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Citation:

Chowdhury, A and Uddin, M and Anderson, K (2022) Trading behaviour and market sentiment: Firm-level evidence from an emerging Islamic market. *Global Finance Journal*, 53. pp. 1-19. ISSN 1044-0283 DOI: <https://doi.org/10.1016/j.gfj.2021.100621>

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Document Version:

Article (Accepted Version)

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# Trading Behaviour and Market Sentiment: Firm-level Evidence from an Emerging Islamic Market

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## Abstract

We provide firm-level evidence from an emerging Islamic market that individual investors' trading behaviour causes weekend sentiment. Using data for 285 companies listed in Dhaka Stock Exchange (DSE) for the period from 2002 to 2019 and applying appropriate econometric techniques, the paper has found evidence of weekend effect both on return and volatility. The results confirm that individual investors' sentiment drive the weekend effect in DSE. 'Information content theory' and 'information processing hypothesis' work for investors so that the market return and volatility become significantly different on Sunday. The market sentiment effect is significant for smaller firms and low dividend yield firms where individual investors are prevalent, suggesting that trading behaviour of individual investors determines weekend sentiment. A positive feedback relationship exists between returns on Sunday and the previous Thursday for both institutions and individuals. Our results are robust in various alternative specifications.

## 1. Introduction

Islamic markets are always interesting to investigate for new insights because of the dynamic features of the investors, institutions, and the markets. Global Islamic financial assets are estimated to reach USD 4.0 trillion by the end of 2020 and due to this rapid growth of Islamic capital markets, it has become increasingly essential to examine their market behaviour (Al-Khazali and Mirzaei, 2017). In recent times, a number of authors have examined such markets. For example, Ahmed (2018) compared the reaction of Islamic equity market and conventional equity markets to political risk. Al-Awadhi (2019) examined causes of deviation from religious trading norms by the Islamic institutional investors while Alhomaidi et al. (2019) compared the return, volatility and liquidity between Islamic stocks and conventional stock listed in Saudi Stock Exchange. Using stock return data from 14 Muslim countries, Bialkowski et al. (2012) show that aggregate level sentiment such as Ramadan can influence the stock return and volatility. Jaziri and Abdelhedi (2018) also find similar results by using various Islamic occasions such as Eid, Ramadan and Hajj as core source of investor sentiment. Canepa and Ibnrubbian (2014) and Rashid et al. (2014) also find evidence that religious sentiment moves the stock return and volatility.

However, these studies do not provide any direct evidence on the link between investor sentiment and weekend effect using stock return from a market which is dominated by Muslim investors. Although weekend effect is a well-researched topic, the consensus is far from conclusive. While authors such as Hansen et al. (2005), Galai et al. (2008) and Philpot and Peterson (2011) conclude that calendar anomalies such as weekend effect are gradually fading out in recent times, Agrawal and Tandon (1994), Yunita and Martin (2012), Zhang et al. (2017) and Gkillas et al. (2021) find evidence in support of weekend effect. Boubaker et al. (2017) find some evidence of weekend effect but point out that data and method may change these results. The authors (Boubaker et al., 2017) suggest to do further research on these market anomalies as the existing results and theoretical explanations are not enough to understand this phenomenon. In this paper, we try to fill this gap by providing the market and firm-level evidence of weekend sentiment from an Islamic emerging market, which will help local and global investors to select optimum portfolios and formulate investment strategies to earn higher returns. More specifically, we look at a rapidly growing emerging Islamic market dominated by small private investors for new evidence on how investor sentiment and the trading of different types of investors causes the weekend effect.

Market sentiment such as negative stock returns and higher variances on Monday are one of the most puzzling empirical findings reported in finance (Wang et al., 1997). Two of the most credible explanations for this weekend effect from earlier studies are ‘information content theory’ and the

'information processing hypothesis'. It has been argued that both the information content effect and information processing effect are the outcome of trading activities of individual rather than institutional investors (Damodaran, 1989; Fortune, 1991; Choudhry, 2000; Lakonishok and Maberly, 1990; Abraham and Ikenberry, 1994). In addition, behavioural finance also provides support to the conjecture that an individual's moods and perceptions are subject to a Monday effect in the equity market (see Rystrom and Benson, 1989). However, Sias and Starks (1995) and Brockman and Michayluk (1998) provided evidence supporting the trading of institutional investors that causes the weekend effect.

While the trading behaviour of individual versus institutional investors as a reason for Monday effect has been rigorously investigated for equity markets from developed countries, little or no substantiation has been documented in emerging Islamic markets. This is possibly due to the difficulty of obtaining similar data for these markets. In this study, therefore, we have filled the gap by using a new set of data from an emerging Islamic market, the Dhaka Stock Exchange (DSE), which allows us to investigate the impact of trading patterns of institutions and individuals on both equity returns and variance following the weekend, considering their individual preference for investment.

DSE is one of the fastest growing equity markets of South Asian region and named as one of the best performing markets in the world (see The Economist, 2011; Rintoul, 2012). Yet, there is no study on DSE that examines the information content and information processing hypothesis using weekend return behaviour. Although there are several studies on DSE that examine time series behaviour of stock return (Chowdhury, 1994), market efficiency (Hassan and Chowdhury, 2008; Azad et al., 2014), time varying risk-return relationship (Basher et al., 2007) and stock market liquidity (Chowdhury et al., 2018), weekend return behaviour of DSE is still remained unexplored. Following this research gap, this study has investigated the information content and processing hypotheses for DSE, the main capital market of Bangladesh, which operates from Sunday to Thursday rather than the usual Monday-Friday for most of the developed countries that had been the prime attention of weekend effect studies. Our study is significantly different from previous studies and makes several contributions to the literature. First, the day-of-the-week effect on Sunday provides an opportunity to add to the evidence that following the information advantage, stock returns and the volatility pattern shift in step with the change in trading days. Second, the trading behaviour of individual investors after the weekend and any positive Thursday-Sunday feedback effect should confirm that the information processing hypothesis holds irrespective of time, size, location and characteristics of the equity market (i.e., both in conventional and Islamic).

In this Islamic equity market (DSE), more than 99 percent are individual investors who hold an average of 42 percent of the stocks traded on the DSE in 2017, whereas less than one percent of these traders are institutions and hold around 18 percent<sup>1</sup> of stocks (including foreign portfolio investment). Therefore, if the weekend effect is a result of the trading behaviour of investors then it should be predominantly due to the trading of individual investors rather than institutional investors. Third, Islam imposes several restrictions on individual investment choice, such as the prohibition on investing in “sin stocks” and interest-bearing securities. As suggested by Canepa and Ibnrubbian (2014), in countries where religion plays a heavy role (as in Bangladesh) in dictating individual investors’ behavioural code and social norms portfolio selection could be affected. Therefore, the results of this paper provide helpful evidence to investors whether Islamic codes and social norms alter the existing knowledge on the weekend effect.

Fourth, Bangladesh has distinctly different economic, institutional, and microstructural features compared to other emerging markets such as China, India or Brazil. For example, it has low integration with world markets; political institutions are very strong and they frequently intervene in the market, sometime for political gains; there is a small-scale bond market, however, treasury bonds are only traded by institutions; most of the investors are Muslim and they prefer not to invest in fixed interest-earning assets, thus the stock market is a good alternative for them. Therefore, an investigation of returns and variance trends for DSE can substantiate the reports of this market anomaly. Our evidence confirms the notion that the weekend effect is not just a feature of developed countries but also of emerging Islamic stock markets. Finally, due to its economic progress<sup>2</sup> and low integration with developed markets, Bangladesh could be a good diversification alternative for international investors. Knowing the confirmed presence of the ‘day-of-the-week’ effect will give advantages to foreign as well as domestic investors for setting their investment strategies in advance.

Using daily market data and firm level data from 270 firms, our major findings include - first, following the trading time hypothesis, weekend sentiment exists in market returns. Mean stock returns are not the same across the weekdays and the “Sunday Effect” is evident. Second, there

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<sup>1</sup> Sponsors, i.e. directors and founder-owners (37.18%) and government (3.63%) hold the remainder of the traded stocks on the DSE. Source: Authors’ calculations from information on the DSE website.

<sup>2</sup> Bangladesh is the second largest exporter of ready-made garments in the world after China and also the eighth most populous market in the world, with 46% of people below age 24 and 40% at prime working age between age 24 and 54. Bangladesh is also the birthplace of microfinance and with more than 95 per cent Muslim population, one of the largest Islamic markets in the world (see Chowdhury (2014) and Islam and Khaled (2005) for detailed characteristics of Bangladesh’s economy and market).

are weekend and reverse mid-week effects identified in market volatility, which is linked to the trading behaviour of investors. Third, weekend sentiment is found to be prominent for smaller firms and firms with a low dividend yield, which supports the argument that in a market dominated by individual investors the weekend effect is stronger for smaller firms than larger companies. Fourth, our robustness test confirms that there is a positive feedback relationship between Sunday returns and the returns of the previous Thursday. The association is stronger for smaller and mid-size firms and we also document this feedback effect in variance. Finally, the return and volatility of Sunday during the Ramadan period are not statistically different from non-Ramadan Sundays.

The paper is divided into five sections. Section 2 reviews the existing literature for evidence of the impact of individuals versus institutions on the weekend effect in line with the information content and processing hypotheses. Our data and methodology for investigating the weekend effect on returns and volatility are discussed in sections 3. Section 4 reports our empirical findings. Section 5 presents our conclusions based on the empirical findings.

## **2. Literature Review**

There are several calendar-based anomalies documented in the literature, such as the January effect, the weekend effect, the week of the month effect, the week of the year effect, the semi-monthly and turn-of-the-month effect, and the holiday effect. Nevertheless, some of the most anomalous empirical findings are associated with the distribution of daily stock returns through the week. This is the “day-of-the-week effect” or “weekend effect” (Jaffe and Westerfield, 1985), where stock returns are negative and returns variance is higher on Monday (see Fama, 1965; French, 1980).

Researchers have tried to provide explanations to rationalize the weekend effect in both returns and volatility rather than simply defining it as a market anomaly. For example, Lakonishok and Levi (1982) argue that the Monday effect is due to the delay between trading and settlement in stocks and in clearing checks. Dyl and Maberly (1988) suggest that managers of publicly owned firms may tend to delay announcements of bad news, or at least news that is not favourable, until the end of the week, after markets have closed. In this line of thought, Damodaran (1989) shows a link between the disclosure of bad news and the weekend effect. Firms usually tend to announce bad news on Fridays and Damodaran (1989) suggests that delaying the announcement of bad news until then might cause the negative Monday returns. Fortune (1991) asserts that firms and governments release good news during market trading, when it is readily absorbed, and store up bad news until after the close on Friday, when investors cannot react until the Monday opening. Focusing on the seasonality in volatility, Barclay et al. (1990) and Foster and Viswanathan (1990)

add that stock returns variance should be highest on Mondays, when the informed trader has maximum information advantage. Variance should decline as the working week progresses as public information arrives. This decrease in the advantage of private information leads to lower returns variance on Fridays. According to Ho and Cheung (1994) volatility variation exists due to noise traders who usually do not trade based on the fundamental value of stocks, but rather trade for liquidity needs. To explain the day-of-the-week effect, Kyle (1985) reports that there is a structural link between trading volume and stock returns variances, particularly on Monday.

