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Econometrics of Seasonality and Stock Market: Some Empirical Evidence from India

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Abstract

Although seasonal fluctuations are a dominant component of most of the aggregate time series, particularly in the Indian economy, little attention is paid to them while studying the relationships among the economic variables. For the stock market, little effort seems to have been devoted to this aspect. Further, whatever studies have been done are confined to simple forms of seasonality. However, as has been shown by a number of studies, most of the aggregate time series exhibit changing rather than constant seasonal pattern. Thus the tests for deterministic seasonality may not reveal much.

An attempt has been made in this paper to explore the nature of seasonal fluctuations in the Indian Stock market. Considering six variables related to share prices, volatility, yield, P-E ratio, P-B ratio and turnover, it is observed that the hypothesis of non-stationary seasonal fluctuations cannot be rejected altogether. There is conclusive evidence in favour of the fact that except the turnover, all the series have seasonal unit root at one frequency or other.

1. Introduction

Seasonality is an important feature of aggregate time series, which has been identified by several authors right since the 1920's (Mitchell, 1927). In use of data at monthly or quarterly frequencies, seasonal fluctuations often creates problems in estimation / inference procedures. Due to this there has been a tendency to adjust for seasonal fluctuations in one-way or the other, so as to have better forecasts. Thus seasonality has occupied an important

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place in the study of forecasting financial variables. However, different seasonal adjustment techniques suffer from different pitfalls. As a result, there does not seem any consensus among econometricians on how to treat seasonal fluctuations in time series.

Of late it has been felt that the seasonality needs to be modeled rather than being treated as a sort of contamination or noise in the data, as has been done traditionally. At the same time effects of traditionally used seasonal adjustment techniques too have been analyzed and the results studied. Specifically, analysis of Dickey, Hasza and Fuller (1984, henceforth referred to as DHF), Hylleberg *et al.* (1990, henceforth referred to as HEGY), Ghysels *et al.* (1994), Franses (1990), Beaulieu and Miron (1993) and others have questioned the use of seasonal differencing operator for the isolation of seasonality in Box-Jenkins type modeling, while Abeysinghe (1994) has done the same in the regression using the dummies.

This paper aims at analyzing some monthly time series related to Indian stock market from this point of view. The paper proceeds as follows: Section II presents a brief introduction to the developments in the econometrics of seasonality and their relevance. Section III presents review of some already existing tests for seasonality. Section IV presents discussion of some studies about the seasonal behaviour in stock markets. Data and Methodology for the present study are discussed in Section V, followed by results of empirical analysis of the Indian financial series in Section VI. Finally, section VII contains concluding observations.

2. Seasonality in Econometric Analysis

Traditionally, for the analysis of seasonality a practice has been to use seasonal dummies as explanatory variables in the regression. In time series analysis, the use of fourth difference operator i.e., $(1\text{-}B^4)$ for quarterly and twelfth difference i.e., $(1\text{-}B^{12})$ for monthly data, has been popular for the removal of the seasonal component. Even the practice of using data adjusted for seasonal fluctuations using traditional filters (e.g. X-11 and X-11 ARIMA used by the Bureau of Census, US Department of Commerce) has been questioned by different authors.

Currently, three classes of time series models are commonly used in modelling the seasonality:

a) Purely deterministic seasonality: a purely deterministic seasonal process is a process generated by seasonal dummy variables such as

$$xt = \mu_t \quad \text{where} \quad \mu_t = m0 + m1S1t + m2S2t + m3S3t \qquad (1)$$

for quarterly frequency and its extension with eleven monthly dummies for monthly frequency. This process can be perfectly forecast and will never change its shape.

b) Stationary seasonal process: A stationary seasonal process can be generated by a potentially infinite auto regression

$$\varphi(B)x_t = \varepsilon_t \tag{2}$$

where ε_t is iid with all the roots of

$$\varphi(B) = 0 \tag{3}$$

lying outside the unit circle but where some are complex pairs with seasonal periodicities. More precisely the spectrum of such a process is given by

$$f(\omega) = \frac{\sigma^2}{\left|\varphi\left(e^{i\omega}\right)\right|^2} \tag{4}$$

which is assumed to have peaks at some of the seasonal frequencies ω. An example for the quarterly data is

$$x_t = \rho x_{t-4} + \varepsilon_t \tag{5}$$

which has peaks at both the seasonal periodicities π/2 (one cycle per year) and π (two cycles per year) as well as at zero frequency (zero cycles per year).

