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More on Calendar Effects on Islamic Stock Markets

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Abstract: There is a long tradition in detecting anomalies of the Efficient Market Hypothesis. Among these are calendar anomalies, first described by French back in 1980. Whilst there is a plethora of studies for well-developed stock markets, there is still a lack of comprehensive studies for some small or emerging financial markets. It is particularly interesting to test not only for calendar effects in the conventional Gregorian calendar but also in other calendars like the Hijri calendar. Thus, the aim of this study is to provide a comprehensive analysis of calendar anomalies on Islamic stock markets. Firstly, we deliver a complete literature review of previous studies dealing with calendar effects on Islamic stock markets showing that there is still a lack of consensus about the effects. Secondly, we analyse whether there are any seasonal patterns in stock markets' returns by conventional estimation techniques. Thirdly, we study whether those calendar effects are still apparent when we control for volatility clustering. In fact, there is evidence for calendar anomalies on all stock markets. However, those effects are prone to changes when different models or distributions are used. One should, therefore, be careful when interpreting calendar effects on Islamic stock markets. The evidence for theories put forward when analysing Western stock markets is – at best – mild.

Keywords: Islamic stock markets, calendar anomalies, day-of-the-week-effect, Ramadan effect, volatility

JEL Classification: G12, G14, G15

1 Introduction

The academic debate between proponents and opponents of the Efficient Market Hypothesis (EMH) shows no sign of abating. The discussion about whether

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financial markets are efficient with respect to the processing of information started with the seminal work of Fama (1970). Clearly, the debate heated up again when Fama and Shiller won the Nobel Memorial Prize in Economic Sciences in 2013. The EMH argues that financial markets take all relevant and available information into account immediately after it has been released. The theory goes even further by assuming that prices reflect expectations as well. Under these circumstances, news only has an impact on asset prices if it is surprising. If a company just announces what everyone previously expected anyway, those companies' shares should not change in value. If the EMH holds, then returns should also not be predictable. Ever since it has been released the EMH has been attacked by researchers, questioning the validity of the theory by presenting counter examples or rather anomalies. One such instance is calendar effects meaning that stock market returns vary significantly between certain days or months. The first one to bring this topic up was French (1980) who found a weekend effect on the US stock market. Whilst the literature on conventional financial markets of industrialised countries is reasonably high, there is not that much empirical evidence for stock markets of developing countries given the fact that some of them were only established a decade or so ago. This justifies a study about some stock markets that have hardly been looked at. Apart from that, behavioural finance has brought forth the role of moods or feelings. This explains why it is especially appealing to analyse Islamic stock markets. Given the religiosity of Muslims and the importance of religious festivities, it is of great importance to study whether the mood of a multitude of people also has an impact on the macro level. Therefore, the aim of this study is to look for potential calendar effects on twenty-four selected Islamic stock markets. We analyse day-of-the-week-effects and monthly effects in the Gregorian and the Hijri calendar. The main question with respect to monthly effects in the Hijri calendar is whether Ramadan has any particular importance on stock markets. This paper is structured as follows: we start with an overview of theoretical assumptions regarding calendar effects and the empirical studies about calendar effects on Islamic stock markets. Section 3 presents the data and the methodology. The results for the respective stock markets are presented in Section 4. Section 5 concludes.

2 Theoretical Assumptions and Literature Review

It is well known that following French's seminal work (1980) a lot of calendar effects were found on western stock exchanges. Thus, one would expect to find those same effects in emerging markets as well, given the lack of efficiency such markets often exhibit. It therefore comes as no surprise that in the last decade a

major advance could be seen in the research of calendar effects on Islamic stock markets.

In this study, we define an Islamic stock market as a financial market that is situated in a country, whose population is either made up of at least 50% Muslims, whose official state religion is Islam, or a combination of both. In addition to the effects that are also apparent in western markets, Islamic stock markets often exhibit a special peculiarity of calendar effects, namely Hijri calendar effects and in particular the Ramadan effect. It is characterised by an above-average mean return during the holy month, often attributed to the “mild states of euphoria” (Białkowski, Etebari, and Wisniewski 2012, 836) caused by fasting. However, many research gaps concerning this topic remain, mainly due to insufficient market data and inappropriate econometric techniques. To close some of those gaps, this study will analyse the returns of twenty-four Islamic stock markets. These markets are examined because they are Islamic, one of the three calendar effects (day-of-the-week-, monthly, or Ramadan effect) has not yet been researched, the research methodology of previous studies was not appropriate e. g. simple ordinary least squares (OLS)¹ and the market data is readily obtainable. The only country that does not fall under one of the first three categories is Jordan where we can truly trust the previous results because the empirical methodology was appropriate in some estimations. We still decided to include Jordan in order to have a comprehensive study of calendar effects on Islamic stock markets. Another motivation for looking at all stock markets again is that in most cases we have a longer period to analyse than the previous studies. Given that there is evidence that calendar effects seem to disappear once they have been reported (Marquering, Nisser, and Valla 2006), it is reasonable to take a fresh look at all markets making use of the longer time series. The practical importance about these effects is that when transaction costs are relatively low and the risk involved stays within reasonable boundaries, they can be exploited by investors. Therefore, to get a broader outlook on the picture, risk in terms of volatility will also be examined in this study.

2.1 Day-of-the-Week Effects

Conventional wisdom for stock markets of industrialised countries says that there is a plethora of reasons for day-of-the-week effects. French (1980) argued that stock returns should be higher on Mondays given the fact that there are three days between Monday and the last trading day. To be precise, he argued

¹ Section 3 describes in detail which methods are suitable.

that returns on Mondays should be three times the returns on other days of the week (Choudhry 2000). On the contrary, others would say that it should be vice versa. Their thoughts are based on the assumption that companies release bad news on non-trading days and good news on trading days (Fortune 1991). Another explanation for the Monday effect is that the trading volume by individual investors is higher on Mondays given that they need the weekend to process relevant financial information (Dicle and Levendis 2014). This fosters noise trading and herding behaviour by investors (Chang, Pinegar, and Ravichandran 1995). Furthermore, Monday effects could just be the result of bad mood of investors. This refers to the “blue Monday hypothesis”. In fact, there is empirical evidence for such a mood driven calendar effect where the effect is even stronger within smaller indices and in collectivist and uncertainty-averse societies (Abu Bakar, Siganos, and Vagenas-Nanos 2014). However, we would not expect a Monday effect in the same manner on Islamic stock markets given that on most of them the trading week runs from Sunday through Thursday. Others argue that settlement procedures could be a determinant of day-of-the-week effects, because investors would have to be rewarded for waiting for their receipt over the weekend (Choudhry 2000). Further explanations for day-of-the-week effects are trading patterns by investors (Admati and Pfleiderer 1989) and seasonality in the release and, more importantly, in the processing of macroeconomic news (Chang, Pinegar, and Ravichandran 1998). A study focusing on the US even finds that day-of-the-week effects are dependent on whether it is a Democratic or Republican presidency without delivering a meaningful explanation for this result (Liano, Liano, and Manakyan 1999). Finally, calendar effects could still just be the result of measurement errors.

Many studies confirmed the existence of a variety of calendar effects on Islamic stock markets before. Table 1 summarises the previous studies on Islamic calendar effects. Looking at the table it is apparent that there is overwhelming evidence for day-of-the-week (DOW) effects on Islamic stock markets. Yet, there are a few stock markets where no DOW effects could be found. These stock markets are the Beirut Stock Exchange, the Bourse de Tunis, and the Palestine Exchange. The Chittagong Stock Exchange, the Damascus Securities Exchange, the Kazakhstan Stock Exchange, and the Iraqi Stock Exchange have not yet been analysed before. Furthermore, it is important to note that not all of the studies came to the same result, as the specific day-of-the-week effects vary, which might be a result of the different approaches as well as different timeframes they used in their studies. A further reason might be, as mentioned above, that calendar effects tend to vanish as soon as the respective research is published (Marquering, Nisser, and Valla 2006). This is enough reason to evaluate DOW effects on all Islamic stock markets again.

Table 1: Overview of previous studies.

Stock Exchange	Paper	Methodology	Result
ADX (Abu Dhabi Securities Exchange)	Al-Khazali (2008)	stochastic dominance analysis	no DOW effect
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	no DOW effect
	Turk Ariss, Rezvanian, and Mehdian (2011)	OLS (robust standard errors)	Wed + Mar +; Jul – no Ramadan effect
ASE (Amman Stock Exchange)	Basher and Sadorsky (2006)	OLS (robust standard errors)	no DOW effect
	Al-Rjoub (2004)	GARCH-M	Thu +; Mon –
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	Sun, Tue, Thu +
	Alrabadi and Al-Qudah (2012)	OLS (robust standard errors), GARCH(1,1); distribution unclear	Sun, Thu +; Mon –
	Dicle and Levendis (2014)	GARCH; GJR	Jan +
BASE (Bahrain Bourse)	Giovanis (2009)	GARCH, EGARCH; GJR; normal, t-distribution, GED	Mon, Thu –
	Al-Hajieh, Redhead, and Rodgers (2011)	Wald-Wolfowitz Runs Test	Mar, Jul –
	Almudhaf (2009)	OLS (robust standard errors)	Ramadan effect
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	Rabi' II, Rajab, Sha'ban, Ramadan +
	Turk Ariss, Rezvanian, and Mehdian (2011)	OLS (robust standard errors)	no DOW effect
			Mon, Tue, Wed + Jan, Feb –; Apr, May, Jul, Aug, Sep, Oct, Dec +
	Al-Hajieh, Redhead, and Rodgers (2011)	Wald-Wolfowitz Runs Test	no Ramadan effect
	Almudhaf (2009)	OLS (robust standard errors)	no Ramadan effect Rabi' I, Sha'ban +

(continued)

Table 1: (continued)

Stock Exchange	Paper	Methodology	Result
BIST (Borsa Istanbul)	Basher and Sadorsky (2006)	OLS (robust standard errors)	Thu, Fri +
	Bildik (2004)	OLS (robust standard errors); Kruskal-Wallis test	Thu, Fri +
	Çiçek (2013)	E-GARCH(1,1); Conditional Student's t-distribution	Jan, Jun +; Aug –
	Oguzsoy and Güven (2003)	OLS	Mon +
	Demirer and Karan (2002)	OLS	Mon, Tue –; Fri +
BRVM (Bourse Régionale des Valeurs Mobilières)	Giovanis (2009)	GARCH, EGARCH; GJR; normal, t-distribution, GED	no DOW effect
	Al-Hajieh, Redhead, and Rodgers (2011)	Wald-Wolfowitz Runs Test	Apr, Jul, Sep, Oct, Dec +
	Almudhaf (2009)	OLS (robust standard errors)	Ramaḍān effect
	Mlambo and Biekpe (2006)	OLS (robust standard errors); Kruskal-Wallis test	Muḥarram, Rajab, Sha'ban, Ramaḍān +
			no DOW effect
BSE (Beirut Stock Exchange)	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	Jan –; May, Sep, Oct, Dec +
BVMT (Bourse de Tunis)	Mlambo and Biekpe (2006)	OLS (robust standard errors); Kruskal-Wallis test	no DOW effect
CASE (Casablanca Stock Exchange)	Mlambo and Biekpe (2006)	OLS (robust standard errors); Kruskal-Wallis test	no DOW effect
DFM (Dubai Financial Market)	Alagidede (2008)	OLS; GARCH(1,1)	Jan +; Apr, Jun, Oct, Nov –
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	Wed, Thu, Fri +
	Al-Barrak (2009)	ANOVA	Jul, Sep, Oct –; Aug +
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	no DOW effect
	Turk Ariss, Rezvanian, and Mehdian (2011)	OLS (robust standard errors)	no DOW effect
DSE (Dhaka Stock Exchange)	Rahman (2009)	OLS (robust standard errors), GARCH; normal distribution	no DOW effect
			Sun –
			Wed, Thu +
			Dec +
			Sun, Mon –; Thu +

