January Effect in Pakistan: A Time Series Analysis

Muhammad Arsalan Hashmi
arsalan.hashmi@pafkiet.edu.pk

Abstract

This study employs daily data from the Karachi Stock Exchange 100 index from 2004-2009 to investigate the presence of the January effect. Our robust econometric modelling reveals anomalous patterns in stock returns around the turn of the year. The anomaly observed in this study, however, was unlikely to represent lucrative arbitrage opportunities at the time essentially because abnormal returns were not large enough to offset transactions costs. This finding provides confidence and assurance in the operational efficiency ofthe Pakistani capital markets.

Key Words: Karachi Stock Exchange, January Effect, Garch Model, Econometric Framework

Introduction

The presence of anomalies in international capital markets has puzzled academic researchers for a long time, (for e.g. Persons, 1919; Fields, 1931). Their greatest concern remains as to what drives these systematic patterns in securities prices. A large part of stock market anomalies research has concentrated on investigating and rationalizing calendar anomalies, (for e.g. Moller and Zilca, 2008; Starks, Yong and Zheng, 2006; Asteriou and Kavetsos, 2006; Sullivan, Timmermann and White, 2001; Lakonishok and Maberly, 1990). Extant studies have reported systematic patterns in stock returns around turn-of-the-month, days-of-the-week, months-of-the-year, holidays, and so on. Although many modern studies have shown that it is difficult to make exceptionally large gains by trading on such anomalies, their existence per se, undermines the famous random walk hypothesis which postulates that it impossible to predict the day-to-day movement in securities prices[1].

The main objective of this study is to investigate the existence of the January effect in the Karachi Stock Exchange. To achieve this aim, we utilise daily stock index data from the

The author is permanent faculty member at College of Management Sciences, PAF-KIET. He has a Master's Degree from University of Glasgow, UK.

[1]For an excellent discussion on this topic see, Malkiel, B. (2007), "A Random Walk Down Wall Street: The Time-Tested Strategy For Successful Investing," 9th Edition, W.W. Norton.

KSE 100 index for a period of six years from January 2004 to December 2009. Our results suggest that the January effect was present in the KSE 100 index during the sample period.

Literature Review

The January effect (or turn-of-the-year effect) is used to refer to a tendency of stock returns to be unusually high in the month of January relative to other months of the year. This anomaly was initially associated with small-cap stocks, (Reinganum, 1983); however, later research has also documented the anomaly in large-cap stocks, (Arsad and Coutts, 1997).

Before considering the modern literature on the January effect, we briefly consider the early research on the subject. In a seminal paper, Rozeff and Kinney (1976) examine monthly data from the NYSE over the period 1904-1974. They report the existence of seasonality in monthly returns over most of the sample period. Although they find significant returns in many calendar months, they attribute the seasonal pattern to disproportionately large January returns. Keim (1983) examines the relationship between market value and abnormal returns, utilising data for NYSE and AMEX stocks over the period, 1963-1979. The paper reports a consistently negative relationship between the two variables, with the relationship being the strongest in the month of January. The author further notes that more than half of the January excess returns were made in the first week of trading. On the contrary, Reinganum (1983) evaluates whether the tax-loss selling hypothesis explains the January anomaly. His results indicate that the tax-based explanation was consistent with the data, however, it cannot exclusively account for the entire effect. Lakonishok and Smidt (1988) employ 90 years worth of data for DJIA to examine a variety of calendar anomalies. Among other things, they document a strong turn-of-the-year effect over the sample period. Moreover, Agrawal and Tandon (1994) provide evidence for the January effect in ten stocks markets from developed and developing economies.

A number of prominent studies give explanations for the January effect. Branch (1977) was one of the leading proponents of the tax-loss selling hypothesis. According to the tax-loss selling hypothesis, at year-end investors sell securities in which they have made losses in order to reduce their taxes on capital gains. The sale of securities at year end depresses their prices, but prices return back in January causing returns to be high during the calendar month. On the other hand, Ritter (1988) argues that the January effect is related to the buying/selling behaviour pattern of investors at turn of the year, which is slightly different from that proposed in the tax-loss selling hypothesis. The paper analyses buy/sell ratio data from Merrill Lynch and documents that the anomaly was due to an abrupt switch by investors from net-selling in December to net-buying in January. He explains that investors' net-sell in December to realize losses for tax reasons and then net-buy in January from their cash holdings. Moreover, Haugen and Lakonishok (1988) assert that the January effect is explained by the portfolio rebalancing hypothesis. Essentially, the hypothesis suggests that high returns on small-cap stocks in January are due to a type of portfolio rebalancing (or portfolio change) by investors. It is argued that institutional investors tend to buy risky securities in January after companies have had a chance to "window dress" their corporate reports are year end. In addition, individual investors invest their proceeds from December sales (due to tax reasons) in January. Therefore, this buying pressure causes returns on small-cap stocks to be high in January.

