

MONTH-RELATED SEASONALITY OF STOCK PRICE VOLATILITY: EVIDENCE FROM THE MALTA STOCK EXCHANGE

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Abstract. This study applies different statistical tests to investigate whether monthly volatility patterns prevailing in a cross-section of stock markets are present on the Malta Stock Exchange. A January effect is detected, together with a variant of the Turn-Of-The-Month effect, in that volatility tends to increase towards the end of the month. Whilst these effects may be attributed to sources identified in previous literature, it is also shown that this seasonality is related to announcement patterns of listed companies.

Introduction

One recurrent research topic in the finance discipline is the volatility of asset prices given that this is directly related to returns and to risks. Empirical analyses of the volatility of financial assets have exposed various “stylised facts”, such as weekly and monthly seasonality and volatility clustering. The main aim of this study is to detect month-related seasonality in volatility on the Malta Stock Exchange (MSE). Such seasonality was observed on various developed and emerging markets as outlined in the next section. This paper inquires whether the seasonality observed on more vigorous markets may also materialise in a much smaller setting such as the one at hand. The investigation extends to whether any detected seasonality is related to the flow of information on MSE. The inherent strengths of the analysis include the use of different empirical methodologies, the availability of a comprehensively long time series of MSE Index observations, as well as the availability of detailed records of company announcements.

The analysis is structured as follows: following a research background and a description of the methodology and the data set, we test for the presence

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of a January effect and a Turn-Of-The-Month (TOM) effect in the MSE Index data. The observed patterns are then discussed in the context of company announcements, in order to infer whether any seasonality may be attributable to information flow. Results are then summarised in the conclusion.

Literature Review

Studies of stock market volatility often point at similar “stylised facts”. These include day-of-the-week effects, volatility following a U-shape throughout the trading day and asymmetric volatility, in that high volatility is more likely to follow negative returns rather than positive ones. Researchers have also focused on monthly effects in stock market data. The main focus of this paper is month-related volatility. As outlined by Tang (1998), whilst empirical studies on monthly seasonality of returns are numerous, investigations of the monthly seasonality of higher moments of returns (such as volatility) are not as common. In this way, most of the studies cited in this section relate to returns rather than volatility *per se*. Despite this, given that returns and volatility are directly related (since both are caused by price changes), existing studies of returns are highly relevant to volatility investigations.

One seasonality issue attracting much attention is the January effect, whereby higher returns can be earned during the month of January – suggesting a higher amount of volatility during this month. Empirical evidence on the January effect includes research by Officer (1975) and Rozeff and Kinney (1976) who found that January returns on Australian and US stocks tend to be higher than those realised during other months. More recent evidence includes the study of Lucey and Whelan (2004) who analysed Irish stock market data for the period 1934-2000 and noted the presence of a January effect.

Different authors suggested diverse explanations for the January effect. For instance Branch (1977) and Dyl (1977) suggested tax-related reasons – in particular investors sell stocks on which they can realise losses at the end of the fiscal year. This depresses stock prices in December, which then recuperate in January.

The actions of fund managers have also been considered as an explanation for the January effect. For instance, Porter, Powell and Weaver (1996)

analysed the share ownership of US fund management companies and found that portfolio rebalancing actions affect stock prices around the turn of the year. In particular, institutional investors “window dress” portfolios at fiscal year ends to divest from risky positions by selling risky stocks such as the ones of smaller companies. Fund managers then take on these positions again in January following the reporting date.

Authors such as Chien, Lee and Wang (2002) suggested that higher January volatility may be a remnant of the fact that the fiscal years of most companies end in December, and earnings are announced in January. This explanation is corroborated by the findings of Camilleri and Green (2005) who analysed volatility prevailing on the Indian stock markets. One notable feature is that a large number of Indian companies terminate their accounting years in March, and the authors found higher volatility during the months of March and April. No evidence of a higher January volatility was found, and this provides confidence that the frequently observed January effect is mostly related to the end of financial year of companies, which usually occurs in December.

Other researchers such as Ogden (1990) argued that the January effect may be explained by seasonal liquidity and cash flow factors whilst Chang and Pinegar (1989) and Kramer (1994) attributed the effect to risk seasonality.