EGX (Egyptian Exchange)	Aly, Mehdi, and Perry (2004)	OLS	Mon –
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	Sun, Thu +
	Dicle and Levendis (2014)	GARCH; GJR	Mon –
	Alagidede (2008)	OLS, GARCH(1,1)	no DOW effect
	Mlambo and Biekpe (2006)	OLS (robust standard errors); Kruskal-Wallis test	no DOW effect Jan +; Feb, Mar, Apr, May, Jun, Jul, Sep, Oct –
IDX (Indonesia Stock Exchange)	Al-Hajjeh, Redhead, and Rodgers (2011)	Wald-Wolfowitz Runs Test	Ramadan effect
	Almudhaf (2009)	OLS (robust standard errors)	Sha'ban +
	Basher and Sadorsky (2006)	OLS (robust standard errors)	no DOW effect
	Choudhry (2000)	GARCH using Student's t-distribution	Mon –
	Wong and Yunto (1999)	OLS; Mann-Whitney test	Tue –; Fri + Jan +
KLSE (Bursa Malaysia)	Dicle and Levendis (2014)	GARCH; GJR	Mon –
	Giovanis (2009)	GARCH, EGARCH; GJR; normal, t-distribution, GED	Jan, Apr, May, Nov, Dec +; Aug –
	Basher and Sadorsky (2006)	OLS (robust standard errors)	Mon –
	Lim, Mun Ho, and Dallery (2010)	Kruskal-Wallis test	Wed, Fri +
	Choudhry (2000)	GARCH using Student's t-distribution	Mon –; Wed, Fri +
	Abdullah et al. (2011)	OLS	Mon –; Fri + (both KLSI)
	Brooks and Persaud (2001)	OLS	Mon, Thu +
	Giovanis (2009)	GARCH, EGARCH; GJR; normal, t-distribution, GED	Jan, Dec +
	Clare, Ibrahim, and Thomas (1998)	OLS (robust standard errors); ARCH(4)-M, distribution unclear	Mon –
	Basher and Sadorsky (2006)	OLS (robust standard errors)	Tue –
KSE (Karachi Stock Exchange)	Hussain et al. (2011)	OLS	Tue +
	Haroon and Shah (2013)	OLS	Mon –; Fri +
	Nishat and Mustafa (2002)	GARCH(1,1); distribution unclear	no DOW effect
	Giovanis (2009)	GARCH, EGARCH; GJR; normal, t-distribution, GED	Jan, Feb, Apr, Jun, Oct, Dec +
	Mustafa (2011)	OLS	Ramadan, Shawwal, Dhū al-Qa'dah +

(continued)

Table 1: (continued)

Stock Exchange	Paper	Methodology	Result
KUSE (Kuwait Stock Exchange)	Al-Barrak (2009)	ANOVA	Sat, Sun
	Al-Loughani and Chappell (2001)	GARCH-M; distribution unclear	Sat +
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	Mon, Tue, Wed, Sat +
	Giovanis (2009)	GARCH, EGARCH; GJR; normal, t-distribution, GED	Jan, Mar, Apr, Oct, Nov, Dec +
MSM (Muscat Securities Market)	Turk Ariss, Rezvanian, and Mehdian (2011)	OLS (robust standard errors)	Wed, Thu +
	Al-Hajieh, Redhead, and Rodgers (2011)	Wald-Wolfowitz Runs Test	Dec +
	Almudhaf (2009)	OLS (robust standard errors)	no Ramadan effect
	Al-Jafari (2012)	GARCH, TARCH, EGARCH; GED	Ramadan effect
PEX (Palestine Exchange)	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	Ramadan +
	Turk Ariss, Rezvanian, and Mehdian (2011)	OLS (robust standard errors)	no DOW effect
	Almudhaf (2009)	OLS (robust standard errors)	no DOW effect
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	Tue, Wed +
QE (Qatar Exchange)	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	Jan, Jun, Dec +
	Turk Ariss, Rezvanian, and Mehdian (2011)	OLS (robust standard errors)	no Ramadan effect
	Almudhaf (2009)	OLS (robust standard errors)	Rabi' II, Jumada I +; Shawwal –
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	no DOW effect

TAD (Tadawul)	Al-Barrak (2009)	ANOVA	no DOW effect Sat
	Ulussever, Guran Yumusak, and Kar (2011)	OLS (robust standard errors), GARCH; distribution unclear	
	Kamaly and Tooma (2009)	GARCH(1,1) and GARCH(2,2) using QMLE; GARCH-M	
	Turk Ariss, Rezvanian, and Mehdiian (2011)	OLS (robust standard errors)	
TSE (Tehran Stock Exchange)	Seyyed, Abraham, and Al-Hajji (2005)	GARCH; distribution unclear	no DOW effect Wed + Aug, Dec + no Ramadān effect lower volatility during Ramadān no Ramadān effect Muḥarram, Rajab + Sat + ; Sun –
	Al-Hajieh, Redhead, and Rodgers (2011)	Wald-Wolfowitz Runs Test	
	Almudhaf (2009)	OLS (robust standard errors)	
	Yahyazadehfazl, Abounoori, and Shababi (2006)	OLS, ARCH / GARCH; distribution unclear	

Notes: DOW: Day-of-the-week. KLSI: Kuala Lumpur Sharia Index; tracked the performance of securities compliant with the Islamic law, the Sharia. The table shows the Islamic stock markets that have already been subject to research regarding calendar effects, as well as methodology and the respective results.

2.2 Monthly Effects

Looking at financial markets of Western industrialised countries, the most prevalent monthly effect is the January effect. The theory behind the January effect is based on the tax year. Accordingly, equity funds and investors sell assets plagued by heavy losses to decrease their tax burden. In January, they would buy other assets again which leads to rising asset prices and returns. A universal explanation for any kind of “inefficiencies” in stock markets would be that there are learning costs and individuals need time to fully incorporate all relevant information. This might well explain why some calendar effects disappear once they are reported publicly. Another general explanation would be that there are noise traders who react to noise rather than information. Of course, the EMH would argue that in such a scenario some “smart money” would come in and exploit the trading behaviour of these irrational investors. However, this might not be possible if there is no such “smart money” (which could well be the case in thin emerging stock markets) or noise traders and informed investors have different investment horizons. Furthermore, a precondition is that short-selling is possible. Hence, “smart money” would buy shares on days with negative returns and (short-) sell them on days with positive returns. If short-selling is forbidden, which is apparently the case in most Islamic stock markets, then the downward pressure on stock prices on days which are thought to have excess returns would be much smaller.

Likewise, positive and negative effects for certain months, as well as a positive January effect were identified on some Islamic stock markets (see Table 1). Again, we find contradictory results when comparing studies focusing on the same stock markets. This requires a re-examination of the prior results.

2.3 Ramadan Effects and Islamic Monthly Effects

The idea of possible Ramadan effects derives from the very meaning of this particular month for Muslims. Higher trading volume on Islamic financial markets during Ramadan, for example, could be caused by the fact that, while Islamic finance prohibits interest (“riba”), Muslims are allowed to trade on stock markets. Hence they could pursue stock trading more actively during the holy month to compensate for foregone profits from suspending interest-rate businesses to comply with Sharia. Furthermore, behavioural finance argues that moods play a crucial role in people’s decisions. Accordingly, Muslims might be optimistic and in good spirits during the holy month given their religious beliefs (Al-Hajjeh, Redhead, and Rodgers 2011). This can in turn influence their

investment decisions in such a way that they expect positive things to happen.² Białkowski, Etebari, and Wisniewski (2012) argue that improved health due to fasting can further encourage Muslims to act more risk prone and invest more in assets. Moreover, Muslims tend to work less while spending lots of money on groceries (Seyyed, Abraham, and Al-Hajji 2005). The same might also apply to Dhu al-Hijjah, which is the month in which Muslims should make a pilgrimage to Mecca.

As noted above, the Ramadan effect and monthly effects following the Islamic calendar are a specialty concerning Islamic stock markets. Białkowski, Etebari, and Wisniewski (2012) found strong presence of Ramadan effects when considering several Islamic stock markets together³ while others found the effect on several stock markets in individual analyses. Apart from that, there is also some evidence for abnormal returns in other months of the Hijri calendar. Once again, some of the studies are conflicting in their results.

3 Data and Methodology

As noted earlier, data concerning Islamic stock markets remains relatively scarce given that some of the stock markets were opened just a few years ago. Table 2 gives an overview of the stock markets, the trading days, the settlement periods, the analysed indices and periods, and the sources of data used in this study.

The Gregorian dates were converted to Islamic Hijri dates to test for effects in Islamic months. The Islamic Hijri calendar is a lunar calendar with twelve months of 29 or 30 days each. The Islamic year consists of 354 or 355 days, which is the reason why the start of Ramadan in the Gregorian calendar of a given year is approximately eleven days prior to its start in the previous year. To identify the calendar effects, we first adopt and adjust the methodology of Aly, Mehdian, and Perry (2004) that was also widely used in previous papers (see Table 1).

² See Al-Hajieh, Redhead, and Rodgers (2011) for a detailed discussion of the role of sentiments on investment decisions with Islamic financial markets.

³ Those markets were the Amman Stock Exchange, the Bahrain Bourse, the Borsa Istanbul, the Bursa Malaysia, the Casablanca Stock Exchange, the Dubai Financial market, the Egyptian Exchange, the Indonesia Stock Exchange, the Karachi Stock Exchange, the Kuwait Stock Exchange, the Muscat Securities Market, the Qatar Exchange, and the Tadawul.

Table 2: List of stock markets under study.

Stock exchange	Trading days	Settlement period	Index	Study period	Source of data
ADX	Sun. – Thu.	T + 2	ADX General	Sept. 2006 – Sept. 2015	Datastream
ASE	Sun. – Thu.	T + 2	ASE General	Jan. 2011 – Sept. 2015	Datastream
BASE	Sun. – Thu.	T + 2	Bahrain All Share	Jan. 2003 – Sept. 2015	Datastream
BIST	Mon. – Fri.	T + 2	BIST National All Share	Jan. 1997 – Sept. 2015	Datastream
BRVM	Mon, Wed, Fri, resp. Mon. – Fri.	T + 5; since Jul. 2007: T + 3	BRVM Composite	Sept. 1998 – Sept. 2015	Datastream
BSE	Mon. – Fri.	T + 3	BLOM BSI	Jan. 2006 – Sept. 2015	Datastream
BVMT	Mon. – Fri.	T + 3	TUNINDEX	Jan. 1998 – Sept. 2015	Datastream
CASE	Mon. – Fri.	T + 5; since May 2001: T + 3	MASI	Jan. 1992 – Sept. 2015	casablanca-bourse.com
CSE (Chittagong Stock Exchange)	Sun. – Thu.	T + 2	CASPI	Sept. 2005 – Sept. 2015	cse.com.bd
DASE (Damascus Securities Exchange)	Sun. – Thu. Mon. – Wed. / Thu.	T + 2	DWX	Feb. 2011 – Sept. 2015	dse.sy
DFM	Sun. – Thu.	T + 2	DFMGI	Sept. 2006 – Sept. 2015	Datastream
DSE	Sun. – Thu.	T + 0	DSEX	Feb. 2013 – Sept. 2015	Datastream
EGX	Sun. – Thu.	T + 3; since Mar. 2007: T + 2	EGX30	Jan. 1998 – Sept. 2015	Datastream
IDX	Mon. – Fri.	T + 3	IDX Composite	May 1983 – Sept. 2015	Datastream
ISX (Iraqi Stock Exchange)	Sun, Tue, Thu, resp. Sun. – Thu.	T + 0	ISX	Jul. 2007 – Sept. 2015	isx-iq.net /Datastream
KASE (Kazakhstan Stock Exchange)	Mon. – Fri.	T + 0	KZHKASE	Apr. 2007 – Sept. 2015	Datastream
KLSE	Mon. – Fri.	T + 6; since Aug. 1997: T + 5; since Dec. 2000: T + 3	FBMKLCI	Jan. 1980 – Sept. 2015	Datastream

(continued)

Table 2: (continued)

Stock exchange	Trading days	Settlement period	Index	Study period	Source of data
KSE	Mon. – Fri.	T + 3; since June 2007: T + 2	KSE 100	Jan. 2009 – Sept. 2015	Datastream
KUSE	Sun. – Thu.	Tuesdays and Saturdays	KWSE	Jan. 2000 – Sept. 2015	Datastream
MSM	Sun. – Thu.	T + 3	MSM 30	May 2008 – Sept. 2015	Datastream
PEX	Sun. – Thu.	T + 2	Al-Quds	Jun. 2003 – Sept. 2015	pex.ps
QE	Sun. – Thu.	T + 3	QE All Share	Feb. 2007 – Sept. 2015	Datastream
TAD	Sat. – Wed. resp. Sun. – Thu.	T + 0	TASI	Nov. 1998 – Sept. 2015	Datastream
TSE	Sat. – Wed.	T + 3	TEDPIX	Mar. 2005 – Sept. 2015	tse.ir

Notes: The table shows the twenty-four stock markets that are subject to research in our study, including twenty stock markets from Table 1 that have already been studied before, and four stock markets new to this line of research. The new markets have their full names in parenthesis behind their respective acronyms. The table includes trading days, settlement periods, researched indices, study period, and the data source. For markets that had one or more shifts in trading days (e. g. BRVM) during the study period, the datasets have been split up for the analysis.

To calculate the daily and monthly continuously compounded returns of the respective indices, we used the following formula:

$$R_t = \ln \left(\frac{P_t}{P_{t-1}} \right) \quad [1]$$

where R_t is the return and P_t is the closing price at time t . Table 3 shows the summary statistics for the continuously compounded return.

We use the following regression equation to test for the day-of-the-week-effect:

$$R_t = \sum_{j=1}^d \alpha_j D_{jt} + \epsilon_t$$

where $1 < d \leq 5$ [2]

where R_t is the return on day t . α_j are the coefficients to be estimated and represent the mean returns on the respective weekdays. d is the number of

Table 3: Summary statistics for R_t .