Investors' trading patterns and the weekend effect are extensively examined in Lakonishok and Maberly (1990), Abraham and Ikenberry (1994), Kamara (1997), Chan et al. (2004), Brusa et al. (2005), and Venezia and Shapira (2007). For example, Lakonishok and Maberly (1990) explain that the higher level of trading activity by individual investors on Monday (particularly more selling transactions) creates this weekend effect. They claim that for sell decisions individuals are basically left on their own and there is a tendency to make decisions over the weekend. Abraham and Ikenberry (1994) provide additional support for this hypothesis using the CRSP equally-weighted index of NYSE and ASE firms over the period 1963 to 1991. They report that selling pressure by individuals is not only higher on Mondays, but is substantially heavier following a decline in the market on the previous Friday. These findings are consistent with individual investors having a positive feedback trading strategy. Abraham and Ikenberry (1994) assert that the negative Monday returns are actually conditional upon the previous Friday's returns. In addition, conditional returns appear to be a function of firm size, with small and medium sized firms exhibiting a stronger conditional effect than large firms. Kamara (1997) claims that individual trading is an important cause of the Monday effect and finds that its magnitude on the S&P 500 declined significantly over the 1962-1993 period, when institutions greatly increased their trading activities. He reports that lower transaction costs and increasingly intensive collection of information reduced the risk of weekend surprises for the institutions. Yet the marginal cost of transactions in the NYSE's smallest capitalization stocks is not much lower for institutions than for individuals, and therefore the Monday effect exists for small capitalization stocks.

In contrast to the previous findings on the US equity market, Sias and Starks (1995) find that stocks with higher institutional holdings exhibit a significantly greater day-of-the-week conditional returns pattern than do stocks held primarily by individual investors. Their data consist of all firms listed on the NYSE for 15 years, from 1977 through 1991. They report two pieces of evidence that are consistent with the institutional investor hypothesis. First, stocks with large institutional holdings exhibit significantly greater turnover on Monday and second, there is a strong positive feedback

effect between Friday and Monday for stocks with higher institutional holdings. Chan et al. (2004) takes a large data set and re-examine the behaviour of institutional and individual investors on the US markets concerning the Monday effect. Their sample includes all firms listed on the NYSE, Amex and NASDAQ during the period 1991–1998. They provide direct evidence that the Monday seasonality is typically strong in stocks with low institutional holdings. The active participation of institutional investors may reduce the magnitude of the Monday effect.

An interesting outcome is reported in Brusa et al. (2000 and 2005). They find a ‘traditional’ weekend effect and a ‘reverse’ weekend effect related to firm size. The ‘reverse’ weekend effect tends to be associated with large firms, whereas the ‘traditional’ weekend effect tends to be associated with small firms. They reach this conclusion by studying the CRSP value weighted index, NASDAQ, S&P 500 and DIJA indices over the period 1963–1998. They also report a positive feedback effect in large firms. Monday returns follow Friday returns particularly when previous Friday returns are positive. They further find evidence that Monday returns are positively related to the volume of medium-sized and block transactions; however, they are negatively related to odd-lot transactions.

Venezia and Shapira (2007) categorize investors on the Israeli stock market into amateur and professional, and investigate their trading pattern after the weekend. Using data from 1994 to 1998, they find that the weekend influences both categories of investors but in opposite directions. Individuals increase both their buy and sell activities, and their propensity to sell is greater than their propensity to buy. Professionals, on the other hand, carry out fewer transactions with almost equal amounts of buying and selling.

In this empirical research we jointly investigate the weekend effect on the return and volatility and whether investors’ trading behaviour influences the effect using the DSE all-share price index. In particular, our major interest is to see how the information content and processing hypotheses work in an equity market which is significantly different from other developed and emerging markets. We examine return and variance jointly because for rational financial investment decision making, returns constitute only one part of the decision process and risk-averse investors are interested to know the variations in volatility (Engle, 1993; and Charles, 2010). Our conditional variance approach overcomes the arguments related to characteristics of time series data, such as error distributions and asymmetry in volatility mentioned in Kiyamaz and Berument (2003), Baker et al. (2008) and Charles (2010). In addition, findings from previous empirical studies are not conclusive whether return and volatility on the opening day reflect the active participation of institutional or individual investors, e.g., Sias and Starks (1995) and Chan et al. (2004). Therefore,



for testing the information processing hypothesis and trading pattern this study considers the behavioural preferences of investors by dividing the listed firms into size-based portfolios, where institutions tend to invest in larger and more liquid stocks (Kamara, 1997; Gompers and Metrick, 2001; and Chan et al., 2005). We also create portfolios based on dividend yield and link the presence of weekend effect and feedback effect on the DSE with investors, since high yields attract institutional investors (see Shleifer and Vishny, 1986; and Allen et al., 2000). Overall, this is to confirm whether the effect is not only a feature of developed economies but can also exist in an emerging market such as Bangladesh, which is an increasingly popular destination for investment. The presence of the ‘Monday effect’ on Sunday will further validate the fact that information advantage theory and the information processing hypothesis work, irrespective of which days the stock market trades on.

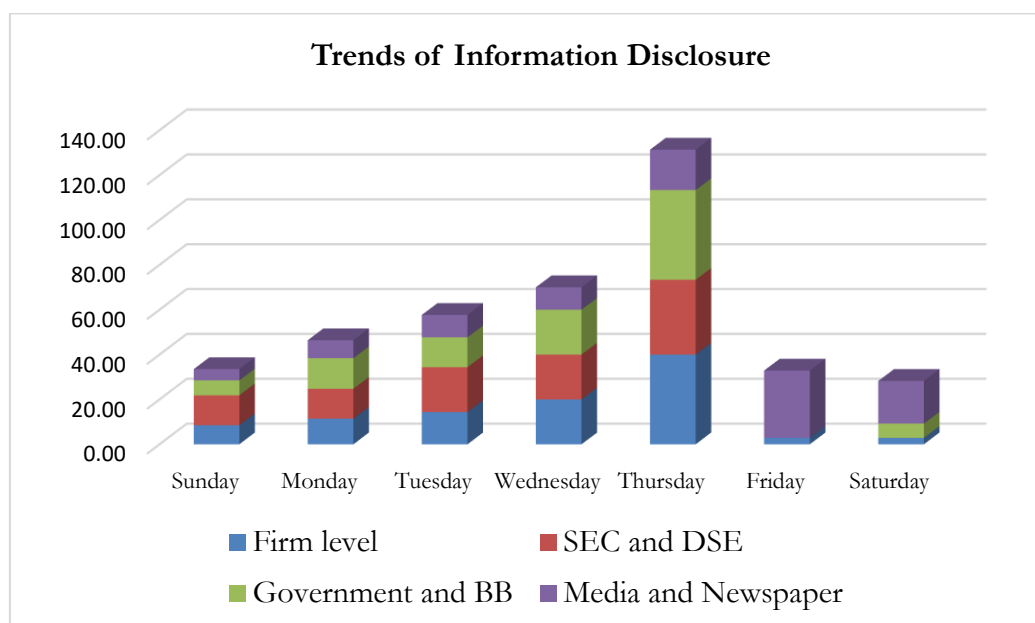
### **3. Data and Methodology:**

#### **3.1. Data:**

In this study we use four different daily observations, i.e., the market index, stock price, market capitalization and dividend yield from January 1st 2002 to June 30<sup>th</sup> 2019. All these data were collected from DataStream. We collected the market capitalization and dividend yield data for all listed companies on the Dhaka Stock Exchange, which is 285 firms over the sample period included in the DSEX index. Following the ‘information content theory’ and ‘information processing hypothesis’ we use the daily DSE All-Share Index from 1<sup>st</sup> January 2002 to 27<sup>th</sup> January 2013) and the DSEX Index from 28<sup>th</sup> January 2013 to June 28<sup>th</sup> 2019 to test the weekend effect and investors’ behaviour on both returns and volatility. We calculate the returns series as the first difference in logarithms of the daily stock index.

Figure 1 summarizes the daily trend of information disclosure from various sources for the period January 2002 to June 2019. We have identified around one hundred information sources and categorized them into four major groups, namely the Security Exchange Commission, Government, Media and Newspapers, and announcements by firms. Using this Figure 1, we want to see the general trend of news and information release in Bangladesh that helps individual investors process news over the weekend and trade actively on Sunday with maximum information advantage. These news and information sources relate to earnings and dividend announcements, the national budget, changes in trading laws, market and company enquiry reports, margin loan rules, market and company level reports and analysis, announcements of the cash reserve ratio, bank rate, deposit rate, capital gain tax and personal tax.

**Figure 1: Timings of Economic and Financial Announcements in Bangladesh**



Note: In this stacked bar graph, each bar colour represents the percentage of information disclosure from each source per day.

Sources: Author's calculation based on information collected from Bangladesh Bank (BB), the National Board of Revenue, the Security Exchange Commission (SEC), the Dhaka Stock Exchange (DSE), The Daily Star, The Financial Express, television channels and annual reports. All data are in percentage form.

It is evident from Figure 1 that authorities release their information towards the end of the week and particularly on Thursday with a few releases over the weekend (Friday and Saturday), although investors cannot trade until Sunday. For example, around forty per cent of firm level, governmental and central bank information come into market on Thursday. Similarly, around thirty-four per cent of SEC and DSE related news are disclosed on Thursday. The media and newspaper, however, publish market related articles and reports mostly on Friday (30%) and Saturday (19%). We therefore conjecture that on Sunday individual investors should be more active and create a pattern of returns and volatility that differs from other weekdays.

Based on the data available from Central Depository Bangladesh Limited (CDBL), Table 1 gives us an idea of the number of domestic institutional and individual investors active in the Dhaka Stock Exchange from 2007 to 2019.

**Table 1: Number of Investors on the DSE**

| Year | Number of Accounts in Operations |                 |                                     |                 |
|------|----------------------------------|-----------------|-------------------------------------|-----------------|
|      | Individual Accounts              | Growth Rate (%) | Institutional Accounts <sup>a</sup> | Growth Rate (%) |
| 2007 | 848,808                          |                 | 3671                                |                 |
| 2010 | 1,581,505                        | 86.32           | 5941                                | 61.84           |
| 2013 | 1,698,117                        | 7.37            | 7196                                | 21.12           |
| 2014 | 1,871,746                        | 10.22           | 8517                                | 18.36           |
| 2015 | 1,989,443                        | 6.29            | 8743                                | 2.65            |
| 2016 | 1,938,406                        | -2.57           | 9056                                | 3.58            |
| 2017 | 1,837,446                        | -5.21           | 10061                               | 11.10           |
| 2018 | 1,747,406                        | -4.90           | 10485                               | 4.21            |
| 2019 | 1,769,329                        | 1.25            | 11863                               | 13.14           |

Source: Author's calculation based on annual report of Central Depository Bangladesh Limited (CDBL)

<sup>a</sup>The institutional investors in Bangladesh are: Investment Corporation of Bangladesh, Schedule Banks, Merchant Banks, Bangladesh Development Bank Limited, Non-Bank Financial Institution, Insurance companies, Leasing companies, Pension funds, Provident funds, Postal savings schemes, Postal life insurance, Co-operative land mortgage banks, Employees insurance funds and Securities deposits.