Bhardwaj and Brooks (1992) argue that the January effect is essentially a low-price effect than a small-firm effect. They point out that low price stocks typically earn abnormally high returns in January, however, this finding normally excludes the impact of transaction costs and bid-ask spreads. Their results suggest that once stock returns are adjusted for transactions costs and bid-ask spreads, no anomalous pattern appears over the 1977-1986 period. The authors further argue that the January effect cannot be easily exploited, because of its non-persistent nature. Furthermore, Kramer (1994) examines if the January effect is caused by macroeconomic seasonality (or uncertainty). The author uses a multifactor model to link macroeconomic risk with expected returns and finds that abnormal returns in January are adequately explained by the model. Last but not least, Kim (2006) provides a risk-based explanation for the January effect. He develops a two factor model, comprising of a common risk factor (which depends upon information uncertainty related to volatility in earnings) and the market risk factor. Stock returns adjusted for the risk factors eliminate the January effect across firm size. In short, the paper considers the January anomaly across firms to be caused by differences in the two risk factors.

Recent studies on the January effect have reported some interesting results. Moller and Zilca (2008) evaluate the daily pattern of the January effect across size deciles. Their findings suggest that returns during the later part of January exhibits mean-reverting behaviour and abnormal returns accrue in a short period during the month. In other words, the paper argues that although abnormal returns are made throughout the month, the intensity of returns is higher during the former part of the month than the latter part. This pattern of stock returns during January is closely matched by trading volume intensity at various times of the month. Starks, Yong and Zheng (2006) examine data from municipal bond closed-end funds over the period 1990-2000, and argue that the January anomaly present at the funds during the sample period was largely explained by their tax-loss selling activities at year-ends. They further argue that funds connected to brokerage firms' exhibit greater tax-loss selling behaviour than independent funds. Asteriou and Kavetsos (2006) investigate the January effect in eight transition economies over the period 1991-2003. Their analysis of monthly stock returns data suggests a strong January seasonal in three countries, i.e. Hungary, Poland and Romania. Moreover, Chu, Liu and Rathinasamy (2004) unlike any previous study, applies the Markov-switching model proposed by Hamilton (1989) to evaluate the January effect in NYSE equally-weighted monthly returns between 1926 and 1992. They argue that the conventional method of modelling stock returns seasonality via dummy variables assumes that the pattern of seasonality remains constant over time. In contrast, the Markov-switching model will allow them to explicitly account for regime shifts and their relationship with January returns. Their findings suggest that the January anomaly was not present in the market as a whole. However, their analysis of small-cap stock portfolios provides evidence of the January effect. Coutts, Kaplanidis and Roberts (2000) examine a range of indices at the Athens Stock Exchange over the ten year period from 1986 to 1996. Their findings suggest the presence of several calendar anomalies including the January effect. However, they maintain that the anomalies cannot be profitably exploited net of transaction costs. Last but not least, Marquering, Nisser and Valla (2006) employ a dynamic approach of evaluating the continuation of prominent calendar anomalies, by assessing if they persist consistently after being reported in the academic literature. Their results suggest that the January effect had disappeared after being reported in academic research.

Data & Summary Statistics

We use daily stock index data from the Karachi Stock Exchange (KSE) 100 index. KSE 100 index was chosen because of it size and prominence relative to other indices listed on Karachi Stock Exchange. The data spans a period of six years from 2004-2009. Therefore, the sample size is in excess of 1400 observations. Daily stock index data is converted into daily stock returns using the following formula:

$\text{Return}_t = \ln (P_t/P_{t-1}) \times 100$

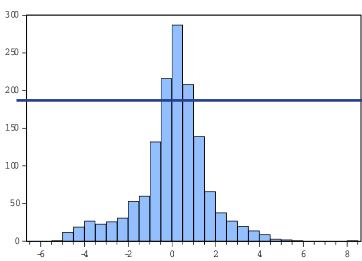
Where,

P_t is the value of the stock index at time t

P_{t-1} is the value of the stock index at time t-1

The summary statistics of stock returns are presented in the table 1 below. They suggest that mean (average) stock returns are positive in the KSE 100 index during the sample period. Moreover, the medians have remained somewhat distinct from the mean, implying that stock returns are not distributed symmetrically. Standard deviation of stock returns is quite high providing support to the common observation that stock prices (and consequently stock returns) are highly volatile, (Chang, Hsiao, Li and Yang, 2005). Furthermore, the negative skewness of stock returns implies that its distribution is skewed to the right and the kurtosis measure greater (or lower) than 3 suggests that stock returns are not mesokurtic. In short, it seems that the distribution of stock returns does not resemble the normal distribution. This hunch is confirmed by the Jarque-Bera test, with the null hypothesis of normality. The Jarque-Bera statistic is statistically significant at the 1% level of significance, suggesting that stock returns are not normally distributed.

Table-1



Series:	STOCK_RETURNS
Sample	1 1417
Observations	1416
Mean	0.052342
Median	0.147558
Maximum	8.250683
Minimum	-6.063133
Std. Dev.	1.616846
Skewness	-0.348795
Kurtosis	4.728406
Jarque-Bera	204.9671
Probability	0.000000

Econometric Framework

The conventional econometric approach to test for the January effect has been to employ a dummy variable regression model (for e.g. Arsad & Coutts, 1997; Coutts & Mills, 1995; Agrawal & Tandon, 1994). We follow the same approach in this study; however, as

the data is time series we suspect there will be an ARCH effect in the residuals. Therefore, we supplement the dummy variable model by using a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model.

Dummy Variable Regression Model

$$R_t = \alpha + \sum_{j=1}^{11} (\theta_j M_{jt}) + \varepsilon_t$$

Where,

R_t denotes the daily stock returns for the index.

M_{jt} denotes a dummy variable for the j_{th} month of the year, with j = 1, 2, …, 12; such that M_{1t} represents a dummy variable for January, M_{2t} represents a dummy variablefor February and so on.

$\varepsilon t$is a white-noise error term with mean 0 and variance σ^2 .

The null hypothesis for the model is as follows:

H0: $\alpha = \theta_1 = \theta_2 = \theta_3 = \ldots\ldots\ldots\ldots = \theta_{11}$

H1 : all the parameters are not simultaneously equal.

The hypothesis will be tested using the Wald test. If the null hypothesis is rejected at the conventional levels of significance, then it is likely that stock returns exhibit some form of seasonality and anomalous pattern.

GARCH Model

In the pioneering work of modelling financial time series, Engle (1982) suggests that high frequency time series variables such as exchange rates, stock returns, etc, tend to possess a phenomenon known as volatility clustering. Volatility clustering is used to describe a phenomenon where there is a systematic tendency in the conditional variance of the error term. In his paper, Engle (1982) proposes the ARCH LM test for detecting volatility clustering in the error term. If volatility clustering (or ARCH effect) is found, then one may use a suitable specification of an ARCH or GARCH model, (Greene, 2008).Several specifications of ARCH and GARCH models were experimented with to adequately account for the conditional variance of the error term. The most parsimonious representation was offered by the GARCH(1,1) model, satisfying conditions such as, stationary solution, positive variance and goodness of fit. The estimated model is as follows:

$$R_t = \alpha + \sum_{j=1}^{11} (\theta_j M_{jt}) + \varepsilon_t$$

$$\sigma_t^2 = \mu + \sum_{j=1}^{p} \gamma_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} \omega_j \sigma_{t-j}^2$$

Results and Discussion

The results obtained from estimating the dummy variable regression model are presented in table 2 below. Mean returns for the month of January are positive and statistically significant at the 10% level of significance. Moreover, mean returns for several other months (for e.g. February, March, etc) also show signs of seasonal variation. Seasonal variation in stock returns is also corroborated by the Wald test, which is a joint test of the linear restriction that mean monthly returns are statistically equal. The Wald test results are presented in table 2 below. The chi-square statistic for the Wald test is statistically significant at the 10% level of significance. Hence, we can conclude that there is reasonable evidence of a positive January effect in our sample. However, the Durbin Watson d statistic value is sufficiently low, perhaps suggesting some form of misspecification in the dummy variable model as opposed to serial correlation in the residuals.