	ADX				ASE	
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	2347	108	110	1205	56	57
Mean	0.00008	0.00159	0.00254	-0.00014	-0.00256	-0.00235
Median	0.00000	0.00331	0.00494	0.00000	-0.00402	-0.00555
Min.	-0.36492	-0.19792	-0.19597	-0.02646	-0.07169	-0.07054
Max.	0.39818	0.18109	0.11284	0.02086	0.05908	0.07095
SD	0.01599	0.06186	0.05839	0.00479	0.02627	0.02432
Skewness	1.37790	-0.23960	-0.89966	-0.15830	-0.21448	-0.08162
Kurtosis	279.9000	1.2498	1.4473	3.0204	0.3307	1.8858
Jarque-Bera	7.662E+06***	8.06242**	24.4389***	463.078***	0.684503	8.5094**
ACF	-0.1392***	0.2809***	0.4056***	0.1206***	0.0309	0.0895

	BASE				BIST	
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	3303	152	156	4868	224	230
Mean	0.00007	0.00146	0.00158	0.00089	0.01927	0.01840
Median	0.00000	0.00357	0.00504	0.00025	0.01438	0.01912
Min.	-0.04920	-0.12716	-0.12990	-0.19689	-0.59082	-0.45831
Max.	0.03613	0.11492	0.11213	0.17676	0.62830	0.48610
SD	0.00561	0.03789	0.03577	0.02356	0.12612	0.11359
Skewness	-0.47159	-0.25483	-0.56973	-0.09522	0.14387	-0.08359
Kurtosis	6.9108	1.6196	1.6924	6.7893	5.3731	2.4944
Jarque-Bera	6685.07***	18.2571***	27.0565***	9356.79***	270.227***	59.8936***
ACF	0.1507***	0.3649***	0.4324***	0.0166	-0.0005	0.1180*

	BRVM		
	Period 1 daily	Period 2 daily	Monthly isl.
# Obs	493	2521	117
Mean	-0.00080	0.00038	0.00704
Median	0.00000	0.00000	0.00772
Min.	-0.04048	-0.10685	-0.41404
Max.	0.03131	0.09085	0.31400
SD	0.00713	0.00902	0.06608
Skewness	-0.64505	-0.29520	-1.41450
Kurtosis	6.6511	21.4600	16.1610
Jarque-Bera	942.888***	48410***	1312.29***
ACF	0.1848***	0.0700***	-0.0937

	BSE		
	Daily	Monthly	Monthly isl.
# Obs	2514	116	118
Mean	-0.00012	-0.00135	-0.00400
Median	0.00000	-0.00551	-0.00472
Min.	-0.10688	-0.20657	-0.20848
Max.	0.08490	0.33836	0.15969
SD	0.00956	0.06325	0.05226
Skewness	0.30650	1.13800	-0.78729
Kurtosis	25.2280	8.8019	4.8806
Jarque-Bera	66709***	399.491***	129.307***
ACF	0.1464***	0.1019	0.3229***

	BVMT		
	Daily	Monthly	Monthly isl.
# Obs	2514	116	118
Mean	-0.00012	-0.00135	-0.00400
Median	0.00000	-0.00551	-0.00472
Min.	-0.10688	-0.20657	-0.20848
Max.	0.08490	0.33836	0.15969
SD	0.00956	0.06325	0.05226
Skewness	0.30650	1.13800	-0.78729
Kurtosis	25.2280	8.8019	4.8806
Jarque-Bera	66709***	399.491***	129.307***
ACF	0.1464***	0.1019	0.3229***

(continued)

Table 3: (continued)

	CASE				CSE	
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	5889	284	292	2379	120	123
Mean	0.00038	0.00783	0.00776	0.00062	0.01231	0.01219
Median	0.00024	0.00723	0.00828	0.00042	0.01030	0.01276
Min.	-0.05017	-0.13230	-0.13682	-0.07765	-0.28159	-0.20399
Max.	0.04555	0.21390	0.16678	0.13071	0.18461	0.16574
SD	0.00668	0.04193	0.04117	0.01440	0.07711	0.06765
Skewness	-0.14691	0.50142	0.16522	0.16919	-0.56673	-0.23697
Kurtosis	7.6988	2.5058	1.3184	6.5346	1.9208	0.2294
Jarque-Bera	14564.9***	86.2039***	22.4779***	4244.03***	24.8707***	1.42091
ACF	0.2982***	0.1709***	0.1668***	0.0249	0.0858	0.1881**

	DASE				DASE	
	Period 1 daily	Period 2 daily	Period 3 daily	Monthly	Monthly isl.	Monthly isl.
# Obs	132	436	217	55	57	
Mean	-0.00463	0.00075	-0.00041	-0.00642	-0.00626	
Median	-0.00614	-0.00075	-0.00041	-0.00574	-0.00838	
Min.	-0.02126	-0.01135	-0.00644	-0.18176	-0.18256	
Max.	0.02521	0.03796	0.01135	0.26860	0.25119	
SD	0.01126	0.00695	0.00229	0.06009	0.05580	
Skewness	0.79138	2.35110	0.95273	1.09360	0.82200	
Kurtosis	-0.0782	7.8069	3.8872	8.4616	9.0975	
Jarque-Bera	13.8119***	1508.89***	169.448***	175.044***	202.983***	
ACF	0.6513***	0.6451***	0.2999***	0.2755***	0.2968**	

	DFM			DSE		
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	2347	108	110	676	31	32
Mean	-0.00013	-0.00299	-0.00162	0.00021	0.00434	0.00441
Median	0.00000	-0.00343	0.00108	0.00000	-0.01003	0.00504
Min.	-0.09621	-0.38662	-0.39528	-0.05358	-0.10042	-0.12161
Max.	0.12205	0.23134	0.18237	0.03685	0.13639	0.11524
SD	0.01797	0.09997	0.09672	0.00987	0.06537	0.05519
Skewness	-0.13882	-0.60282	-1.04900	-0.12424	0.41985	-0.04500
Kurtosis	6.3268	2.1578	2.7149	2.5617	-0.4271	-0.2241
Jarque-Bera	3922.04***	27.4927***	53.9556***	186.579***	1.14639	0.07775
ACF	0.0420**	0.2889***	0.3414***	0.0477	-0.0708	-0.0670

	EGX			IDX		
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	4608	212	217	8456	388	400
Mean	0.00043	0.00929	0.00973	0.00045	0.00965	0.00951
Median	0.00000	0.00992	0.01211	0.00000	0.00634	0.00961
Min.	-0.17992	-0.31483	-0.36774	-0.22527	-0.40998	-0.49807
Max.	0.18369	0.27073	0.33171	0.40310	0.67692	0.62401
SD	0.01681	0.09427	0.09617	0.01498	0.08724	0.08629
Skewness	-0.34343	-0.16163	-0.02970	2.53460	0.72885	-0.09736
Kurtosis	9.6432	0.8782	1.1634	85.8970	11.2110	11.7360
Jarque-Bera	17944.9***	7.73632**	12.27***	2.61E+06***	2066.27***	2296.02***
ACF	0.1670***	0.1378**	0.1035	0.2357***	0.1561***	0.1667***

(continued)

Table 3: (continued)

	ISX Period 1			ISX Period 2		
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	245	20	22	1032	52	55
Mean	0.00808	0.08522	0.07840	0.00000	-0.00019	-0.00052
Median	0.00124	0.01616	0.01723	-0.00024	-0.00125	-0.00100
Min.	-0.24667	-0.14681	-0.17978	-0.04431	-0.11165	-0.12138
Max.	0.34704	0.77364	0.61208	0.04320	0.14245	0.12193
SD	0.04218	0.21478	0.17145	0.00752	0.04128	0.04744
Skewness	1.55620	2.03150	1.52600	0.29270	0.40870	0.16494
Kurtosis	24.1190	3.6088	2.4585	6.2611	2.2955	0.7902
Jarque-Bera	6037.22***	24.6098***	14.0792***	1700.37***	12.865***	1.68028
ACF	0.4034***	0.0315	0.1926	0.1504***	0.2055	-0.0726

	ISX Period 3			KASE		
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	337	17	17	2209	101	104
Mean	-0.00041	-0.00725	-0.00579	-0.00051	-0.01114	-0.01133
Median	0.00035	0.00682	0.00593	0.00000	-0.00493	-0.00250
Min.	-0.25408	-0.15409	-0.16962	-0.12962	-0.52538	-0.49761
Max.	0.02983	0.10605	0.10400	0.13568	0.30711	0.26854
SD	0.01805	0.07458	0.06582	0.01968	0.10750	0.10828
Skewness	-9.80040	-0.57261	-0.83960	-0.01649	-1.15170	-0.89557
Kurtosis	122.7600	-0.5083	0.9138	10.2910	5.3402	3.8948
Jarque-Bera	217013***	1.112	2.58877	9748.35***	142.343***	79.6349***
ACF	-0.0936*	-0.4272*	-0.3157	0.0397*	0.2047**	0.2622***

	KLSE			KSE		
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	9304	428	440	1738	80	81
Mean	0.0022	0.00477	0.00453	0.00103	0.02223	0.02481
Median	0.00000	0.00819	0.00790	0.00056	0.02571	0.02727
Min.	-0.24153	-0.42660	-0.31467	-0.05135	-0.09930	-0.11153
Max.	0.20817	0.26877	0.27595	0.05301	0.23566	0.19887
SD	0.01333	0.07457	0.06986	0.01053	0.05244	0.05230
Skewness	-0.40030	-0.70024	-0.57133	-0.17299	0.58188	0.45221
Kurtosis	40.3520	4.5489	2.7961	3.3313	2.8145	1.4375
Jarque-Bera	631478***	403.987***	167.27***	812.314***	30.9192***	9.73443***
ACF	0.1065***	0.1645***	0.1775***	0.0952***	-0.0349	0.0330

	KUSE			MSM		
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	4087	188	193	1911	88	90
Mean	0.00034	0.00740	0.00766	-0.00034	-0.00764	-0.00635
Median	0.00002	0.01527	0.01053	0.00000	0.00372	0.00564
Min.	-0.09335	-0.28228	-0.26106	-0.08651	-0.25762	-0.32788
Max.	0.06303	0.17697	0.17846	0.08039	0.12789	0.10348
SD	0.00865	0.05583	0.05509	0.01137	0.05358	0.05941
Skewness	-0.87646	-0.79812	-0.90620	-0.95415	-1.70980	-2.32600
Kurtosis	13.0400	3.4908	3.7113	15.4280	5.3735	9.2360
Jarque-Bera	29481***	115.411***	137.181***	19241.7***	148.748***	401.042***
ACF	0.0352**	0.4023***	0.3833***	0.2383***	0.3533***	0.1490

(continued)

Table 3: (continued)

	PEX			QE		
	Daily	Monthly	Monthly isl.	Daily	Monthly	Monthly isl.
# Obs	3,000	147	151	2,259	103	106
Mean	0.0031	0.00627	0.00622	0.00049	0.01125	0.01112
Median	-0.00025	-0.00219	0.00122	0.00055	0.01166	0.01303
Min.	-0.11406	-0.29213	-0.26852	-0.09220	-0.29280	-0.35824
Max.	0.18336	0.31308	0.39243	0.08339	0.18722	0.17643
SD	0.01354	0.08215	0.08326	0.01291	0.07500	0.07548
Skewness	0.73109	0.71036	0.86435	-0.66434	-1.08130	-1.77590
Kurtosis	15.0860	4.2139	4.8521	10.8740	4.0043	7.2747
Jarque-Bera	28716.8***	121.126***	166.926***	11295.1***	88.8875***	289.455***
ACF	0.2208***	0.3292***	0.2713***	0.1925***	0.1893*	0.0970

TAD		
Period 1 daily	Period 2 daily	Monthly isl.
# Obs	567	202
Mean	-0.00001	0.00779
Median	0.00050	0.01103
Min.	-0.11682	-0.28533
Max.	0.16400	0.21749
SD	0.01505	0.07637
Skewness	-0.61376	-0.84990
Kurtosis	13.5830	2.1643
Jarque-Bera	29714***	63.7443***
ACF	0.0572***	0.1333*

	Daily	Monthly	Monthly isl.	TSE
# Obs	2396	124	127	
Mean	0.00069	0.01327	0.01336	
Median	0.00020	0.00613	0.00918	
Min.	-0.06735	-0.12900	-0.12853	
Max.	0.06735	0.18299	0.18566	
SD	0.00857	0.05681	0.05318	
skewness	-0.03889	0.56778	0.39233	
kurtosis	14.6730	0.2074	0.1249	
Jarque-Bera	21494.2***	6.88457**	3.34055	
ACF	0.0110	0.3371***	0.4170***	

Note: The table shows the summary statistics for the continuously compounded returns. The asterisks indicate the 10 % (one asterisk), 5 % (two asterisks) or 1 % (three asterisks) significance levels of the Jarque-Bera-test and the autocorrelation function (ACF) with one lag.

trading days per week and can go from 2 to 5. Hence, only three coefficients would have to be estimated if trading occurs on only three days of the week. D_{jt} takes the value of 1 for the respective trading day and 0 otherwise. For instance, D_{1t} takes the value of 1 for Sunday and 0 otherwise on the Abu Dhabi Securities Exchange. ϵ_t represents the error term that contains all unobserved factors influencing R_t .

