table 2

Summary Statistics of Beta-based and Market Portfolio

	Beta-Based Portfolios									Market Portfolio		
	High-Beta Portfolio			Medium-Beta Portfolio			Low-Beta Portfolio					
Months	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.
January	9.466	(28.868)	1405	0.454	(18.470)	2669	4.625	(26.319)	1381	1.161	(1.352)	18
February	4.459	(27.596)	1314	1.226	(14.086)	2637	2.760	(16.605)	1337	0.349	(0.945)	18
March	-0.740	(21.217)	1372	-2.247	(14.123)	2669	-0.263	(21.351)	1354	0.163	(1.361)	18
April	3.985	(22.366)	1436	2.182	(16.113)	2819	2.304	(20.820)	1425	0.244	(1.025)	18
May	2.657	(21.794)	1408	-3.094	(13.896)	2758	0.875	(23.596)	1389	0.089	(1.067)	18
June	-1.174	(22.717)	1424	-2.265	(12.891)	2762	1.779	(21.804)	1395	0.427	(1.718)	18
July	0.743	(19.947)	1420	0.989	(12.692)	2715	-0.189	(19.222)	1425	0.494	(0.824)	18
August	-1.145	(23.329)	1276	-1.350	(13.380)	2489	-2.352	(17.022)	1265	0.125	(1.354)	18
September	-0.059	(19.080)	1390	0.550	(12.787)	2688	0.248	(23.727)	1360	0.191	(0.722)	18
October	0.677	(19.494)	1401	0.024	(14.657)	2709	-0.989	(19.220)	1392	0.382	(0.847)	18
November	2.278	(21.092)	1125	-0.232	(13.177)	2162	1.319	(19.288)	1124	0.061	(1.162)	18
December	1.422	(26.892)	1350	2.555	(16.495)	2569	4.344	(23.796)	1330	0.128	(1.068)	18

we observe that in medium-beta portfolio, the average returns of December (2.555 percent) are higher than the portfolio returns for other months. Thus, we expect that the month of December may outperform in case of medium-beta portfolio. The mean values of beta-based portfolio returns provide a clue for the presence of the January and December effect in PSX: a theme, which we explored in this study.

We further observe that in both high-beta and low-beta portfolios, stock returns as well as their standard deviations are high in January. However, in the portfolio of medium-beta firms, the returns are high in the month of December (2.555 percent), whereas, the standard deviation of returns is high in the month of January with the value of 18.470 percent. Similarly, in case of market portfolio, average returns are high in January having the value of 1.161 percent.

We test normality of stock returns by applying Kolmogorov-Smirnov test of normality. The results provide evidence that month vice returns for full sample and beta-based portfolios are not normally distributed. However, the monthly returns of KSE-100 Index are normally distributed. This evidence suggests that the stochastic dominance (SD) approach is the appropriate technique to test the monthly calendar anomalies in PSX.

3.2. The January Effect in Firms' Stock Returns

In this subsection, we examine the January effect. For this purpose, we test the SD of January returns and the returns of other calendar months. As Table 1 shows, on average, the returns of January are higher than that of non-January months. Therefore, we examine the SD of January over all remaining calendar months. First, CDF is used to examine the visual dominancy. Next, we apply formal test to check SD of the underlying month over the other months. CDF presents the comparison between the two underlying distributions. Analysis of the graph gives a clue of SD.

Figure 1 shows the CDFs of four months that are selected based on higher stock returns. From Table 1, we examine that the top four months on the basis of their returns are January (3.832 percent), December (2.717 percent), April (2.668 percent), and February (2.418 percent). Therefore, we present the CDFs of only these four months. The remaining months' CDFs are omitted to reduce clutter. On the whole, the CDF of January and December lie to the right side of the other CDFs, implying that returns in January or December are expected to outperform over the remaining calendar months. To proceed further, the formal test of stochastic dominance is used to examine which of the month stochastically dominates over the other months.