Table-2

Dependent Variable: Stock returns
Method: Ordinary Least Squares
Number of observations: 1416

Variable	Coefficient	Std Error	t-stat
Constant	-0.268**	0.15	-1.786
January	0.498***	0.21	2.37
February	0.652***	0.217	3.005
March	0.429**	0.209	2.049
April	0.348*	0.208	1.672
May	0.005	0.209	0.028
June	0.355*	0.207	1.716
July	0.221	0.206	1.072
August	0.196	0.208	0.943
September	0.458**	0.22	2.08
October	0.442**	0.215	2.057
November	0.316	0.214	1.472
F-statistic			1.677*
Durbin-Watson d statistic			1.675
Wald statistic			17.62*

*** ** * denotes statistical significance at 1%, 5% and 10% respectively.

To investigate whether the error term in the dummy variable model possesses a pattern of volatility clustering; an ARCH LM test was run on the residuals at various lags. Table 3 presents the results from the test. It is apparent from the test results that residuals do exhibit volatility clustering. Both the F-statistic and the LM statistic are statistically significant at the 1% level at all the lags. Therefore, using a suitable ARCH/GARCH model becomes necessary for robust modelling of stock returns.

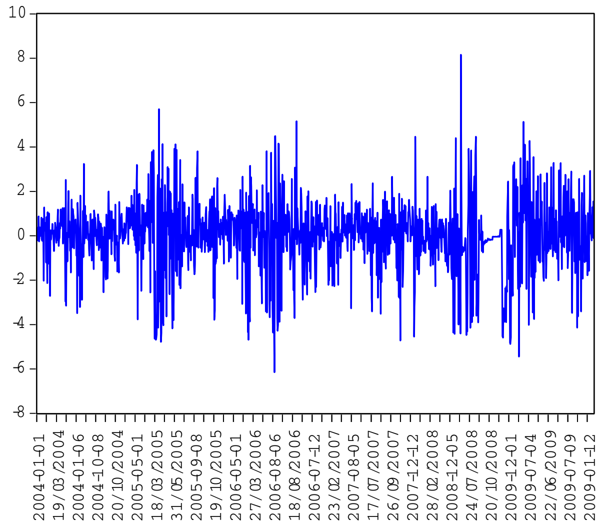
Table-3

Autoregressive Conditional Heteroscedaticity (ARCH) Test

	Lag 1	Lag 4	Lag 8	Lag 12
F-stat	219.11***	81.06***	43.63***	30.28***
LM statistic	189.96***	264.45***	281.14***	290.81***

*** denotes statistical significance at the 1% level.

RESID



After some inevitable experimentation with model specification, the GARCH (1, 1) model was selected on the basis of generating the lowest value of the Schwarz Criterion and Akaike Information Criterion. In accordance with prior studies in this area, the Quasi Maximum Likelihood (QML) approach proposed by Bollerslev and Wooldridge (1992) was used for estimation purposes. Regression results from

GARCH (1,1) model present slightly different results as compared to the dummy variable model.However, mean returns for January remain positive and are statistically significant at the 10% level of significance. Thus, our robust modelling of stock returns provides evidence of the January anomaly in the KSE 100 Index.

Table-4

Dependent Variable: Stock returns
Method: Quasi Maximum Likelihood - ARCH (Marquardt)
Number of observations: 1416

Variable	Coefficient	Std Error†	z-stat
Conditional Mean Equation			
Constant	0.106	0.108	0.977
January	0.264*	0.14	1.88
February	0.172	0.159	1.085
March	0.07	0.141	0.496
April	0.144	0.144	1.004
May	-0.288	0.208	-1.383
June	0.7	0.161	0.436
July	-0.059	0.144	-0.411
August	-0.04	0.149	-0.272
September	0.004	0.131	0.036
October	0.02	0.149	0.138
November	-0.009	0.122	-0.079
Conditional Variance Equation			
Constant	0.09***	0.034	2.647
ε^2_{t-1}	0.206***	0.034	5.979
σ^2_{t-1}	0.769***	0.038	19.789

*** ** * denote statistical significance at 1%, 5% and 10% level
† Bollerslev-Wooldridge robust standard errors

Conclusion

The main objective of this study was to investigate the existence of the January effect in the Karachi Stock Exchange 100 index. To achieve this aim, we utilize daily stock index data for a period of six years from 2004-2009. On the econometric front, we supplement the traditional method of testing for calendar anomalies with a dummy variable model, by using a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model. Our results provide statistical evidence of a positive January effect during the sample period. This finding is consistent with prior studies on the subject. The observed anomaly, however, was unlikely to present lucrative arbitrage opportunities at the time essentially because abnormal returns were not large enough to offset transactions costs, which typically, range between 1-3 percent.