To test for monthly effects, we use the following regression equation:

$$R_t = \sum_{j=1}^m \beta_j D_{jt} + \epsilon_t \quad [3]$$

where R_t is the continuously compounded return in month t . β_j are the coefficients to be estimated and represent the mean continuously compounded returns in the respective months. m is the number of trading months and goes from 1 to 12 given the fact that both the Gregorian and the Islamic calendar have 12 months. D_{jt} takes the value of 1 for the respective month and 0 otherwise. ϵ_t represents the error term that contains all unobserved factors influencing R_t .

The OLS method is used to estimate the coefficients. Like most of the other papers we use Newey–West HAC standard errors and covariances given the fact that, in analysing time series data, autocorrelation as well as heteroscedasticity of residuals are often an issue. In an alternative specification we also include an AR (1) term for returns to better account for autocorrelation. Equations [2] and [3] are estimated without an intercept to avoid perfect multicollinearity. However, it is important to note that we estimate those OLS regressions just as an illustration to compare the results with those of other studies.

Due to shifts in trading days during the study period, the data sets for the BRVM, the Damascus Securities Exchange, and the Tadawul had to be split into segments for the test for the day-of-the-week-effect. For the Iraqi Stock Exchange, we split the time series into three study periods and removed the period from 3 April 2009 until 29 October 2009 due to four reasons. Firstly, the Iraqi Stock Exchange introduced an electronic trading system on 19 April 2009. Secondly, there were no index values available for July and August. Thirdly, the index was rebalanced in September 2009 (Kaehler, Weber, and Aref (2014, 158) and lastly, on 18 March 2014 the index was extended from 37 to 60 components. Consequently, we use the following segments for the study period:

- BRVM P1: 17.09.98 – 09.11.01
- BRVM P2: 03.01.06 – 01.09.15
- DASE P1: 30.01.11 – 07.08.11
- DASE P2: 15.08.11 – 23.07.14
- DASE P3: 04.08.14 – 01.09.15

- ISX P1: 01.07.07 – 02.04.09
- ISX P2: 01.11.09 – 17.03.14
- ISX P3: 18.03.14 – 01.09.15
- TAD P1: 19.10.98 – 28.06.13
- TAD P2: 01.07.13 – 01.09.15

For the test for monthly effects, we only use the period 2 segment for the Iraqi Stock Exchange, due to the fact that sample sizes are too small in the other two periods. The segments for the other markets are abolished and tested fully for monthly effects.

At the same time, risk and return must always be considered together. This comes from the very fact that individuals tend to be risk-averse. Thus, they want to be rewarded for higher risk by higher return. This phenomenon is expected to play an even larger role here with respect to other financial markets given that Muslims are perceived to be more risk averse than Christians and atheists (Benjamin, Choi, and Fisher 2010). We would, therefore, have to see whether there are still significant calendar effects in returns once the risk of returns is taken into account. Risk in financial markets is measured by the volatility of stock returns: Hence, we define the equation for stock returns as follows:

$$R_t = \eta + \varphi_1 R_{t-1} + \sum_{j=1}^g \zeta_j D_{jt} + \epsilon_t \quad [4]$$

where $1 < g \leq 4$

In comparison to the simple OLS regression, we model the stock returns to follow an AR(1) process where R_{t-1} is the continuously compounded return of the previous trading day. The reason for this is that when we look at the Durbin–Watson statistics, strong first order autocorrelation was apparent in most time series. Furthermore, we include a maximum of four dummy variables for the maximum number of trading days per week minus one. This is due to the constant included in this equation. Clearly, we would only include two dummies for a market, which is open on three days, because including a dummy for every trading day would again lead to perfect multicollinearity.

In addition, we model the conditional variance with a GARCH-model based on Bollerslev (1986). The general equation for a GARCH (m,s) model would look like this where h_t is the conditional variance:

$$h_t = \omega + \kappa_1 \epsilon_{t-1}^2 + \dots + \kappa_m \epsilon_{t-m}^2 + \mu_1 h_{t-m} + \dots + \mu_s h_{t-s} \quad [5]$$

Initially, we stick to a GARCH(1,1) model, an approach that is also used by Choudhry (2000). The conditional variance is then defined as follows:

$$h_t = \omega'z_t + \sum_{j=1}^g \xi_j D_{jt} + \kappa_1(|\varepsilon_{t-1}|)^2 + \mu_1 h_{t-1} \quad [6]$$

In this equation, g refers to the number of trading days minus one. Thus, g would be four for a stock market with five trading days. We do not include a dummy for every day given that a constant is part of the equation. When we account for volatility clustering using monthly data, we do not include dummies for the respective months in the estimation for the conditional variance given the lower number of observations.

However, there is good reason to believe that stock markets do not react to good and bad news in the same manner. This is the idea of the E-GARCH model by Nelson (1991). In our case, the following equation is estimated:

$$\ln(h_t) = \omega'z_t + (\kappa_1|\varepsilon_{t-1}| + \gamma_1\varepsilon_{t-1}) + \mu_1 \ln(h_{t-1}) \quad [7]$$

In this case, ω is defined as $\bar{\omega}$ minus $\sqrt{2/\pi} \cdot \kappa_1$ (Lucchetti and Baliotti 2011). Again, we include dummy variables for all but one trading day. According to Baker, Rahman, and Saadi (2008), it is not appropriate to exclude the intercept in a GARCH estimation, hence, the estimated equation for the E-GARCH(1,1) that we use has the following form:

$$\ln(h_t) = \omega'z_t + \sum_{j=1}^g \xi_j D_{jt} + (\kappa_1|\varepsilon_{t-1}| + \gamma_1\varepsilon_{t-1}) + \mu_1 \ln(h_{t-1}) \quad [8]$$

We include g dummy variables where g is the number of trading days minus one. The error term of the previous period ε_{t-1} is included twice: once as real value and once as absolute value. Thus, the coefficient γ_1 tells us whether positive and negative shocks have a different impact on the log-conditional variance. If the coefficient γ_1 has a value of zero, then both positive and negative shocks would have the same effect. If the value of γ_1 is larger than zero, then positive shocks have a stronger effect than negative shocks and vice versa. The usual assumption is that negative shocks are more important. The E-GARCH model is especially appealing given the fact that it saves us from the problem of negative variances.

The main reason for employing such GARCH models comes from the very features of stock market returns which are that returns tend to be auto-correlated, leptokurtic or rather non-normally distributed and that there is strong evidence for volatility clustering among them. Under these circumstances, inferences based on ANOVA would not be appropriate given the fact that it requires the data to be normally distributed, stationary, and independent (Baker, Rahman, and Saadi 2008). It is neither sufficient to use standard errors corrected

for heteroscedasticity because they still do not take the distribution of the data into account (Baker, Rahman, and Saadi 2008), nor is OLS appropriate because it ignores the volatility clustering. ARCH and GARCH models do account for volatility clustering and the non-normality of returns. However, there is another problem stemming from the so called “leverage effect”. This effect describes the fact that changes in volatility and stock market returns are negatively correlated (Alberg, Shalit, and Yosef 2008) with which symmetric GARCH models cannot cope. Therefore asymmetric variants of GARCH models need to be introduced like E-GARCH, GJR, TGARCH, NGARCH or APARCH. Their estimation techniques will be briefly described here. The GJR was proposed by Glosten, Jagannathan, and Runkle (1993) for which we use the following model:

$$h_t = \omega'z_t + \sum_{j=1}^g \xi_j D_{jt} + \kappa_1 (|\varepsilon_{t-1}| + \gamma_1 \varepsilon_{t-1})^2 + \mu_1 h_{t-1} \quad [9]$$

The Threshold GARCH (TGARCH) model is based on Zakoian (1994). The respective model for the conditional variance is:

$$\sqrt{h_t} = \omega'z_t + \sum_{j=1}^g \xi_j D_{jt} + \kappa_1 (|\varepsilon_{t-1}| + \gamma_1 \varepsilon_{t-1}) + \mu_1 \sqrt{h_{t-1}} \quad [10]$$

The non-linear GARCH (NGARCH) uses a simplified version of expression [10] where γ_i is zero. The model itself is based on Higgins and Bera (1992):

$$\sqrt{h_t}^\delta = \omega'z_t + \sum_{j=1}^g \xi_j D_{jt} + \kappa_1 (|\varepsilon_{t-1}|)^\delta + \mu_1 \sqrt{h_{t-1}}^\delta \quad [11]$$

Finally, we employ an Asymmetric Power ARCH (APARCH) model proposed by Ding, Granger, and Engle (1993).

$$\sqrt{h_t}^\delta = \omega'z_t + \sum_{j=1}^g \xi_j D_{jt} + \kappa_1 (|\varepsilon_{t-1}| + \gamma_1 \varepsilon_{t-1})^\delta + \mu_1 \sqrt{h_{t-1}}^\delta \quad [12]$$

Obviously, the APARCH model is just an extension of the other models and could reduce to an NGARCH, TGARCH, or simple GARCH model under certain circumstances.

Furthermore, it is of great importance which distribution is used. The default is mostly the Gaussian distribution. However, a normal distribution can probably not capture the statistical properties of stock market returns (i. e. negative skewness and fat tails). Thus, it seems to be advantageous to use the (skewed) Student's t-distribution,⁴ the (skewed) generalised error distribution (GED), or

⁴ Clearly, the normal distribution and the t-distribution would be nearly identical if the number of observations goes to infinity.

the double exponential error distributions like Baker, Rahman, and Saadi (2008) did. Then one can compare the results based on different distributions by looking at the information criteria.⁵ We use the normal distribution, the t-distribution, and the GED for the simple GARCH(1,1) model and the t-distribution for the other models. Then we compare the models based on the Akaike criterion (AIC) and the Bayesian information criterion or Schwarz criterion (BIC) and present the model with the best fit.

Thus, the key indicator for detecting calendar effects in our study are GARCH models given the inappropriate assumptions of OLS. Previous results from OLS regressions are therefore deemed as unreliable and we have to examine calendar effects in those markets again.

4 Results and Interpretation of the Return Analysis

4.1 Day-of-the-Week Effects

Firstly, we take a look at the results of the OLS estimations. In order to save space, Table 4 just shows the main findings of the respective estimations instead of the entire estimation output.⁶ This table summarises the estimation outcomes for daily, monthly, and Islamic monthly effects. The latter two will be discussed in the next two sections. When we look at the estimation of the day-of-the-week effect based on equation (3) – i. e. OLS with robust standard errors – we find overwhelming evidence for calendar effects. The only exceptions are the Abu Dhabi Stock Exchange, the second period for the DASE, and the second and third estimation period for the Iraqi Stock Exchange where we could not find any calendar anomalies based on daily returns. The overall effects, however, vary between the stock markets. Several markets reveal positive Thursday and negative Monday effects. Friday and Saturday also seem to be trading days with relatively higher returns on several markets which might be related to weekend effects. The overall fit (adjusted R^2) of these models is, however, very low. When looking at the regression diagnostics, we can detect several problems of the estimations. The first problem is autocorrelation: according to the Durbin-Watson Statistic we can reject the null hypothesis of no

⁵ For instance, Alberg, Shalit, and Yosef (2008) compared the results based on the Akaike information criterion.

⁶ Of course, we are happy to share the detailed results upon request.

⁷ These cases are Dhaka, Iraq P3, and Tehran.

Table 4: Overview of OLS results.