Another frequently observed monthly effect, is the turn-of-the-month (TOM) pattern as discussed for instance by Lakonishok and Smidt (1988) who found that returns tend to be significantly higher on the last trading day of the month and the subsequent three trading days. Cadsby and Radner (1992) examined stock indices from ten countries for the period 1962-1989 and detected TOM effects in six markets. Similarly, Agrawal and Tandon (1994) examined stock index data of eighteen countries between 1971 and 1987, and concluded that the TOM effect was becoming less pronounced, since it was only present in seven countries during the 1980s, as compared to eleven countries during the 1970s.

Kunkel, Compton and Beyer (2003) examined daily stock market data for 19 countries from 1998 to 2000, and found the presence of a TOM effect in at least 15 of these markets. In particular, the TOM period accounts for around 87% of monthly return in those markets where it is present. Booth, Kallunki, and Martikainen (2001) analysed Helsinki Stock Exchange data for the

period 1991-1997 and found higher stock returns during the TOM. The authors attributed this TOM effect to higher trading activity and increased “buy” orders during the particular days, and they specified that the increased trading activity is mainly attributable to larger traders.

Overall, the above evidence implies that the TOM effect is not confined to any one particular country, and thus it is not likely to emanate from sampling errors or market structure since the latter typically differs across trading venues.

One possible cause of the TOM effect may be that individual investors postpone the purchases of stocks till around the receipt of their monthly salaries. This issue was discussed by Maberly and Waggoner (2000) who studied data for futures contracts on the S&P500 Index, as a proxy for the prices of the underlying stocks. They found that the TOM effect changed over the period 1982-1999. In particular no TOM effects were present in the post-1990 data. Additionally, the authors attributed other changes in the TOM effect to the individuals’ changes in investment practices over time; namely the tendency of moving away from direct stock purchases to investing indirectly through fund management companies.

If the TOM effect is indeed a remnant of the salaries payment pattern, it might be sensitive across countries where differences in the latter patterns exist. This issue was investigated by Ziemba (1991) in the context of Japan, where salaries are typically paid during days 20-25 of the month. The author confirmed that the TOM effect materialises about one week earlier in Japan and this suggests that this effect is related to salaries payment patterns. Thus overall, one may think of the TOM effect as the cause of the increase in cash available for investment, probably originating from individuals’ salaries. This is likely to result in a surge in trading activity and stock price movements.

Methodology

We now turn to the methodological approaches of this study. Monthly seasonality of stock prices is often modelled through dummy variables; for instance by specifying a model with eleven dummy variables, one may estimate the differences in volatility of eleven months, in relation to the remaining month. This approach of modelling seasonality was called into

question by various authors. For instance Chien, Lee and Wang (2002) noted one main shortcoming in that Ordinary Least Squares regressions assume the absence of heteroskedasticity of returns, which goes against the empirically observed “stylised facts” of stock market data. This may lead to flawed test statistics that are biased towards rejecting the null hypothesis of no seasonality in returns. Nonetheless, this limitation should not be of concern for our purposes due to a number of reasons. Firstly, this research also employs the Kruskal-Wallis test as an alternative non-parametric methodology in order to avoid relying on one criterion. In addition, authors such as Kunkel, Compton and Beyer (2003), noted that this limitation may be addressed by using a large data sample, such as the one at hand.

As outlined above, a further objective of this paper is to inquire whether any volatility patterns are related to company announcements on the grounds that stock prices should respond to news. We thus analyse the news announcements of MSE-listed companies for a five year period from October 2000 to September 2005 and classify the latter into different categories. This enables us to detect which types of news tend to result in pronounced volatility.

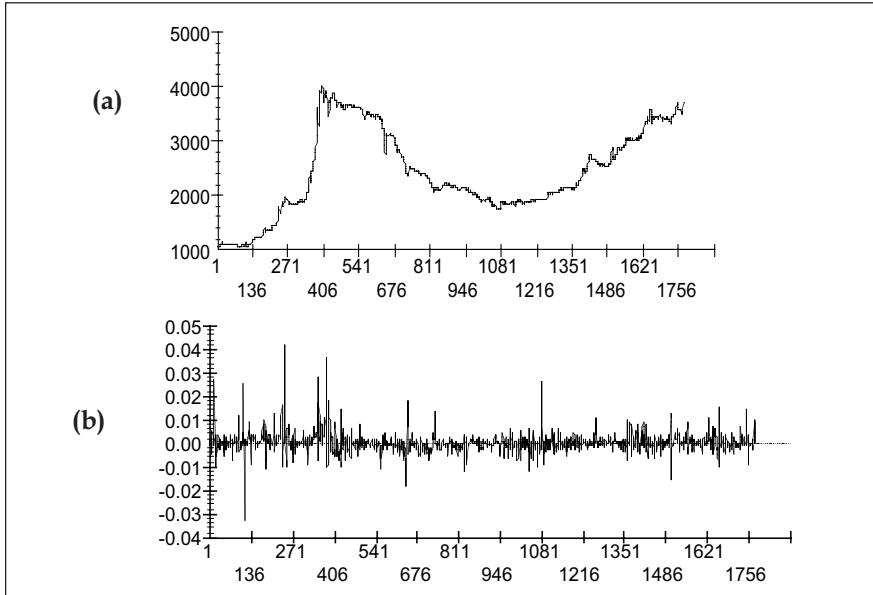
The above methodologies are discussed in more detail in the subsequent sections, when they are applied to the data set.

