

Monday Effect in Maritime Financial Variables: an Anomaly in Baltic Exchange Dry Index (BDIY:IND)

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ABSTRACT

Baltic Dry Index (BDIY:IND) is daily reported by Baltic Exchange. The index is a benchmark for the prices of ship chartering contracts which is a proxy for the maritime economy however the calendar anomalies of BDIY:IND have not yet been researched. This article investigates the day of week effects on BDIY:IND returns from 2014-03 to 2020-03. In this study, GARCH models were used to investigate the calendar effect on stock returns, and the Bootstrapping GARCH Regression is used to obtain the results with higher reliability. Regarding the correlation of time-based observations, the standard Bootstrap method does not apply to time series data; thus, the Bootstrap procedure based on resampling of GARCH's regression model residues is used in the present study. Based on a bootstrapping asymmetric GJR-GARCH approach, the results indicate that the Monday returns are significantly positive, which is in contrast with the usual findings in stock markets. It means the parties involved in shipping markets can still use information analysis as means to obtain further returns. The monetary figures of ship chartering contracts involve quite a large sum of money depends on movement of Baltic Dry Index hence having a knowledge of its behavior is vital for making smarter decisions for investors, shipowners and shipbrokers.

1. Introduction

Numerous empirical studies were carried out to investigate the calendar effects on stock returns. They have revealed that the returns tend to be higher (or lower) than their average level. Most of the studies focus on the US stock markets [1, 2]. Some others study the stock markets in other developed countries [3, 4], and a smaller number of studies focus on developing countries [5-7], most of these studies have used the western calendars and Abalala and Sollis, 2015 have used the Islamic calendar. But the nature of Baltic Exchange indexes are different, The reporting of prices by Baltic Exchange in London is made Monday to Friday, but the quoting of prices brokers, which finally makes the index is 24/7 and the industry itself, unlike the stock market, is working round the clock.. From all the indexes of the Baltic Exchange, the Baltic Dry Index is a standard benchmark for the price of freight rates. However, the calendar effect has never been investigated. The calendar effects that researchers most significantly favor include:

- January
- Days of the Week

The studies of calendar effects are mostly associated with financial behaviors because the anomaly of calendar effects goes against the efficient market hypothesis which holds that all prices follow a random

walk, without any particular trend. The efficient market hypothesis ensures that no abnormal returns can be made based on the available information. Osborn (Osborne, 1959, 1962) indicated that the stock and commodity prices are in a random walk and that stock price changes are random. This implies that techniques based on past price information cannot generate the returns higher than normal. Samuelson (Samuelson, 2016) proposed a logical theory associated with the efficient market hypothesis, according to that if the market is competitive, the normal commercial returns would be zero. Based on this theory, unexpected price changes in uncertain markets should act as an independent random variable. They argue that unexpected price changes are the indicative of new information. Because new information cannot be deduced from past observations, new information must stay independent throughout the time. As a result, if the unexpected normal return is zero, the unanticipated changes in asset prices will be time-independent. Will the capital markets still be effective if the behavior of the people is not logical? For example, what would happen if the information for all investors were unbiased, cost-free, and valuable but they are over-relied on? Could this lead to a rise in the current market price? Would, under such circumstances, there be a learning process that could help the market return to a

logical equilibrium? Three scenarios of market efficiency are defined as follows:

- **Weak market efficiency:** Information associated with past prices and returns will not contribute to greater returns.
- **Semi-strong market efficiency:** No investor can achieve higher returns on their investments through new trading methods based on publicly available information.
- **Strong market efficiency:** No investor can achieve excess returns using the available information, whether public or non-public.

Obviously, the third market efficiency scenario is the strongest type of efficiency. If the markets are strongly efficient, then the prices can fully reflect all available information. Moreover, if stock market anomalies end up causing inefficiencies, they should be immediately eliminated upon their discovery and reporting. According to Zaremba [8], once one of these anomalies is publicized, and the part of that anomaly will disappear or go into reverse. Thus, if information flow is steady and prices reflect all information, Monday return (the first business day of the week) is expected to be approximately three times higher than that of the rest of the weekdays, and this can be attributed to the three consecutive calendar days between market closing on Friday and market opening on Monday. But if we accept that information flow is unimportant on the weekends, Monday's returns should be the same as the rest of the weekdays. Nevertheless, studies show that neither of the aforementioned hypothesis was confirmed in the stock exchange of the US and many other countries [9].