Table 3 presents the results of SD test for the month of January with respect to other months. The table has two parts. In first part, named as "January *versus* other months", the p-values for testing the null hypothesis that $H_0: X >_s Y$, that is, the target month stochastically dominates over non-target months at s^{th} order, are given. The second panel shows the p-values for the reverse hypothesis, $H_1: Y >_s X$, that is, the non-target month SD dominates over target month. The SD1, SD2, and SD3 denote SD at order first, second, and third, respectively. The p-values presented in the first part of the table show that the month of January is stochastically dominating over other calendar months.
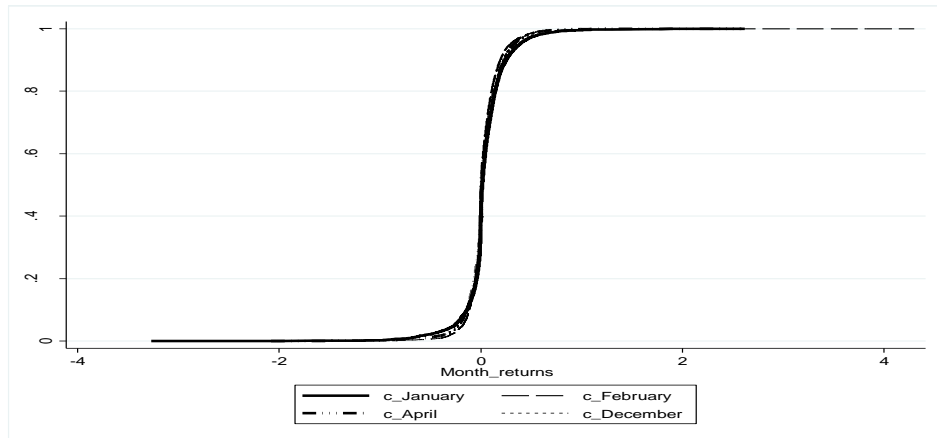
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Fig. 1. CDFs of Returns of All Listed Firms

Table 3

Test Results for January Month; Sample: All Listed Firms

	January *versus* other Month			Other Month *versus* January		
	KS P-value					
Months	SD1	SD2	SD3	SD1	SD2	SD3
January	**Winner**					
February	0.007	0.000	0.253	0.000	0.000	0.000
March	0.592	0.032	0.295	0.000	0.000	0.000
April	0.278	0.004	0.248	0.000	0.000	0.001
May	0.183	0.003	0.229	0.000	0.000	0.000
June	0.382	0.018	0.282	0.000	0.000	0.000
July	0.121	0.000	0.212	0.000	0.000	0.000
August	0.253	0.017	0.350	0.000	0.000	0.000
September	0.097	0.000	0.158	0.000	0.000	0.000
October	0.481	0.022	0.243	0.000	0.000	0.000
November	0.155	0.001	0.188	0.000	0.000	0.000
December	0.653	0.398	0.385	0.000	0.000	0.000

Note: This table presents the results for the stochastic dominance of January in all publicly listed firms included in the sample. The number of comparison between any two calendar months is C(12,2)=66. Winner month "January" months' results are presented only. The first panel namely January *versus* other months tests the null hypothesis that the month of January dominates over other calendar months. The SD1, SD2, and SD3 are the stochastic dominance orders. The p-values are calculated through the simulation method proposed by Barrett and Donald (2003).

Put differently, we do not reject the null hypothesis that the target month (January) dominates over the non-target month, as the p-values for the first and third order of SD are greater than any acceptable level of significance except for the SD1 of February, where it is 0.007. This implies that the month of January is strongly dominating over other calendar months in first and third SD orders. However, the p-values of SD2 show that January is weakly dominating over all non-January months at the second order of SD except the month of December.

Overall, the results suggest that January strongly dominates over non-January months at all three order of stochastic dominance during the examined period.

3.3. The January Effect in Low-Beta and High-Beta Portfolio

In this subsection, we examine the January effect in high-beta and low-beta portfolios. We do so, because the descriptive statistics presented in Table 2 clearly suggest that the mean returns of January are high from the mean returns of the rest of months in case of both high- and low-beta portfolios. Furthermore, Figures 2 and 3 demonstrate the CDFs of returns for those months that have relatively higher returns in both high- and low-beta portfolios. In particular, the CDFs of the top four months ranked based on the mean values of stock returns are presented in the figure and the CDFs of returns of the other months are not presented in order to avoid the clutter in the figure.

Table 2 shows that in high-beta portfolio, on average, the highest returns are for the month of January with a value of 9.466 percent. The mean returns of the months of February (4.459 percent), April (3.985 percent), and May (2.657 percent) are at second, third, and fourth position, respectively. The CDFs of January and February are the most right. This implies that both January and February seem to dominate over the rest of months of the year. In contrast, the CDF of April month and the CDF of May are most left side. Thus, Figure 2 clearly indicates that in case of high-beta portfolio, the month of January or February may dominate over other months, at certain SD orders.

