Calendar anomaly: unique evidence from the Indian stock market
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Abstract
Purpose – The purpose of this paper is to ascertain the monthly seasonality in the Indian stock market after taking into consideration the market features of leptokurtosis, volatility clustering and the leverage effect.
Design/methodology/approach – Augmented Dickey-Fuller, Phillips-Perron and Kwiatkowski-Phillips-Schmidt-Shin tests are deployed to check stationarity of the series. Autocorrelation function, partial autocorrelation function and Ljung-Box statistics are employed to check the applicability of volatility models. An exponential generalized auto regressive conditionally heteroskedastic model is deployed to test the seasonality, where the conditional mean equation is a switching model with dummy variables for each month of the year.
Findings – Though the financial year in India stretches from April to March, the stock market exhibits a November effect (returns in November are the highest). Cultural factors, misattribution bias and liquidity hypothesis seem to explain the phenomenon.
Research limitations/implications – The paper endeavors to provide a review of possible explanations behind month-of-the-year effect documented in literature in the past four decades. Further, the unique evidence from the Indian stock market supports the argument in the literature that monthly seasonality, by nature, may not be a consistent/robust phenomenon. Therefore, it needs to be examined from time to time.
Originality/value – As the seasonality in the stock market and resultant anomalies are dynamic phenomena, the paper reports the current seasonality/anomalies prevalent in the Indian market. This would aid investors in designing short-term investment portfolios (based on anomalies present) in order to earn abnormal returns.

Keywords Market efficiency, Indian stock market, Calendar anomaly, November effect, Volatility models

1. Introduction
Jamie Dimon, Chairman of JP Morgan, identified the Indian economy as the “sole bright spot” in the ongoing period of global uncertainty. He stated that India was the world’s fastest growing country and had good prospects over the coming few decades (The Economic Times, 2016c). In today’s time of global market integration, this aspect warrants an investigation into the Indian stock market efficiency, which is the purpose of this paper.

The tendency of financial asset returns to exhibit systematic patterns at certain calendar times is referred to as the calendar anomaly (Brooks, 2014). This seasonality can offer the investors the chances to earn extraordinary returns (Jacobs and Levy, 1988). The aim of this paper is to test the presence of the month-of-the-year effect in the Indian stock market. This refers to the systematic patterns observed across different months of the year.

While the literature is rife with the evidences of the January effect, the Indian stock market exhibits signs of the November effect – which is appealing due to the fact that the financial year in India runs from April to March.

For better exposition, the paper presents a section on the literature review (Section 2). Section 3 explains the data and the methodology employed. The analysis is presented in Section 4, while the conclusion forms Section 5 of the paper.
2. Literature review

The earliest evidences of seasonality in the stock markets date back to 1940s. Wachtel (1942) stated that the earliest signs of seasonality could be observed only in the post-1926 data. He recorded instance of significant rise in the DJIA index from December to January. Ever since, there have been studies on various calendar patterns – day-of-the-week effect, month-of-the-year effect, Halloween effect, holiday effect, semi-month effect, turn-of-the-month effect (Smirlock and Starks, 1986; Thaler, 1987a,b; Lakonishok and Smidt, 1988; Barone, 1990; Agrawal and Tandon, 1994; Balaban, 1995; Al-Khazali et al., 2008; Floros, 2008; Philpot and Peterson, 2011; Compton et al., 2013; Wang et al., 2013; Sharma and Narayan, 2014; Patel and Sewell, 2015; Jaisinghani, 2016). However, there are studies that could not detect any seasonal pattern (Zinbarg and Harrington, Jr, 1964; Dyl and Maberly, 1988; Cheung and Coutts, 1999). Studies have also reported that the seasonal patterns did not exist all the time. While Mehdian and Perry (2002), Wong et al. (2006), Lean et al. (2007) reported that the seasonal pattern (the January effect) had been fading, Easterday et al. (2009) had reported its persistence. Zhang and Jacobsen (2013) reported that the monthly seasonalities had been sample specific.

As already stated, the aim of this paper is to test the presence or absence of the month-of-the-year effect in the Indian stock market. Whether there is in the past on the Indian stock market, Hamid and Dhakar (2003) reported that the seasonality did not remain consistent over time. With this paper, the authors aim to report the current state of the market efficiency. Moreover, the paper endeavors to go beyond most of the previous studies on the Indian market and tries to explain the probable reason behind the seasonality.

A plethora of research in the past has documented that the month-of-the-year effect exhibits itself in the form of higher returns in January (Keim, 1983; Reinganum, 1983; Jaffe and Westerfield, 1985; Pettengill, 1986; Aggarwal and Rivoli, 1989; Wilson and Jones, 1993; Agrawal and Tandon, 1994; Mills and Coutts, 1995; Ligon, 1997; Asteriou and Kavetsos, 2006; Floros, 2011; Beyer et al., 2013). This phenomenon has been so prevalent that the month-of-the-year effect is often referred to as the “January effect” in the literature. The January effect had also been reported to be causing other anomalies like the size effect, the value effect, the contrarian and the momentum effects (Keim, 1983; Reinganum, 1983; Blume and Stambaugh, 1983; Hawawini and Keim, 1998; Yao, 2012). There is yet another phenomenon termed as the “other January effect” that measures the predictive power of the January returns for the returns of other months (Bohl and Salm, 2010).