Researchers and financial activists have long been interested in modeling calendar influences on stock markets because of its applicability in stock return prediction. The purpose of this research is to see whether the days of the week have an impact on BDIY:IND returns. If yes, which days of the week have the most and least significant effects? Drawing on the questions raised, one can hypothesize that the days of the week have a significant effect on BDIY:IND returns. To achieve the research objectives and find answers to the research question, the article was organized into six sections. After going through the introduction in section 1, a review of the literature is presented in the second section. In section 3, the research methodology, including the GARCH and Bootstrap simulation methods in the regression model, is discussed. Section 4 presents the statistical bases. Section 5 is devoted to the findings of the research and analysis of the results. The final section which is the concluding section, will close the paper.

In this section, attempts are made to briefly review the findings of relevant studies. International studies can be divided into two classes. The first class consists of the preliminary studies on calendar effects which address the calendar effects on stock returns without using

advanced modern statistics and econometric models. The results presented in these studies are mostly twofold.

1- For instance, without using any statistical tests, Caporale [10] concluded that stock returns in the US were negative on Monday and positive on Friday. Using least squares regression and T and F tests, Udayani [11] indicated that stock returns were insignificantly negative on Monday. Gkillas [12] and Miss [13] confirmed the validity of weekend effects. Jaffe and Westfield [14], Condoyanni [15], and Gkillas [12] applied least squares regression on Japan, Singapore, Australia, Canada, England, and the rest of the European countries and found that stock returns are significantly negative on Mondays.

2- In the second series of studies, the days of week effects on stock returns were found to be contrary to those of Series 1. For example, Akbalik and Ozkan [16] confirmed significant negative returns on Tuesday in Thailand and Malaysia and significant negative returns on Wednesday in Taiwan. Jaffe and Westfield [14], as well as Chiah and Zhong [17] showed negative Tuesday returns in a number of Pacific countries. Overall consistency among the preliminary studies, which were briefly reviewed above, was first challenged by Sullivan, & Timmermann [18]. For the first time, Sullivan used a Bootstrap approach to address errors in data mining and rejected the day of the week effects. These researchers warned of potential risks of data mining, claiming that the results are mere illusions presented by data mining methods. They also rejected Monday's negative effect and argued that reduction in transportation costs enables investors to regularly enjoy some returns on Monday. Sewell [19], Liu [20], Schwartz [21], Lu [22] revealed that the calendar effects are less pronounced, especially in developed countries.

There were no detailed academic studies of calendar anomalies in the Baltic Exchange indexes. Since the BDIY:IN is the proxy of the maritime economy and is the most important index Our study focuses on the Dry Bulk Index. GARCH models were used to investigate the calendar effect on stock returns, and Bootstrapping GARCH Regression is employed to obtain results with higher reliability. Considering the correlation of time-based observations, the standard Bootstrap method does not apply to time series data; thus, Bootstrap procedure based on resampling of GARCH's regression model residues is used in the present study. We find only weak evidence of the day of the week effects in the conditional mean return for the BDI index. A statistically significant day of the effects are found, and the affected day is Monday, and the 'Monday effect' is positive, which is in contraction with stock market findings. Typically, in the latter, the Monday effect is negative [1], When statistically significant day of the week effects are found in the conditional mean return, the effect is always negative for the days other than Monday. Statistically significant evidence for day of

the week effects in the conditional variance is found, the effect is positive. For the weekdays other than Mondays, the effect is negative, which contradicts the financial market results where the effect does not follow a specific pattern [2]. In most cases, positive conditional mean Monday effect is found for BDIY:IN is always statistically significant. According to the earlier discussion of EMH, these results are inconsistent with the efficient market hypothesis, since for some of these cases, other than the Monday effect for the conditional variance with similar signs does not exist.

2. Methodology

Calendar effects on individual stocks or the total return index are visible. Rossi [9] claims that calendar effects are more easily detected in market indexes or large stock portfolios than in individual stock prices. Therefore, as we discussed earlier in the present study, the attempts are made to investigate the day of week effects on the BDIY:IN.