Table 1 shows clearly that the market is dominated by individual investors and there are only a few institutional investors trading in this equity market. Over the last nine years, total investors more than doubled, from 0.85 million to 1.77 million. However, the vast majority of them consist of individuals, (more than 99.33%). Only 0.67% are institutional accounts in 2019. These few institutional investors hold on average 18 percent of the stocks traded on the DSE in 2017, whereas individual investors hold around 42 percent of stocks<sup>3</sup>. In developed stock markets a form of polarization between individual and institutional investors is evident, yet domination by individuals is fairly common in emerging markets. For example, Ng and Wu (2007) report that on the Shanghai and Shenzhen Stock Exchanges 99.5% of accounts belong to individuals out of 68.8 million investors and they hold about 80 percent of total trade value of the sample. Conversely, in the US

<sup>3</sup> From Datastream's Industry Database, as of June 2017, the 18% of traded stocks held by institutional investors are distributed among 19 industries and 236 listed companies (out of 338). The general tendency of these institutional investors is that they have greater holdings in firms with higher market capitalizations. For example, they hold an average of 20.98% of traded stocks of the financial sector and this sector has the highest percentage of market capitalizations in the market (i.e. 42.63%). Similarly, institutional investors hold around 20% traded stocks of Pharmaceuticals, Cements and Fuel and Power industries. The market capitalizations of these three sectors are also higher in the DSE than others industries. Altogether, the data reported in the Industry Database of Datastream indicate that institutional/foreign investors mostly target large cap stocks on the DSE.

the mean percentage of institutional holdings of stocks traded in all three markets (NYSE, Amex and NASDAQ) was 14.6% in 1981, 21.9% in 1990 and 31.0% in 1998 (see Chan et al., 2004). It has further increased to 67 percent of all US stocks in 2010 (see Blume and Keim, 2012). This implies that between developed and emerging equity markets, it is in the latter where most of the investors are individual. Therefore, if investors' trading behaviour influences the price of any equity market then it should be evident on a recently emerging market such as the DSE. All our data has been tested to ensure that there is no 'unit-root' in the time series. Similarly, we winsorised our data by one per cent to avoid the outlier problems across the dataset.

### 3.2. Methodology

Many previous studies investigated the weekend effect by regressing returns on four daily dummy variables (e.g., French, 1980; Jaffe and Westerfield, 1985; Smirlock and Starks, 1986). However, the use of this methodology has two drawbacks and could give misleading inferences (Kiymaz and Berument, 2003; Berument and Kiymaz, 2001). First, errors in the model may be autocorrelated and second, error variance may be heteroskedastic. French et al. (1987) and Nelson (1991) also emphasize these characteristics of autocorrelation and conditional heteroscedasticity. To address the first issue, we include lagged values of the returns in equation (i). To avoid the second limitation, we allow the variance of errors to be time-dependent. This conditional heteroscedasticity will capture any time variation in stock returns variance (Kiymaz and Berument, 2003; Berument and Kiymaz, 2001). As Connolly (1989) mentions, there is much evidence that stock returns have time varying variance and many studies of market anomalies failed to take that into consideration.

We therefore model our returns using the following stochastic model:

$$R_t = a_0 + a_1D_{1t} + a_2D_{2t} + a_3D_{3t} + a_4D_{4t} + \sum_{i=1}^n b_i R_{t-i} + \varepsilon_t \quad (i)$$

Where  $R_t$  is the daily return,  $D_1, D_2, D_3$ , and  $D_4$  are dummy variables for Sunday, Monday, Wednesday and Thursday at time  $t$ , and  $n$  is the lag order.  $\varepsilon_t$  is the error term that follows a Gaussian process. The dummy variable for Tuesday is excluded from the equation to avoid the dummy variable trap. Moreover, Tuesday is in the middle of the trading week and we are examining the trading pattern around the weekend.

We next apply the generalized autoregressive conditional heteroscedasticity (GARCH) model to investigate the weekend effect in terms of volatility. The GARCH model, developed by Bollerslev

(1986), has been a major tool to capture the three empirical features most often observed in stock returns data: leptokurtosis, skewness and volatility-clustering. Here the assumption is that conditional variance,  $h_t$  is a function of three terms – a constant ( $\omega$ ), shocks or news-impact from the previous period ( $\varepsilon_{t-1}^2$ ) measured as the lag of the squared residual from the mean equation, and last period forecast variance ( $h_{t-1}^2$ ). A simple time varying variance model using a GARCH (1, 1) process is:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 \quad (\text{ii})$$

Engle (2001) states, “GARCH (1, 1) is the simplest and most robust of the family of volatility models” and it is also the most widely applied. We therefore use the GARCH (1, 1) model to investigate the weekend effect on volatility. However, many previous papers have included exogenous variables in the variance equation to check their significance for the returns volatility (e.g., Choudhry, 2000; Balaban et al., 2001; Berument and Kiyamaz, 2001 and 2003; Baker et al., 2008). Following those studies, some exogenous variables are also allowed in our GARCH (1, 1) model to see their possible effect on the variance. To be specific, this study allows the conditional variance equation to change for each day of the week to check the weekend effect on volatility. Thus, the specific GARCH (1, 1) model becomes:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \sum_{m=1}^n D_m \pi_m \quad (\text{iii})$$

Where  $D$  represents the exogenous variables (i.e. dummy variables as in equation i), particularly each weekday and  $\pi$  is the corresponding weight for  $D$ . Therefore, if  $\pi$  is found statistically significant for any weekday then we can assert that the weekend effect exists in the variance equation. To increase the persistence of the GARCH (1, 1), we have excluded returns on any structural break dates from our model and the Bai and Perron (1998) approach is used to determine the structural break in return series. The study uses a GARCH process under the assumption that the conditional distribution of the error term,  $\varepsilon_t$ , follows a Gaussian Error Distribution.

To investigate the degree to which the weekend effect is related to firm size, we follow the methodology of Keim (1985) and Brusa et al. (2000). We initially divide all the listed firms on the DSE into ten deciles. We then create three sub-portfolios from them based on reverse ranking firms’ market values. The firms in the first and second deciles are the “smallest group”, the third to seventh deciles are the “medium sized group” and the last two deciles are the “largest group”. We apply the time varying conditional variance model to judge the significance of returns and volatility of each value weighted sub-portfolio on Sunday. The returns equation is as follows:

$$RS_t = \alpha_0 + \alpha_1 \psi_{it} + \alpha_4 RS_{t-1} + \varepsilon_t \quad (v)$$

Where  $RS_t$  is the Sunday returns,  $\psi_i$  are the value weighted returns of the largest, mid-sized and smallest firms, respectively, at time  $t$ , and  $RS_{t-1}$  is the one period lag value of Sunday returns to minimize the autocorrelation problem.  $\varepsilon_t$  is the error term that follows the Gaussian Error Distribution,  $h_t [\varepsilon_t \sim (0, h_t)]$ . Based on the statistical significance of each sub-portfolio, i.e.,  $\psi$ , we should be able to assert which category of investors and their trading activities influences the Sunday returns.

Next, we use a modified variance equation to examine how the volatility of each sub-portfolio affects the variance of Sunday returns:

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \sum_{i=1}^p \xi_i \pi_i \quad (vi)$$

Where  $\xi$  is the exogenous variable, i.e., each sub-portfolio, and  $\pi$  is the corresponding coefficient. Therefore, if  $\pi$  is found to be statistically significant for any portfolio then we can state that the weekend effect on volatility is the result of trading patterns of a certain group of investors, since investors have different preferences for risk holding.

Further, we investigate how the dividend preference of equity investors influences the weekend effect. If individuals' trading activity determines the pattern of returns and variance on Sunday then it should be reflected in lower dividend paying firms. Therefore, we further break down all the listed firms on the DSE into two portfolios (i.e., high and low dividend yield portfolios) based on the daily value weighted dividend yield from January 2000 to June 2017. We use median dividend yield to define the categories, where high dividend yield firms have larger annual median dividend yields than low dividend yield firms. The use of the value weighted dividend yield helps us to control the size effect and make the estimation unbiased<sup>4</sup>. Finally, we run the time varying conditional variance model as stated in equations (vii) and (viii) for each portfolio to see which type of stock activity influences the returns and variance on Sunday:

$$RS_t = \alpha_0 + \alpha_1 \delta_{1t} + \alpha_2 \delta_{2t} + \alpha_3 RS_{t-1} + \varepsilon_t \quad (vii)$$

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<sup>4</sup>This study uses value weighted dividend yield because Keim (1985) asserts that the difference in abnormal returns across dividend yield portfolios may be related to systematic differences in market capitalization (i.e. size of the firms) among portfolios. Furthermore, positive dividend yields and market value are inversely related (see Keim, 1985 for further discussion). Therefore, to control these effects and associations we create portfolios based on value weighted dividend yields. In addition, due to the categorical restrictions (see DSE website, [www.dsebd.org](http://www.dsebd.org)) large and prudent firms in DSE usually declare dividends on a regular basis. By creating portfolios based on value weighted dividend yields we also control their influences.

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \sum_{m=1}^q \phi_m \theta_m \quad (\text{viii})$$

where  $RS_t$  is the Sunday returns and  $\delta_{1t}$ , and  $\delta_{2t}$ , are the portfolios (low and high, respectively) based on dividend yields. In equation (viii),  $\phi_m$  represents the vector of portfolios with low and high yield dividend-paying firms. To minimize the problem of autocorrelation between returns we use the one period lag of Sunday returns  $RS_{t-1}$ . We assume that the error term  $\varepsilon_t$  follows the Gaussian Error Distribution. Based on the statistical significance of each coefficient for the sub-portfolios, i.e.  $\alpha_1$  and  $\alpha_2$  in the returns equation and  $\theta_m$  in the variance equation, we should be able to compare the influence of institutions' and individuals' trading patterns on Sunday.

## 4. Empirical Results

### 4.1 Summary of the Data

Table 2 presents the summary statistics of the daily returns generated from the DSE All-Share price index.

**Table 2: Summary Statistics of Daily Returns on the DSE**

|              | All days  | Sunday     | Monday    | Tuesday   | Wednesday | Thursday   |
|--------------|-----------|------------|-----------|-----------|-----------|------------|
| Mean (%)     | 0.0414*** | -0.2140*** | 0.2443*** | 0.0505*** | 0.1808*** | -0.0545*** |
| Median (%)   | 0.0000    | 0.0000     | 0.0003    | 0.000     | 0.0002    | 0.0000     |
| Max (%)      | 19.1776   | 19.1776    | 14.2362   | 6.9986    | 5.3660    | 3.6847     |
| Min (%)      | -26.9068  | -26.9068   | -7.3584   | -6.4850   | -8.6612   | -5.5358    |
| SD           | 0.0148*** | 0.0215***  | 0.0143*** | 0.0109*** | 0.0104*** | 0.0069***  |
| Skewness     | -1.1942   | -2.2656    | 2.9504    | 0.2498    | 0.1778    | -0.4878    |
| Kurtosis     | 64.6350   | 45.9546    | 27.1390   | 10.2839   | 15.3214   | 12.5829    |
| Observations | 4565      | 913        | 913       | 913       | 913       | 831        |

\*\*\*, \*\*, \* denotes the significance at 1%, 5% and 10% level

The average daily returns are negative for Sunday and Thursday, followed by positive returns for other days of the week. The lowest average returns are reported on Sunday (-0.214%) and the highest on Monday (0.2443%). Sunday also has the most variable returns, with the minimum (-26.91%) and maximum (19.18%) daily returns in our daily price dataset. Therefore, the standard deviation of returns is highest on Sunday (0.0219%). At the opposite end of the spectrum the lowest standard deviation is on Thursday (0.007%), where the maximum and minimum returns across the sample are lowest as well. All these daily returns and standard deviation are statistically significantly different, both from zero and from each other. Similar findings are reported in many existing studies, e.g. French (1980), Rogalski (1984) and Smirlock and Starks (1986). The returns

on the first day of the trading week (Sunday) at -0.2140% are much worse than on the second day (Monday) of 0.2443%, which is also in line with the previous literature. Interestingly, Farag (2013) reports positive average returns on Sunday (the opening day) for the Egyptian market using the EGX 30 index. Similarly, Al-Loughani and Chappell (2001) find higher positive returns on Saturday (the opening day) for the Kuwait stock market using the KIC index. However, the returns variance of the EGX 30 index is highest on Sunday (Farag, 2013). Based on these results we can see that in comparison to the stock markets of other Islamic countries which do not operate from Monday to Friday, the behaviour of the DSE is far more in line with developed equity markets. The Sunday effect does exist here too.