Over the past, several likely explanations have been documented for the month-of-the-year-effect, many of which are developed in the context of the January effect. They are summarized below.

**Tax-loss selling hypothesis**

This is one of the argued explanation for the month-of-the-year effect (Jones et al., 1987; Chen and Chan, 1997; Al-Saad and Moosa, 2005). This refers to the practice of selling of stocks at the financial year-end to record losses, which helps in reducing the tax burden. As the new financial year begins and the heavy selling stops, prices regain their initial levels. This gets reflected in the form of higher returns in the first month of the financial year.

Authors who have advocated this hypothesis include Dyl (1977), Keim (1983), Reinganum (1983), Johnston and Cox (1996), Ligon (1997), Sias and Starks (1997), Pandey (2002) and Chen and Singal (2004). However, Keim (1983) argued that with the arbitrage opportunity to enter markets with non-taxable investors, the ability of this hypothesis to explain the January effect had been decreasing. Reinganum (1983) argued that not all of the January effect could be attributed to the tax-loss selling because the January effect had been observed even for the portfolios that had been least likely to undergo tax-loss selling.
Authors who could not obtain evidence in support of this hypothesis include Chan (1986), Pettengill (1986), Tinic et al. (1987), Jones et al. (1987), Lee (1992), Raj and Thurston (1994), Fountas and Segredakis (2002), Mehdian and Perry (2002) and Zhang and Jacobsen (2013). Tinic et al. (1987) quoted Constantinides (1984) that the rational investors would not wait till the year-end to undertake tax-loss selling. Gultekin and Gultekin (1983) reported evidences showing seasonality to be in line with the tax year, but they stated that it did not imply cause and effect relationship. Agrawal and Tandon (1994) reported that while the pattern in some countries could be explained by this hypothesis, it was not supported by all the countries.

Apart from tax-loss selling at the year-end, Wachtel (1942) contended one more reason that induced heavy selling at the year-end: the need for cash before Christmas.

**Parking the proceeds hypothesis**
It was proposed by Ritter (1988) and he contended it to be a generalization of the tax-loss selling hypothesis. He argued that after engaging in the tax-loss selling at the year-end, the investors park their proceeds for some time and re-enter the market in the new year. As the investors under consideration are individuals, they invest in low priced stocks and hence their buying and selling affects the prices.

**Tax-gain selling hypothesis**
Similar to the concept of tax-loss selling that is applicable to the loser stocks, tax-gain selling could be applicable to the winner stocks. Also called the December effect, this is explained as the rise in the prices of winner stocks in December caused by the investors’ intention to postpone their sale till January to postpone payment of capital gains taxes by one year.

Chen and Singal (2003) contended that while the tax-loss selling was the most appropriate explanation for the January effect, tax-gain hypothesis was for the December effect.

**Information hypothesis**
According to this hypothesis, January is associated with the release of important financial information. Hence, it is the period of increased uncertainty and anticipation. This phenomenon makes January different from other months of the year, and could be a possible reason for the January returns being different from the returns of other months.

Rozeff and Kinney (1976) argued it to be one possible explanation even though they did not conduct an independent investigation into the same.

Authors who could not get evidence supporting this hypothesis include Keim (1983), Gultekin and Gultekin (1983), Chen and Singal (2003) and Henker and Paul (2012). Keim (1983) perceived the recurrence of this pattern every year as irrational.

The information hypothesis can also be studied through two other aspects:

1. **Pre-budget rally**: this seems to be an explanation more suitable for the Indian market where the announcement of the annual budget by the central government is a very important event and makes an impact on the stock markets as well (The Economic Times, 2016b). Parikh (2009) discovered significantly higher December returns and argued it to be caused by the leaking of budget related information that begins during December-January.

2. **Macroeconomic news announcement hypothesis**: another related concept to this hypothesis is the announcements of the macroeconomic news. Gerlach (2007) reported that the January effect was stronger when the days of the macroeconomic news announcements formed part of the study sample. Nikkinen et al. (2007) contended this hypothesis as an explanation for other calendar anomalies.
Window dressing hypothesis (portfolio rebalancing hypothesis)
This hypothesis states that the December/January effect could be caused by the practice of window dressing by institutional investors at the year-end. While the institutional investors held riskier stocks throughout the year in anticipation to earn higher returns, they juggled their portfolios and held safer stocks at the year-end before disclosing them to the public. They also got rid of loss making stocks to present a good picture to the public. A confirmation of window dressing hypothesis would imply that the seasonality is caused primarily by the institutional investors (Henker and Paul, 2012).


On the other hand, Ligon (1997), Mehdian and Perry (2002) and Chen and Singal (2003) did not obtain supportive evidence to this hypothesis. Sias and Starks (1997) contended that the tax-loss selling hypothesis was more important than the window dressing hypothesis.

Liquidity hypothesis
According to this hypothesis, higher returns are experienced in the periods when the investors have extra funds at their disposal, which they invest in the market.