Data Description

This Section offers a brief description of the empirical setting and the data set. MSE was set up in 1990 and whilst trading was initially done manually, an electronic trading system was introduced in 1995. Being one of the smallest European exchanges, MSE is characterised by modest trading activity which may be attributed to the small size of the country and the low number of listings as compared to other mature exchanges. As at September 2005, the securities traded on MSE comprised 14 equities, 28 corporate bonds, and several government bonds. As at the same month, the total market capitalisation was around Euro 6,075 million, whilst the equity market capitalisation stood at around Euro 2,746 million. The total number of deals on MSE for the period January–September 2005, was 12,170 and around two-thirds of the latter constituted transactions in the equity market.

The data set shows the MSE Index Closing observations as from 1st June 1998 till 31st August 2005 and includes 1777 observations. The index value depends on all the shares traded on the exchange. The plots of the MSE Index (levels) as well as log returns for the sample period are shown in Figure 1.

Figure 1
Time Series Plots for (a) MSE Index and (b) MSE Log Returns



The MSE Index Log Return data set features an excess kurtosis of 21.4 and a positive skewness of 2.03. A Jarque-Bera Test Statistic of 35,108 permits the rejection of the null hypothesis of normality at the 99% level of confidence when compared to the respective Chi-Squared critical value.

The use of index data offers the inherent advantage that the observations are not biased by any peculiar effects taking place within individual stocks. The time series spans over seven years and this should enhance the robustness of the fitted regressions. Yet we should also note that there are limitations inherent in working with such a long time period. In particular the data set may include changes in the trading setup, such as revised exchange fees,

which are not accounted for. Some of these changes may well affect the underlying volatility process.

Given that a considerable part of the underlying stocks do not on average trade every day, the Index is subject to non-synchronous trading effects as outlined by Camilleri (2005). This implies that changes in the fundamental values of the underlying stocks might not be reflected in the Index immediately, due to lack of trading activity. This may affect the empirical findings of this investigation in the sense that we might find that seasonality patterns occur at a later stage, as compared to other exchanges. Despite this, the delay due to non-synchronous trading may only be expected to amount to a few days. Thus, we might expect the TOM effect to materialise with few days' delay as compared to other trading venues. As for the January effect, this might still be expected to materialise in the same month, since the non-synchronous trading effects are not so pronounced as to obtain a large number of shares which go untraded for around one month.

The study now proceeds with tests for January effects and TOM effects.

January Effects in Volatility

Having reviewed the relevant literature and outlined the main features of the data, we now turn to the investigation relating to January effects. The modulus series of daily log returns was regressed on an intercept and eleven dummy variables denoting the months of February–December. Each dummy variable takes the value of one during the respective month, and it takes a value of zero otherwise. The results shown in Table 1 indicate that all the coefficients of the dummy variables are negative, suggesting that return volatility is somewhat higher during the month of January. The dummy variables relating to the period April–October are significant at least at the 95% level of confidence. Thus, whilst January volatility is higher, the difference in daily returns volatility becomes more pronounced between April and October.

A further regression was estimated in order to represent the January effect through a more parsimonious model. This time, the modulus of daily log returns was regressed on an intercept and a dummy variable taking the value of one during the month of January and zero otherwise.