Stock Exchange	Model	Results
ADX	OLS (robust standard errors)	no DOW effect Mar***, May** +; Dec*** - Sha'ban* -; Rabi I** +, Rabi II***, Ramadan* +
	OLS – AR(1)	no DOW effect Mar** +, May** +; Sept*, Dec*** - Dhu al-Hijjah* -; Rabi I***, Ramadan*** +
ASE	OLS (robust standard errors)	Sun*; Mon*** -, Thu** + Jan*** +; May*, Jul*, Aug** - Jumada II***, Sha'ban* -
	OLS – AR(1)	Mon***, Thu**, Sun** + Jan*** +; May*, Jul** Aug* - Sha'ban*, Jumada II*** -
BASE	OLS (robust standard errors)	Thu*** +; Mon** - no MOTY effect Rabi I** +
	OLS – AR(1)	Thu** +; Mon** - Jan* +; Dec** - Rabi I* +
BIST	OLS (robust standard errors)	Thu***, Fri*** + Jan*, May**, Aug**, Nov** +; Jun** - Muharram**, Rajab***, Sha'aban* Ramadan* +
	OLS – AR(1)	Thu***, Fri*** + Jan*, May**, Aug**, Nov** +; Jun** - Muharram, Rajab +
BRVM	OLS (robust standard errors)	P1: Wed*** - P2: Mon**, Fri** + Jan*, Mar*, Jun**, Dec* +; Jul* - Safar*** +
	OLS – AR(1)	P1: Wed*** - P2: Mon**, Tue*, Fri** + Jan**, Mar*, Jun**, Dec* +; Jul** Safar*** +
BSE	OLS (robust standard errors)	Tue** -; Fri** + No MOTY effect Rabi II*** +; Dhu al-Hijjah* -
	OLS – AR(1)	Tue** -; Fri** + Apr* + Rabi II** +

(continued)

Table 4: (continued)

Stock Exchange	Model	Results
BVMT	OLS (robust standard errors)	Thu***, Fri*** + Apr***, May*, Aug**, Sep* + Rabi II***, Sha'aban**, Ramadan*** +
	OLS – AR(1)	Thu***, Fri*** + Apr**, Aug** + Rabi II***, Sha'aban*, Ramadan*** +
CASE	OLS (robust standard errors)	Wed***, Thu***, Fri** + Feb***, Mar***, May*, Sep*** +; Jul* – Rabi I*, Jumada I*, Dhu al-Hijjah*** +
	OLS – AR(1)	Wed***, Thu** + Feb**, Mar***, May**, Sep*** + Jumada I*, Dhu al-Hijjah*** +
CSE	OLS (robust standard errors)	Tue***, Thu*** +; Sun*** – Jan*, Jun**, Sep*** + Muharram**, Ramadan*** +
	OLS – AR(1)	Tue***, Thu*** +; Sun*** – Jun**, Sep*** + Muharram**, Ramadan*** +
DASE	OLS (robust standard errors)	P1: Mon*, Tue**, Thu*, Sun*** – P2: no DOW effect P3: Mon***, Thu** – Mar*, Sep**, Nov*, Dec** – Safar**, Rabi II* –
	OLS – AR(1)	P1: Tue*, Sun** – P2: no DOW effect P3: Mon***, Thu* – Sep**, Nov**, Dec** – Rabi II**, Dhu al-Hijjah* –
DFM	OLS (robust standard errors)	Thu*** + May**, Aug* +; Jul**, Dec** – Muharram* –; Rabi II***, Ramadan* +
	OLS – AR(1)	Thu*** + May*, Aug** +; Jul**, Sep**, Dec*** – Rabi II**, Ramadan** +; Dhu al-Hijjah* –
DSE	OLS (robust standard errors)	Tue*** +; Sun*** – Apr***, May* –; Jun** + Rabi II*, Jumada I*** –; Sha'ban*, Schawwal***, Dhu al-Hijjah*** +
	OLS – AR(1)	Tue***+; Sun*** – April***, May* –; Jun*, Sep* +

(continued)

Table 4: (continued)

Stock Exchange	Model	Results
EGX	OLS (robust standard errors)	Safar***, Jumada I*** –; Sha'aban* Schawwal***, Dhu al-Hijjah*** +
		Mon* –; Thu*** +
	OLS – AR(1)	Jan*** +
		Sha'aban** +
IDX	OLS (robust standard errors)	Mon** –; Thu*** +
		Jan*** +
	OLS – AR(1)	Sha'aban** +
		Mon** –; Thu*** +
ISX	OLS (robust standard errors)	Jan*** +
		Sha'aban** +
	OLS – AR(1)	Wed**, Thu*, Fri*** +
		Jan**, Feb** +
KASE	OLS (robust standard errors)	Sha'aban**, Dhu al-Qidah* +
		Mon* –; Wed**, Fri*** +
	OLS – AR(1)	Jan** +
		Sha'aban*, Dhu al-Qidah* +
KLSE	OLS (robust standard errors)	P1: Sun** +
		P2: no DOW effect
	OLS – AR(1)	P3: no DOW effect
		P2: Aug*** –
KSE	OLS (robust standard errors)	P2: Muharram**, Rajab* +; Rabi II*** –
		P1: no DOW effect
	OLS – AR(1)	P2: no DOW effect
		P3: no DOW effect
KALX	OLS (robust standard errors)	P2: Aug* –
		P2: Muharram**, Rajab* +; Rabi II*** –
	OLS – AR(1)	Mon***, Tue** –
		Sep* –
KASE	OLS (robust standard errors)	Rabi I* +; Rajab*** –
		Mon***, Tue** –
	OLS – AR(1)	Sep** –
		Rajab*** –
KLSE	OLS (robust standard errors)	Mon*** –; Wed***, Thu*, Fri ***+
		Jan***, Feb** +; Sep* –
	OLS – AR(1)	Jumada I**, Dhu al-Qi'dah*** +
		Mon*** –; Wed***, Fri*** +
KSE	OLS (robust standard errors)	Jan*** +; Sep* –
		Jumada I**, Dhu al-Qi'dah** +
	OLS – AR(1)	Tue***, Wed***, Thu*, Fri*** +
		Jan**, Apr*, May***, Jul**, Aug***, Oct***, Dec** +

(continued)

Table 4: (continued)

Stock Exchange	Model	Results
KUSE	OLS – AR(1)	Muharram***, Rabi I***, Rajab**, Dhu al-Hijjah*** + Mon** –; Tue***, Wed***, Fri*** + Jan**, Feb***, Apr*, May**, Jul**, Aug***, Oct***, Dec** + Muharram***, Rabi I***, Rajab**, Dhu al-Hijjah*** +
		Sun* –; Tue*, Wed**, Thu*** + Apr*, May*** + Rabi I**, Rabi II* +
	OLS – AR(1)	Sun** –; Tue*, Wed**, Thu*** + Apr*, May*** +; Jul** – Rabi I*, Sha'aban* +
		Tue* + Apr** –; May* + Rabi II** +
PEX	OLS (robust standard errors)	Mon* + Apr**, Nov** –; May** + Muharram*, Rabi II* +; Jumada II* –
		Thu** + Feb* +; Jun** – Jumada I*** –; Dhu al-Hijjah* +
	OLS – AR(1)	Thu** + Feb** +; Jun** – Rabi II**, Jumada I***, Dhu al-Qi'dah* –; Dhu al-Hijjah** +
		Thu* + Jan**, Apr*, May*** + Rabi II***, Dhu al-Hijjah* +
QE	OLS (robust standard errors)	no DOW effect Jan**, Apr*, May***, Aug* + Rabi II***, Ramadan*, Dhu al-Hijjah* +
		P1: Sat**, Wed**, + P2: Mon** –; Thu** + Jan***, Apr** + Rabi II* +
	OLS – AR(1)	P1: Sat**, Wed** + P2: Mon** –; Thu** + Jan***, Apr* + Rabi II**, Rajab* +
TAD	OLS (robust standard errors)	
	OLS – AR(1)	

(continued)

Table 4: (continued)

Stock Exchange	Model	Results
TSE	OLS (robust standard errors)	Tue*, Wed***, Sat** + Apr*, May* + Muharram*, Ramadan* +
	OLS – AR(1)	Tue*, Wed***, Sat*** + Mar* –; Apr** + Muharram*** +

Note: DOW: Day-of-the-week; MOTY: Month-of-the-year; the table shows estimation results for OLS regressions with robust standard errors, and with an AR(1) term for returns, where the continuously compounded return is the dependent variable. The asterisks indicate whether a coefficient is significantly different from zero at the 10 % (one asterisk), 5 % (two asterisks) or 1 % (three asterisks) significance level. The datasets for the BRVM, the DASE, the TAD, and the ISX had to be split in several sub-periods (see Section 3). For the estimation of the monthly effects for the ISX only period 2 of the dataset was used due to the small sample sizes of the other two periods.

autocorrelation in all but three cases.⁷ When we use a Breusch-Godfrey test with a lag order of 5, we can reject the null hypothesis of no autocorrelation up to order five in all but two cases (Chittagong and Iraq P3). A simple approach to control for serial correlation is to include lags of the dependent variable in the estimation. In this case, we included the lagged return to control for first order autocorrelation. The results of these estimations are also presented in Table 4 (line OLS – AR(1)). What we see is that there are notable changes in the results when we include an AR(1) term. At least in one third of the cases the results differ. That alone shows that the results critically depend on slight specification changes. Also the predictive power of the models measured by the adjusted R^2 increases when we include the lagged return. The second problem is volatility clustering. We conducted ARCH-LM tests with a lag order of 1. When estimating the initial OLS regression, we can reject the null hypothesis of no ARCH effects in all but two cases (Beirut and Iraq P3). The same is true for the models including the AR(1) term. Given the volatility clustering prevalent in stock market returns, OLS is not an appropriate estimation technique because it cannot account for this phenomenon. Therefore, we cannot trust the previous results but should rather stick to other approaches. However, we still presented the OLS results as some sort of benchmark to make the results comparable to other studies.

Let us move to the results of the volatility models, which are presented in Tables 5.1 to 5.3. Firstly, the impact of the AR(1) term is apparent. With the exception of four cases, the coefficient ϕ_1 is significantly different from zero. Secondly, looking at the results for the respective trading days, we see that the results differ substantially from

Table 5.1: Results for the GARCH models for daily returns (part 1).

Coefficient	ADX		ASE		BASE		BIST		BRVM P1		BRVM P2		BSE		BVM		CASE	
	E-GARCH(1,1)	t	GARCH(1,1)	GED	GARCH(1,1)	GED	GJR(1,1)	t	GARCH(1,1)	GED	E-GARCH(1,1)	t	NGARCH(1,1)	t	E-GARCH(1,1)	t	TGARCH(1,1)	t
Distribution																		
η	0.000249		0.000303		0.042555***		0.001465***		-0.000029***		0.000286**		0.000044		0.000518***		0.000347***	
φ_1	0.159453***		0.047955*		0.000368***		0.019567		0.108135***		0.039787***		0.029838***		0.215124***		0.206536***	
Monday	-0.000668*		-0.000601**		-0.000368**		-0.000704		0.000029		-0.000102		-0.000636***		-0.000646***		-0.000325**	
Tuesday	-0.000072		-0.000304		-0.000368**		-0.000976				-0.000341**		-0.000400**		-0.000847***		-0.000229	
Wednesday	0.000153		-0.000164		-0.000368***		-0.000572		0.000029***		-0.000455**		-0.000191		-0.000307**		0.000007	
Thursday	✓		✓		✓		0.000544		✓		-0.000024		-0.000034		-0.000200		0.000026	
Friday			✓				✓		✓		✓		✓		✓		✓	
Saturday																		
Sunday	-0.000019		-0.000615**		-0.000368***		-0.000074***		0.000015		-0.638050**		0.000171		-1.908520***		0.000001	
ω	-0.787914***		-0.000001		0.000006**		0.111722***		0.510511**		3.341460		14.849100		0.450642***		0.223925***	
κ_1	0.374038***		0.171352***		0.170741***		0.154074***				-0.572169				-0.026399		0.062701*	
γ_1	-0.064937***																	
μ_1	0.950112***		0.703332***		0.802359***		0.873674***		0.589470***		0.892053***		0.705764***		0.855924***		0.817579***	
δ													1.277710***					
Monday	-0.006368		0.000008**		-0.000003		0.000139***		-0.000027*		-0.551175**		0.000497		0.019742		-0.000001	
Tuesday	-0.151061		0.000003		-0.000006*		0.000054*				0.120904		0.000165		0.125442		0.000003**	
Wednesday	0.125187		0.000004		-0.000003		0.000098***		0.000002		-0.251069		-0.000077		0.072553		0.000000	
Thursday	✓		✓		✓		0.000127***				-0.021714		-0.000174		-0.058690		0.000001	
Friday			✓				✓		✓		✓		✓		✓		✓	
Saturday																		
Sunday	0.344292*		0.000006		-0.000009**													
AIC	-15784.6		-9707.2		-26206.7		-24714.0		-3868.8		-26727.9		-36135.5		-37654.1		-45992.4	
BIC	-15698.2		-9635.8		-26121.3		-24616.7		-3826.8		-26635.0		-36037.4		-37557.6		-45892.2	

Note: The tables shows estimation results of some GARCH(1,1) variants where the dependent variable is modelled as an AR(1) process. The asterisks indicate whether a coefficient is significantly different from zero at the 10 % (one asterisk), 5 % (two asterisks) or 1 % (three asterisks) significance level. Check marks indicate which day is the omitted reference day. The datasets for the BRVM, the DASE, and the TAD had to be split in several sub-periods (see Section 3).

Table 5.2: Results for the GARCH models for daily returns (part 2).