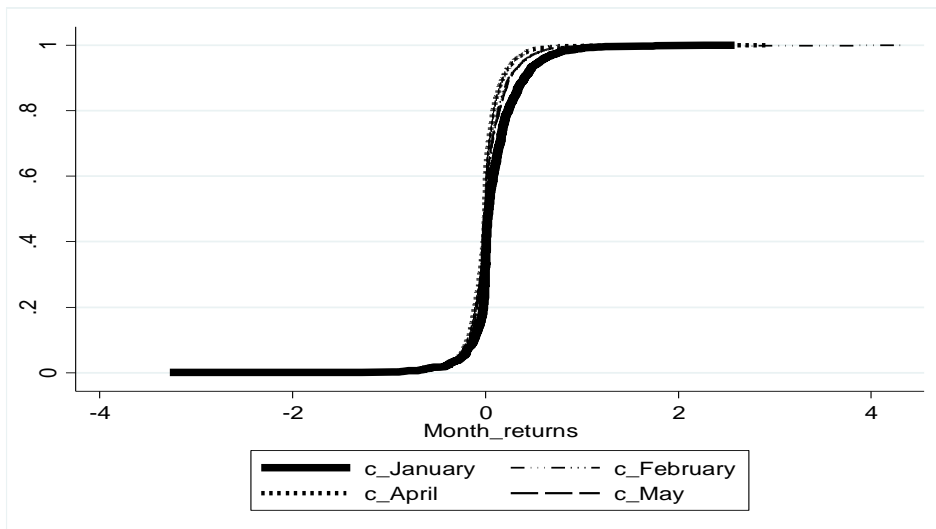**Fig. 2. The CDFs of Monthly Returns of High Beta Portfolio**

Figure 3 shows the top four months' CDF of returns for low-beta portfolios. These months are January with the average returns of 4.625 percent, December with the mean returns of 4.344 percent, February having the mean return of 2.760 percent, and April with the mean returns of 2.304 percent. We can observe from the figure that the CDF curves of the month of January and December appear on the right side as compared to the remaining months' CDFs. Thus, we predict that there may be the January or December

anomaly in low-beta portfolio returns. Therefore, similar to the case of high-beta portfolio, we consider January as a "winner" month in low-beta portfolio and formally test the dominance of the month of January by applying SD approach. In sum, Figure 2 and Figure 3 exhibit the dominance of January or February over other calendar months in high-beta portfolio and January or December in low-beta portfolio returns. We now formally test the presence of the monthly anomaly in beta-based constructed portfolios returns. First, we test the SD of January *versus* the non-January months.

Fig. 3. The CDFs of Monthly Returns of Low-Beta Based Portfolio
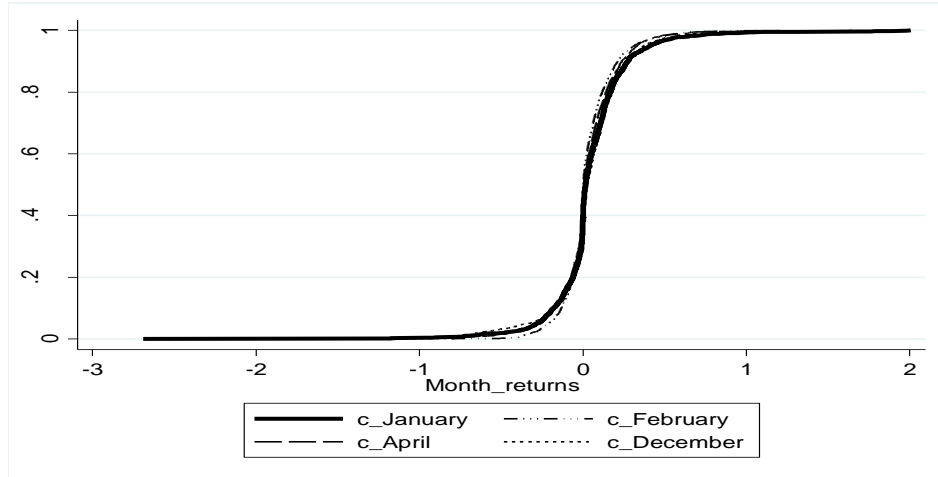
In order to confirm this preliminary observation, we apply the formal test of SD by considering January as a "winner" month. The estimated p-values for testing the stochastic dominance order are given in Table 4. We first divide the table into three main columns labelled as "High, Medium, and Low Beta Portfolios", and then each portion is further divided into two sub-panels: "January *versus* other Month", and "Other Month *versus* January". The estimated p-values of the KS type test for SD1, SD2, and SD3 are presented. The sub-panel labelled as "January *versus* other Month" states the null hypothesis that the month of January stochastically dominates over other month. On the other hand, the second sub-panel labelled as "other month *versus* January" tests the opposite hypothesis, that is, the underlying month stochastically dominates over January. For low-beta and high-beta portfolios, the p-values given in the panel "January *versus* other month" are in favour of not rejecting the null hypothesis for the all three SD orders tested in this study. This implies that the month of January dominates over other months in both high-beta and low-beta portfolios at the first, second, and third order of SD. The p-values presented in panel "Other month *versus* January" confirm the dominance of January in both portfolios.