According to Miron (1994), a crucial fact about series displaying stationary stochastic seasonality is that they are not qualitatively different from series displaying any kind of stationary stochastic variation. Their spectra have power at all frequencies including both the seasonal and business cycle frequencies, as is the case with any stationary stochastic process. The relative amount of power at the two sets of frequencies differs but there is no logic way to say how much of the power at particular frequencies is due to particular lags in the autoregressive representation. Hence there is generally no reason to treat stationary stochastic seasonality different from other stationary stochastic variation. Standard statistical techniques produce consistent coefficient estimates for such processes.

c) A series x_t is an integrated seasonal process if it has a seasonal unit root in its autoregressive representation. More generally it is integrated of order d at frequency θ if the spectrum of x_t takes the form

$$f(\omega) = c\left(\omega-\theta\right)^{-2d} \tag{6}$$

for ω near θ. This is conveniently denoted by

$x_t \sim I_\theta(d)$

The familiar seasonal differencing operator advocated by Box and Jenkins (1970) can be written as

$$(1-B^4)x_t = \varepsilon_t = (1-B)(1+B+B^2+B^3) \quad (7)$$

$$= (1-B)(1+B)(1-iB)(1+iB)$$

It has four roots with modulus one: 1, -1, i, and $-i$, i.e., $e^{2\pi.0.i/4}$, $e^{2\pi.2.i/4}$ $e^{2\pi.1.i/4}$ and $e^{2\pi.(-1).i/4}$. Noting that a root a $e^{2\pi.j.i/s}$ with s denoting the number of observations per year denotes j cycles per annum, these four roots correspond to zero, two and one cycles per year, respectively.

According to HEGY, they have long memory so that shocks last forever, and may in fact change the seasonal pattern permanently. They have variances, which increase linearly since the start of the series and are asymptotically uncorrelated with processes with other frequency unit roots. A complete solution to the equation (5) contains both cyclical deterministic terms corresponding to seasonal dummies plus long non-declining sums of past innovations or their changes. Thus a series generated by such a process has a component that is seasonally integrated and may also have a deterministic seasonal component, depending upon the starting values of series generated by the above process will be inclined to have a seasonal with peak that varies slowly through time, but if the initial deterministic component is large, it may not appear drift very fast.

According to Beaulieu and Miron (1993), of the above three main definitions of seasonality found in econometric literature, it is the nonstationarity due to seasonal unit roots that raises the most complicated statistical issues. In addition, investigation of seasonal unit roots logically precedes the examination of other kinds of seasonality since such examinations can produce spurious results if seasonal unit roots are present but not accounted for. The same has been pointed out by Abeysinghe (1991) also. According to Abeysinghe (1994), a unit root seasonal process can generate a very regular seasonal pattern over a long period of time. Therefore economic time series which display deterministic seasonal behaviour and those which show a stochastic (moving) seasonal pattern could both be approximated by a unit root seasonal process. However, if seasonal dummies are used with seasonally integrated series then spurious regression is very likely. If y and x are seasonally integrated at the same frequency, then the frequency of observing spurious relations could be very high. This frequency increases with the sample size. Further, integration at different seasonal frequencies does not produce spurious results.

Another approach has been to remove the stochastic trend present in the time series by first order differencing filter under the assumption that seasonal fluctuations are stationary around a deterministic seasonal pattern. The coefficient of determination of such a regression is then interpreted as amount of variation that can be explained by deterministic seasonality. As discussed in Beaulieu and Miron (1991) (cited in Franses (1995)), a comparison of R^2 values across several auxiliary regressions and of successive values of estimated coefficients of seasonal dummies may be used to yield insights into common aspects of various macro economic time series. However, Franses et al. (1995) have shown that neglecting seasonal unit roots this way may yield spuriously high R^2 values. In contrast to the standard regression theory for stationary series the R^2 has a non-degenerating asymptotic distribution. Thus, moderate and spuriously high values of R^2 are to be expected from the simple regression of first difference of the variable under consideration on the seasonal dummies. Even for small samples they have shown that high R^2 values are reported when the presence of seasonal unit roots is neglected. Further this tendency increases with the number of roots on the unit circle. Even for the coefficients of dummies they find that the time series processes with seasonal unit roots can yield any kind of estimates for such dummy parameters. A comparison of the estimated coefficients across several time series may then be hazardous.