Table 1
Monthly Seasonality of Volatility

	<i>Coefficient</i>	<i>Standard Error</i>
Intercept	0.0033 ***	0.0003
Dummy Variables:		
February	-0.0007 *	0.0004
March	-0.0006	0.0004
April	-0.0015 ***	0.0004
May	-0.0009 **	0.0004
June	-0.0011 ***	0.0004
July	-0.0013 ***	0.0004
August	-0.0018 ***	0.0004
September	-0.0014 ***	0.0004
October	-0.0016 ***	0.0004
November	-0.0006 *	0.0004
December	-0.0002	0.0004
<p>R² = 0.0280 Adjusted-R² = 0.0219 F-Statistic = 4.6120</p>		

The table shows results for Monthly Seasonality of Volatility Regressions, where volatility is measured in terms of the Modulus of Log Returns. The explanatory variables are dummies for the months of February to December. Statistical significance is denoted by ***, **, and * for the 99%, 95% and 90% levels of confidence respectively.

The results shown in Table 2 indicate that the increase in January volatility is significant at the 99% confidence level as compared to the rest of the year. Given the limitations of the dummy variable approach, including the fact that t-tests may cause problems when applied to non-normal distributions such as the ones under review, an alternative non-parametric test was used in order to confirm the above indication of increased January volatility. This is the Kruskal-Wallis test which is defined by the formula:

$$H = \{[12/n(n+1)][\sum_{i=1}^k (TR_i)^2/n_i]\} - 3(n+1) \quad (\text{Equation 1})$$

where *n* is the number of observations (in our case 1776), *k* is the number of groups (in our case three: January; April-October period; and Rest-of-the-Year), *TR_i* is the sum of rankings obtained for each group, and *n_i* is the number of observations within the particular group. The statistic is Chi-squared distributed with *k*-1 degrees of freedom.

Table 2
Monthly seasonality of Volatility – Parsimonious Model

	<i>Coefficient</i>	<i>Standard Error</i>
Intercept	0.0022 ***	0.0001
January Dummy Variable	0.0011 ***	0.0003

$R^2 = 0.0082$ Adjusted- $R^2 = 0.0077$ F-Statistic = 14.7281

The table shows results for the parsimonious model relating to the January Effect. Volatility is measured in terms of the Modulus of Log Returns and the explanatory variable is a dummy for the month of January. Statistical significance is denoted by *** for the 99% level of confidence.

The observations of daily log returns modulus were ranked, assigning a value of 1 to the lowest return, and a value of 1776 to the highest one. The ranks were then classified into the January, April-October and Rest-Of-The-Year groups. For each of the three groups, the sum and the count of ranks was calculated. This yielded an H-statistic of 33.79. Comparing this to the Chi-squared critical value with 2 degrees of freedom, allows us to reject the null hypothesis that the returns are the same across groups at the 99% level of confidence.

Overall, these tests unanimously confirm the observation that MSE volatility as measured by the daily return modulus is highest in January. The April-October period tends to be the least volatile throughout the year.

Turn-of-the-Month (TOM) Effects in Volatility

We now turn to investigate the presence of TOM effects on MSE. The first analysis involves regressing the series of log return modulus on a dummy variable taking the value of one during the TOM period and zero otherwise.

The TOM period was initially defined as the last trading day of the month and the first three trading days of the subsequent month, in line with the findings of Lakonishok and Smidt (1988). The results are shown in Table 3 Regression A, and indicate that volatility tends to decrease during the TOM period, although the change is insignificant. This goes counter to the evidence described in Section 2, and therefore other definitions of the TOM

period were formulated. For instance TOM was defined as the last nine trading days of the month together with the first four trading days of the subsequent one, and then it was defined as the last five trading days of the month plus the subsequent two trading days.

Various regressions were thus estimated, and the model which mostly resembled a TOM effect was obtained when the TOM period was defined as the period ranging from the fifth last trading day of the month till the third last trading day of the month. Results are shown in Table 3 Regression B, and indicate increased volatility during the TOM period, which is significant at the 90% level of confidence.

Prior to discussing the implications of this finding, we confirm this effect through a Kruskal-Wallis test, defined in Equation 1. In this case, the number of observations n is 1776, and k refers to two different groups i.e. the TOM period and Rest-of-The-Month. The series of modulus of log returns was ranked, assigning a value of 1 to the lowest value. The ranks were then grouped into two as stated above. For each of the groups, the sum and the count of ranks was calculated. This yielded an H-statistic of 5.70. When comparing the H-statistic to the Chi-squared critical value with 1 degree of freedom, we may reject the null hypothesis that the volatility is the same across the two periods, at the 95% level of confidence.