Coefficient	CSE		DASE P3		DFM		DSE		EGX		IDX		ISX P2		KASE	
	E-GARCH(1,1)	t	E-GARCH(1,1)	t	E-GARCH(1,1)	t	GARCH(1,1)	GED	TGARCH(1,1)	t	GARCH(1,1)	t	NGARCH(1,1)	t	GARCH(1,1)	GED
Distribution																
H	0.002031***		-0.000506**		0.001443**		0.000323		0.001345***		0.000532***		0.000228		0.000000	
ϕ_1	0.075497***		0.241481***		-0.007076		0.105250***		0.172731***		0.184041***		0.104126***		0.011146	
Monday	-0.002803***		-0.000166		-0.002533***		-0.000346		-0.001455***		-0.001006***		-0.000605*		-0.000350	
Tuesday	0.000142		0.000542		-0.001044		0.001094		-0.000747		-0.000579**		-0.000221		0.000000	
Wednesday	-0.001207**		0.000563		-0.001235		0.000076		-0.001345***		-0.000347		-0.000593**		0.000000	
Thursday	✓		✓		✓				✓		-0.000689***		✓		0.000023	
Friday											✓					✓
Saturday	-0.003600***				-0.001816**		-0.003166***		-0.001345**				-0.000575*		-0.000003	
Sunday	-0.783969***		0.000009***		-1.167290***		-0.000014**		-0.000004		-0.000001		0.000001			
ω	0.332981***		0.017865*		0.343664***		0.159531***		0.173495***		0.110694***		0.267137***		0.143679***	
κ_1	-0.059954***				-0.063839***				0.160634***							
γ_1	0.958267***		-1.009020***		0.944288***		0.772024***		0.835573***		0.903933***		0.794758***		0.845182***	
μ_1													0.690656***			
δ	-0.083282		-0.000002*		0.125467		-0.000011		-0.000021*		0.000015		-0.000001		0.000008	
Monday	0.105815		0.000000		0.363924**		0.000032**		0.000032***		-0.000010		0.000005		0.000041	
Tuesday	0.016686		0.000003***		0.451866**		0.000008		0.000015		0.000004		-0.000002		-0.000013	
Wednesday	✓		✓		✓				✓		-0.000001		✓		0.000020	
Thursday											✓					✓
Friday																
Saturday	0.748552***				1.294840***		0.000076***		0.000051***				0.000004			
Sunday	-14477.3		-2043.3		-13388.8		-4495.5		-26280.4		-53766.0		-7783.9		-12414.5	
AIC	-14390.6		-2006.2		-13302.4		-4432.3		-26183.9		-53674.5		-7709.8		-12334.7	
BIC																

Note: The tables shows estimation results of some GARCH(1,1) variants where the dependent variable is modelled as an AR(1) process. The asterisks indicate whether a coefficient is significantly different from zero at the 10 % (one asterisk), 5 % (two asterisks) or 1 % (three asterisks) significance level. Check marks indicate which day is the omitted reference day. The datasets for the BRVM, the DASE, and the TAD had to be split in several sub-periods (see Section 3).

Table 5.3: Results for the GARCH models for daily returns (part 3).

Coefficient	KISE		KSE		KUSE		MSM		PEX		QE		TAD P1		TAD P2		TSE	
	E-GARCH(1,1)	t	E-GARCH(1,1)	t	GARCH(1,1)	GED	GARCH(1,1)	GED	NGARCH(1,1)	t	APARCH(1,1)	t	GARCH(1,1)	GED	TGARCH(1,1)	t	APARCH(1,1)	t
Distribution																		
η	0.000634***		0.001668***		0.000000		0.000224		-0.000045		0.001016**		0.000620***		0.000968***		0.000350***	
ϕ_1	0.151421***		0.081942***		0.000000		0.260082***		0.129040***		0.128596***		0.041583***		0.115806***		0.334063***	
Monday	-0.001143***		-0.001826***		0.000000		-0.000224		-0.000099		-0.000656		-0.000507***		-0.001797***		-0.000468***	
Tuesday	-0.000368*		-0.001072**		0.000000		-0.000224		0.000192		-0.000560		-0.000484***		-0.001081*		-0.000159	
Wednesday	0.000045		0.000083		0.000000		0.000093		0.000226		-0.000380		✓		-0.000080		✓	
Thursday	-0.000222		-0.000882*		✓		✓		✓		✓		✓		✓		✓	
Friday	✓		✓															
Saturday																		
Sunday																		
ω	-0.473626***		-0.817310***		0.000000		-0.000067		-0.000826**		-0.000933		0.000628***		0.000738		-0.000188	
κ_1	0.243389***		0.283060***		0.000009**		-0.000001		0.000003		0.000004		-0.000620***		-0.000006		-0.000485***	
γ_1	-0.048093***		-0.127822***		0.256656***		0.296231***		0.242805***		0.222646***		0.200363***		0.189460***		0.000005*	
μ_1	0.979138***		0.950103***		0.782700***		0.727515***		0.819666***		0.157529***		0.805465***		0.852119***		-0.104574*	
δ									1.280210***		0.817496***		0.811986***		0.744699***		0.744699***	
Monday	0.498324***		0.594162***		-0.000001		0.000000		-0.000002		-0.000001		-0.000017		-0.000024		0.754747***	
Tuesday	-0.180910**		-0.015899		-0.000008		0.000002		-0.000008		-0.000007		0.000007		0.000012		-0.000007**	
Wednesday	0.182309**		0.105993		-0.000014**		0.000004		0.000003		0.000007		✓		0.000009		-0.000005	
Thursday	0.023589		0.018719		✓		✓		✓		✓		✓		✓		✓	
Friday	✓		✓															
Saturday																		
Sunday																		
AIC	-61272.2		-11482.7		-0.000004		0.000009***		0.000004		-0.000002		0.000020**		0.000070***		0.000003	
BIC	-61165.1		-11400.8		-29788.8		-14218.0		-19949.8		-15116.7		-24703.3		-3921.6		0.000002	
					-29700.4		-14140.2		-19859.7		-15025.1		-24615.8		-3856.5		-18332.7	
																	-18240.2	

Note: The tables shows estimation results of some GARCH(1,1) variants where the dependent variable is modelled as an AR(1) process. The asterisks indicate whether a coefficient is significantly different from zero at the 10 % (one asterisk), 5 % (two asterisks) or 1 % (three asterisks) significance level. Check marks indicate which day is the omitted reference day. The datasets for the BRVM, the DASE, and the TAD had to be split in several sub-periods (see Section 3).

the simple OLS regressions presented in Table 4. Hence, the inclusion of an AR(1) term and the simultaneous estimation of the volatility have a large impact. Nevertheless, there is still overwhelming evidence for day-of-the-week-effects in stock market returns when looking at the GARCH models. Thirdly, we find ARCH effects to be very important. In all but two cases the coefficient κ_1 is significantly different from zero. In addition, the lagged conditional variance seems to be of utmost importance given that the coefficient μ_1 is significantly different from zero in any case. The estimations are plagued with non-stationary volatility given that if κ_1 and μ_1 add up to more than one, the volatility increases over time. The result is an explosive conditional standard deviation. However, this problem is well known for other emerging stock markets (see e. g. McMillan and Thupayagale 2009). We also find that positive and negative shocks (ergo good and bad news) do in fact have a different impact on the volatility of stock market returns. Oddly enough, the effect of negative shocks is not always larger than that of positive shocks. Furthermore, there are some stock markets where positive shocks even lead to an increase in volatility. However, this is also found in other studies (e. g. Kaehler, Weber, and Aref 2014). Fourthly, the importance of the day dummies on stock market volatility is ambiguous. On several stock markets, there are no daily effects with respect to stock market volatility. In many cases, we found that non-trading days are meaningful, albeit the sign of the effect is sometimes positive and sometimes negative. The weekend effect is characterised by negative returns on the first trading day of the week. On all but two stock markets (Tadawul and KUSE), we find the average return to be lower at the beginning of the trading week.⁸ Thus, the weekend effect really seems to matter – also on Islamic stock markets. There is not much evidence that risk and return are strongly correlated when it comes to daily calendar effects. There are 22 cases in which there are significant effects for both the conditional mean and the conditional variance. If risk and return were correlated, a day with a higher mean return should also be a day with higher volatility. However, this scenario applies to only six cases while in 16 cases the effects go in opposite directions (higher mean return but lower volatility and vice versa). Thus, this does not seem to play a particular role in explaining stock market anomalies on Islamic stock markets.

As argued above, causes for weekend effects are manifold. According to Singal (2006), unhedged short sales are one of the main reasons for this effect. However, in all but one stock market under study short sales are not allowed (Angel 2004).⁹ Another widely circulated explanation for the weekend effect has to do with the publishing of company information. Some argue that

⁸ BRVM P1 is not considered here given that the trading days were Monday, Wednesday, and Friday.

⁹ The Borsa Istanbul is the only stock market under study where short selling is legal.

companies publish bad news on the weekend after markets close, which drives down stock prices and, consequently, returns on the first day of the trading week (Fortune 1991).

A possible explanation for day-of-the-week effects may be the idea that settlement procedures influence the return on certain trading days. For example, a settlement period of three days (on a market with five trading days) would mean that if an investor buys on the second trading day and sells on the third trading day, he or she has to pay for the transaction on the last trading day, but receives money on the first trading day of the following week. Thus, one would expect returns to be higher on the third trading day, to compensate for the longer period the investor has to wait for his money on which he or she cannot receive interest during that period.¹⁰ Table 2 shows the settlement periods of all stock markets under study. The results not only find no support for this hypothesis but also are in sharp contrast to this theory. There are seven cases where there are significant results and in each case the return is negative whereas the theory proposed the opposite.

When we take a closer look at the results in Tables 5.1–5.3, we find substantial differences in the results with respect to the previous studies mentioned in Table 1. There are only two cases where we come to the same conclusion (no DOW effect): this applies to the Muscat Securities Exchange where our results are in line with those of Al-Jafari (2012) and Kamaly and Tooma (2009). In every other case, they differ at least marginally from the previous studies. This shows that we have to be very cautious when it comes to interpreting the results. Yes, in several cases the estimation technique of the previous studies was not appropriate. However, there is still a multitude of cases where the estimation approach is similar or equal to ours and yet the results differ.

4.2 Monthly Effects

Let us move to the analysis of the monthly calendar effects. Again, Table 4 also presents the results for the preliminary OLS estimations. The only instances where we do not find significant monthly effects are the Bahrain Stock Exchange and the Beirut Stock Exchange. With the exception of those two stock markets, there is strong evidence for calendar anomalies. Autocorrelation also seems to be a problem here – at least when we look at the Durbin Watson statistic. However, in this case there are five stock markets where we could not reject the null

¹⁰ Cf. for example Agrawal and Tandon (1994); Clare, Ibrahim, and Thomas (1998); Gibbons and Hess (1981).

hypothesis of no autocorrelation.¹¹ Following the procedure employed with daily data, we include an AR(1) term in a second step. Here the inclusion of the lagged dependent variable leads to meaningful changes in 12 cases. There is not as much evidence for ARCH effects as before. Nonetheless, we employ models accounting for volatility clustering for all stock markets.

Tables 6.1 and 6.2 display the outcomes of the GARCH estimations for monthly calendar effects. Firstly, there is once again strong evidence that the ARCH and GARCH effects play a role. Secondly, none of the results presented in Table 4 applies when we examine the conditional volatility simultaneously. Thirdly, we can reject that one size fits all when it comes to the “right” model. Only the APARCH model seems to be of minor relevance.

At first sight, some of the monthly effects we found exhibit similarities to the turn-of-the-year effect observed on Western financial markets. The turn-of-the-year effect is characterised by the combination of a positive December and a positive January effect. The average returns in January are positive in all but three cases. However, the effect is only significant on five stock markets. Two explanations for the effect are the tax-loss-selling hypothesis and the parking-the-proceeds hypothesis. The first one’s impact on returns is, however, ambiguous. On the one hand, investors might be willing to sell stocks in December that lost value in order to decrease the tax burden which would lead to a downward pressure on prices in December. On the other hand, it could also cause above average returns in December, due to two possible situations. Either investors are unwilling to sell winner stocks if the realised tax losses do not offset the capital gains tax, to postpone paying taxes which is why higher prices have to be realised on the markets, to change investors’ minds. Or because they reinvest their newly freed funds right away which both would bring about a positive December effect (Singal 2006). The parking-the-proceeds hypothesis causes above average positive returns in January because investors sell loser stocks at the end of December to realise a deductible tax loss and, unlike the tax-loss-selling hypothesis do not reinvest but hold the proceeds until January. Then, when they reinvest the money, they tend to buy small company stocks, putting the prices of those under pressure and, in the end, driving their respective prices up causing a positive January effect (French and Trapani 1994). Recent research by Sikes (2014) confirms that these motives do in fact play a role – especially for institutional investors. Overall, theory cannot give a definite answer to the question whether December returns should be high or low. It is important to note that the turn-of-the-year effect in the traditional way is not applicable to all stock markets given that some have different tax years.

¹¹ These are the BRVM, the Amman, the Chittagong, the Dhaka, and the Istanbul stock market.