Finally, the famous fourth (or twelfth, in case of monthly series) difference used as a filter for seasonal components implicitly assumes the presence of seasonal unit roots at all frequencies, which is indeed a tall claim, as is evident from the results of a few studies carried out for different countries. The choice of inappropriate filter does in turn distort further investigations. Franses (1991) argues on the basis of simulation results and of empirical evidence that even though graphical evidence leads one to believe the changing seasonal pattern, considering a model with seasonal filter while the one with deterministic dummies is appropriate yields a deterioration of forecasting performance. Hence, they conclude, that the recognition of the presence, or better, of the absence of seasonal unit roots can have important implications for forecasting and model building.

Compounded by all these facts currently available literature does not say anything definitive about the nature of seasonality in variables related to Indian stock market.

3. Tests for Seasonal Unit Roots

The first test for the presence of seasonal unit roots was presented by Hasza and Fuller (1982) which seeks to test as to which of the differences – first, fourth or both are necessary to eliminate the nonstationary component of the time series under consideration. DHF proposed another test, which attempts to test the appropriateness of using the fourth difference operator. However, this test too is not that much useful looking at the above discussion, because it tests the presence of four seasonal unit roots simultaneously against the alternative of not a single unit root.

HEGY has proposed a test that allows for the presence of seasonal unit root at each frequency irrespective of whether or not there is a unit root at the other frequencies.

Suppose the variable x_t is generated by the following stochastic process

$$\varphi(B)_{xt} = \varepsilon t \tag{8}$$

then HEGY make use of the following proposition (originally due to Lagrange) to rewrite the autoregressive polynomial:

Any (possibly infinite or rational) polynomial, which is finite valued at distinct, non zero, possibly complex points θ_1, θ_2, θ_3, ... θ_p can be expressed in terms of elementary polynomials and a remainder[1]*, as follows:*

$$\varphi(B) = \sum_{k=1}^{p} \frac{\lambda_k \Delta(B)}{\delta_k(B)} + \Delta(B)\ \varphi^{**}(B) \tag{9}$$

where λ_k are a set of constants, $\varphi^{**}(B)$ is a polynomial (possibly infinite or rational),

$$\delta_k(B) = 1 - \frac{1}{\theta_k} B \text{ , and } \Delta(B) = \prod_{k=1}^{p} \delta_k(B) \tag{10}$$

Adding and subtracting $\Delta(B)\sum\lambda_k$ to have the right hand side of equation (9), we have

$$\varphi(B) = \sum_{k=1}^{p} \lambda_k \Delta(B) \frac{(1-\delta(B))}{\delta_k(B)} + \Delta(B)\ \varphi^*(B) \tag{11}$$

where $\varphi^*(B) = \varphi^{**}(B) + \sum\lambda_k$ (12)

The polynomial will have a root at θ_k if and only if $\lambda_k = 0$. Thus testing for unit roots can be carried out equivalently by testing for parameters $\lambda = 0$ in an appropriate extension.

The above test, though originally developed for quarterly data by HEGY, has been extended for monthly data by Beaulieu and Miron (1993) and Franses (1990).

In case of monthly frequency, there are a total of twelve unit roots possible, which can be obtained by factorizing $(1-B^{12})$:

$$1, \quad -1, \quad \pm i, \quad -\frac{1}{2}(1 \pm \sqrt{3}i), \quad \frac{1}{2}(1 \pm \sqrt{3}i), \quad -\frac{1}{2}(\sqrt{3} \pm i), \frac{1}{2}(\sqrt{3} \pm i)$$

where the first one is non-seasonal while all the others are seasonal unit roots, corresponding to the 6, 3, 9, 8, 4, 2, 10, 7, 5, 1 and 11 cycles per year, as may be verified by looking at the explanation given above for quarterly data. The frequencies of these roots are 0, π, $\pm\pi/2$, $\pm 2\pi/3$, $\pm\pi/3$, $\pm 5\pi/6$, and $\pm\pi/6$, respectively. In case of monthly frequency,

1 Proof of this may be found in HEGY.

Franses (1991) suggests the following regression, using the above procedure given by HEGY.