Table 3
Turn of the Month Volatility Regressions

	Regression A		Regression B	
Intercept	0.00231 ***	(0.00009)	0.00223 ***	(0.00008)
TOM Dummy	-0.00007	(0.00020)	0.00041 *	(0.00022)
R ²	0.00007		0.00195	
Adjusted R ²	-0.00049		0.00139	

The table shows two TOM volatility regressions. In Regression A, the TOM period was defined as the last trading day of the month and the first three trading days of the subsequent month. In Regression B, the TOM period was defined as the period ranging from the fifth last trading day of the month till the third last trading day of the month. Volatility was measured in terms of the modulus of daily log returns. The latter series was regressed over an intercept and a Dummy variable taking a value of one in the TOM period and a value of zero otherwise. Coefficients are shown with standard errors in brackets. Statistical significance is denoted by *** and * for the 99% and 90% levels of confidence respectively.

The finding that the “TOM” effect tends to take place towards the end of the month on MSE, runs counter to our initial expectations that this effect might occur later as compared to other exchanges due to non-synchronous trading. We cannot rule out the possibility that this “TOM” effect is a remnant of the fact that a considerable part of Maltese pay-cheques is paid on the final Friday of the month. This may fall during the period from the fifth last trading day to the last one. One further notion which may explain this discrepancy is the trading practices of individual investors. For instance, whilst overseas investors might first transfer their money to fund managers who then purchase listed shares, a substantial part of the local investors might be purchasing shares directly, rather than through intermediaries, and therefore the surge in trading activity reaches the exchange earlier as compared to other exchanges. In addition, we cannot rule out the possibility that our finding of a “TOM” effect might also constitute a pure coincidence.

Another possible explanation for the month-related seasonality in volatility might lie in news announcement patterns of the companies listed on MSE, and this issue is investigated in the next section.

Relating Monthly Seasonality To News Releases

This section inquires whether the volatility seasonality discussed above is related to company announcements. The announcements for the five-year period October 2000-September 2005 were classified into six categories as described hereunder.

- **AGM:** This category includes announcements relating to annual general meetings, board of directors meetings, extraordinary general meetings, and appointments of directors and senior management.
- **Capital:** This category comprises announcements relating to changes in capital, such as mergers, changes in shareholders and offers for the sale of shares.
- **Strategy:** These announcements relate to indications about company strategies, such as agreements of collaboration with other companies, the establishment of subsidiaries or divestments from related companies, merger announcements when these are related to changes in strategy, changes in markets and business areas, and restructuring of operations.
- **Accounts:** This category relates to announcements on final and interim

results (which are not accompanied by dividend announcements), amendments to accounts and approval of audited accounts.

- Dividend: These announcements are related to dividends, and at times these are also accompanied by final accounts announcements.
- Other: This group picks all other announcements which do not fall under any of the above categories.

The five year period under review, included 1022 announcements. AGM announcements amounted to 506, Capital announcements amounted to 47, a further 44 announcements related to Strategy, 174 announcements were of an Accounts nature, Dividend announcements amounted to 37, whilst the remaining 214 were of Other nature.

Following basic finance concepts, we may expect stock price changes (and therefore volatility) to be related to these news announcements. Yet, we may deduce that not all the announcements are of uniform importance. For instance, a large portion of the AGM announcements tend to be of a routine nature, such as communications of details regarding when and where the AGM is being held. Such announcements may be forecasted to some degree, and therefore they should not induce material price changes. Conversely, Dividend announcements may be expected to induce price changes – especially if the proposed dividend is somewhat different from that of previous years. Announcements relating to Capital and Strategy tend to be of a longer-term nature and thus they may also be expected to induce material price changes, especially when such announcements are not anticipated by the market.

We now inquire which kind of announcements, if any, may be responsible for the first monthly seasonality pattern identified above, where it was found that volatility tends to be somewhat high in January-March, it abates during the April-October period, and then rises again in November and December. Thus, the company announcements as grouped in the above six categories were further classified by the period during which they were issued. The number of announcements in each sub-category was then divided by the number of months in the particular period, in order to adjust for the different number of months in each of the periods. The result was further divided by five, in order to obtain the average number of announcements per sub-category on an annual basis (given that the announcement data span over 5 years). Results are shown in Table 4.

Table 4
Number of Company Announcements Per Month

	All	AGM	Accounts	Capital	Dividend	Strategy	Other
Jan. - Mar.	14.47	7.93	1.93	0.80	0.93	0.93	1.93
Apr. - Oct.	19.34	9.51	3.86	0.63	0.60	0.57	4.17
Nov. - Dec.	12.80	5.40	1.00	1.30	0.20	1.00	3.90

The table shows the average number of MSE company announcements, for the period October 2000-September 2005. The second column shows the total announcements (e.g. on average there were around 14 announcements per month during the period January-March in any one year of the sample). The remaining columns show the number of announcements by a more detailed categorisation.