To observe whether the January effect strongly or weakly exists, we do a comparison of the p-values for the null hypothesis with the p-values of the reverse null hypothesis. By comparing the p-values for the case of high-beta portfolios, we examine that the month of January strongly dominates over the remaining months of the year at all the three examined orders of SD.

Table 4

SD Tests for Beta-Based Constructed Portfolio: January versus Non-January Months

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	January *versus* Other Months			Other months *versus* January			January *versus* Other Months			Other Months *versus* January			January *versus* Other Months			Other Months *versus* January		
							KS P-value											
Months	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3
January	**Winner**															**Winner**		
February	0.694	0.303	0.453	0.000	0.000	0.000	0.039	0.000	0.000	0.000	0.705	0.667	0.133	0.008	0.175	0.000	0.002	0.040
March	0.969	0.521	0.442	0.000	0.000	0.000	0.195	0.000	0.063	0.000	0.000	0.000	0.977	0.520	0.431	0.000	0.000	0.000
April	0.702	0.500	0.432	0.000	0.000	0.000	0.019	0.000	0.000	0.048	0.710	0.674	0.884	0.355	0.438	0.002	0.000	0.000
May	0.851	0.415	0.440	0.000	0.000	0.000	0.099	0.000	0.001	0.000	0.000	0.000	0.915	0.385	0.404	0.000	0.000	0.000
June	0.980	0.518	0.433	0.000	0.000	0.000	0.044	0.000	0.001	0.000	0.000	0.000	0.882	0.389	0.395	0.000	0.000	0.000
July	0.939	0.363	0.402	0.000	0.000	0.000	0.016	0.000	0.000	0.000	0.706	0.671	0.759	0.276	0.401	0.000	0.000	0.000
August	0.996	0.736	0.696	0.000	0.000	0.000	0.085	0.000	0.000	0.000	0.000	0.000	0.870	0.289	0.372	0.000	0.000	0.000
September	0.872	0.283	0.363	0.000	0.000	0.000	0.007	0.000	0.016	0.000	0.566	0.674	0.748	0.115	0.283	0.000	0.000	0.000
October	0.956	0.522	0.456	0.000	0.000	0.000	0.155	0.000	0.054	0.000	0.020	0.325	0.980	0.482	0.403	0.000	0.000	0.000
November	0.944	0.456	0.413	0.000	0.000	0.000	0.077	0.000	0.019	0.000	0.000	0.160	0.769	0.160	0.329	0.000	0.000	0.000
December	0.999	0.526	0.451	0.000	0.000	0.000	0.022	0.000	0.000	0.023	0.711	0.659	0.748	0.115	0.283	0.633	0.408	0.678

Note: For each constructed portfolio, the number of comparison between any two calendar months is C(12,2) = 66. The results for only winner month "January" are   presented. The first panel namely January *versus* other months tests the null hypothesis that the month of January dominates over other calendar months. The SD1, SD2, and SD3 are the stochastic dominance orders. The p-values are calculated through the simulation method proposed by Barrett and Donald (2003).

The p-values suggest that in low-beta portfolio, the month of January strongly outperforms in all the three examined orders over the other months except December, where it weakly dominates. More specifically, the month of January weakly dominates over December at the SD2 and SD3 stochastic order. Yet, January strongly dominates over December at the first stochastic order as the p-value for January is 0.748, whereas, the corresponding figure for December is 0.633. In short, in low-beta portfolio, January strongly dominates over the rest of the months except the month of December at all the three examined SD orders, although it weakly dominates over December at the second and third order of SD.