Table 2 also shows that the daily returns are positively skewed except on Sunday and Thursday. Each of the daily returns shows excess kurtosis, i.e. they are fat-tailed compared to the normal distribution. The Jarque-Bera (JB) test confirms the non-normal distribution of daily returns (not reported). Finally, we run the LB (Ljung and Box, 1978) test for detecting possible autocorrelation in daily returns series up to 5 lags (results are not reported). The LB statistics are found not to be statistically significant for Sunday and Tuesday for any lag. This implies that there is no serial correlation between returns on these respective weekdays. Nevertheless, significant autocorrelations exist between the returns of Monday, Wednesday and Thursday up to one week.

#### 4.2 Weekend Sentiment in DSE

To investigate the validity of information content theory and weekend effect on the DSE, we follow the procedure explained in the literature, e.g. French (1980), Gibbons and Hess (1981), Jaffe and Westerfield (1985), Berument and Kiyamaz (2001), Kiyamaz and Berument (2003) and develop a regression model based on equation (i):

$$R_t = \alpha_0 + \alpha_1 Sun + \alpha_2 Mon + \alpha_3 Wed + \alpha_4 Thu + \sum_{i=1}^n \alpha_i R_{t-i} + \varepsilon_t \quad (ix)$$

The results in column (1) and (2) of Table 3 shows the outcome of the OLS estimation in equation (ix).



Table 3: Three Models of Daily Returns and Volatility on the DSE

|                                                    | (1)               | (2)               | (3)                        | (4)                        |
|----------------------------------------------------|-------------------|-------------------|----------------------------|----------------------------|
|                                                    | OLS               | OLS               | GJR-GARCH                  | Modified TGARCH            |
| Dep. Var.                                          | Market Returns    | Market Returns    | Market Returns             | Market Returns             |
| <b>Estimation of mean and volatility equation</b>  |                   |                   |                            |                            |
| <b>Returns Equation</b>                            |                   |                   |                            |                            |
| Sunday                                             | -0.003314***      | -0.002920***      | -0.001223**                | -0.002623***               |
| Monday                                             |                   | 0.001679**        | 0.001762***                | 0.000384                   |
| Wednesday                                          |                   | 0.001045          | 0.001937***                | 0.000463                   |
| Thursday                                           |                   | -0.001181*        | -0.000499                  | -0.000025                  |
| Return <sub>t-1</sub>                              | -0.044784***      | -0.038223**       | 0.035978*                  | 0.068270***                |
| Return <sub>t-2</sub>                              | 0.040772***       | 0.040044***       |                            |                            |
| C                                                  | 0.001074***       | 0.000685          | -0.0000208                 | 0.000009                   |
| <b>Volatility Equation</b>                         |                   |                   |                            |                            |
| $\omega$                                           |                   |                   | 0.000011***                | 0.000108***                |
| $\alpha$                                           |                   |                   | 0.029627***                | 0.179379***                |
| $\beta$                                            |                   |                   | 0.823107***                | 0.737644***                |
| $\gamma$                                           |                   |                   | 0.245448***                | 0.097080***                |
| Sunday                                             |                   |                   |                            | 0.000127***                |
| Monday                                             |                   |                   |                            | -0.000224***               |
| Wednesday                                          |                   |                   |                            | -0.000219***               |
| Thursday                                           |                   |                   |                            | -0.000110***               |
| <b>Log Likelihood</b>                              | 13119.79          | 13130.10          | 13809.16                   | 14336.78                   |
| <b>Ljung-Box Q-Statistic</b>                       |                   |                   |                            |                            |
| 2                                                  | 0.0414(0.980)     | 0.0033(0.998)     | 0.1113(0.946) <sup>a</sup> | 0.0860(0.958) <sup>a</sup> |
| 5                                                  | 2.1708(0.704)     | 8.2860(0.141)     | 0.8878(0.971) <sup>a</sup> | 0.1975(0.999) <sup>a</sup> |
| 10                                                 | 13.080(0.109)     | 13.633(0.136)     | 1.5240(0.999) <sup>a</sup> | 0.4773(1.000) <sup>a</sup> |
| <b>Breusch-Godfrey Serial Correlation LM Test:</b> |                   |                   |                            |                            |
|                                                    | 2.1769(0.1135)    | 1.1620(0.3129)    |                            |                            |
| <b>ARCH-LM Test:</b>                               |                   |                   |                            |                            |
| 1                                                  | 13.8376***(0.000) | 13.2573***(0.000) | 0.0652(0.799)              | 0.0722(0.788)              |
| 5                                                  | 4.0562***(0.001)  | 3.9380***(0.000)  | 0.1762(0.972)              | 0.0394(0.999)              |
| 10                                                 | 2.6462***(0.003)  | 2.5723***(0.000)  | 0.1489(0.999)              | 0.0473(1.000)              |

<sup>a</sup> standardized squared residuals; \*\*\*, \*\* and \* denote significance at the 1%, 5% and 10% levels respectively; standard error and probability are in [] and () respectively.

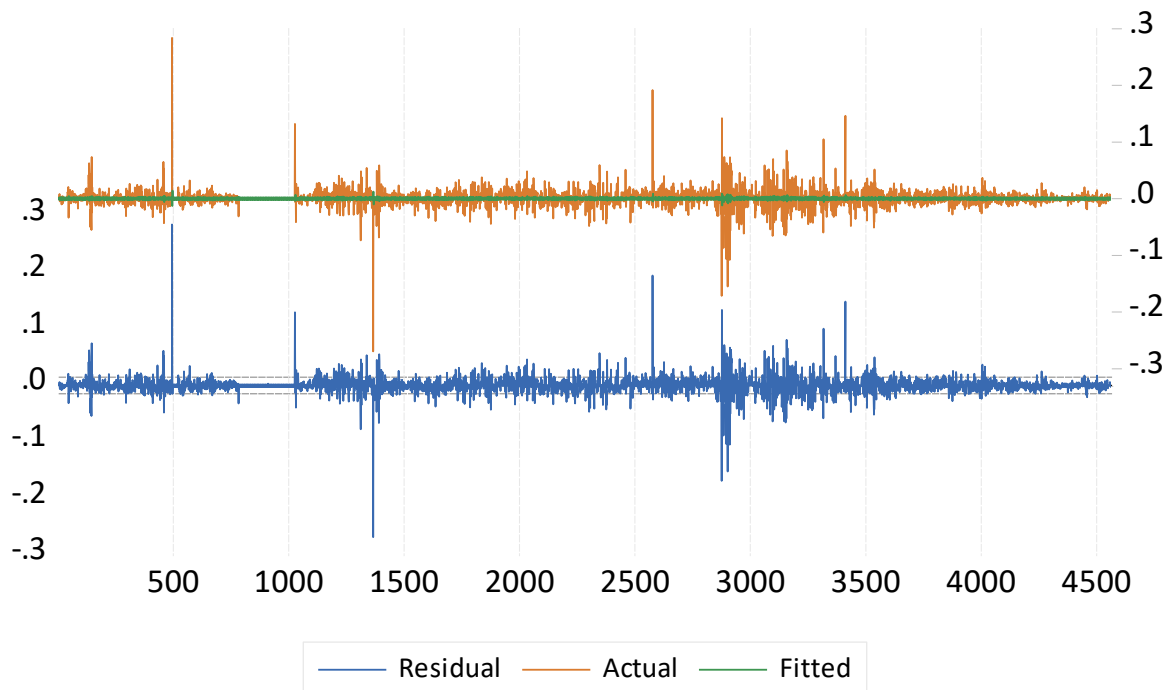
The first column of results is an initial check of the weekend effect (“Sunday versus the average of all other days”). There is indeed a highly significant weekend effect, i.e. returns on the first day of the trading week are significantly worse. Our main OLS model is in the second results column (2). Results show that Sunday<sup>5</sup> has the most negative returns (-0.29%) which is statistically significant at the 1% level, while Monday has the highest positive returns (0.17%) and significant at 5% level. Figure 1 shows an almost monotonic increase from Sunday to Thursday in the amount of information released daily, but it is clear that traders do not trade heavily Thursday’s information before the closing of trade on that day. Instead, Sunday is significant, which means information rolls over the weekend and affects the opening day. The findings are consistent with the results reported in Table 2. Indeed, significantly negative returns on the opening day are evident in most of the equity markets in previous studies (see French, 1980; Keim and Stambaugh, 1984; Jaffe and Westerfield, 1985; Wang et al., 1997; Chia et al., 2008). Using cross-sectional returns data, Chowdhury and Sharmin (2012) report a similar outcome for the DSE. Our results therefore confirm the idea that the weekend effect is not just a feature of the stock markets of the United States and other developed countries but also of emerging markets, as stated by Choudhry (2000). In addition, the null hypothesis that the day of the week dummy variables are jointly equal to zero is rejected using the Wald test (not reported).

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<sup>5</sup> Since Bangladesh is a Muslim country, we performed a robustness check for the Ramadan effect in DSE all-share price and DSEX index. This Ramadan effect refers to significantly higher stock returns during the ninth month of the Islamic calendar (see Al-Khazali, 2014). Ramadan is the most venerated month of the lunar (Hijri) calendar during which Muslims fast from dawn until sunset and gifts are shared with the poor. The 12 months derived from the lunar cycle are separated by the appearance of the new moon and the number of days in a month average between 29 and 30 days, making the Islamic year approximately 11 days shorter than the Gregorian year. Recently, researchers have examined this moving calendar anomaly for Muslim countries. There are mixed results available for different markets. For example, Seyyed et al. (2005) find no significant change in Ramadan mean returns on the Saudi market, but a noticeable decline in volatility. Contrary to other studies on Muslim countries, Almudhaf (2012) finds 4 out of 12 countries, Bialkowski et al. (2012) find 11 out of 14 countries and Al-Khazali (2014) finds 15 countries’ stock markets are affected by the Ramadan period. In this line of thought, this study has investigated whether the stock returns and volatilities of Sundays during Ramadan periods are significantly different from Sundays of non-Ramadan periods. Using an ANOVA F-test, a Welch (1951) F-test and a Brown-Forsyth (1974a, 1974b) test, our results confirm that over the sample period from 2002 to 2019, there is no statistically significant difference between the returns and volatilities of Sundays during Ramadan periods and returns and volatilities of Sundays during non-Ramadan periods (results are available on request). This implies that Ramadan has little or no impact on Sunday seasonality on the DSE. This may be due to the fact that the majority population of Bangladesh is Muslim but the traditional culture of this country is still different from other Muslim countries.

The value of the  $F$  statistics is 19.14 and 13.13, with  $p$ -value near to zero which implies overall significance of our model in column (1) and (2). We apply the Akaike Information Criterion (AIC) to determine the autoregressive order  $[R_{t-i}]$  as included in equation (ix) to minimize the possible autocorrelation between returns. The Ljung-Box Q test also supports that, using up to ten lags, the null hypothesis (i.e. the residuals are not autocorrelated) is rejected. The value of the Breusch-Godfrey Serial Correlation LM Test is 2.18 and 1.16, which again is not statistically significant at the 10 percent level. We therefore conclude that there is no serial correlation in the model. Finally, we perform the Lagrange Multiplier Autoregressive Conditional Heteroskedasticity test as suggested by Engle (1982) using up to ten lags. The result indicates the presence of an ARCH effect, i.e. variances are not homoscedastic. Figure 2 similarly indicates the presence of volatility clustering of our model shown in column (2) of Table 3.

**Figure 2: Volatility Clustering of the OLS Model of Daily Returns on the DSE**



Given that both an ARCH effect (Table 3) and volatility clustering (Figure 2) are indicated, we apply two separate specifications for the returns and volatility equations to capture the weekend effect. First, we model the conditional variance of the returns equation as a GARCH (1, 1) process (Equation ii) and re-estimate the returns equation with the conditional variance to see the weekend effect in returns only. Second, we use a modified GARCH (1, 1) process to investigate the weekend effect on both the returns and volatility equations by including daily dummies as exogenous variables (equation iii).