$$\varphi^*(B)y_{8,t} = \pi 1\, y_{1,t-1} + \pi 2\, y_{2,t-1} + \pi 3\, y_{3,t-2} + \pi 4\, y_{3,t-1} + \pi 5\, y_{4,t-2}$$

$$+ \pi 6\, y_{4,t-1} + \pi 7\, y_{5,t-2} + \pi 8\, y_{5,t-1} + \pi 9\, y_{6,t-2} + \pi 10\, y_{6,t-1}$$

$$+ \pi 11\, y_{7,t-2} + \pi 12\, y_{7,t-1} + \mu_t + \varepsilon_t \qquad (13)$$

where

$$y_{1,t} = (1+B)(1+B^2)(1+B^4+B^8)y_t$$

$$y_{2,t} = -(1-B)(1+B^2)(1+B^4+B^8)y_t$$

$$y_{3,t} = -(1-B^2)(1+B^4+B^8)y_t$$

$$y_{4,t} = -(1-B^4)(1-\sqrt{3}B+B^2)(1+B^2+B^4)y_t$$

$$y_{5,t} = -(1-B^4)(1+\sqrt{3}B+B^2)(1+B^2+B^4)y_t$$

$$y_{6,t} = -(1-B^4)(1-B^2+B^4)(1-B+B^2)y_t$$

$$y_{7,t} = -(1-B^4)(1-B^2+B^4)(1+B+B^2)y_t$$

$$y_{8,t} = (1-B^{12})y_t \qquad (14)$$

Here π_1 and π_2 correspond to the roots 1 and -1 respectively, while the other π's correspond to unit roots at the other frequencies. We can consider the t-ratios for π_1 and π_2 and F-statistics for each of the pairs $\{\pi_3,\pi_4\}$, $\{\pi_5,\pi_6\}$, $\{\pi_7,\pi_8\}$, $\{\pi_9,\pi_{10}\}$ and $\{\pi_{11},\pi_{12}\}$, all of which follow non-standard distributions. Critical values for all of these have been given in Franses and Hobijn (1997). The null hypothesis in each of these is that of unit root at corresponding frequency against the alternative hypothesis of no unit root at that frequency. The above regression can be augmented by a linear trend and seasonal dummies. This is a defensive strategy from power considerations (Ghysels, Lee and Noh, 1994). The equation is further augmented by lags of the dependent variable to render the error term white noise.

4. Review of Literature

As stated earlier, seasonality has been studied for last several decades and seasonality of stock markets is not an unknown phenomenon. Rozeff and Kinney (1976) observed that in the US market, January returns are significantly larger than returns for the remaining months. Keim (1983) reported concentration of the 'January effect' in the smallest firm size decile. Roll's (1983) investigation of the daily data for small firm stocks uncovered significant presence of the phenomenon in the first four trading days of January after which it is less prominent. Gultekin and Gultekin (1983) examined monthly price indices in 16 non – US capital markets over the 1959-1979 period. They found pervasive international evidence in 13 out of 16 markets about January having the highest mean monthly return. Reinganum (1983), Berges, McConnell and Schlarbaum (1984) and Santesmases (1986) testing the US, Canadian, and Spanish stock markets respectively, verified persistence of the 'January effect' even after controlling for the tax impact, suggesting that there are other factors also which induce seasonal behaviour in the stock market.

For India, considering the RBI monthly index series for the period 1960-1989, Broca (1991) failed to find any evidence of seasonality. Even for the sub-period-wise analysis, he could not find any evidence for any sub period of 10 and 20 years, to explore the possibility of seasonality being observed at any one time but disappearing in the other. He attributed this contrast in the results of Indian stock market to, inter alia, the underdeveloped nature of Indian stock market.

Sinha et al. (1999a) have endorsed these findings, considering the RBI index for the three sub periods: 1981-1986 (pre-reforms period), 1987-1992 (mild reforms period) and 1993-1998 (vigorous reforms period). Along with this they also examined the behaviour of the BSE sensex for the period 1995-1999, but could not reject the hypothesis of no seasonality for any of the periods. However, both of these studies were based on a non-parametric test. Sinha, et al. (1999b) tested the presence of seasonality in industrial production and share prices using the dummy variable regression, for the three sub-periods. For SPI, this study suggested that in the whole period taken together, hypothesis of no seasonality could not be rejected. The results of the sub period analysis suggest that the Indian market manifests some signs of seasonality in the second sub period but these diminished in the last sub-period. They attribute this to the stock scam of 1992, which shook the confidence of investors.

Very recently, Mohanty and Kamaiah (2000) tested for the seasonal unit roots in Indian Stock Exchange using the data of BSE Sensex and BSE-100 for the period 1983-1999. They fail to confirm the presence of seasonal unit roots in the data. However, their findings do indicate the presence of deterministic seasonality in the data.

Results of all of these studies except the last one become doubtful in view of Abeysinghe's (1991, 1994) observations cited above. The last study, though considers the possibility of nonstationary stochastic seasonality, but has considered prices only.