These results support the findings of many earlier studies for many emerging and developed studies. For instance, Li and Gong (2015) have found that the January anomaly in Japan. Likewise, Wong, Neoh, Lee, and Thong (1990) and Haugen and Jorion (1996) have also documented the presence of the January anomaly in New York Stock Market. Wong, *et al.* (1990) examined the January phenomenon in Malaysia Stock Market. Our results are also in favour of Keim (1983), who has documented that the January anomaly is higher for small-sized (generally considered as risky) firms than large-sized (commonly viewed as less risky) firms. Similarly, Sum (2010) found that the January effect is high, particularly in the small-cap portfolio.

Turning to the result for medium-beta portfolio, given in "January *versus* Other Month" panel, we observe that January does not stochastically dominate over the other calendar months of the year at either examined SD order. The reported p-values are either zero or considerably less than any commonly acceptable level of significance, providing strong evidence of the rejection of the null hypothesis.

When we look at the p-values for the reverse null hypothesis, we find that in most of the cases, the null hypothesis is rejected at any acceptable level of significance. We find that for the case of first order of SD, the null hypothesis is rejected for all months except December and April. For the second order of SD, for 6 out of 11 months, the p-values provide evidence of the rejection of the constructed null hypothesis, that is, January dominates over the other months. Finally, for the third order of SD, we find

evidence in favour of the rejection of the null hypothesis for 4 months. However, one should note that the null hypothesis that December stochastically dominates over January is not rejected at either examined stochastic dominance order. This suggests that December stochastically outperforms over January in case of medium-beta portfolio. This finding is in agreement with the information provided by the CDFs presented in Figure 3. This motivates us to test the stochastic dominance of December over other calendar months in the next sub-section.

3.4. Exploring the December Effect in Medium-Beta Portfolio

In this sub-section, we investigate the December effect in returns of medium-beta portfolio. The descriptive statistics presented in Table 2 suggest that in medium-beta portfolio, on average, the returns in December (2.555 percent) are higher as compared to the remaining calendar months. Before applying the formal test for testing the stochastic dominance of the month of December, we present the CDFs of top four months ranked based on average returns. Figure 4 shows the CDFs of monthly returns of medium-beta portfolio for the top four months ranked based on their average returns over the examined period. These four months are December, April, February, and July. By doing a thorough assessment of the CDFs, we observe that the CDF of December appears on the most right side with the return of 2.555 percent and the CDF of April appears at the second position with returns of 2.182 percent. Thus, the CDFs suggest the likelihood of the presence of either the December or April effect in medium-beta portfolio returns.

Fig. 4. The CDFs of the Monthly Returns of Medium-Beta Portfolio
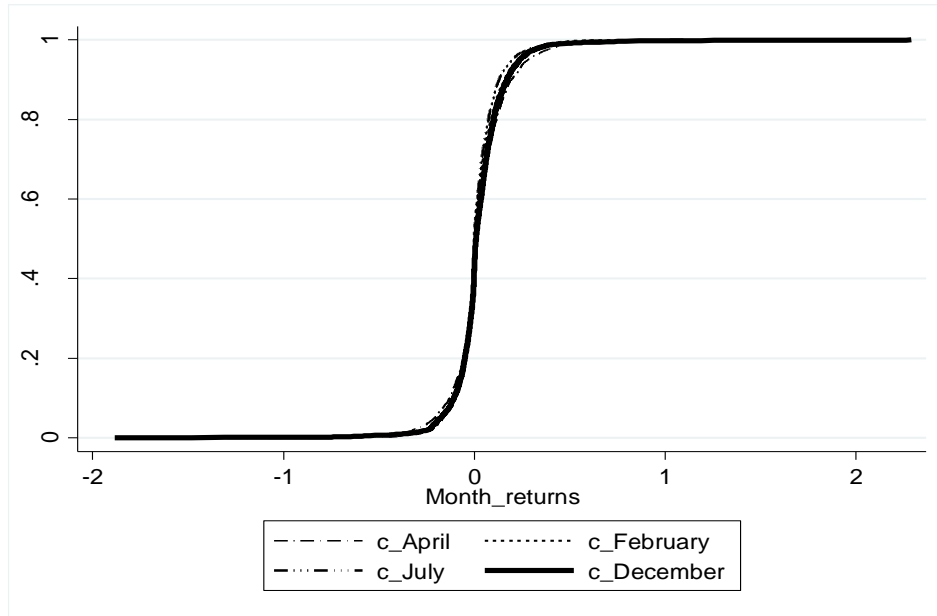
The p-values of the KS tests are presented in Table 5 for testing the SD of December. Note that the remaining attributes in Table 5 are similar to those in Table 4.