One disadvantage of modelling the conditional variance as GARCH (1, 1) with the day of the week dummies is the possibility of being too restrictive (Kiyamaz and Berument, 2003). On the other hand, the GARCH (1, 1) specification requires that  $|\alpha + \beta| < 1$ , in order to prevent the equation variance from exploding (Bollerslev, 1986). Furthermore, each of  $\omega$ ,  $\alpha$ , and  $\beta$  has to be positive in order to satisfy the non-negativity of conditional variances for each given time  $t$  (Bollerslev, 1986).

To capture the volatility clustering and conditional variance under the restrictions of being non-negative and non-explosive, we applied various GARCH models by including additional terms in the conditional variance equation, e.g. GARCH (1, 1), GARCH (2, 1), GARCH (2, 2), TGARCH, EGARCH, CGARCH, and PARCH for both equations (ii) and (iii). The results are not reported here but we identified the Threshold GARCH (TGARCH or GJR-GARCH) as being the most appropriate under these restrictions. The rest of the models are either explosive, i.e.  $|\alpha + \beta| > 1$ , fail to satisfy non-negativity or fail to capture the volatility clustering. Nevertheless, it is important to mention that the findings on the weekend effect on the returns and volatility equations remain robust under each of the GARCH processes.

The GJR model is a simple extension of GARCH with an additional term added to account for possible asymmetries (see Glosten et al., 1993). The leveraging effect allows us to differentiate between good news (increased stock prices) and bad news (decreased stock prices). The conditional variance under the first specification, to see the weekend effect in returns, is now given by

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \quad (\text{x i})$$

Where  $I_{t-1} = 1$  if  $\varepsilon_{t-1} < 0$  or  $I_{t-1} = 0$  otherwise.

Here,  $h_t$  is still the conditional variance. For a leveraging effect,  $\gamma > 0$ , and the condition for non-negativity is  $\omega > 0$ ,  $\alpha > 0$ ,  $\beta \geq 0$  and  $\alpha + \gamma \geq 0$ .

To examine the weekend effect on both returns and volatility we identified a modified GARCH process following the TGARCH (1, 1) model. The modified model is

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} + Sun \pi_1 + Mon \pi_2 + Wed \pi_3 + Thu \pi_4 \quad (\text{x ii})$$

The definition of and conditions in model (xii) remain similar to equation (xi). We drop Tuesday from the model to avoid the dummy variable trap and also assume that the conditional distribution of the error term follows the Gaussian Error Distribution.

Column (3) of Table 3 reports the results of our GJR-GARCH estimation. The time-varying conditional variance is allowed to follow a TGARCH specification to see the possible weekend effect on returns. The lowest returns are observed on Sunday (-0.12%) and the highest returns on Wednesday (0.19%). They are also statistically significant in the returns equation. This finding is similar to our previous OLS estimation and is in line with existing literature. In the variance part, the estimated coefficients of the constant term, the coefficient of the lagged value of the square residual (0.03) and the lagged value of the conditional variance (0.82) are all statistically significant at the 1% level. The sum of  $\alpha$  (ARCH term) and  $\beta$  (GARCH term) implies persistent effect of shocks to the conditional variance. The asymmetry term  $\gamma$  is positive (0.25) and significant, suggesting that bad news increases volatility on the DSE. Thus, negative shocks imply a higher next period conditional variance than positive shocks of the same magnitude.

Looking at the Ljung-Box Q statistics towards the bottom of the column, for standardized squared residuals we accept the null hypothesis that the residuals are not autocorrelated up to ten lags (Engle, 2001). Engle's (1982) ARCH-LM test implies that there is no ARCH effect on the residuals. Indeed, allowing time varying variance in the estimation process provides more efficient estimates for the returns equation, which is in line with previous expectations (Enders, 1995; Berument and Kiyamaz, 2001). The low standard errors (not reported) for the estimated parameters of the returns equation clearly explain that efficiency (Berument and Kiyamaz, 2001). Overall, the presence of the weekend effect is strongly evident on the DSE under this conditional variance structure.

Finally, in our modified TGARCH (1, 1) model we allow the conditional variance of the returns to change for each day of the week. The objective is to see whether any weekday has an impact on volatility. Table 3 shows the results of the modified TGARCH (1, 1) model in the rightmost column (4). The returns and variance equations give similar outcomes. Sunday has the lowest returns of -0.26%, which is statistically significant at the 1% level, but none of the other daily returns are statistically significant. The standard errors are very low for each of the estimated coefficients (not reported) and all of these results are in line with our previous findings, i.e., our OLS estimation, GJR-GARCH estimation and Table 2.

We present the results for conditional variance in the middle of the rightmost column (4) in Table 3. The volatility is positive influenced by Sunday and also statistically significant in the modified TGARCH (1, 1) model at a 1% level of significance. The coefficients of Monday, Wednesday and Thursday are also statistically significant, but they negatively affect market volatility. Therefore, our results indicate a significant rise in volatility on the opening day of the market. A similar finding for the first day of trading is also reported in several earlier papers, e.g., for the US (Gibbons and

Hess, 1981), for Indonesia, Malaysia, South Korea, Philippines, Taiwan and Thailand (Choudhry, 2000), for the S&P 500 (Berument and Kiyamaz, 2001), and for Germany and Japan (Kiyamaz and Berument, 2003). To explain the possible reason for the highest variance being on the opening day French and Roll (1986), Barclay et al. (1990) and Foster and Viswanathan (1990) claim that stock returns variance should be highest on Mondays because the informed trader has his maximum information advantage then. This supports the argument of information content theory.

We also see in the rightmost column (4) that the coefficients of the ARCH and GARCH terms are statistically significant. The sum of  $\alpha$  and  $\beta$  is relatively high (0.1794 and 0.7376 respectively), meaning a strongly persistent shock on the conditional component. Similar to GJR-GARCH, the asymmetry term  $\gamma$  is positive (0.10) and significant, suggesting that bad news increases volatility on the DSE. The standard squared residual shows no autocorrelation between returns as the Ljung-Box Q statistics are insignificant, as is reported at the bottom of the rightmost column. Further, there is no remaining ARCH effect in residuals up to ten lags, which implies that the modified TGARCH model successfully captures the volatility clustering.

In summary all three of the models that appear plausible (OLS, GJR-GARCH and modified TGARCH) clearly suggest the presence of a Sunday effect on both equity returns and volatility.

### **4.3 Firm-level trading behaviour**

As suggested by Rystrom and Benson (1989), investors are influenced by moods, perceptions and emotions that are systematically different on the first day of trading. This assertion is at least as plausible as suggesting such ultra-rationality as, for example, investors being acutely sensitive to settlement procedures. Rystrom and Benson (1989) further assert that the moods of fundamental and technical analysts may be influenced by a pall of Monday depression and a beautiful stock in the glow of optimism on Friday may look more like an overvalued sell candidate in the gloom of Monday morning. Following this behavioural finance line of thought, our objective is to find out the trading patterns of investors or who moves the market on the opening day of the DSE, which is Sunday. In particular we use firm size and dividend yield as proxies to determine which group of investors (i.e., individuals or institutions) is influencing the returns and volatility on Sunday.

As stated in Section 4, in order to investigate the relationship between the weekend effect and firm size, we create ten portfolios using all DSE listed firms according to the ranking of their daily average market value. We then calculate value weighted daily mean returns for each of the ten portfolios. We also determine the standard deviation of the equity returns to see the volatility for each day. The results are in Table 4.

**Table 4: Firm-Level Daily Returns and Standard Deviations on the DSE  
Grouping by Market Value Deciles**

| Deciles     |      | Sunday     | Monday    | Tuesday  | Wednesday | Thursday   | F <sup>a</sup> |
|-------------|------|------------|-----------|----------|-----------|------------|----------------|
| Small<br>1  | Mean | -0.1916*** | -0.0005   | 0.0031   | 0.0401    | -0.0498*   | 4.850          |
|             | SD   | 2.3131     | 0.7661    | 0.7641   | 0.6244    | 0.8984     | (0.000)        |
| 2           | Mean | -0.1424*** | 0.0215    | -0.0655  | -0.0811   | 0.0371     | 1.876          |
|             | SD   | 2.0189     | 0.9388    | 1.1431   | 1.4786    | 1.0136     | (0.114)        |
| 3           | Mean | -0.1234*** | 0.0546**  | -0.0124  | 0.0566*   | -0.0475**  | 3.100          |
|             | SD   | 1.8132     | 1.4438    | 1.0211   | 1.0922    | 1.1913     | (0.016)        |
| 4           | Mean | -0.0782*   | -0.0868   | 0.0435*  | 0.0988*** | -0.0051    | 1.385          |
|             | SD   | 1.9478     | 1.8788    | 1.2146   | 1.0987    | 1.0582     | (0.239)        |
| 5           | Mean | 0.0964**   | 0.1464**  | -0.0487  | 0.0915*   | -0.0355**  | 5.113          |
|             | SD   | 1.2145     | 1.4011    | 1.2234   | 1.0754    | 1.4172     | (0.000)        |
| 6           | Mean | 0.0795**   | 0.1717**  | 0.0811** | 0.0787    | -0.0315*   | 2.879          |
|             | SD   | 1.3154     | 1.5629    | 1.1916   | 1.0199    | 0.8249     | (0.023)        |
| 7           | Mean | -0.0467    | 0.1021*   | 0.0922   | 0.0964**  | -0.0641*** | 2.699          |
|             | SD   | 1.8416     | 1.8313    | 1.6261   | 1.9161    | 1.8749     | (0.031)        |
| 8           | Mean | -0.0072    | 0.0732**  | 0.0667*  | 0.1121*   | 0.0311     | 3.213          |
|             | SD   | 1.1282     | 1.6768    | 1.1011   | 1.9067    | 1.388      | (0.013)        |
| 9           | Mean | 0.1624     | 0.1211    | -0.0390* | 0.0874*** | 0.0752     | 0.897          |
|             | SD   | 1.1271     | 1.4045    | 1.2866   | 1.2367    | 1.6761     | (0.466)        |
| Large<br>10 | Mean | 0.1825**   | 0.1455*** | 0.1041   | 0.1066**  | 0.0876     | 3.321          |
|             | SD   | 1.7541     | 1.5199    | 1.5531   | 1.6833    | 1.0987     | (0.011)        |

All data are in percentage form.

\*\*\*, \*\* and \* indicate significance at the 1%, 5% and 10% levels respectively.

<sup>a</sup> Anova F-test with probability in ( ) that shows the results of a test for equality of means between the returns series of the five weekdays.

*Note:* The standard deviations for each day in each decile are also statistically significant at the 1 percent level.