Authors who reported evidences in favor of this hypothesis include Ogden (1990), Ligon (1997), Ignatius (1998), Booth et al. (2001), Parikh (2009), Beyer et al. (2013) and Sharma and Narayan (2014).

Optimistic expectations hypothesis
According to this hypothesis, returns are higher when the investors have optimistic expectations about the nearby future prospects.

Wachtel (1942) contended that the higher returns at the turn-of-the-year could partly be explained by the investors’ expectations of better business prospects in the upcoming spring. Ciccone (2011) contended that turn-of-the-year was a period of renewed optimism. He associated it with the ‘false hope syndrome’ and argued that it partly explained the January effect. Sakakibara et al. (2013) also acknowledge the optimism induced at the beginning of a new year.

Summer holiday effect
According to this hypothesis, a surge in the market returns was observed in the time before the investors left for long summer holidays. This might be because of the tendency of the investors to invest their idle cash in the market and also rebalance their portfolios before leaving for the holidays.

Al-Saad and Moosa (2005) contended this as an explanation for the observed July effect.

Risk measurement hypothesis
According to this hypothesis, risk is not consistent across the year, and higher returns in certain months of the year are compensation for the underlying higher risks.

Rogalski and Tinic (1986), Barone (1990) and Khaksari and Bubnys (1992) reported evidence in support of this explanation. Rozeff and Kinney (1976) reported results that partially supported this hypothesis.

Officer (1975) and Chen and Chien (2011) did not report evidence in support of this hypothesis.

Varying opportunity cost of capital
Officer (1975) stated that the seasonality in the opportunity cost of capital might cause the seasonality in returns. Opportunity cost of capital might, in turn, be affected by the fiscal and monetary policies.
Cultural factors
Chan et al. (1996) stated that the seasonality was also caused by cultural factors. As the culture varied across different economies, different seasonality had been reported for different economies. Chen and Chien (2011) also argued in favor of the role of culture on the stock market.

Others
Keim (1983) also suggested some non-economic factors that could lead to the finding of the month-of-the-year effect, for example:

- outliers;
- more instances of listing and de-listing at the year-end;
- errors in databases. However, Reinganum (1983) refuted this argument;
- survivorship bias. However, this argument is not valid when a study is conducted at the index level; and
- bias induced by rebalancing portfolios every year-end. However, this argument is not valid when a study is conducted at the index level.

Anomalies, by nature, may not be a consistent phenomenon and therefore literature is rife with inconsistent findings regarding anomalies with respect to time and market. Similar nature of findings are reported in this recent commentary on anomalies in the Indian stock market.

3. Data and methodology

Data
The study is conducted at an index level as Officer (1975) reported that it might be difficult to detect any seasonal pattern at the stock level. The study is based on returns calculated using monthly closing prices of the Nifty 500 Index rather than daily[1], which represents the top 500 companies from 73 industries, and hence is considered a fair representative of the Indian stock market. As on March 31, 2016, the index constituents captured about 94 percent of the free float market capitalization of all the National Stock Exchange (NSE) listed companies (National Stock Exchange of India Limited, 2016). The study period stretches from June 1999 to September 2015. Based on availability of data, this is the maximum period for which this study could be done. The data is taken from a financial database Ace Equity®. All the analysis is performed using financial software EViews 9.5®.

Objective
As already stated, the objective of the paper is to test the presence of month-of-the-year effect in the Indian stock market. For this, the following hypothesis has been proposed:

Null hypothesis: There is no month-of-the-year effect in the Indian stock market.
Alternate hypothesis: There is presence of month-of-the-year effect in the Indian stock market.

Methodology
Before testing for the seasonality, the study tests the stationarity of the series, which is imperative to be examined in order to understand its properties and behavior (Brooks, 2014).

First, stationarity of the price series is checked. As it is observed to be non-stationary, a corresponding returns series is computed as follows:

\[ r_t = \ln \left( \frac{p_t}{p_{t-1}} \right) \]  
(1)
where \( r_t \) is the return at time \( t \), \( \ln \) represents the natural log, \( p_t \) and \( p_{t-1} \) are the closing prices at time \( t \) and \( t-1 \), respectively. As the returns series is detected to be stationary, all the analysis is performed on this stationary series.

A series is said to be stationary (in the weak form; or covariance stationary) if it exhibits the following three properties:

1. a constant mean (\( \mu \));
2. a constant variance (\( \sigma^2 \)); and
3. a constant covariance structure (\( \gamma_s \)).

While there are two types of non-stationarity – deterministic and stochastic – most of the financial time series, if not stationary, exhibit stochastic non-stationarity (Brooks, 2014). Hence, the paper focuses only on testing the stochastic non-stationarity.

If, for the equation:

\[
Y_t = C + \varphi Y_{t-1} + u_t
\]

where \( C \) is a constant and \( u_t \) is a white noise error term, the value of \( \varphi = 1 \), the series \( Y_t \) is said to be non-stationary, or, in other words, is said to have a unit root. In a stationary series, \( \varphi < 1 \).