Table 6.1: Results for the GARCH models for monthly returns – Gregorian calendar (part 1).

Coefficient	ADX	ASE	BASE	BIST	BRVM	BSE	BVMT	CASE	CSE	DASE	DFM
Model	GARCH(1,1)	E-GARCH(1,1)	GARCH(1,1)	NGARCH(1,1)	E-GARCH(1,1)	GARCH(1,1)	E-GARCH(1,1)	GARCH(1,1)	E-GARCH(1,1)	GARCH(1,1)	TGARCH(1,1)
Distribution	GED	t	GED	t	t	GED	t	t	t	Normal	t
η	0.000943	0.009383***	-0.014379***	0.000563	0.014715**	0.000305	-0.001732	0.003858	0.004783	-0.004414	-0.039353
φ_1	0.114613***	0.249715***	0.375949***	0.051086	0.193880***	0.120956***	0.150379**	0.243854***	0.165637	0.357002***	0.224480**
January	0.000208	-0.003448	0.031982***	0.032259	0.009762	-0.000238	0.004675	0.001489	0.013526	0.000401	0.060822*
February	0.021383*	0.005866	0.029136***	0.026403	-0.018482	-0.007602***	0.021955**	0.020272	-0.016206	-0.007277*	0.037560
March	0.028590***	0.017123**	0.017123**	0.025828	0.005079	-0.005076	-0.003357	0.015582*	-0.031013	0.010683**	0.059835
April	0.011851	-0.007925	0.013548**	0.042732	-0.007203	0.007516***	0.021252**	-0.001008	-0.001355	0.002857	0.013290
May	0.019557*	-0.018930***	0.016743**	0.023269	-0.020398**	-0.012331**	0.007875	0.005803	-0.003894	-0.006700	0.099729***
June	-0.000735	0.005144***	0.006961	-0.042126	-0.001902	-0.002180	0.004022	-0.007189	0.051941	0.003721	0.045055
July	0.014139	-0.012688***	0.011323**	0.014468	-0.038104***	-0.021257***	-0.000433	-0.015025*	0.022380	-0.001195	0.015368
August	0.017497	-0.014562	0.023278***	0.034202	-0.003627	-0.013841***	0.010118	-0.002685	-0.010266	0.018288*	0.079114*
September	0.007426	-0.014062*	0.004108	-0.017728	-0.018243***	-0.020669***	0.010572	0.019646*	0.050574	-0.004376	0.024626
October	0.018000	-0.004425	0.020869***	0.039058	-0.007594	-0.006757***	0.001807	-0.011913	-0.001292	0.005440	0.105340***
November	-0.008271	0.001878	0.015158**	0.032982	-0.009830***	-0.004741	0.010965	0.002547	-0.000493	-0.009906***	0.039277
December	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
ω	0.000103	-1.451630**	0.000010	0.000034	-4.279410***	0.000065	-3.542110	0.000377*	-1.628090**	0.000000	0.005215*
K_1	0.208596	0.730725***	0.082306		0.451434***	0.367745**	0.220310	0.278695	0.036665	1.642970***	0.426588**
γ_1		0.285972*		0.004814	0.375681***		0.238243		-0.349409		0.301195
μ_1	0.818909***	0.848321***	0.925414***	0.854803***	0.365793*	0.756187***	0.479493	0.521489**	0.696828***	0.049241	0.211688
δ				6.275630**							
AIC	-463.1	-626.8	-576.0	-371.6	-688.2	-743.3	-810.5	-1037.4	-261.9	-208.0	-215.6
BIC	-409.9	-568.6	-524.7	-310.3	-628.6	-684.6	-750.2	-975.5	-211.9	-176.2	-162.8

Note: The table shows estimation results of some GARCH(1,1) variants where the dependent variable is modelled as an AR(1) process. The asterisks indicate whether a coefficient is significantly different from zero at the 10 % (one asterisk), 5 % (two asterisks) or 1 % (three asterisks) significance level. Check marks indicate which day is the omitted reference day. There are no results for the DSE and the ISX because the time period was too short.

Table 6.2: Results for the GARCH models for monthly returns – Gregorian calendar (part 2).

Coefficient	EGX	IDX	KASE	KLSE	KSE	KUSE	MSM	PEX	QE	TAD	TSE
Model	TGARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	NGARCH(1,1)	GJR(1,1)	GARCH(1,1)	TGARCH(1,1)	GARCH(1,1)	GARCH(1,1)	TGARCH(1,1)
Distribution	t	t	Normal	t	t	t	t	t	t	t	t
η	-0.007749***	0.004350	0.008714	-0.006345	0.023177**	-0.015311	-0.003419	-0.003307	-0.006123	0.003932	-0.013618
ϕ_1	0.123258***	0.161014***	0.325061***	0.143520***	0.094127***	0.397937***	0.293513***	0.059060***	0.118152	0.154438	0.413701***
January	0.080509***	0.009361	-0.033313	0.025747**	0.003396	0.022006	0.018930	0.023296**	0.022099	0.025442	0.016018
February	0.070788*	0.009212	-0.002047	0.012753	0.008404	0.026183	0.021366	0.009844	0.021814	0.003195	0.039060**
March	-0.013065	0.006556	0.014995	0.016801*	-0.022346*	0.073825	0.010920	0.007969	0.023593	-0.002036	-0.000969
April	-0.002935	0.010641	-0.019974	0.012819	-0.007947	0.033760*	-0.009932	0.004300	0.033003	0.048200	0.045144**
May	0.027345***	0.001912	0.022919	0.016151	-0.004882	0.050961***	0.022442*	-0.009484	0.033174	0.004744	0.030237*
June	-0.029883	0.010501	-0.021189	0.005420	-0.025831**	0.015660	0.024118*	-0.003465	0.014161	-0.019028	0.004976
July	0.012976	-0.010658	-0.001456	0.010986	0.000338	-0.003691	0.009040	-0.005158	-0.007668	0.012497	0.019937
August	0.017101	-0.001889	0.014270	0.013378	0.000768	0.017696	0.013010	0.002128	0.023630	0.028740	0.021174
September	0.018396	-0.016578	-0.026192	-0.008133	-0.062433***	0.028847*	0.006533	-0.009470	0.009380	0.011045	0.026024
October	0.039014*	0.003327	-0.004493	0.004194	0.003459	0.027739*	0.009368	0.007557	0.018996	-0.012365	0.028435
November	0.023620	0.005963	-0.004187	0.024054**	-0.009127	0.001341	-0.001837	-0.000321	0.010572	-0.013813	0.012997
December	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
ω	0.002283***	0.000081	0.003315**	0.000082	0.000003	0.001388***	0.000060	0.000056	0.000099	0.000258	0.000741
κ_1	0.232658**	0.152819**	0.841459***	0.227028***	0.045157	0.072593	0.194295**	0.000568*	0.289442*	0.248221**	0.000691
γ_1	0.547051					1.748200		-376.564000*			-186.078000
μ_1	0.532472***	0.870654***	-0.061931	0.780039***	0.963632***	0.133366	0.822414***	0.971639***	0.708723***	0.754201***	0.742825***
δ					.90727						
AIC	-415.8	-951.4	-185.2	-1182.5	-716.8	-586.3	-679.4	-440.0	-280.4	-514.0	-353.1
BIC	-355.4	-884.1	-143.6	-1113.6	-649.0	-528.2	-621.3	-386.3	-235.8	-457.8	-302.4

Note: The table shows estimation results of some GARCH(1,1) variants where the dependent variable is modelled as an AR(1) process. The asterisks indicate whether a coefficient is significantly different from zero at the 10 % (one asterisk), 5 % (two asterisks) or 1 % (three asterisks) significance level. Check marks indicate which day is the omitted reference day. There are no results for the DSE and the ISX because the time period was too short.

In Bangladesh (CSE and DSE), in Egypt (EGX), and in Pakistan (KSE) the fiscal year runs from 1st July to 30th June. In Kuwait (KUSE) and in Pakistan (KSE) the fiscal year starts at the beginning of April and lasts until the end of March. The fiscal year in Iran (TSE) is 21st March to 20th March. Thus, we would not expect the traditional turn-of-the-(fiscal)-year effects on these stock markets.

Given that we included a constant η but no dummy for December in our estimation, we can interpret the coefficient for the constant η as the average return in December. Looking at the results in Table 6.1 and 6.2, we see that the average returns in December are positive in almost half of all cases. In three cases the stock returns in December were significantly positive and in two cases negative. Oddly enough, there was a significant effect at the turn of the year on the EGX even though Egypt has a different tax year. Apropos countries with different fiscal years: the change of the tax year does not seem to play a role on the CSE, the EGX, and the QE. The traditional effect can be found on the KSE and TSE with negative returns in the last month of the tax year and positive returns in the first month of the fiscal year. In Kuwait, the returns in the first and the last month of the tax year are both positive which could refer to a combination of the tax-loss-selling and the parking-the-proceeds hypotheses.

Still we have to be cautious when interpreting the results. There is no single case where we find the same effects as the previous studies. Our results presented in the table are subject to substantial changes when we use different models or distributions. This caveat applies to all outcomes presented in this study.

4.3 Islamic Monthly Effects

Finally, we turn to the results of the Islamic monthly effects depicted in Table 4. Previous studies mainly focused on the Ramadan effect and argued that the above average positive returns observed are due to the positive mood caused by fasting.¹² Other research supports this notion. Wright and Bower (1992), for example, found that happy people are more likely to anticipate a positive outcome for future events. Hirshleifer and Shumway (2003) connected sunshine to a positive mood which in turn leads to higher stock returns. On the other hand, there is the obligation to pay the zakat, or, to be more specific, the zakat al-fitr, which can be understood as a form of tax, paid at the end of Ramadan. It is paid either in natural produce or in an equivalent amount of cash. However, the

¹² For an in-depth explanation on how fasting during Ramadan influences the mood see Białkowski, Etebari, and Wisniewski (2012) p. 836.

amount of money or produce to be paid is minimal and unlikely to cause investors to sell stocks to generate liquidity (Al Qaradawi 2000). So we rather expect a positive Ramadan effect.

We use the assumption of mood-dependent decisions and expect that Islamic months, in which a positive collective mood would be anticipated, should show evidence for positive returns and vice versa. To be able to verify – or refute – our expectations we check the findings of our regression model against Schimmel's (2010) insights into the meaning of the Islamic months. The majority of our findings appears to comply with the premise. When looking at the OLS results, we find positive Ramadan effects on the ADX, BIST, BVMT, CSE, DFM, and TSE. On the other hand, the GARCH models (see Table 7.1–7.2) show significant positive Ramadan effects on the ADX, CSE, DASE, DFM, and TSE.

As an alternative we employed a model with daily data including dummies for all days plus a Ramadan dummy. We find significant positive returns during Ramadan on eight stock markets. On the other markets, the returns tend not to be significantly different during Ramadan. On ten stock markets, there is evidence for lower volatility during Ramadan. In order to further evaluate whether there are any Ramadan effects with respect to volatility, we computed two other GARCH models for all stock markets. The first approach uses the same equation for the returns that we used in Tables 7.1 and 7.2 but includes a Ramadan dummy in the equation for the conditional standard deviation. The second approach follows Seyyed, Abraham, and Al-Hajji (2005). The difference with respect to the first approach is that the equation for the returns only includes a Ramadan dummy. For the sake of brevity, we will only discuss the results briefly. When we used the first approach (including all monthly dummies in the equation for the log return) we only found significant Ramadan effects on volatility for the BASE, BVMT, DFM, and TSE. However, this applies to only some models.¹³ When considering solely the models with the best fit, only the effect for the TSE persists. On the other hand, there was some evidence for lower volatility during Ramadan for the BRVM, BSE, BVMT, CSE, DFM, ISX, and KLSE when using the second approach following Seyyed, Abraham, and Al-Hajji (2005).¹⁴ Again, only considering the models with the best fit, the effects on

13 The cases where we found significant Ramadan effects were BASE (GJR – t distr.), BVMT (GARCH – normal distr.; GARCH – t distr.; GARCH – GED, E-GARCH – t distr. GJR – t distr. TGARCH – t distr.), DFM (GARCH – normal distr.; GARCH – t distr.) and TSE (E-GARCH – t distr.).

14 Significant Ramadan effects on volatility were present in the following models: BSE (GARCH – normal distr.); BRVM (GARCH – GED; E-GARCH – t distr.), CSE (GARCH – normal distr.; GARCH – GED), DFM (GARCH – normal distr.; GARCH – t distr.; E-GARCH – t distr.), ISX (E-GARCH), KLSE (GARCH – normal distr.), BVMT (GARCH – normal distr.; GARCH – t distr.; GARCH – GED; E-GARCH – t distr.; GJR – t distr.; TGARCH – t distr.).

Table 7.1: Results for the GARCH models for monthly returns – Hijri calendar (Part 1).