In inquiring which of the announcement categories might be responsible for the volatility pattern across the months of the year, we should look for a pattern where the number of announcements per month is highest in the January-March period and lowest in the April-October period. Starting with the total number of announcements, we note that these do not follow the desired pattern, and thus the monthly volatility pattern is unlikely to be induced by the announcements in general. This may be expected to some degree, since as outlined above a number of announcements tend to be of a routine nature. The announcement categories which somewhat follow the volatility pattern across the periods are Strategy and Capital. It is surprising that Dividend announcements do not follow the volatility pattern—since we may reasonably expect dividend announcements to materialise in considerable price changes. Despite this, if we add the number of announcements for these three categories (i.e. Capital, Dividend and Strategy) we obtain 2.67 announcements per month during the January-March period, 1.80 announcements per month during the April-October period and 2.50 announcements per month during the November-December period. In this way, we may attribute the seasonality of monthly volatility to “patterns” in Capital, Dividend and Strategy announcements.

The second investigation of company announcements, relates to whether the latter may be responsible for the TOM effect in the MSE Index outlined above. The company announcements were classified again into two as per the date of issue. The first sub-category included those announcements issued during days 1-24 of the month, whilst the second sub-category included those announcements issued during days 25-30. (Seven announce-

ments issued on day 31 were discarded). The number of announcements in each sub-category was then divided by 60, given the sixty months in the sample. Finally, the results were adjusted to account for the fact that the first period includes 24 days (and we thus divide by 24) whilst the second period includes 6 days (thus dividing by 6). Results are shown in Table 5 and these disclose a tendency to issue announcements towards the end of the month. This tendency is evident in all sub-categories, except for Strategy. We may thus state that the higher volatility towards the end of the month noticed above may be (partly) attributable to company news announcement patterns.

Table 5
Number of Company Announcements Per Day

	All	AGM	Accounts	Capital	Dividend	Strategy	Other
Days 1-24	0.517	0.269	0.072	0.025	0.013	0.025	0.113
Days 25-30	0.753	0.325	0.189	0.031	0.047	0.022	0.139

The table shows the incidence of company announcements issued during the first 24 days of the month, as compared to announcements issued during days 25-30. The total number of announcements in the sample occurring during these two periods was divided by 60 to adjust for the 60 months in the sample. The results were then adjusted to account for the different number of days in each of the two periods and thus the results were divided by 24 and by 6 respectively. The second column shows the total announcements (e.g. on average there were around 0.517 announcements per day which were issued on days 1-24, whilst there were around 0.753 announcements per day which were issued on days 25-30 during the sample period). The remaining columns show the number of announcements by a more detailed categorisation.

Overall we may state that the January effects and the TOM effects in volatility may be partly attributed to patterns in news announcements.

Conclusion

This study applied various empirical tests to investigate whether month-related volatility patterns prevailing on various stock markets feature on MSE. The tests confirmed that MSE volatility is subject to monthly seasonality. It was shown that a January effect exists on MSE, in that volatility tends to be higher during this month as compared to the rest of the year. A related finding was that the lowest volatility months on MSE are April to October.

This monthly seasonality might emanate from various sources identified in previous literature, which include seasonal liquidity and cash flow factors, tax-related reasons, risk seasonality and companies closing off their financial years in December. Yet, it was also shown that the January variation in volatility on MSE is also related to company announcement patterns—in particular announcements relating to capital, dividends and strategy.

A second seasonality feature in MSE volatility is the TOM effect—although in this particular case it might be more sensibly thought of as an end-of-the-month effect. It was shown that the pronounced end-of-month volatility may be attributable to a tendency for companies to issue announcements towards the end of the month. Yet, we may also attribute this effect to an increase in cash available for investment due to salaries payments, in line with previous literature.

Whilst most of the above results are statistically significant and were confirmed through the application of different methodologies, we still cannot rule out the possibility that these findings might be confined to the specific period under review.

These results add further evidence to that in the existing literature, and they are of particular interest given that they emanate from a smaller stock market as compared to the ones which have been analysed so far. Additional research potential lies in further volatility modelling using MSE data, with particular reference to “stylised facts” empirically observed on other markets, such as day-of-the-week effects.

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