The paper employs both the unit root tests (Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test) as well as the test for stationarity (Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test). These tests are considered an improvement over the Dickey-Fuller (DF) test. The DF test is based on the equation:

\[
Y_t = \varphi Y_{t-1} + u_t
\]

Subtracting \( Y_{t-1} \) from both the sides:

\[
\Delta Y_t = \psi Y_{t-1} + u_t
\]

where \( \Delta Y_t = Y_t - Y_{t-1} \); \( \psi = \varphi - 1 \)

The test examines the null hypothesis that the series has a unit root, that is, \( \varphi = 1 \) or \( \psi = 0 \).

The ADF test further augments the DF test with \( p \) lags of \( \Delta Y_t \), the underlying equation becomes:

\[
\Delta Y_t = \psi Y_{t-1} + \sum_{i=1}^{p} a_i \Delta Y_{t-1} + u_t
\]

The maximum value of lag \( p \) in the study is set as 12 as the data has monthly frequency.

The PP test further adjusts for the possible autocorrelation in the residuals.

The KPSS test, when employed along with the aforementioned tests, works as a tool for confirmatory data analysis: while the ADF and the PP tests have a null hypothesis that the series has a unit root, KPSS on the contrary, has a null hypothesis that the series is stationary.

EViews determines the value of \( p \) based on Schwarz’s Information Criteria (SIC). The model that minimizes the value of the information criteria is chosen. The objective is to ensure employment of a parsimonious model. Under SIC, the value is calculated as follows:

\[
SIC = \frac{k}{T} \ln T + \ln \left( \frac{RSS}{T} \right)
\]
where \( k \) is the number of parameters in the model; \( T \) is the number of observations; and RSS is the residual sum of squares of the model.

A non-stationary series can be converted into a stationary series by differencing, that is, by creating a change series from the original series (Tsay, 2005). The number of times a series needs to be differenced determines its order of integration. If a series is integrated of order \( d \), i.e., \( Y_t \sim I(d) \), it requires to be differenced \( d \) times to induce stationarity. The differenced series is integrated of order zero, i.e., \( \Delta^d Y_t \sim I(0) \). Further analysis is to be performed only on a stationary series.

Now, to test for the seasonality in the series, a switching model is employed wherein the switches are in the form of dummy variables, and are deterministically determined based on the months of the year. The regression equation is as follows:

\[
rt = \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + \gamma_4 D_{4t} + \gamma_5 D_{5t} + \gamma_6 D_{6t} + \gamma_7 D_{7t} + \gamma_8 D_{8t} + \gamma_9 D_{9t} + \gamma_{10} D_{10t} + \gamma_{11} D_{11t} + \gamma_{12} D_{12t} + ut
\]  

(7)

where \( r_t \) is the underlying stationary series and \( D_{1t} \) to \( D_{12t} \) are the dummy variables for each month of the year. To avoid the problem of dummy variable trap, the regression is applied without an intercept term.

However, financial data have been commonly found to exhibit properties such as leptokurtosis, volatility clustering, and leverage effect (Brooks, 2014). A data set is said to be leptokurtic if it contains more extreme values, evident in the form of fat tails when presented graphically. Volatility clustering means that certain periods exhibit high volatility while other periods exhibit low volatility. Leverage effect refers to the tendency of the volatility to react differently to price rises and price falls of the same magnitude. These properties warrant the employment of non-linear models.

Hence, it is desirable to test if the data requires the model to account for non-linearity. Tsay (2005) states that if a series does not exhibit serial correlation but is still serially dependent; the dependence could be captured using the volatility models.

To test for serial correlation in the series, autocorrelation function (ACF or correlogram), partial autocorrelation function (PACF) and Ljung-Box test statistic are employed. The ACF is a graphical representation of autocorrelations for different lags \( s = 1, 2, 3, \ldots \). The PACF measures the correlation between an observation at time \( t \) and at time \( t-s \), after controlling for the effects of the intermediary observations. Ljung-Box test statistic enables to test whether the autocorrelations upto lag \( m \) are jointly insignificant. The test statistic is calculated as follows:

\[
Q = T \sum_{s=1}^{m} \frac{\tau_s^2}{T-s} \tag{8}
\]

where \( \tau_s \) represents autocorrelation coefficient for lag \( s \).

The presence of serial dependence in the series is tested by employing the ACF, the PACF and the Ljung-Box test statistic on the absolute and the squared values of the underlying series.

The most commonly employed volatility models in the field of finance are the Auto Regressive Conditionally Heteroskedastic (ARCH) models.

Under the models of ARCH family, there are two equations: the conditional mean, and the conditional variance of the error term of conditional mean.

ARCH model: for the ARCH(1) model, the conditional variance equation is as follows:

\[
\sigma_t^2 = \sigma_0 + \sigma_1 u_{t-1}^2 \tag{9}
\]
where $\sigma_t^2$ is the conditional variance of the error term $u_{t-1}^2$ is the lagged squared error term. Here, the conditional variance of the error term depends on the lagged value of the error term. This model is generalizable to ARCH($q$) by including squared error terms up to $q$ lags.