Coefficient	ADX	ASE		BASE		BIST		BRVM		BSE		BVMT		CASE		CSE		DASE		DFM			
Model	TGARCH(1,1)	t	TGARCH(1,1)	t	E-GARCH(1,1)	t	GARCH(1,1)	t	E-GARCH(1,1)	t	E-GARCH(1,1)	t	GARCH(1,1)	t	GARCH(1,1)	t	GARCH(1,1)	t	GJR(1,1)	t	E-GARCH(1,1)	t	
Distribution		t		t		t		t		t		t		t		t	Normal		t		t		
H		-0.016762		0.008782*		0.006325		0.012548		-0.005270***		0.002363		0.006303		0.018994***		-0.008269		-0.012455**		-0.029962	
ϕ_1		0.277868***		0.266591***		0.310595		0.027271		0.097018***		0.178341**		0.195071		0.173763**		0.236590**		0.341549**		0.389141***	
Muharram		0.013066		-0.007706		-0.019841		0.024195		0.010991		0.005813		0.004560		-0.024073***		0.042115*		-0.004129		0.019941	
Safar		0.044727**		-0.008786		-0.007625		-0.025697		0.020842***		-0.000119**		-0.002993		-0.020050**		-0.008151		0.006324		0.057143	
Rabi' al-awwal		0.053823***		0.004528		0.003545		-0.012251		0.023829***		0.019929		-0.005396		-0.006597		0.013293		0.021943***		0.048391	
Rabi' al-thani		0.031323**		0.003567		-0.005663		-0.001482		0.0000702		0.006982		0.012649		-0.007042		-0.007567		0.001756		0.042145	
Jumada al-awwal		0.025431		-0.004943		-0.006366		0.006803		-0.013261*		-0.001663		-0.008455		-0.011680		0.040444		0.015395***		0.039643	
Jumada al-thani		0.020488		-0.023197**		-0.006897		-0.011471		-0.003044		-0.005110**		-0.001353		-0.009845		0.011163		0.005410		0.029792	
Rajab		0.030458**		-0.005763		0.014109		0.042761*		0.003549		-0.019785		-0.011513		-0.018175*		0.037047		0.008145		0.021021	
Sha'aban		-0.000041		-0.017645***		-0.001525		0.005005		0.009628		-0.005224		0.008596		-0.020849		0.023911		0.001723		-0.001410	
Ramadan		0.060176***		-0.004839		-0.010982		0.016936		0.007224		-0.006254		0.004298		-0.006523		0.053245**		0.022084***		0.089044**	
Shawwal		0.006452		-0.008303		-0.006745		-0.021265		0.024156		-0.010020		0.003555		-0.008041		0.010809		0.014954***		-0.002112	
Dhu al-Qi'dah		0.016782		-0.012119*		-0.012533		0.008272		0.004851***		-0.007723		-0.015818		0.004521		0.017505		0.005140		0.016652	
Dhu al-Hijjah		✓		✓		✓		✓		✓		✓		✓		✓		✓		✓		✓	
ω		0.000033		0.000017		-10.465100***		0.000037		-8.871190***		-0.457874**		0.000568**		0.000076		0.000274		0.000000		-5.321950***	
κ_1		0.000367***		0.000325**		-0.172476		0.041425		0.810648***		0.387180***		0.080061		0.154308**		0.055504		1.962460		0.287483	
γ_1		-197.005000***		-248.618000***		-0.461960**		0.232258		0.232258		0.144507								-0.685747***		-0.533006***	
μ_1		0.995266***		0.988572***		-0.507109**		0.952235***		-0.399689***		0.971754***		0.462357***		0.814560***		0.877270***		0.219068***		-0.026806	
δ																							
AIC		-416.1		-680.3		-612.6		-373.2		-706.2		-788.5		-879.2		-1050.1		-297.7		-243.6		-268.4	
BIC		-362.2		-621.7		-557.8		-314.8		-646.1		-725.8		-821.9		-987.7		-252.8		-207.2		-215.2	

Note: The table shows estimation results of some GARCH(1,1) variants where the dependent variable is modelled as an AR(1) process. The asterisks indicate whether a coefficient is significantly different from zero at the 10 % (one asterisk), 5 % (two asterisks) or 1 % (three asterisks) significance level. Check marks indicate which day is the omitted reference day. There are no results for the DSE and the ISX because the time period was too short.

Table 7.2: Results for the GARCH models for monthly returns – Hijri calendar (Part 2).

Coefficient	EGX	IDX	KASE	KLSE	KSE	KUSE	MSM	PEX	QE	TAD	TSE
Model	E-GARCH(1,1)	GARCH(1,1)	TGARCH(1,1)	GARCH(1,1)	E-GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	E-GARCH(1,1)	GARCH(1,1)	GARCH(1,1)	GARCH(1,1)
Distribution	t	t	t	t	t	t	t	t	t	Normal	Normal
η	-0.003651	0.006050	-0.012402	0.002006	0.031417***	0.003026	0.001612	0.002039***	0.011297	0.003688	-0.019674
ϕ_1	0.105481	0.219917***	0.045182	0.104435**	0.055173***	0.273955***	0.196591**	0.029385***	-0.024165	0.147296*	0.477538***
Muharram	-0.014188	-0.005875	0.015016	0.002926	0.001684	0.009969	0.015267	0.011266	0.001411	0.014516	0.025296**
Safar	0.018378	-0.000861	0.057752	-0.010682	-0.026191**	0.006694	0.008882	0.006280***	-0.010094	0.021646	0.010341
Rabi' al-awwal	0.038413	-0.005364	0.027651	-0.004160	-0.019229	0.023017	0.011567	0.005727***	0.008019	0.003919	0.030237
Rabi' al-thani	-0.022231	0.008680	0.003788	0.012878	-0.030568***	0.008766	0.028904*	0.002163	0.077641*	0.029140*	0.022987
Jumada al-awwal	0.011852	0.005640	-0.027811	0.005519	-0.017531***	0.003414	0.001848	-0.020535	0.010548	0.016638	0.022737
Jumada al-thani	0.009148	-0.005020	0.008791	0.004553	-0.009318	0.001066	-0.019866	-0.022284***	0.001964	-0.020242	0.005688
Rajab	0.000672	0.006617	-0.039518	0.010060	-0.037557***	-0.018091	0.009096	0.012465***	-0.006835	0.010585	0.020256
Sha'aban	0.043032	-0.001497	0.021345	0.008652	-0.028432**	0.005917	-0.000180	-0.025159***	-0.014519	-0.008628	0.046930***
Ramadan	0.037503	0.005503	-0.029365	-0.000863	-0.004189	0.004969	0.018182	0.008665	0.024170	0.011877	0.025065**
Shawwal	0.002554	-0.015344	0.013753	-0.006076	-0.028197*	-0.002445	-0.014430	0.012951	0.005398	0.001114	0.028629
Dhu al-Qi'dah	0.021967	0.005379	0.005156	0.019669**	-0.018163	0.008037	0.019072	-0.019430**	-0.004410	-0.014769	0.029625
Dhu al-Hijjah	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
ω	-5.080180***	0.000089	0.000951	0.000084	-0.933669	0.000361	0.000148	-0.603476	0.001557	0.000261	0.000034
κ_1	0.515414***	0.181624*	0.163853	0.200932***	0.431186**	0.127074	0.230881	0.905374	0.308903	0.352566*	0.285459*
γ_1	0.102143	0.806066	0.806066	0.011695	0.011695			0.010215			
μ_1	0.026034	0.859185***	0.832894***	0.799715***	0.873050***	0.742077***	0.744370***	0.992526***	0.537740***	0.631621***	0.752320***
δ											
AIC	-389.5	-1017.0	-171.4	-1226.8	-741.1	-593.5	-681.8	-427.7	-282.5	-551.1	-393.7
BIC	-328.8	-949.2	-124.0	-1157.4	-672.8	-538.2	-623.3	-373.5	-237.4	-497.7	-348.3

Note: The table shows estimation results of some GARCH(1,1) variants where the dependent variable is modelled as an AR(1) process. The asterisks indicate whether a coefficient is significantly different from zero at the 10 % (one asterisk), 5 % (two asterisks) or 1 % (three asterisks) significance level. Check marks indicate which day is the omitted reference day. There are no results for the DSE and the ISX because the time period was too short.

the BRVM, BSE, and the KLSE are no longer significant. Overall, there seems to be some mild evidence for the positive Ramadan effect found by Białkowski, Etebari, and Wisniewski (2012).

Let us discuss the other Islamic months: although Muharram is considered a month of grief, according to Schimmel (2010), mourning Husain pays heavenly rewards, which could manifest itself in positive expected returns. In the majority of cases (16 out of 22) average returns in Muharram are higher. However, the effect is only positively significant on the CSE and the TSE, and negatively significant on the CASE. Safar is considered a month of misfortune so it seems appropriate that there would be a negative effect. Such a negative effect is apparent on three stock markets while we also found a positive effect for the respective month in three countries. In Rabi'al-awwal the birthday of the Islamic prophet is celebrated and, thus, a positive collective mood would be anticipated. Accordingly, significant positive Rabi'al-awwal effects are apparent on the ADX, the BRVM, the DASE, and the PEX. Rajab is a month in which every prayer promises a seventy-fold reward, hence, fitting the premise of positive mood and expectations. It is also the month of Muhammad's ascension to heaven. The empirical evidence is mixed. We found significant higher returns on three and lower returns on two stock markets, respectively. In Sha'aban the Night of Records takes place, which is generally associated with happiness. However, there is more evidence for lower returns in that month than for higher returns due to a positive mood. The last month of the Islamic year (Dhu al-Hijjah) is the month of the pilgrimage, which plays an important role in Islam and may also cause a positive collective mood. The other possibility may be that commercial activity is rather low in this month while sales in food retailing increase. In fact, the empirical evidence is mixed: we find significantly higher returns on four stock markets but also lower returns on two other markets.

Apart from that, the zakat may, in general, still be a reason for Islamic monthly effects that cannot be explained conventionally or by the mood in certain Islamic months. Whilst there is no consensus about the percentage to be paid on investments, Guermat, Al-Utaibi, and Tucker (2003) found that all investors they polled nevertheless paid the zakat. Thus, they may sell stocks to fulfil the obligation of zakat depending on the percentage to be paid, causing stock prices to decrease. Yet other research is indicative of zakat incentivising investment rather than saving which in turn may lead to higher stock prices (Hassan 1987). The problem, however, is that the influence of zakat is hard to measure, because the term of payment is different for every individual.¹⁵

¹⁵ The payment is due annually, after one's wealth exceeded the minimum amount of net worth ("nisab") for longer than one lunar year. If one's wealth falls below the nisab the payment obligation no longer applies.

5 Conclusions

The aim of this study was to shed some more light on the question of whether there are anomalies in the EMH. We took the approach of analysing potential calendar effects on Islamic stock markets because there we had the opportunity to observe different calendar effects at the same time by taking into account the Gregorian and the Hijri calendar. New theories provided by behavioural finance support this decision. According to them, moods or feelings influence the decisions of individuals. Therefore, religious festivities like Ramadan lead to a superb feeling among Muslims, which might translate into more risky investment decisions. Apart from that, religion seems to play a larger role in everyday life decisions in Islamic countries. In Christian countries, on the contrary, many people do not even know when the period of fasting takes place. And even if they know about religious rules or traditions, they do not follow them which is unheard of in most Islamic countries.

Our approach was to conduct a comprehensive study focusing on all Islamic stock markets. None of the previous studies has looked at the entirety of those financial markets.

Firstly, we provided a complete literature review with respect to calendar effects on Islamic stock markets. The overview showed that there are notable differences in the results of the previous studies which was also a motivation for our study. Secondly, our estimations showed that there is some evidence for calendar effects on almost every market. However, we also found that the results are subject to changes when different estimation techniques are used. Given the statistical properties of stock market returns, OLS is not an appropriate approach. Thus, one cannot trust studies solely based on OLS regression without hesitation. In fact, models accounting for volatility clustering are much more capable of dealing with the main features of financial time series. Our study showed that most effects found when applying OLS could not be confirmed when we turned to other estimation techniques. Thus, there is always a caveat when it comes to interpreting such results. Thirdly, the analysis clearly showed that one size does not fit all when it comes to estimating stock market volatility. The estimations confirmed that all GARCH variants are relevant. Therefore, they should all be considered when analysing stock market returns.

Even though we are cautious with interpreting calendar effects we still have to take empirical results as given. The results might yet be meaningful for investors. The GARCH models emphasised the importance of time-varying volatility. This is certainly an important result from a practical point of view. Knowing the large volatility, some investors might be tempted to try to exploit calendar anomalies.

Thus, it could merely be a matter of time until these effects disappear. On the other hand, the results are still (economically) meaningful. Even if it might not be possible or practical to exploit all such discrepancies from the EMH, it is nonetheless useful to know which trading days or months are particularly predestined for selling or buying shares on the respective stock markets.

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