With regard to medium-beta portfolio, we find some striking results. Specifically, we find that the returns of December outperform over all remaining calendar months' returns at all the three examined SD orders. The p-values for the null hypothesis: December *versus* other months is considerably greater than the acceptable level of significance, suggesting that the null hypothesis is not rejected at the given level of significance. On the opposite side, the p-values of the null hypothesis of other months *versus* December are nearly zero in all calendar months except for April. Thus, we can conclude that December stochastically dominates over the other months of the year at all the three examined SD orders in case of medium-beta portfolio. However, we also find that April weakly dominates over December at all the three SD orders having p-values 0.032, 0.019, and 0.108, respectively. In contrast, the p-values for December are 0.0714, 0.565, and 0.510, respectively, which indicate that December is strongly dominating over the month of April.

Turning to the results for high beta and low beta portfolios, we also observe some interesting evidence. For example, in case of high-beta portfolio, the reported p-values for null hypothesis of December *versus* other month provide evidence in favour of the rejection of the null hypothesis. These results suggest that December does not stochastically dominate over other calendar months at either examined stochastic dominance order. In general, these results are confirmed by the p-values reported for the reverse null hypothesis that other month stochastically dominates over December. Yet, one should note that in some cases, the month of December stochastically dominates over the other months. For example, December stochastically dominates over June, in particular, at the first, second and the third stochastic order. Similarly, December stochastically dominates over March and July, although at only the third stochastic dominance order. It can also be observed from the table that in high-beta portfolio, the eight months namely January, February, April, May, July, September, October, and November appear to dominate stochastically over December.

For low-beta portfolio, we observe that December stochastically dominates over all other calendar months except the month of January. This evidence holds for all three examined stochastic dominance orders. Taking together the results presented in Table 4 and Table 5, we come to the conclusion based on the reported p-values that for medium-beta portfolio, the month of December is dominating over all the other calendar months, and for high-beta and low-beta portfolios, the month of January is dominating. Our results are consistent with the results of Sum (2013). The stochastic dominance of both January and December may suggest the existence of another anomaly called the turn-of-the-year (hereafter TOY) effect.[5] This evidence is in line with the several prior existing studies including Sikes (2014), Tangjitprom (2011), Ritter and Chopra (1989), and Lakonishok and Smidt (1984). However, to arrive at the final conclusion whether the TOY effect is really present in Pakistan equity market, one should formally test the phenomenon.[6]

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[5]TOY effect implies that returns are high during the month of December and January as compared to the other months.

[6]We did not do so because our focus is testing the January and December effects separately.

Table 5

SD Tests for December Month with Respect to other Month

	High Beta Portfolio						Medium Beta Portfolio						Low Beta Portfolio					
	December *versus* Other Months			Other Months *versus* December			December *versus* Other Months			Other Months *versus* December			December *versus* Other Months			Other Months *versus* December		
							KS P-value											
Months	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3	SD1	SD2	SD3
January	0.000	0.000	0.000	0.999	0.526	0.451	0.023	0.711	0.659	0.022	0.000	0.000	0.633	0.408	0.678	0.748	0.115	0.283
February	0.000	0.000	0.000	0.000	0.717	0.670	0.857	0.610	0.527	0.000	0.000	0.000	0.129	0.002	0.152	0.000	0.004	0.061
March	0.020	0.000	0.255	0.000	0.000	0.001	0.998	0.543	0.478	0.000	0.000	0.000	0.812	0.401	0.548	0.000	0.000	0.000
April	0.000	0.000	0.000	0.041	0.693	0.631	0.0714	0.565	0.510	0.032	0.019	0.108	0.505	0.177	0.487	0.000	0.000	0.000
May	0.000	0.000	0.000	0.000	0.655	0.558	0.987	0.490	0.467	0.000	0.000	0.000	0.489	0.220	0.463	0.000	0.000	0.000
June	0.200	0.012	0.282	0.000	0.000	0.000	0.926	0.284	0.401	0.000	0.000	0.000	0.631	0.269	0.460	0.000	0.000	0.000
July	0.007	0.000	0.166	0.000	0.105	0.423	0.763	0.254	0.402	0.000	0.000	0.000	0.459	0.126	0.450	0.000	0.000	0.000
August	0.013	0.000	0.435	0.000	0.000	0.000	0.955	0.439	0.581	0.000	0.000	0.000	0.518	0.121	0.397	0.000	0.000	0.000
September	0.008	0.000	0.113	0.000	0.002	0.056	0.538	0.061	0.373	0.000	0.000	0.000	0.576	0.270	0.684	0.000	0.000	0.000
October	0.009	0.000	0.040	0.000	0.092	0.539	0.996	0.480	0.434	0.000	0.000	0.000	0.695	0.319	0.496	0.000	0.000	0.000
November	0.001	0.000	0.007	0.000	0.704	0.667	0.970	0.448	0.429	0.000	0.000	0.000	0.319	0.074	0.320	0.000	0.000	0.000
December									**Winner**									