Generalized ARCH (GARCH) model: besides being more parsimonious than the ARCH model, the GARCH model also overcomes some of its limitations. For the GARCH (1, 1) model, the conditional variance equation is as follows:

$$\sigma_t^2 = \omega_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2$$

Here the conditional variance of the error term depends on the lagged value of the error term as well as its own lagged value. Similar to the lines of ARCH ($q$) model, this model is generalizable to GARCH ($p$, $q$) model by including squared own lags up to $p$ terms and squared error terms up to $q$ lags. However, Brooks (2014) states that a model higher than GARCH (1, 1) order is rarely required in the field of finance.

Exponential generalized auto regressive conditionally heteroskedastic (EGARCH) model: an improvement over the GARCH model, an EGARCH model also accounts for the leverage effect in the data. The conditional variance equation is as follows:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{|u_{t-1}|}{\sigma_{t-1}^2} + \alpha \left[ \frac{u_{t-1}}{\sigma_{t-1}^2} \right]$$

Parameters of the model are estimated on the basis of quasi-maximum likelihood technique. It involves finding the most likely values of the parameters, using an iterative process, which would generate the underlying data.


4. Analysis

Table I summarizes the tests for stationarity of the monthly closing prices. The $p$-values for both the ADF test (0.934) and the PP test (0.917) exhibit that the test statistics are insignificant at the 1 percent level. This indicates that the null hypothesis that the series has a unit root cannot be rejected. Further, the KPSS test with a test statistic

<table>
<thead>
<tr>
<th>Test</th>
<th>Test statistic</th>
<th>$p$-value</th>
<th>Comment</th>
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</thead>
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<tr>
<td>Closing prices</td>
<td></td>
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</tr>
<tr>
<td>ADF test</td>
<td>-0.208</td>
<td>0.934</td>
<td>$H_0$ not rejected</td>
</tr>
<tr>
<td>PP test</td>
<td>-0.330</td>
<td>0.917</td>
<td>$H_0$ not rejected</td>
</tr>
<tr>
<td>KPSS test</td>
<td>1.589</td>
<td>critical value</td>
<td>$H_0$ rejected</td>
</tr>
</tbody>
</table>

| Returns    |                |           |                  |
| ADF test    | -13.504        | 0.000     | $H_0$ rejected   |
| PP test     | -13.544        | 0.000     | $H_0$ rejected   |
| KPSS test   | 0.074          | critical value | $H_0$ not rejected |

Notes: ADF Test $H_0$: the series has a unit root; PP Test $H_0$: the series has a unit root; KPSS Test $H_0$: the series is stationary.
(1.589) higher than the critical value at the 1 percent level (0.739), rejects the null hypothesis of a stationary series.

Now, as already stated, a first-difference series (returns series) is calculated as the log-price differentials to convert the price series into a stationary series. Table I summarizes the results for the returns series. The ADF test and the PP test (with \( p \)-values = 0.000) reject the null hypothesis that the series has a unit root. The KPSS test (with test statistic 0.074 < critical value 0.739) could not reject the null hypothesis that the series is stationary.

Thus, the confirmatory data analysis indicates that while the monthly closing prices series is not stationary, the returns series exhibits stationarity. This implies that the closing price series is integrated of order 1 (\( Y_t \sim I(1) \)), whereas the returns series is integrated of order 0 (\( \Delta Y_t \sim I(0) \)). Hence, the further tests are conducted on the monthly returns series. Figure 1 demonstrates the graphical representation of the two series over time.

Figure 1. Monthly closing prices and monthly returns.

Notes: (a) Closing prices; (b) returns
The next step is to test if there is non-linearity in the returns series that needs to be taken into consideration for the choice of the model. While Figure 2 summarizes the descriptive statistics of the series, Figure 3 and Table II capture the aspects of serial correlation and serial dependence.

The descriptive statistics (Figure 2) reports a kurtosis of 5.193. The value, being greater than 3, indicates that the returns series is leptokurtic (Brooks, 2014).

Figure 3 depicts the ACF and the PACF of three series: the returns, the squared returns and the absolute returns, upto 12 lags. The dotted vertical lines depict significance at the 5 percent level. For the returns series, the ACF or the PACF are not significant at any lag. This result is in sync with the one reported by Gultekin and Gultekin (1983) where the autocorrelation upto 12 lags were not significant for most of the countries. However, the ACF and PACF are significant for both the squared returns and the absolute returns series.

Table II reports the Ljung-Box test statistic (called the $Q$-stat) for the three series upto 12 lags. While the null hypothesis of no autocorrelation jointly upto 12 lags could not be rejected for the returns series, it is rejected for the other two at 1 percent level. This supports the findings of the Figure 3.

Together, the figures and the tables lead to the conclusion that while there is no serial correlation in the monthly returns series, it still fails to exhibit serial independence. The finding favors the employment of the volatility model.

![Figure 2. Histogram and descriptive statistics of monthly returns](image1)

![Figure 3. Autocorrelation and partial autocorrelation statistics of monthly return, monthly squared returns and monthly absolute returns](image2)
Table III presents the results of the EGARCH model. The conditional mean equation is a dummy variable regression equation, which is further augmented with a second equation for the conditional variance of the residuals. The results depict that on an average, November yields the highest returns of 3.4 percent per month. With a test statistic of 2.155 (p-value 0.031), the returns are statistically significant at 5 percent level. While the average returns are negative in January, February and March, and positive in rest of the months, none of them appear to be statistically significant at the 5 percent level.