The average returns on Sunday show an interesting pattern across firm sizes. Mean returns on Sunday are negative for small firms (-0.192% and -0.142% respectively for decile 1 and 2) and four of the mid-sized firms (deciles 3, 4, 7 and 8), but positive for the other deciles. Furthermore, the standard deviation for the smallest decile is highest on Sunday (2.31%). The returns and standard deviation are also both statistically significant at the 1% level for this smallest decile. The negative

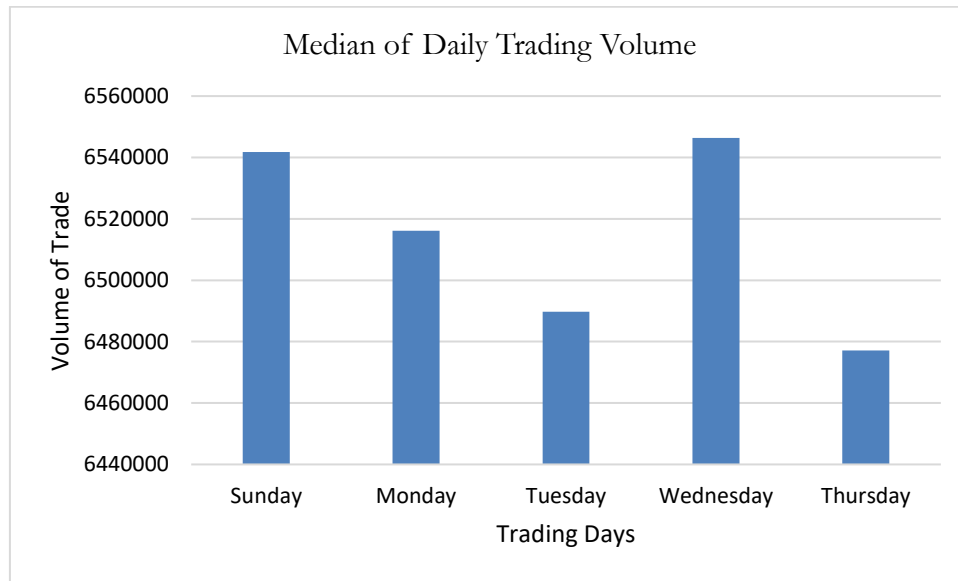
mean returns and larger variance for small firms on Sunday are an indication of their importance in the weekend effect.

For other weekdays, mean returns are negative for most of the deciles on Thursday (i.e., decile 1 and from 3 through to 7) and four deciles of Tuesday (i.e., decile 2, 3, 5 and 9). Indeed, the returns pattern on Thursday and Sunday strongly supports the information processing hypothesis. The hypothesis suggests that individuals will, in general, be more aggressive sellers of shares early in the trading week, particularly on Monday following declines in the market on the prior Friday (Abraham and Ikenberry, 1994). Hence a different returns pattern on Sunday may be following bad news released in the prior week, and this is particularly strong for smaller firms.

Surprisingly, on the other hand, the mean returns on Monday and Wednesday from the smallest to the largest portfolios are all positive and statistically significant except for deciles 1 and 4 of Monday and decile 2 of Wednesday, which are negative but not significant. The positive returns on Wednesday might indicate a possible ‘reverse mid-week effect’ on the DSE regardless of the size of the firms. However, Wednesday is only statistically significant in the GJR-GARCH model and is not significant in our OLS and modified TGARCH models, as reported in Table 3. For the US equity market, Brusa et al. (2000 and 2005) find a “reverse weekend effect” on Monday, particularly for large firms. They report mean returns being negative for smaller firms on Sunday but these transform into significantly positive returns for larger firms. However, on the DSE equity returns on Wednesday are positive across all sizes of firms except the second smallest decile. Hence, the market shows a sign of “reverse mid-week effect”, which could be due to the trading volume. We, therefore, report the median trading volume of DSE in Figure 3, and it shows that the median number of trades is highest on Wednesday as expected. Consequently, the DSE displays a tendency of “mid-week effect” like many other markets. For example, in their paper Chordia et al. (2001) have documented this kind market characteristic and suggested that the trading activity could be higher in the middle of the week and market might showcase “reverse mid-week effect”.



**Figure 3: Median Daily Trading Volume on the DSE**



To further examine the extent to which firm size is related to the weekend effect, we categorize our observed firms into three sub-portfolios based on the smallest 20%, mid-sized 60% and largest 20%. We then apply a time-varying conditional variance model to assess the significance of each portfolio on Sunday returns and volatility. The first half of Table 5 summarizes the mean returns and standard deviation for these sub-portfolios.

**Table 5: DSE Mean Returns and Standard Deviations for Portfolios Grouped by Size and Dividend Yield**

| Portfolio(s)               |           | Sunday     | Monday    | Tuesday | Wednesday | Thursday   |
|----------------------------|-----------|------------|-----------|---------|-----------|------------|
| Based on the size of firms |           |            |           |         |           |            |
| <b>Small</b>               | Mean      | -0.1636*** | 0.0057    | -0.0191 | 0.0047    | -0.0135**  |
|                            | Std. Dev. | 1.8445     | 0.5973    | 0.7641  | 0.6247    | 0.6350     |
| <b>Mid-size</b>            | Mean      | -0.0463*   | 0.0783*   | 0.0523* | 0.1223    | -0.0216*   |
|                            | Std. Dev. | 0.8862     | 1.3331    | 0.9671  | 1.0446    | 1.0876     |
| <b>Large</b>               | Mean      | 0.1495**   | 0.1131*** | 0.0405  | 0.1162*** | 0.0478     |
|                            | Std. Dev. | 1.0796     | 1.4356    | 1.0676  | 1.1471    | 1.0015     |
| Based on Dividend Yield    |           |            |           |         |           |            |
| <b>Low</b>                 | Mean      | -0.0879**  | 0.0417    | 0.0340  | 0.0411    | -0.0310*** |
|                            | Std. Dev. | 1.3244     | 1.1642    | 0.6887  | 0.6649    | 0.6544     |
| <b>High</b>                | Mean      | 0.1154     | 0.1018*** | 0.0652  | 0.0987*** | -0.0033    |
|                            | Std. Dev. | 1.0196     | 1.1435    | 0.9976  | 0.9873    | 0.7223     |

All data are in percent.

\*\*\*, \*\* and \* indicate significance at the 1%, 5% and 10% levels respectively.

Note: The standard deviations for each portfolio are found statistically significant at 1 percent level.

The returns of the smallest 20 percent and mid-sized portfolios are negative (-0.1636% and -0.0463%) on Sunday and statistically significant at the 1% and 5% level. However, for the largest portfolios mean returns are positive on this opening day (0.1495 percent), which is also statistically significant. These results, therefore, further lend weight to our hypothesis that substantial trading of smaller firms is what influences the Sunday returns to be negative. For the US equity market Abraham and Ikenberry (1994) and Brusa et al. (2000, 2005) also report that mean returns of smaller portfolios are negative on Monday and claim this is due to the trading pattern of individual investors. The mean returns of the smallest 20 percent of firms are also negative on Tuesday (-0.019%) and Thursday (-0.0135%) although only Thursday's mean returns is statistically significant. Beside Sunday, the mean returns are only negative for the mid-sized portfolio on Thursday (-0.0216%), and they are positive for other weekdays. The results on Monday and Wednesday for the three sub-portfolios are similar to those reported in Table 5, i.e., mean returns are all positive and many of those are significant at different level. The standard deviation of the smallest portfolio is the highest (1.6445%) on Sunday compared to the other portfolios on that day. It is also higher than the standard deviations on any other weekdays for that sub-portfolio. This further indicates that the weekend effect is probably caused by trading in smaller firms.

The second half of Table 5 shows the mean returns and standard deviations of portfolios based on dividend yield. We divide all the listed firms on DSE into two groups based on their median value of daily dividend yield over the observed sample period. Each group – low DY and high DY - include 50% of all listed firms. Then we calculate value weighted mean returns and standard deviations and apply the conditional variance approach to capture the association between investors' trading behaviour and weekend effect. As for firm size, we document some interesting patterns in mean returns when grouping stocks by dividend yield. First, returns are negative (-0.0879%) and significant at the 1% level for low DY companies on Sunday. Second, the mean returns of the high DY portfolio on Sunday are positive but not significant. Third, the mean returns on Monday, Tuesday and Wednesday are significantly positive for both groups. Finally, standard deviation is higher on Sunday for Low-DY and Monday for High-DY portfolios.

We report the results of the conditional variance models, designed to capture the influence of investors' trading behaviour on the weekend effect (on the Sunday return), in Table 6. The first and second results columns present the outcome for portfolios based on firm size; the results for portfolios based on dividend yields are in the third and fourth results columns. We use the GARCH (1, 1) and modified GARCH (1, 1) models as stated in equation (ii) and (vi) for firm size. However due to non-negativity and non-explosive restrictions we apply a modified TGARCH (1,

1) or GJR-GARCH (1, 1) model as stated in equation (xi) for dividend yield. The modified GARCH (1, 1) and TGARCH (1, 1) approach allow us to include exogenous variables in the variance equation to check the significance of each portfolio's effect on volatility. Indeed, they help to substantiate our conjecture that the trading activities of individual investors determine the weekend effect on both returns and volatility.

**Table 6: Alternate Models of Returns and Volatility on the DSE,  
Grouping Portfolios by Size and Dividend Yield**

|                                                   | (1)                    | (2)            | (3)                        | (4)             |
|---------------------------------------------------|------------------------|----------------|----------------------------|-----------------|
|                                                   | Firm Size (Portfolios) |                | Dividend Yield (Portfolio) |                 |
|                                                   | GARCH                  | Modified GARCH | GARCH                      | Modified TGARCH |
| Dep. var.                                         | Sunday                 | Sunday         | Sunday                     | Sunday          |
| <b>Estimation of mean and volatility equation</b> |                        |                |                            |                 |
| <b>Returns Equation</b>                           |                        |                |                            |                 |
| Small                                             | -0.026716***           | -0.087185      |                            |                 |
| Mid-size                                          | 0.022381               | 0.046288       |                            |                 |
| Large                                             | 0.019122               | 0.000607       |                            |                 |
| Low yield                                         |                        |                | -0.054381***               | -0.069350       |
| High yield                                        |                        |                | -0.021523***               | 0.023690        |
| Return(-1)                                        | 0.006726**             | 0.022482***    | 0.022755                   | 0.014966***     |
| C                                                 | -0.000821***           | -0.0001051     | -0.000769***               | -0.000648***    |
| <b>Volatility Equation</b>                        |                        |                |                            |                 |
| $\omega$                                          | 0.000184***            | 0.000463*      | 0.000183***                | 0.000469**      |
| $\alpha$                                          | 0.349857**             | 0.336720**     | 0.359855**                 | 0.367651*       |
| $\beta$                                           | 0.599857***            | 0.565989***    | 0.599855***                | 0.571262***     |
| $\gamma$                                          |                        |                |                            | 0.053073        |
| Small                                             |                        | 0.004419*      |                            |                 |
| Mid-size                                          |                        | -0.002384      |                            |                 |
| Large                                             |                        | -0.002991***   |                            |                 |
| Low yield                                         |                        |                |                            | 0.020143***     |
| High yield                                        |                        |                |                            | 0.012733        |
| <b>Log Likelihood</b>                             | 1592.765               | 1548.499       | 1592.734                   | 1544.230        |
| <b>Ljung-Box Q-Statistic</b>                      |                        |                |                            |                 |
| LB <sup>2</sup> (1)                               | 0.0473 (0.828)         | 0.0123 (0.912) | 0.0457 (0.831)             | 0.0002 (0.987)  |
| LB <sup>2</sup> (5)                               | 0.1892 (0.999)         | 1.5679 (0.905) | 0.1867 (0.999)             | 1.2942 (0.936)  |
| LB <sup>2</sup> (10)                              | 0.3060 (1.000)         | 1.6558 (0.998) | 0.3054 (1.000)             | 1.3746 (0.999)  |
| <b>ARCH-LM Test:</b>                              |                        |                |                            |                 |
| 1                                                 | 0.0467 (0.823)         | 0.0122 (0.912) | 0.0453 (0.832)             | 0.0002 (0.987)  |
| 5                                                 | 0.0378 (0.999)         | 0.3066 (0.909) | 0.0373 (0.999)             | 0.2524 (0.939)  |
| 10                                                | 0.0308 (1.000)         | 0.1589 (0.999) | 0.03078(1.000)             | 0.1312 (0.999)  |

\*\*\*, \*\* and \* denote significance at the 1%, 5% and 10% levels respectively. Probabilities are in brackets.