Note: For each constructed portfolio, the number of comparison between any two calendar months is C(12,2) = 66. The results for only winner month "December" are   presented. The first panel namely December *versus* other months tests the null hypothesis that the month of December dominates over other calendar months. The SD1, SD2, and SD3 are the stochastic dominance orders. The p-values are calculated through the simulation method proposed by Barrett and Donald (2003).

3.5. The January Effect in KSE-100 Index Returns

After presenting the strong evidence of monthly anomaly in firm stock returns as well as in stock returns of portfolios constructed based on the level of systemic risk, we present results for the January effect in overall Pakistan Stock Exchange (PSX).

Similar to other cases, we start by constructing CDFs. Figure 5 presents the CDFs of the top four months' KSE-100 Index returns, namely, January (1.161 percent), July (0.494 percent), June (0.427 percent), and February (0.349 percent). The figure shows that the CDF of January and July are to the most right. The graph clearly gives an indication of the January or July effect in equity market of Pakistan.

Table 6 presents the p-values of KS test for monthly returns of KSE-100 Index. In the fists panel, the p-values for the null hypothesis that January stochastically dominates over other months at the first order (SD1), the second order (SD2), and the third stochastic order (SD3) are presented. Similarly, in the second panel, the p-values for the reverse null hypothesis are presented.

Fig. 5. The CDFs of Monthly Returns of KSE-100 Index
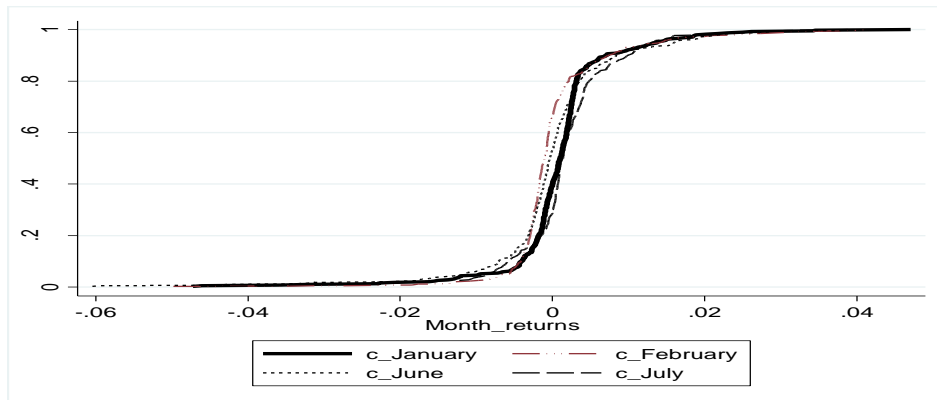
Comparing the p-values of January with other months, we observe that the month of January strongly dominates over rest of the months. In particular, the p-values reported in the first panel of the table are considerably greater than any acceptable level of significance for all the examined stochastic dominance orders. This result suggests that the null hypothesis that the month January stochastically dominates over the other calendar months is not rejected at any acceptable level of significance. The dominance of January over other months is generally confirmed by the p-values in the second panel of the table for testing the reverse null hypothesis.

Nevertheless, we find February weakly dominates over January at the second order of SD. For instance, the p-values for January *versus* February for the SD1, SD2, and SD3 of SD orders are 0.789, 0.245, and 0.366, respectively. On the other hand, the p-values for February *versus* January are 0.000, 0.013, and 0.003, respectively, showing a strong dominance of January over February at the first and third order and weak dominance of February over January at the second order of stochastic dominance.