Financial time series, in general, and stock prices, in particular, are prone to volatility. Nonetheless, rather of prices, stock returns (which are characterized by steady time series) are used in modeling.

$$R_t = \log(P_t - P_{t-1}) \quad (1)$$

In equation (1), R_t denotes the return, P_t is the total index of the stock price in period t and P_{t-1} represents the total stock price index in period $(t-1)$.

Following is a description of the regression model which was presented by two researchers to address the effects caused by the day of the week and utilized in the present study [10]:

$$R = b_1 D_{1t} + b_2 D_{2t} + b_3 D_{3t} + b_4 D_{4t} + b_5 D_{5t} + CR_{t-1} + \varepsilon_t \quad (2)$$

Where R_t is the daily stock returns, D_{it} ($i = 1, 2, 3, 4, 5$) denote the independent and virtual model variables and represent the day of week returns from Monday to Friday. ε_t indicates the model error. Besides, R_{t-1} was added to the regression equation to avoid autocorrelation of errors.

Now we discuss the GARCH and set up an appropriate GARCH variant, Stock volatility clustering is often seen in fiscal data, especially when residuals are correlated over time. In his arch paper, Engle modeled volatility clustering while assuming that conditional heteroscedasticity is an auto-correlated function influenced by the previous residuals. In fact, this model allows one to prevent the immediate disappearance of shock effects over time. Engle indicated that when the degree of correlation among the residuals is strong, the Arch method's efficiency is much higher than that of the conventional least squares method [23]. Therefore, since the time-series data used in the present study are

actually daily high-frequency data, the arch effects are quite expectable and can be ascertained via some tests. On the other hand, the coefficients estimated through the observation of arch effects are not really reliable. That's why variance modeling is required, as well as GARCH models, which are basically Engle's ARCH model in a generalized form. GARCH models are much smaller than the ARCH model, and GARCH (1,1) is the most popular structure for much financial time series [24]. The E-GARCH model which was first proposed by Nelson [25] obviates the need to apply constraints on the parameters of the ARCH model. In fact, the variance will always remain positive by defining conditional heteroscedasticity in the logarithmic form. Therefore, the model can account for the fact that negative shocks bring about larger conditional heteroscedasticity than similar positive shocks. Here is how it is defined:

$$\log(\sigma_{t-1}^2) = W_0 + \log(\sigma_{t-1}^2) + W_2 \frac{u_{t-1}}{\sigma_{t-1}^2} + W_3 \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (3)$$

The model of GJR-GARCH which is defined below is another asymmetric model presented by Glosten [26]:

$$\sigma_t^2 = W_0 + W_1 u_{t-1}^2 + W_2 \sigma_{t-1}^2 + W_3 u_{t-1}^2 i_{t-1} \quad (4)$$

Studies on Engle's asymmetric test proved that the asymmetric models fit the present study best [27]. Thus, among E-GARCH and GJR-GARCH models with multiple lags, only one is selected based on Akaike, Schwartz, and Hennan-Quinn information criteria. The equation used to estimate GARCH asymmetric models is the same as the one presented in equation (2), but the variance models are different and are determined based on equations (3) and (4).

Now we set up a Bootstrap percentile confidence intervals in the GARCH model. Since the day of the week, the effects do not follow any predetermined theory, and these results are reported, explored, and accounted for after they are tested using different models, and since empirical evidence hold that the Stock returns distributions significantly deviate from the normal distribution [28]. Bootstrap method is used to make the statistical inferences based on confidence intervals mainly because it doesn't need any assumption of normality.