The first results column of Table 6 shows that the negative Sunday returns are driven by small firms (-2.672%, significant at 1%). The coefficients for the mid-sized 60 percent and largest 20 percent are positive but are not statistically significant. According to this model, the Sunday returns on the DSE are not only influenced largely by smaller firms but the negative returns are solely due to them. On the other hand, in the modified model (results column (2)) the returns are not significant for any portfolio. Nevertheless, smaller firms are affecting Sunday's returns negatively and the highest volatility still belongs to the smallest portfolio (0.442%), which is statistically significant. These findings are consistent with our previous results from Table 5: the trading activity in smaller firms causes the negative equity returns and increased volatility on Sunday. The estimated coefficients of the constant term, the lagged value of the square residuals and the lagged value of the conditional variance are all statistically significant in both models. However, the sum of the ARCH term and the GARCH term implies low persistence of shocks to the conditional variance (i.e., 0.7496 and 0.7026 respectively in the GARCH and modified GARCH models).

On the other hand, both dividend yield portfolios are statistically significant in the returns equation presented in column (3) of Table 6. However, it is evident that Sunday returns are largely dragged down by the low DY firms, i.e., with returns of -5.44% and -6.94% respectively in the GARCH (1, 1) and the modified TGARCH (1, 1) models. The high DY portfolio influences the Sunday's returns negatively (-2.15%) in the GARCH (1, 1) model and positively (+2.37%) in the modified TGARCH (1, 1). In the variance equation (column (4) of Table 8), we see the highest (and significant) volatility of 2.01% occurring with the low DY portfolio. The high yield firms have a positive effect on Sunday returns volatility (i.e., 1.27%) and not statistically significant. These findings are also in line with our previous findings and implies that the weekend effect on returns and volatility is due to the trading behaviour of individual investors on the DSE, as displayed in low dividend yield firms. Nonetheless, the sum of  $\alpha$  (ARCH term) and  $\beta$  (GARCH term) show strong persistent effect of shocks to conditional variance. Finally, the asymmetric term  $\gamma$  is positive but not significant in column (4), which means that bad news increases the volatility of the Bangladesh equity market on Sunday. Thus, any negative shocks should increase the next period's conditional variance more than positive shocks of similar size.

We run several specification tests and report them at the end of Table 6. The Ljung-Box Q statistics check the adequacy of conditional returns and the validity of the conditional variance equation. For standardized residuals (LB) and squared residuals (LB<sup>2</sup>) the null hypothesis is that the residuals are not serially correlated (results are reported up to 10 lags). Engle's ARCH-LM test shows that there is no ARCH effect in the residuals, because the test result is close to zero. Finally, the Wald

test confirms that the coefficients of the returns and variance equations for all four models are significantly different from zero.

Our findings strengthen the assertions of Kim and Stambaugh (1984), Gibbon and Hess (1981), and Brusa et al. (2000, 2005) that the weekend effect is stronger for small firms than large firms<sup>6</sup>. This is consistent with the conjecture of Osborne (1962), Ritter (1988), Lakonishok and Maberly (1990), Abraham and Ikenberry (1994) and Kamara (1997) that a weekly variation in trading activity by individuals is an important cause of the day-of-the-week effect. Lakonishok et al. (1992), Blume and Zeldes (1993) and Barber and Odean (2005) suggest that individual investors generally have greater holdings in small firms. Our results, therefore, suggests two different perspectives on the Bangladesh stock market. First, the information processing hypothesis is probably effective here: individual investors use their weekends to gather and process information and become active players on Sunday. Second, because this market is largely dominated by individual investors, the weekend effect strongly exhibits itself in smaller firms' stock prices. Individuals demonstrating this particular behaviour on Sunday may be due to several reasons, such as liquidity needs or rebalancing (Abraham and Ikenberry, 1994), an absence of brokerage firms (Miller, 1988; Lakonishok and Maberly, 1990), less participation by institutional investors as they set their strategic plans (Osborne, 1962), and a low-cost advantage over trading of smaller firms (Kamara, 1997).

#### **4.4 Robustness Checks for market sentiment**

It is empirically proven that first order serial correlation in daily returns is not equal across weekdays. For example, several early researchers document a higher correlation between Monday and the previous Friday (Keim and Stambaugh, 1984; Bessembinder and Hartzel, 1993; Abraham and Ikenberry, 1994; Brusa et al., 2000 and 2005). In an extensive study on returns autocorrelation, Bessembinder and Hartzel (1993) found an unusually high correlation for at least 100 years

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<sup>6</sup> For robustness purposes we have checked the weekend effect on the DSE-20 and DS-30 (from 2013), which is the large cap index of this market. We do this investigation with the argument that if the weekend effect is due to small investors' trades and hence is observed in small cap stocks, then there should be no weekend effect on the large cap index, i.e. the DSE-20 & DS-30 (constructed with twenty or thirty blue-chip shares of the market). To examine the weekend effect and significance of Sunday on return and volatility, we have applied equations (x), (ii) and (iii) respectively for OLS, GARCH (1, 1) and modified GARCH (1, 1) models. Results from OLS estimation show that Sunday returns are positive and not statistically significant. Similar results are also found in the GARCH (1, 1) approach, where Monday and Thursday are found to be significant at the 5% level. Finally, Sunday is further found not to be significant even at the 10% level in our modified volatility model (i.e. modified GARCH (1, 1)), whereas Monday and Thursday are found to be significant at the 5% and 1% levels respectively (detailed results are available on request). Altogether, our findings confirm that there is no Sunday seasonality on the DSE-20 & DS-30 indices and the market is not moved on Sunday by the trading of large cap firms.

between Monday's returns and the prior Friday's returns. Using the CRSP equally-weighted index of NYSE and ASE firms, Abraham and Ikenberry (1994) also report that the highest positive correlation is between Friday and subsequent Monday returns. Scholes and Williams (1977) claim that this first-order serial correlation in daily returns may be due to non-synchronous trading.

However, Keim and Stambaugh (1984), Jaffe and Westerfield (1985) and Bessembinder and Hertzl (1993) contend that measurement errors in stock index returns that arise from non-synchronous trading cannot explain the high correlation observed in Friday-Monday returns. Abraham and Ikenberry (1994) provide a natural explanation for this returns correlation. They assert that it is a delayed response of individual investors to the information revealed on the previous trading day. Lakonishok et al. (1992), Brusa et al. (2005) and Venezia and Shapira (2007) also link this feedback relationship to the weekend behaviour of investors. They assert that the conditional weekend effect is the result of the differential trading patterns of institutional and individual investors.

In this section, following the influence of individual investors on the weekend effect, we further check the robustness of the relationship by analysing the correlation between Thursday-Sunday returns. Using firm-level evidence we explore whether the weekend effect is driven by the trading behaviour of individual investors. We conjecture that in Bangladesh the Thursday-Sunday returns autocorrelation should be higher for smaller firms, where individual investors have greater holdings.

To test this hypothesis, we calculate the contemporaneous correlations between Sunday returns and variance and the returns and variance of the previous Thursday. We divide all the listed firms into small, mid-sized and large groups similar to the previous section. We report the results in Table 7, where the first three results columns show the correlations between returns and results columns four to six show the correlations between variances.

**Table 7: Thursday-Sunday Correlations between Returns and Volatility for Size Portfolios on the DSE**

|        |          | Thursday                    |                       |                      |                              |                       |                      |
|--------|----------|-----------------------------|-----------------------|----------------------|------------------------------|-----------------------|----------------------|
|        |          | Correlation between returns |                       |                      | Correlation between variance |                       |                      |
|        |          | Smallest                    | Mid-size              | Largest              | Smallest                     | Mid-size              | Largest              |
| Sunday | Smallest | 0.2278***<br>[6.2145]       | 0.0856**<br>[2.7634]  | 0.0628<br>[0.1153]   | 0.2436***<br>[4.8956]        | 0.0933**<br>[2.5960]  | 0.0722<br>[1.5577]   |
|        | Mid-size | 0.0876**<br>[2.0644]        | 0.1416***<br>[3.8978] | 0.0138<br>[0.7655]   | 0.1096**<br>[2.2321]         | 0.1233***<br>[5.1663] | -0.0342<br>[-0.3266] |
|        | Largest  | 0.0658<br>[1.4844]          | 0.0259*<br>[1.7684]   | -0.0022<br>[-0.7764] | 0.0471<br>[1.4261]           | 0.0246*<br>[1.8747]   | 0.0230<br>[0.6383]   |

\*\*\*, \*\* and \* indicate significance at the 1%, 5% and 10% levels respectively. t-statistics are in [ ]

As expected, the highest and significantly positive Thursday-Sunday contemporaneous correlation (0.2278) is between returns for the smallest firms. Surprisingly, the Sunday returns of the smallest group is also significantly correlated with the Thursday returns of the mid-sized (0.0856). There is a strong Thursday-Sunday positive returns correlation (0.1416) between mid-sized firms as well. The Sunday returns of mid-sized firms are also influenced by the smallest group (0.0876) of Thursday and this is statistically significant at the 5% level. The Thursday-Sunday returns for the largest firms are barely correlated and the correlation is not statistically significant.

Conversely, we use the residuals from the returns models of each firm-size portfolio to determine the contemporaneous correlation between the variances of Thursday-Sunday returns. The results are very much consistent with those of the returns: the highest and significant positive correlation is found in the smallest group (0.2436) and then between mid-sized firms (0.1233). The correlation between the variances of the largest firms is again very low and not statistically significant. The variance of the smallest portfolio is positively influenced by the variance of mid-sized (0.0933) as well. Finally, the Sunday returns variance for mid-sized firms is positively correlated (0.1096) with the smallest firms and it is significant at the 5% level. These contemporaneous correlation results for the DSE are similar to those of Abraham and Ikenberry (1994). They report a positive correlation between Monday returns and the returns from the previous Friday, and it is particularly strong for small and mid-sized stocks.

We extend the analysis by dividing firms into ten deciles and focusing on the firm-level characteristics. We create unconditional and conditional Sunday proportions following the methodology suggested in Brusa et al. (2000). Here the unconditional proportion represents the total number of positive and negative returns on Sunday. These results are reported in columns



(1) and (2) of Table 8. The results in column (3) and (4) show the conditional Sunday proportion. It represents the number of positive (negative) Sunday returns given that the preceding Thursday return is positive (negative). The statistics for unconditional and conditional independence are given in results column (5). To check the independence we split the Thursday-Sunday returns series into positive-positive, negative-negative, positive-negative and negative-positive categories and calculate Pearson's  $\chi^2$  and the Phi Coefficient. Pearson's  $\chi^2$  is used to measure overall unconditional independence and the Phi Coefficient is to measure conditional independence, i.e. the association between the Thursday and Sunday returns series. While the correlation coefficient only measures the linear association between series, the nonparametric Phi Coefficient measure is robust to departures from linearity. Finally, the  $\tilde{\alpha}$ -statistics, at the bottom of each decile's cell in columns (3) and (4), test whether the conditional positive (negative) proportions are significantly different from the unconditional positive (negative) proportion, given that the preceding Thursday returns were positive (negative).