Thus, the null hypothesis of no month-of-the-year effect gets rejected and it can be argued that the Indian stock market does exhibit monthly seasonality in returns in the form of the November effect. This is intriguing, given the fact that the literature in general reports the evidence of January effect. This is further more intriguing because the financial year in India stretches from April to March.

### Table II. Ljung-Box Q-stat of monthly returns, monthly squared returns and monthly absolute returns

<table>
<thead>
<tr>
<th>Lags</th>
<th>Returns</th>
<th>Squared returns</th>
<th>Absolute returns</th>
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<td>2.554</td>
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<td>6.641</td>
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</tbody>
</table>

Comment: $H_0$: not rejected $H_0$: rejected $H_0$: rejected

Note: $H_0$: No autocorrelation

Table III. The EGARCH model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>z-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean equation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D1 (JANDUM)</td>
<td>−0.004</td>
<td>−0.188</td>
<td>0.851</td>
</tr>
<tr>
<td>D2 (FEBDUM)</td>
<td>−0.003</td>
<td>−0.187</td>
<td>0.852</td>
</tr>
<tr>
<td>D3 (MARDUM)</td>
<td>−0.005</td>
<td>−0.297</td>
<td>0.767</td>
</tr>
<tr>
<td>D4 (APRDUM)</td>
<td>0.003</td>
<td>0.205</td>
<td>0.838</td>
</tr>
<tr>
<td>D5 (MAYDUM)</td>
<td>0.010</td>
<td>0.455</td>
<td>0.649</td>
</tr>
<tr>
<td>D6 (JUNDUM)</td>
<td>0.014</td>
<td>1.006</td>
<td>0.315</td>
</tr>
<tr>
<td>D7 (JULDUM)</td>
<td>0.003</td>
<td>0.287</td>
<td>0.774</td>
</tr>
<tr>
<td>D8 (AUGDUM)</td>
<td>0.006</td>
<td>0.350</td>
<td>0.727</td>
</tr>
<tr>
<td>D9 (SEPDM)</td>
<td>0.028</td>
<td>1.772</td>
<td>0.076</td>
</tr>
<tr>
<td>D10 (OCTDUM)</td>
<td>0.015</td>
<td>0.789</td>
<td>0.430</td>
</tr>
<tr>
<td>D11 (NOVDUM)</td>
<td>0.034</td>
<td>2.155</td>
<td>0.031</td>
</tr>
<tr>
<td>D12 (DECDUM)</td>
<td>0.026</td>
<td>1.791</td>
<td>0.073</td>
</tr>
<tr>
<td>Variance equation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\omega$</td>
<td>−0.453</td>
<td>−1.957</td>
<td>0.050</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.287</td>
<td>2.780</td>
<td>0.005</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.018</td>
<td>0.232</td>
<td>0.817</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.957</td>
<td>24.546</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Calendar anomaly
While the evidence of the November effect had been reported in the past (He and He, 2011), it had been for the US stock market and contended to be a reaction to the implementation of the Tax Reforms Act.

The findings of the paper are similar to the findings of Chakrabarti and Sen (2008) who reported a November effect in India. The findings are in contrast with the findings of Ignatius (1998) who reported a December effect; Pandey (2002) who reported January effect; Selvarani and Jenefa (2009) who reported strong April and January effect; Jaisinghani (2016) who reported weak evidence of positive April and December effect and strong evidence of positive September effect. Sehgal and Tripathi (2005), Bodla and Jindal (2006) and Singh (2014) reported no evidence of monthly seasonality in the Indian stock market.

The possible reasons for the discrepancy in the findings of different authors could be difference in the study period as well as the methodology employed (Khaksari and Bubnys, 1992). As Zhang and Jacobsen (2013) also put it, monthly seasonality could not be observed consistently across different sample periods of reasonable lengths and across different methodologies. Bhardwaj and Brooks (1992) contended that the lack of persistence of the seasonality pattern had been a deterring factor for the investors to capitalize on it.

The possible explanations for the exhibition of such pattern can be enumerated as follows.

Cultural factors (Diwali effect)

Diwali is one of the most celebrated festivals in India. Though originally a festival of Hindus, now-a-days it is celebrated widely across different communities in India and other countries. It is usually observed in October end or in November. Many Indians associate the celebration of Diwali as the beginning of their New Year (Daily News and Analysis, 2014). While Diwali marks the beginning of New Year for Jains (Jasvant and Mehta, 2016), Gujarati New Year begins a day after Diwali (The Economic Times, 2015). Across the world, Diwali is reported to mark the beginning of a new financial year for Indian businesses (CNN, 2014). In the USA, Diwali is increasingly being identified as the Indian New Year (Khandelwal, 2002).

Studies in the past have reported that the returns in the stock markets are not driven solely by rational and financial aspects, but there are behavioral and emotional biases involved (Brahmana et al., 2012). Studies in the past on issues like Friday the thirteenth (Kolb and Rodriguez, 1987; Lucey, 2001; Auer and Rottmann, 2014); lucky numbered days (Haggard, 2015); football world cups (Kaplanski and Levy, 2014) further support the argument. Besides, Shiller (1998) in his discussion paper contended that one possible explanation for the January effect could be the human behavior to perceive New Year as a new beginning. Anderson et al. (2007) conducted a laboratory experiment and concluded that subconscious psychological factors drove the January effect.