The bootstrap resampling method is used in the regression model residuals to avoid data mining hazards and present reliable results. In fact, the conventional Bootstrap method does not apply to time series data. Hence, Bootstrap method is applied in the present study based on the resampling of regression model residues [29]. In Bootstrap resampling that is

used in the regression problems, the residuals are resampled as follows:

- First, t random samples are extracted among the estimated residuals of regression model (2), where t denotes the size of residues. The extracted samples are denoted by ε_t^*
- In the next step, the ε_t^* samples are used to calculate the value of the value of R_t^* as follows:

$$R_t^* = b_1 D_{1t} + b_2 D_{2t} + b_3 D_{3t} + b_4 D_{4t} + b_5 D_{5t} + CR_{t-1} + \varepsilon_t^* \quad (5)$$

The new R_t^* value is used to re-estimate E-GARCH model (1,1). The above steps are repeated for B times, where B refers to Bootstrap placement. Therefore, we have B values for each of the coefficients. By sorting these values, one can obtain the bootstrap percentile confidence interval for each coefficient. The value selected for B could be much large in practice. B value is proposed to estimate the precisions ranging from 50 to 200 and estimate the sample distributions ranging from 200 to 100. The strong law of large numbers can be used to justify this procedure [30].

3. Data and Results

Statistical data associated with Total BDIY:IND is required to implement the models described in the previous section. Statistical data associated with the total BDIY:IND were received from Baltic Exchange on a daily basis (1/1/20014 till 26/12/2020).

The following steps were taken to estimate the Bootstrap asymmetric GARCH regression model:

- Calculate the Total Return Index using equation (1)
- Use asymmetric E-GARCH, GJR-GARCH models (Equations 2 to 4) with multiple lags.
- Select asymmetric E-GARCH (1,1) model based on the information criteria presented by Akaike, Schwartz, and Hennan-Quinn.
- When models (2) to (4) are estimated, apply Bootstrap re-sampling (with 1000 iterations) on regression model residuals (2), and until Bootstrap percentile confidence intervals are obtained from coefficients of (E-GARCH (1,1)).

The results obtained from the estimation of models (2) to (5), using MATLAB software are presented in Tables 1 and 2. The following points are outlined from these results.

The results were obtained from the estimation of GARCH (1, 1) asymmetric regression model as well as Bootstrap percentile confidence interval. As can be seen, Monday return b_1 (0.001) can be recognized as the highest positive return within Bootstrap percentile confidence interval (0.0002 0.002) and is thus considered to be significant ($p=95\%$). Moreover, the

significant positive return of Monday (as mentioned in Section 2) is confirmed in the present study.

Table 1. Estimation of E-GARCH (1,1) using Bootstrap resampling: Coefficients of the mean equation

| SD | Coefficients of the mean equation | | |
|--------|------------------------------------------|----------|-------------|
| | Bootstrap percentile confidence interval | Estimate | Coefficient |
| 0.0003 | (-0.0002, 0.0008) | 0.001* | b_1 |
| 0.0003 | (-0.0002, 0.0009) | 0.0002 | b_2 |
| 0.0003 | (-0.0002, 0.0009) | -0.0001 | b_3 |
| 0.0003 | (-0.0002, 0.0009) | 0.0002 | b_4 |
| 0.0003 | (-0.0002, 0.0009) | 0.0005 | b_5 |
| 0.0188 | (-0.0002, 0.0009) | 0.5776 | C |

Table 2. Estimation of E-GARCH (1,1) using Bootstrap resampling: Coefficients of the variance equation

| SD | Bootstrap percentile confidence interval | Estimate | Coefficient |
|--------|------------------------------------------|----------|-------------|
| 0.2167 | (-5, 0.09) | -3.8052 | w_0 |
| 0.0622 | (-0.16, 0.14) | 1.0508 | w_1 |
| 0.02 | (0.527, 0.95) | 0.6535 | w_2 |
| 0.034 | (-0.105, 0.106) | 0.0459 | w_3 |

An estimated GARCH model (either symmetric or asymmetric) should not only enjoy good fitting, but should cover all the dynamic aspects associated with the mean and variance models. Residuals estimated in both mean and variance models should not be auto-correlated, and neither should they indicate any behavior corresponding to conditional volatility in the variance model. The test results are given in Table 3. As can be observed, the mean model residuals are not auto-correlated. The variance model revealed no sign of auto-correlation or conditional heteroscedasticity in the residuals.

Table 3. Test results

| Test | Value |
|--------------------------------------|----------|
| Akaike | -10.1193 |
| Schwartz | -10.0997 |
| Hennan Quinn | -10.1120 |
| Mean model ARCH (7) | 0.0475 |
| Variance model ARCH (7) | 0.09275 |
| Mean model LBQ ² (12) | 0.0874 |
| Variance model LBQ ² (12) | 0.09818 |
| R-bar | 0.2952 |

The following results were obtained from Bootstrap asymmetric GARCH regression model:

- Wednesday returns are negative while other days of the week returns are positive.
- Monday returns were found to be the only significant returns.