These studies suggest that there is a need to give a fresh look at seasonality in Indian stock market, keeping in mind the possibility of stochastic seasonality and taking other variables, along with the prices.

5. Objectives and Methodology

In view of the above results, a comprehensive analysis of seasonality in the Indian stock market is necessary. This paper intends to do precisely this. The analysis has been done in terms of six variables related to the Mumbai Stock Exchange - monthly average of sensex, volatility of sensex (calculated as relative range), monthly volatility, monthly average of the BSE National Index, PE ratio PB ratio of the BSE sensex, monthly turnover of the BSE scrips, and yield percent of the sensex. Data for all the variables except the Monthly volatility have been taken from RBI (2001). For the last one, the data have been taken from Biswal and Kamaiah (2001). The series is subjected to the monthly version of HEGY test, suggested by Franses (1990) and discussed above. The HEGY regression is augmented by a linear trend, eleven seasonal dummies and lags of the dependent variable to render the series white noise. The regression is first run without any lag and if there is any autocorrelation of twelfth order (as suggested by the LM test for autocorrelation), the equation is run with 12 lags. Out of these those lags significant at 15% are retained and the regression is run again. The residuals of this equation are tested for autocorrelation using the LM test again. If still the hypothesis of no autocorrelation is rejected at 5 per cent, the regression is run with 24 lags and then the lags chosen. Only when the residuals come out to be white noise is the equations retained. Another statistic used to test white noise in the residuals is the LM test for heteroskedasticity[2]. If in the regression chosen on the basis of autocorrelation, the hypothesis of no heteroskedasticity is rejected at 5%, the same search procedure as mentioned above is repeated again. The results with this are presented separately.

6. Discussion of Results

In all, six variables have been considered. All the variables except the yield on the sensex have considered in logarithms. The results have been shown in Table 1. Column 3 of this table contains number of lags required to render the residuals in HEGY regression white noise in each of the variables. Columns 4 and 5 contain values of the t-statistic for the null hypothesis of seasonal unit root and unit root at frequency π. Remaining columns contain F statistics for the null hypotheses of unit roots at the other seasonal frequencies. When residuals in the equation chosen on the basis of autocorrelation show significant heteroskedasticity, results of the new equation too are presented, in the next row.

2 Though in application, Franses (1998) talks of uncorrelated series only (p.113), Franses and Hobijn (1997, p.28), while discussing the test, write " the order of the polynomial is usually determined using diagnostic checks such that the estimated error process is approximately white noise".

Table 1: The results of the Franses' test

Variables	n	Lags	t_1	t_2	$F_{3,4}$	$F_{5,6}$	$F_{7,8}$	$F_{9,10}$	$F_{11,12}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
SENA	116	0	-3.6224***	-2.6517*	7.9414****	11.0077****	12.348****	9.9623****	6.3939**
	102	2,13,14	-2.7225	-2.4939*	16.9739****	11.0605****	10.5199****	11.9056****	12.3687****
NAT	116	0	-3.3559**	-3.1826***	6.4767**	10.7402****	10.6243****	10.228****	5.4883*
	101	2,3,14,15	-2.1237	-2.0227	10.8009****	9.422****	4.6511	9.4252****	9.7916****
SENY	107	3,4,7	-2.3007	-6.3885****	19.3771****	12.383****	7.5247***	3.4956	18.7734****
SENV	114	0	-4.2438****	-3.6037****	10.849****	4.8266	20.666****	10.3976****	14.0459****
MVT	156	0	-4.545****	-2.9852***	20.9389****	23.1292****	20.4208****	18.7006****	20.3104****
SENPE	114	0	-2.0117	-3.9294****	6.5539**	8.7273****	10.0677****	6.8268***	7.3808***
SENPB	114	0	-2.1766	-3.9285****	5.9662**	9.1261****	9.4177****	6.9633***	7.6859***
TO	115	0	-1.7658	-3.7903****	16.5428****	18.532****	10.4903****	8.5974****	9.6182****

*: significant at 10%. **: significant at 5%, ***: significant at 2.5% and ****: significant at 1%.

No augmentation of the basic HEGY equation was required to remove serial correlation in five out of six variables – only the equation for yield on the sensex showed significant 12^{th} order serial correlation in the basic HEGY regression without any augmentation. In the case of sensex yield (SENY), we have to add three lags - 3^{rd}, 4^{th} and 7^{th} to the right hand side of the equation to do away with the serial correlation. Further, the residuals of the equations thus selected are free from heteroskedasticity in all but two cases – those of sensex and BSE National Index. In these two cases, more lags had to be added to do away with heteroskedasticity. The lags chosen out of 12 lags too failed to remove serial correlation. Consequently, we chose lags out of 18 lags.