**Table 8: Conditional and Unconditional Proportions of Sunday Returns on the DSE**

|                 |             | (1)                              | (2)      | (3)                            | (4)      | (5)                                                     |
|-----------------|-------------|----------------------------------|----------|--------------------------------|----------|---------------------------------------------------------|
|                 |             | Unconditional Sunday proportions |          | Conditional Sunday proportions |          | Unconditional and conditional independence <sup>a</sup> |
|                 |             | Positive                         | Negative | Positive                       | Negative |                                                         |
| <b>Smallest</b> | No. of Obs. | 390                              | 523      | 385                            | 401      | [244.15]***                                             |
|                 | Proportion  | 42.72                            | 57.28    | 51.53                          | 55.45    | (0.58)                                                  |
| <b>1</b>        | z-statistic |                                  |          | 2.48**                         | 1.98**   |                                                         |
|                 | Obs.        | 417                              | 496      | 347                            | 388      | [11.98]***                                              |
| <b>2</b>        | Proportion  | 45.67                            | 54.33    | 54.67                          | 57.36    | (0.16)                                                  |
|                 | z-statistic |                                  |          | 1.87*                          | 2.35**   |                                                         |
| <b>3</b>        | Obs.        | 443                              | 470      | 331                            | 351      | [81.36]***                                              |
|                 | Proportion  | 48.52                            | 51.48    | 49.23                          | 50.61    | (0.41)                                                  |
| <b>4</b>        | z-statistic |                                  |          | 2.02**                         | 2.06**   |                                                         |
|                 | Obs.        | 415                              | 498      | 309                            | 311      | [234.16]***                                             |
| <b>5</b>        | Proportion  | 45.45                            | 54.55    | 51.27                          | 50.60    | (0.57)                                                  |
|                 | z-statistic |                                  |          | 1.95**                         | 2.11**   |                                                         |
| <b>6</b>        | Obs.        | 441                              | 472      | 387                            | 358      | [13.48]***                                              |
|                 | Proportion  | 48.30                            | 51.70    | 55.38                          | 51.41    | (0.07)                                                  |
| <b>7</b>        | z-statistic |                                  |          | 2.03*                          | 2.86***  |                                                         |
|                 | Obs.        | 518                              | 395      | 412                            | 307      | [4.35]                                                  |
| <b>8</b>        | Proportion  | 56.74                            | 43.26    | 53.47                          | 42.19    | (0.04)                                                  |
|                 | z-statistic |                                  |          | 1.14                           | 0.97     |                                                         |
| <b>9</b>        | Obs.        | 428                              | 485      | 451                            | 367      | [574.16]***                                             |
|                 | Proportion  | 46.88                            | 53.12    | 52.33                          | 48.15    | (1.00)                                                  |
| <b>10</b>       | z-statistic |                                  |          | 2.49***                        | 3.16***  |                                                         |
|                 | Obs.        | 446                              | 467      | 322                            | 289      | [2.93]                                                  |
| <b>Largest</b>  | Proportion  | 48.85                            | 51.15    | 49.03                          | 44.21    | (0.03)                                                  |
|                 | z-statistic |                                  |          | 1.03                           | 1.16     |                                                         |
| <b>10</b>       | Obs.        | 519                              | 394      | 405                            | 267      | [9.66]                                                  |
|                 | Proportion  | 56.84                            | 43.16    | 57.43                          | 44.64    | (0.11)                                                  |
| <b>10</b>       | z-statistic |                                  |          | 0.89                           | 1.05     |                                                         |
|                 | Obs.        | 484                              | 429      | 301                            | 248      | [4.06]                                                  |
| <b>10</b>       | Proportion  | 53.01                            | 46.99    | 48.12                          | 42.58    | (0.05)                                                  |
|                 | z-statistic |                                  |          | 1.83*                          | 0.80     |                                                         |

<sup>a</sup> Unconditional and conditional independence respectively measure overall independence and association between Thursday and Sunday returns. We calculate Pearson's  $\chi^2 = \sum_{i,j} \frac{(\hat{n}_{i,j} - n_{i,j})^2}{\hat{n}_{i,j}}$  to measure the overall independence (where  $\hat{n}_{i,j}$  and  $n_{i,j}$  are the overall and actual expected counts in each cell) and the Phi coefficient  $\sqrt{\chi^2/N}$  to measure the association between the two returns series. The results of Pearson's  $\chi^2$  are reported in [ ] and the Phi coefficient in ( ). The  $\chi^2$ -statistics test whether the conditional proportions of positive (negative) Sunday returns are significantly different from the unconditional proportions of positive (negative) Sunday returns. The sample of returns includes 1826 (i.e., 913+913) observations over an eighteen year period 2000-2017. All proportions are in percentage form.

\*\*\*, \*\* and \* indicate significance at the 1%, 5% and 10% levels respectively.

The results given in Table 8 are very interesting. We see that there are more negative returns than positive returns (i.e. proportion of positive returns less than 50%) for most of the deciles except 6, 9 and 10, where there are slightly more positive returns than negative. In particular the positive returns are substantially higher for one of the mid-sized (deciles 6) and larger firms (deciles 9 and 10). For the conditional Sunday proportion, a negative Sunday return following negative returns on the Thursday is more likely for deciles from 1 through 4 and 7. Consistent with the previous literature, the  $\alpha$ -statistics show that strong autocorrelations exist between Sunday returns and preceding Thursday returns for some of the mid-sized firms, such as deciles 3, 4, 5 and 7. Autocorrelation also exists between Thursday-Sunday returns in smaller decile 1 and 2. These results are similar to those of Keim and Stambaugh (1984), Gibbon and Hess (1981) and Abraham and Ikenberry (1994), since they report higher autocorrelations for small and medium size firms.

However, Brusa et al. (2000) report no autocorrelation between Friday-Monday returns for small and large firms using the DJIA and NASDAQ stock indices, but strong autocorrelation for mid-sized firms. Thus, the autocorrelation characteristics for the DSE across firm size are similar but not identical to those of the US equity market. The significance of the  $\alpha$ -statistics for both positive and negative returns in deciles 1 to 3 and 6 through 8 means that given a positive Thursday return, the following Sunday returns are more likely to be positive, and the same for negative returns. Thus positive (negative) Sunday returns follow positive (negative) returns on the Thursday. Similar to the US market (Brusa et al., 2000), we do not find any such correlation for large firms, except that for the largest decile positive returns in the conditional Sunday proportions are statistically significant at the 10% level. This implies that positive Sunday returns may follow positive returns on the previous Thursday for the largest stocks, but the same is not true for negative returns.

Pearson's  $\chi^2$  and the Phi coefficient provide similar results to those of the  $\alpha$ -statistics. Applying the unconditional independence test, Pearson's  $\chi^2$  is found to be statistically significant for deciles 1 through 5 and 7. We therefore reject the null hypothesis that the returns series of Thursday and Sunday are independent for these small and mid-sized firms. Furthermore, we see a very strong unconditional association between the Thursday-Sunday returns series for firms in deciles 1, 3, 4 and 7. This is because the Phi coefficient is 0.58, 0.41, 0.57 and 1.00 for deciles 1, 3, 4 and 7 respectively. These findings are very much consistent with our previous results.

Overall, we see a conditional returns pattern in our sample. This pattern depends on firm size, where small and mid-sized firms exhibit a stronger conditional effect between Thursday and

Sunday. This finding is in line with the argument of Abraham and Ikenberry (1994). Using the CRSP value-weighted index of NYSE and ASE firms over the period 1963-1991 they find that institutional investors generally have a greater presence in large-cap stocks. Therefore, positive autocorrelation is consistent with the notion that the trading behaviour of individuals has greater impact on small and mid-sized stocks and may have occurred as a delayed reaction to negative information revealed in the previous trading session. In addition, the Thursday-Sunday returns and variance autocorrelation on the DSE may be the consequence of information revealed in the prior trading session. Altogether, the positive autocorrelation between Thursday-Sunday equity prices is strongly documented in small and mid-sized firms on the DSE. This supports our conjecture related to individual investors. Brusa et al. (2005) report that small stocks in the US market during the 1988-98 period also exhibit a positive autocorrelation between Friday and Monday returns. In another study on the US equity market, Lakonishok et al. (1992) also find this positive feedback trading in small stocks, but they claim that institutional investors are responsible for this effect. In Venezia and Shapira (2007), the coefficient of the behavioral variables turns out to be significantly related to stock returns. They also agree that this is due to the behaviour of certain types of investors that may affect stock prices after the weekend.

## **5. Summary**

We have applied conditional variance approaches to investigate the weekend effect and the influence of investors' trading behaviour on returns and volatility on the Dhaka Stock Exchange. This anomaly is extensively documented in previous studies for developed and some emerging equity and non-equity markets but very little has been documented for emerging Islamic markets.

Using daily market data from January 2001 to June 2019, we have found several interesting results that contributes to the literature. First, following the trading time hypothesis of French (1980), we find that the day-of-the-week pattern exists in returns following information content theory. Mean stock returns are not the same across the weekdays: Sunday's returns are significantly negative compared to the other trading days. Unlike most other markets the DSE operates from Sunday to Thursday; hence there is a "Sunday Effect". Second, we have applied a conditional variance model using daily returns series and document a weekend effect on volatility. The day-of-the-week dummy for Sunday is statistically significant for both returns and variance equations under both GJR-GARCH and CGARCH (1, 1) specifications. These findings support the arguments of Clark (1973), Kyle (1985), and Schwert (1990) that stock market variance is positively linked to trading volume. On the Dhaka Stock Exchange the average trading volume is highest on Wednesday and

the next highest volume is on Sunday. Hence heavy trading might be the reason for the “weekend effect” and the “reverse mid-week effect” we have found on Sunday and Wednesday respectively. Earnings and macroeconomic announcements are often disclosed on the DSE on Thursday and over the weekend. Most investors might therefore take long or short positions on Wednesday as they try to predict the announcement, then reshuffle their positions on Sunday based on the details of the announcement. As French and Roll (1986) and Barclay et al. (1990) observed, returns variance may be highest on the first day of the trading week because investors have their maximum information advantage to trade then.

Third, we find that the trading pattern of individual investors influences the weekend effect. Sunday returns tend to be negative for smaller firms and firms with a low dividend yield, where individuals tend to have greater holdings than institutions. The equity variance is also found to be significantly higher on Sunday. These results are consistent with previous studies, e.g., Gibbons and Hess (1981), Keim and Stambaugh (1984), Abraham and Ikenberry (1994), Kamara (1997), Brusa et al. (2000), and Chan et al. (2005) even though the DSE is dominated by individuals, as are the Shanghai and Shenzhen markets. In a market dominated by individual investors the weekend effect is stronger for smaller firms than larger companies. To explain the dynamics Abraham and Ikenberry (1994) assert that the weekend phenomenon is more complex than has been previously reported, and appears to be influenced by the trading behaviour of individual investors. In addition, this result validates the argument that regardless of the size of the economy and its firms, investors’ preference towards small versus large stocks still influences the weekend effect.

Fourth, in our robustness test, we have identified a positive feedback relationship between Sunday returns and the returns of previous Thursday. This pattern is also a function of firm size, where small and mid-sized firms show a stronger conditional effect between Thursday and Sunday. This conditional relationship adds weight to our argument about individual investors’ behaviour (Abraham and Ikenberry, 1994; Brusa et al. 2005). We also document the feedback effect between Thursday-Sunday returns residuals. This means that the Sunday returns variance is substantially influenced by the variance of the previous Thursday. Finally, we find from another robustness test that returns and volatility of Sundays during the Ramadan period are not significantly different from that of non-Ramadan Sundays. Moreover, there is no weekend effect found in the DSE 20 index, which confirms that negative returns and higher volatilities on Sunday are the results of trading of small firms.

We have provided strong evidence of a weekend effect on both returns and volatility in this important Islamic market. The effects happen on a Sunday which is the first day of the Bangladesh

working week. Since it is mainly those companies that are particularly popular with private investors (small size and low dividend yield) that are most affected, the evidence suggests that the effects are due to ‘information content theory’ and the ‘information processing hypothesis’ working on individual investors. Depending on trading costs, these results could be used to develop profitable trading strategies, both for local investors and international investors who wish to diversify into a market that is not strongly correlated with developed markets.

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