Thus, the significant difference among the returns of Monday and other days of week indicates that the day of week effect on the total price of Dry Baltic Index is confirmed during 2014-2020.

Wednesday returns are negative, Wednesday is the last of the week in Middle Eastern countries, which could explain it; however, it needs more research.

4. Possible Explanations for the Monday Effect

The empirical evidence suggests that the day of the week effects do exist. In particular, there is evidence of a positive Monday.

The results reported are interesting compared with the typically obtained results for stock calendar markets. Furthermore, since Monday is the first working day of the week, our finding of a positive Monday effect directly contrasts with the results on the first day of week effects obtained for stock markets. In the latter, the first day of the week effect (the Monday effect) is negative.

A possible explanation for a positive Monday effect is the link to the price of fixtures and contracts which are happening on Saturday and Sunday in Middle Eastern countries and the reflection of those fixtures on Monday at Baltic Exchange.

5. Conclusion

The Baltic Exchange Dry index is a benchmark for the prices of ship chartering contracts, and having a knowledge of its behavior is of high importance, but the day of the week effect in this index has never been examined before. Previous studies in the stock markets show that the calendar effects were on the decline. Two hypotheses can possibly be put forward for this:

- Markets are becoming more efficient.
- The more modern and robust statistical methods used in recent studies to identify these effects have challenged the results of preliminary studies, claiming that the results of such studies are mere illusions produced by data mining methods.

Modeling calendar effects in the financial markets are considered vital by the academics and financial practitioners mainly in terms of their applications in index returns prediction. Thus, the attempts were made to explore the day of week effect on Baltic Dry Index returns over 2014 - 2020. According to Bootstrap asymmetric GARCH regression model, Monday returns were found to be most significantly positive.

The results obtained from statistical and econometric methods reveal that the investors, ship owners, and ship brokers involved in Baltic Exchange market can still use information analysis as means to obtain further returns. This, however, is found to be in sharp contrast with the efficient market hypothesis. In most cases, the positive conditional mean Monday effect is found for BDIY:IND is always statistically significant.

According to the earlier discussion of EMH these results are inconsistent with the efficient market hypothesis since for some of these cases, other than the Monday effect for the conditional variance with similar signs does not exist. Other bootstrap resampling approaches, such as movable blocks bootstrap resampling in time series, were not included in this work. This is due to the fact that various methodologies must be handled separately in different settings and investigations. Therefore, considering the importance of stock market anomalies and their exploitation by stock market investors, the study of calendar effects by these models is advisable.

Possible explanations for the observed Monday effect in BDIY:IND could be the fact that shipping economy and contract fixtures are active during Thursday and Friday and Monday is the start of the week for reporting to Baltic Exchange.

6. References

- 1- Wong, K.A., T.H. Hui, and C.Y. Chan, *Day-of-the-week effects: evidence from developing stock markets*. Applied Financial Economics, 1992. 2(1): p. 49-56.
- 2- Berument, H. and H. Kiymaz, *The day of the week effect on stock market volatility*. Journal of economics and finance, 2001. 25(2): p. 181-193. .
- 3- al, c.e., 1993.
- 4- Davidson, S. and R. Faff, *Some additional Australian evidence on the day-of-the-week effect*. Applied Economics Letters, 1999. 6(4): p. 247-249.
- 5- Abalala, T. and R. Sollis, *The Saturday effect: an interesting anomaly in the Saudi stock market*. Applied Economics, 2015. 47(58): p. 6317-6330.
- 6- Basher, S.A. and P. Sadorsky, *Day-of-the-week effects in emerging stock markets*. Applied Economics Letters, 2006. 13(10): p. 621-628.
- 7- Mlambo, C. and N. Biekpe, *Seasonal effects: Evidence from emerging African stock markets*. South African Journal of Business Management, 2006. 37(3): p. 41-52.
- 8- Zaremba, A., *Performance persistence in anomaly returns: Evidence from frontier markets*. Emerging Markets Finance and Trade, 2020. 56(12): p. 2852-2873.
- 9- Rossi, M. and A. Gunardi, *Efficient market hypothesis and stock market anomalies: Empirical evidence in four European countries*. Journal of Applied Business Research (JABR), 2018. 34(1): p. 183-192.
- 10- Caporale, G.M. and A. Plastun, *Calendar anomalies in the Ukrainian stock market*. Guglielmo Maria Caporale and Alex Plastun (2017). Calendar anomalies in the Ukrainian stock market. Investment Management and Financial Innovations (open-access), 2017. 14(1): p. 104-114.