One probable explanation for the November effect could be the positive mood of the investors which is infused by the festival. The stock market behavior is affected by the mood of the investors has been documented before by Jacobsen and Visaltanachoti (2009), Ariss et al. (2011) (investors’ mood hypothesis); Bakar et al. (2014) (the blue Monday hypothesis). The impact of Diwali on the mood of the Indian market is also evident in the practice of the e-commerce retailers like Amazon and Flipkart who make special arrangements ahead of the festival (The Economic Times, 2016a).

This argument is also supported by the misattribution bias. It refers to the tendency of a decision maker to misattribute her/his mood to the decision making. This implies that the same situation can be assessed differently in different moods. This bias has been reported to be applicable to economic decision making as well (Nofsinger, 2005).

This upshot of Diwali in India could also be put forth as a corollary argument for the observation of January effect soon after the Christmas (the festival of Christians). Wachtel (1942) supported this argument. Zhang and Jacobsen (2013) also argued in favor of the Christmas hypothesis. Returns in the holy month of Ramadan (the festival of Muslims)
being higher that the rest of the months has also been documented before by Al-Hajieh et al. (2011) and Bialkowski et al. (2013). Ke et al. (2014) had documented the Spring Festival effect. On the similar lines, Sakakibara et al. (2013) had reported “Dekansho-bushi” effect.

**Liquidity hypothesis**

Most of the employers in India announce their annual bonus at the time of Diwali (Govindarajan, 2016). Besides, people also save their earnings throughout the year for the festive eve (Parikh, 2009). This leads to large funds available at the investors’ disposal. This could be another probable explanation for the November effect.

Supportive evidence to these probable explanations had been provided by Parikh (2009) who argued that this festive season and the extra cash-in-hand regenerated the Indian economy in general, boosted consumer demand and hence the industrial production, and induced a positive mindset for the investors in the stock market. Similar argument had been presented before by Ogden (1990).

Chen and Chien (2011) contended that the increased liquidity also made the investors less risk averse.

In addition, the need for cash on the eve of Diwali could also induce investors to exit the stock market, thereby lowering the returns in the month of the exit (probably October). The lower prices in October, when used as a base for calculating November returns, could get exhibited in the form of higher November returns.

**Validation**

To validate the findings, following analysis is undertaken.

**Two-month period analysis.** As the date of Diwali celebration is decided on the basis of Hindu calendar, it varies every year as per the Gregorian calendar. Every year, it falls either in October or November. Therefore, further analysis is carried based on six two-month periods every year, treating October and November as one period. Results, as reported in Table IV, depict that the average return generated in November-end is 5.3 percent per two months. This, along with other periods, accounts to be statistically significant.

**Analysis based on daily data.** Further, a graphical analysis of daily closing values of the index for days around Diwali is undertaken[5]. However, as is evident from Figure 4, only certain cases show a rise whilst the others show decreasing trend. Over the period under study, the index exhibits a rising trend post-Diwali in ten years.

**Analysis of trading strategy.** The paper tests the trading strategy of buying at the end of other months of the year, and selling at the end of November. The results are reported in

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>z-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean equation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DEC + JAN DUM</td>
<td>0.063</td>
<td>221.792</td>
<td>0.000</td>
</tr>
<tr>
<td>FEB + MAR DUM</td>
<td>0.043</td>
<td>3.409</td>
<td>0.001</td>
</tr>
<tr>
<td>APR + MAY DUM</td>
<td>0.003</td>
<td>0.204</td>
<td>0.838</td>
</tr>
<tr>
<td>JUN + JUL DUM</td>
<td>0.027</td>
<td>0.943</td>
<td>0.346</td>
</tr>
<tr>
<td>AUG + SEP DUM</td>
<td>0.038</td>
<td>2.045</td>
<td>0.041</td>
</tr>
<tr>
<td>OCT + NOV DUM</td>
<td>0.053</td>
<td>3.084</td>
<td>0.002</td>
</tr>
<tr>
<td><strong>Variance equation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\omega$</td>
<td>−8.828</td>
<td>−3.9E+102</td>
<td>0.000</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>0.918</td>
<td>10.176</td>
<td>0.000</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>−0.825</td>
<td>−1928.157</td>
<td>0.000</td>
</tr>
<tr>
<td>$\beta$</td>
<td>−0.832</td>
<td>−16.643</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Table IV. Two-month period analysis: the EGARCH model

Calendar anomaly
Table V and exhibit that the returns are positive with respect to all the months of the year, with average being 7.00 percent.