Looking at the t and F-statistics for the presence of unit roots, in sensex (SENA), only t_2 is not significant at 5%. However, at 1%, t_1 and $F_{11,12}$ are not found significant[3]. Thus, though the proof about frequencies corresponding to zero, alongwith 7and 5 cycles per year is not certain, we cannot reject the hypothesis of no unit root at the frequency π, at least. If we take into account the heteroskedasticity also, the null hypothesis of no unit root at zero frequency is not rejected at all, while that at frequency π is rejected at 10% only. All the F-statistics are significant at 1%. Looking at these two, it can be safely said that the Sensex contains one seasonal unit root – that at the frequency π , in addition to the non-seasonal unit root.

Coming to other share price index, the BSE National Index (NAT), six out of the seven statistics under consideration (two t- and five F- statistics) are significant at 5%. One F-statistic – $F_{11,12}$ is significant at 10% only. Three F-statistics – $F_{5,6}$, $F_{7,8}$ and $F_{9,10}$ are significant at 1%. However, if the heteroskedasticity of residuals too is taken into account, neither of the t-statistics is significant. Of the F-statistics, the $F_{5,6}$ is not significant at all. All others, are significant at 1%.

In case of yield on sensex (SENY), the basic HEGY equation has shown significant serial correlation, which is removed by adding three lags of the dependent variable to the equation. This augmented equation is free from heteroskedasticity also. The hypothesis of unit roots at zero, 4 and 8 cycles per annum cannot be rejected at all, while that of unit root at frequency corresponding to 1 and 11 cycles per annum is significant at 2.5% only. All the other statistics exceed the corresponding 1% critical values. Thus, sensex yield too cannot be said to be stationary.

Other parameters of the markets considered are: sensex volatility (measured as relative range of the Sensex, SENV), monthly volatility (MV, given by Biswal and Chandra, 2001), sensex yield (per cent per annum), sensex PE ratio (SENPE), Sensex PB ratio (SENPB), and monthly turnover of the BSE scrips (TO). In all these cases, no augmentation was

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3 Here t_i refers to the t-statistic to test the hypothesis that $\pi_i = 0$ while $F_{j,k}$ denotes the F-statistic to test the hypothesis that $\pi_j = \pi_k = 0$.

required for the removal of serial correlation. Further, the residuals of these equations were free from heteroskedasticity also.

In case of sensex volatility, all statistics, except the $F_{5,6}$ are significant at 1 pc. However, in case of the other measure of volatility, namely, the monthly volatility of Biswal and Kamaiah, all the statistics except the t-statistic corresponding to 6 cycles per annum are significant at 1%. The latter too is significant at 2.5%. Thus the result about nature of seasonality in volatility is uncertain. For PE and PB ratios of the sensex scrips, t_1 is not significant at all, while $F_{3,4}$ is significant at 5% only. Thus, while the process is not stationary, we are not sure whether this non-stationarity extends to sub-annual fluctuations also. Finally, in case of turnover of BSE scrips, all the statistics corresponding to the seasonal frequencies are significant at 1%, while that at zero frequency is not significant at all. This indicates the presence of only one unit root – that at zero frequency in the turnover data.

7. Concluding Observations

This paper explores the presence of nonstationary stochastic seasonality in the Indian Stock Market. It is found that the hypothesis of seasonal unit roots cannot be rejected altogether if we look at parameters other than prices. Zero frequency unit root is a common feature in all the series considered here, except the two representing volatility (it is also present in the price series, if the residuals are made white noise in true sense, by removing heteroskedasticity in addition to serial correlation). The conclusion about non-stationarity at other frequencies is mixed. However, along with the presence of non-seasonal unit root one important observation is clear that all the parameters considered here, with the exception of turnover ratio, exhibit nonstationarity at some frequency or the other. According to Franses (1991), the power of the test statistics may be low, except for the joint F-test for all complex π_i and hence significance levels of 10%, or even higher, may be more appropriate. Even looking at this, our results stand valid. This also implies that the use of common seasonal filter is totally invalid. A series not filtered at all, is not appropriate either. What is needed is to apply suitable filter taking into account the structure of the series suggested by our results, which needs to be further confirmed by long series, which will, however, take quite some time to be available.

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