11- UDAYANI, V., *Pengujian Monday Effect dan Rogalski Effect pada Return Saham LQ-45 di Bursa Efek Indonesia*. 2016, STIE Perbanas Surabaya.

12- Gkillas, K., et al., *Day-of-the-week effect and spread determinants: Some international evidence from equity markets*. International Review of Economics & Finance, 2021. 71: p. 268-288.

13- Miss, S., M. Charifzadeh, and T.A. Herberger, *Revisiting the monday effect: a replication study for the German stock market*. Management review quarterly, 2020. 70(2): p. 257-273.

14- Jaffe, J. and R. Westerfield, *Patterns in Japanese common stock returns: Day of the week and turn of the year effects*. Journal of financial and quantitative analysis, 1985. 20(2): p. 261-272.

15- Condoyanni, L., J. O'HANLON, and C.W. WARD, *Day of the week effects on stock returns: international evidence*. Journal of Business Finance & Accounting, 1987. 14(2): p. 159-174.

16- Akbalik, M. and N. Ozkan, *Day of the week effect in the stock markets of fragile five countries after 2008 global financial crisis, in Global Financial Crisis and Its Ramifications on Capital Markets*. 2017, Springer. p. 507-518.

17- Chiah, M. and A. Zhong, *Day-of-the-week effect in anomaly returns: International evidence*. Economics Letters, 2019. 182: p. 90-92.

18- Sullivan, R., A. Timmermann, and H. White, *Dangers of data mining: The case of calendar effects in stock returns*. Journal of Econometrics, 2001. 105(1): p. 249-286.

19- Sewell, M., *The efficient market hypothesis: Empirical evidence*. International Journal of Statistics and Probability, 2012. 1(2): p. 164.

20- Liu, L., *The turn-of-the-month effect in the S&P 500 (2001-2011)*. Journal of Business & Economics Research (JBER), 2013. 11(6): p. 269-276.

21- Schwert, G.W., et al., *Handbook of the Economics of Finance*. chap, 2003. 15: p. 939-974.

22- Lu, X. and H. Gao, *The day of the week effect in Chinese stock market*. The Journal of Asian Finance, Economics and Business, 2016. 3(3): p. 17-26.

23- Dutta, A., *Modelling volatility: symmetric or asymmetric garch models*. Journal of Statistics: Advances in Theory and Applications, 2014. 12(2): p. 99-108.

24- Bae, H.-O., et al., *Volatility flocking by cuckersmale mechanism in financial markets*. Asia-Pacific Financial Markets, 2020. 27(3): p. 387-414.

25- Nelson, D.B., *Conditional heteroskedasticity in asset returns: A new approach*. Econometrica: Journal of the Econometric Society, 1991: p. 347-370.

26- Glosten, L.R., R. Jagannathan, and D.E. Runkle, *On the relation between the expected value and the volatility of the nominal excess return on stocks*. The journal of finance, 1993. 48(5): p. 1779-1801.

27- Feng, X. and C. Zhang, *A Perturbation Method to Optimize the Parameters of Autoregressive Conditional Heteroscedasticity Model*. Computational Economics, 2020. 55(3): p. 1021-1044.

28- Gong, P. and J. Dai, *Monetary policy, exchange rate fluctuation, and herding behavior in the stock market*. Journal of Business Research, 2017. 76: p. 34-43.

29- Harris, P., et al., *Introducing bootstrap methods to investigate coefficient non-stationarity in spatial regression models*. Spatial Statistics, 2017. 21: p. 241-261.

30- Krause, J., *Introduction to bootstrap*, in *Introducing Bootstrap 4*. 2016, Springer. p. 23-32.