Future research should, among other things, be directed at not only re-examining this anomaly but also investigating other recently documented anomalies, such as, momentum effects, contagion effects, etc in the Pakistani stock markets using robust econometric approaches like stochastic volatility (SV) modelling, spectral analysis and so on.

References

Agrawal, A. and Tandon, K. (1994).Anomalies or illusions? Evidence from stock markets in eighteen countries. Journal of International Money and Finance, 13, 83-106.

Arsad. Z, and Coutts, A. (1997).Security price anomalies in the London international stock exchange: A 60 year perspective.Applied Financial Economics, 7, 455-464.

Asteriou, D. and Kavetsos, G. (2006). Testing for the existence of the January effect in transition economies. Applied Financial Economics Letters, 2, 375-381

Branch, B. (1977). A tax loss trading rule. Journal of Business 50, 198-207.

Bhardwaj, R. and Brooks, L.(1992).The January anomaly: Effects of low share price, transaction costs, and bid-ask bias.The Journal of Finance, 47(2), 553-575.

Bollerslev, T. and Wooldridge, J. (1992). Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time Varying Covariances.Econometric Reviews, 11, 143–172.

Chang,Y., Hsiao, C., Li, Q., and Yang, J. (2005).The relationship between stock returns and volatility in international stock markets.Journal of Empirical Finance, 12, 650-665.

Chu,C., Liu, T., and Rathinasamy,R. (2004). Robust test of the January effect in stock markets using Markov-switching model. Journal of Financial Management and Analysis, 17, 22-33.

Coutts, A., Kaplanidis, C. and Roberts, J. (2000).Security price anomalies in an emerging market: The case of the Athens stock exchange. Applied Financial Economics, 10, 561-571.

Coutts, A.and Mills, T. (1995).Calendar effects in the London stock exchange FTSE indices. The European Journal of Finance, 1, 79-93.

Engle, R. (1982).Autoregressive conditional heteroscedasticity with estimates of the variance of the United Kingdom inflation. Econometrica, 50, 987-1007.

Fields, M. (1931). Stock prices: A problem in verification.Journal of Business, 4, 415-418.

Greene, W. (2008).Econometric Analysis. 6th Edition, Prentice Hall.

Hamilton, J. (1989).A new approach to the economic analysis of nonstationary time series and the business cycle. Econometrica, 57, 357-384.

Haugen, R and Lakonishok, J. (1988).The incredible January effect: The stock market's unsolved mystery. Dow Jones-Irwin, Homewood, Illinois.

Keim, D. (1983).Size-related anomalies and stock return seasonality: Further empirical evidence. Journal of Financial Economics, 12, 13-32.

Kramer, C. (1994).Macroeconomic seasonality and the January effect.The Journal of Finance, 49, 1883-1891.

Lakonishok,J. and Maberly, E. (1990).The weekend effect: Trading Patterns of individual and institutional investors. The Journal of Finance, 45, 231-243.

Marquering, W., Nisser. J., and Valla, T. (2006). Disappearing anomalies: A dynamic analysis of the persistence of anomalies.Applied Financial Economics, 16, 291-302.

Moller, N. and Zilca, S. (2008).The evolution of the January effect. Journal of Banking and Finance, 32, 447-457.

Persons, W. (1919).Indices of business conditions. The Review of Economic Statistics, 1, 5-107

Reinganum, M. (1983).The anomalous stock market behavior of small firms in January:Empirical tests for tax-loss selling effects. Journal of Financial Economics, 12, 89-104.

Ritter, J. (1988).The buying and selling behavior of individual investors at the turn of the year. The Journal of Finance, 43, 701-717.

Rozeff, M. and Kinney, W. (1976).Capital market seasonality: The case of stock returns.Journal of Financial Economics, 3, 379-402.

Starks,L., Yong. L., and Zheng, L. (2006).Tax-loss selling and the January effect: Evidence from municipal bond closed-end funds. The Journal of Finance, 61, 3049-3067.

Sullivan, R., Timmermann, A., and White, H. (2001). Dangers of data mining: The case of calendar effects in stock returns.Journal of Econometrics, 105, 249-286.