Table 6

Stochastic Dominance of January Month in KSE-100 Index Returns

| Months | January *versus* Other Month | | | Other Month *versus* January | | |
| | KS P-value | | | | | |
	SD1	SD2	SD3	SD1	SD2	SD3
January	**Winner**					
February	0.789	0.245	0.366	0.000	0.013	0.003
March	0.726	0.533	0.489	0.000	0.000	0.000
April	0.000	0.022	0.029	0.000	0.000	0.000
May	0.974	0.455	0.471	0.000	0.000	0.000
June	0.797	0.723	0.683	0.000	0.002	0.000
July	0.001	0.069	0.036	0.000	0.000	0.000
August	0.976	0.552	0.462	0.000	0.000	0.000
September	0.926	0.288	0.359	0.000	0.000	0.000
October	0.537	0.256	0.353	0.000	0.004	0.003
November	0.936	0.347	0.367	0.000	0.000	0.000
December	0.000	0.060	0.341	0.008	0.000	0.000

Note: This table presents the results for the stochastic dominance of January in KSE-100 Index returns. The number of comparison between any two calendar months is C(12,2)=66. Winner month "January" months' results are presented only. The first panel namely January *versus* other months tests the null hypothesis that the month of January dominates over other calendar months. The SD1, SD2, and SD3 are the stochastic dominance orders. The p-values are calculated through the simulation method proposed by Barrett and Donald (2003).

The results given in Table 6 are consistent with the findings of Boudreaux (1995) for Denmark, Germany, and Norway Stock Markets, Haugen and Jorion (1996) and Haug and Hirschey (2006) for US market, Annuar (1987) for Kuala Lumpur Stock Market, Fountas and Segredakis (2002) for selected emerging market , Lean, *et al.* (2007) for Asian stock markets, and Li and Gong (2015) for Japanese equity market.

The main reasons of the January effect can be liquidity constraint, tax-loss-selling hypothesis, and omitted risk factor. Some researchers have attributed the tax-loss-selling

hypothesis as the main reason for the presence of the January effect in stock returns. For example, Branch (1977) and Wachtel (1942) explaining the large January returns argue that the year-end tax loss selling is one of the major causes of the January anomaly. The main explanation of the January effect is that individuals are likely to sell losing stocks at the end of the year to realise capital losses to avoid tax payments and repurchase them again in the month of January. Our analysis suggests that this effect appears more prominent in case of both low-risk and high-risk firms. However, for moderately risky firms, we show the presence of the December effect in stock returns.

4. CONCLUSIONS

In this study, we test monthly anomaly in Pakistan Stock Exchange. For this, we test the January effect for all publicly listed firms, beta-based portfolios, and KSE-100 Index returns by using stochastic dominance (SD) theory. By applying the KS type test of SD, we find substantial evidence of the existence of the January effect in our sample of listed firms as well as in equity market index returns. We also find that the January effect exists in both high-beta and low-beta portfolios. In contrast, the December effect exists in low-beta portfolio. The possible explanation of these results is the year-end bonuses received in January. These bonuses are generally used to purchase stocks, causing the bullish trend of stock prices in January, [Al-Saad and Moosa (2005); Shao and Hur (2016); Sun and Tong (2010)]. The size effect explains that small cap stocks outperform in the month of January [Banz (1981); Keim (1983); Rozeff and Kinney (1976)]. Furthermore, high beta stocks are more traded in January and may result in high returns [Rogalski and Tinic (1986)]. The movements in bid-ask spread can also be one of the reasons of high returns in January [Lakonishok and Smidt (1984); Ligon (1997)].

Our results have several important implications for different participants of stock market such as firms, money, and mutual fund managers, investors, academicians, researchers, and policy-makers. Our results suggest that investors may get abnormal returns by forecasting stock returns patterns and designing their investment strategies by taking into account the January and December effects. Our findings are also of significance to portfolio managers in order to get portfolio diversifications. Based on the findings we present here, we suggest that Security and Exchange Commission of Pakistan should instruct the firms to explicitly report sufficient and necessary information in their financial reports, which lessens information asymmetries and in turn, helps in improving market efficiency. We test the monthly anomaly at PSX firms on the basis of systemic risk firms. However, our study can be extended by examining the monthly calendar anomalies based on other firm-specific characteristics such firm size, growth, the market value of firms, the level of leverage, etc. Moreover, testing calendar anomalies in commodity or derivative market can also help enhance our understanding of market anomalies.

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