**Analysis at sector level.** Further, analysis is conducted on nine sectoral indices of the NSE and results are reported in Table VI. As is evident, along with other months, statistically significant returns are exhibited in November by five indices – bank (4.8 percent per month), finance (4.2 percent per month), FMCG (3.2 percent per month), IT (7.5 percent per month) and pharma (2.9 percent per month). With reference to another calendar anomaly (turn-of-the-month effect), Sharma and Narayan (2014) reported that the effect varied from firm to firm depending upon their sectors.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Average returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy Dec Sell Nov</td>
<td>0.076</td>
</tr>
<tr>
<td>Buy Jan Sell Nov</td>
<td>0.085</td>
</tr>
<tr>
<td>Buy Feb Sell Nov</td>
<td>0.082</td>
</tr>
<tr>
<td>Buy Mar Sell Nov</td>
<td>0.095</td>
</tr>
<tr>
<td>Buy Apr Sell Nov</td>
<td>0.084</td>
</tr>
<tr>
<td>Buy May Sell Nov</td>
<td>0.080</td>
</tr>
<tr>
<td>Buy Jun Sell Nov</td>
<td>0.084</td>
</tr>
<tr>
<td>Buy Jul Sell Nov</td>
<td>0.071</td>
</tr>
<tr>
<td>Buy Aug Sell Nov</td>
<td>0.044</td>
</tr>
<tr>
<td>Buy Sep Sell Nov</td>
<td>0.032</td>
</tr>
<tr>
<td>Buy Oct Sell Nov</td>
<td>0.038</td>
</tr>
<tr>
<td>Average</td>
<td>0.070</td>
</tr>
</tbody>
</table>

**Table V.**
Average returns based on trading strategy

**Figure 4.**
Daily closing values of Nifty 500 index around Diwali

Note: Arrows depict Diwali every year
To summarize, though the robustness tests provide further credence to the November effect, the pattern is not consistent throughout the period of study, and is not evident across all sectors. However, this is in tune with the findings of literature, as Zhang and Jacobsen (2013) stated "If one requires an anomaly to be statistically significant and with consistent signs in all
subperiods of reasonable length and across different estimation methods, there may be no monthly anomalies [...] Many months significantly under- or outperform over the full period and in subperiods, but few have done so persistently throughout the ages. This suggests that monthly calendar anomalies change over time, or that these anomalies do not exist. Whether or not anomalies exist seems to depend strongly on the chosen sample period and sample length.

5. Conclusion
This paper sets out to test the evidence of monthly seasonality in the Indian stock market from 1999 to 2015. The seasonality is tested after taking into consideration the statistical features of the returns – stationarity, leptokurtosis, volatility clustering, and leverage effect. The results exhibit that over a period of 16 years (1999 to 2015), the returns in November had been the highest amongst all the months. Cultural factors like celebration of Diwali, a positive frame of mind of the investors, and higher cash at their disposal seem to explain the phenomenon. This aspect may be considered analogous to the Christmas hypothesis studied in western economies.

Brooks (2014) stated that the presence of seasonality in the stock returns need not be an evidence of market inefficiency. He put forward two reasons to support his argument. First, if the seasonality could not be profitably employed in designing an investment strategy, courtesy the transaction costs, it did not imply market inefficiency. Second, if the seasonality in the returns is mirrored by an underlying seasonality in the risks, it again did not imply market inefficiency. While Reinganum (1983) contended that the strategy was not profitable after adjusting for the transaction costs, Chen and Singal (2003) reported mixed evidences for employing the strategy for different months of the year, and Beyer et al. (2013) contended that the strategy was exploitable. Jaisinghani (2016) reported that designing the investment strategies based on the calendar patterns could still be profitable in India. Moreover, the analysis of this paper reports seasonality even after accounting for the time varying volatility. Hence, the November effect in India indeed seems to be an indication of market inefficiency, thereby offering opportunities for exploitation by the investors. However, a disclaimer needs to be appended as the seasonality is not persistent across study periods and across the methodologies employed. But, as stated by Zhang and Jacobsen (2013), “Clearly, the evidence we report here is speculative, but suggests that the Christmas hypothesis put forward by Wachtel in 1942 may deserve more attention.” However, in this case, the argument is put forward for the Diwali hypothesis.

Notes
1. Merton (1980) (cited in Zhang and Jacobsen, 2013) stated that the length of the observation period mattered more than the intervals for the returns.
2. A deterministic non-stationarity refers to a series that has a linear trend making it non-stationary. However, the series is stationary around that trend, and hence, is also known as trend-stationary (Brooks, 2014).
3. A parsimonious model refers to a model that uses as less number of parameters as possible to describe the underlying data as accurately as possible (Brooks, 2014).
4. Colloquially, Diwali is often referred to as the ‘Indian Christmas’ (NBC News, 2015).
5. For this, the date of Diwali celebration is taken from www.world-timedate.com.

References


**Further reading**


**About the authors**

Harshita is a Doctoral Student of Finance at the Department of Management Studies, Indian Institute of Technology Delhi (IIT Delhi). She is a Senior Research Fellow of the University Grant Commission. Her doctoral work is in the area of asset pricing. She has completed her post-graduation from Shri Ram College of Commerce, University of Delhi. She has recently published a paper titled “Indian stock market and the asset pricing models” which she also presented at the 4th Economics and Finance Conference organized by the International Institute of Social and Economic Sciences at London. Harshita is the corresponding author and can be contacted at: harshita@dmsiitd.org

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