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Modelling Volatility of the Market Returns of Jordanian Banks: Empirical Evidence Using GARCH framework

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Abstract

This paper investigates the intrinsic nature of volatility in three of the core indices and the Jordanian traditional banks individually that are traded in Amman stock exchange (ASE). Daily stock market returns are used during the period beginning on 3rd January 2010 until 31st December 2015. For this end, Generalized Autoregressive Heteroscedasticity (GARCH) and its extension GARCH-M models have been applied. The results show that majority of the return series of the Jordanian commercial banks have negative skewness, relatively high kurtosis and provide evidence for departure from normal distribution. The estimated models found evidence for existence of volatility clustering which is well captured within the GARCH framework. The results obtained from the GARCH-M model are strongly consistent with the positive relationship between risk and return. The findings also suggest that stocks of the banking sector provide a larger risk premium for investors compared with the whole market and the financial sector, since the estimated risk premium parameter was the highest one for the banking sector index relatively.

Indexing terms/Keywords

Amman stock exchange indices, stock returns, volatility, GARCH, volatility clustering.

1. Introduction

Over the last decades, the world has witnessed substantive and radical environmental changes. These accelerated changes have massive consequences on the financial markets especially in emerging economies which affect the business and financial settings. The financial markets characterized by high sensitivity, in general, and the banking sector in particular are considered to be one of the most affected sectors among others (Wided, 2014).

Consequently, analyzing and modelling volatility of the financial time series have been become popular in the last three decades as a response to the environmental changes which led to higher volatility in the asset returns during periods of increased uncertainty. Volatility implies time-varying dispersion of the returns around the mean value reflecting a measure of risk when volatility increases during times of stress in the market. (Emenic and Ani, 2014; Poon and Granger, 2003). The attempts to modelling market asset returns is one of the key issues for market participants, since the fluctuations in returns might lead to gigantic losses (Gujarati, 2003).

The analysis of intrinsic nature and modelling volatility of assets returns became popular after the proposed Autoregressive Conditional Heteroscedasticity (ARCH) model by Engle (1982) and its extension Generalized ARCH (GARCH) model which was developed by Bollerslev (1986). The purpose of constructing these models is to capture stylized features of high frequency data and contribute to our understanding of the behaviour of the market return volatility and provide valuable information for the portfolio managers, investors and market regulators alike.

Numerous of stylized facts of the asset returns have been documented in the literature. Exhibit of volatility clustering is one of the core features of asset return series where volatility clustering implies that large variations in returns tends to be followed by large variations and low variations of returns tends to be followed by low variations. This finding is documented by (Mandelbrot 1963; Fama 1965; Black 1976; Nelson 1991; Bollerslev et al 1992; Engle & Paton 2001; Kalu 2010 and Elsheikh & Suliman 2011).

A pondering in structure of financial models concerning the relationship between risk and return will show a lot of evidence relating the returns with associated risk. Theoretical relationship between risk and return has been explained in many studies. For instead, William Sharp (1963) proposed single index model as a model to explain dependency of rate of asset return on the variance of the common factor and the firm-specific variances. The capital asset pricing model (CAPM) was developed by Sharp (1964) also explained that the returns of an asset depend on the degree of associated risk. Stephen Ross (1976) developed the arbitrage pricing theory (APT) in attempts to describe the risk factors affecting the rate of returns. In this aspect, Generalized Autoregressive Heteroscedasticity in mean model (GARCH-M) developed in (1987) by Engle, Lilien and Robins, which related the conditional mean to its conditional variance; this model allows the variance (or standard deviation) to inter in the conditional mean equation of the return.

As documented in the literature, there are numerous studies that attempt to understand the nature of volatility in the financial markets that lead to various consequences depending on the questions of the study. The present study attempts to give answers to couple of questions, that there are volatility clustering in the returns series of the Jordanian commercial banks and whether the theoretical relationship between risk and return is working or not. Yet, majority of such work have focused on financial markets in the developed countries whereas studies on emerging markets are relatively scarce. Particularly, there is no work on the

Jordan financial market namely, Amman stock exchange (ASE), in our best knowledge, especially, related with the banking sector in Jordan. Therefore, Jordanian regulators, investors, and academics seek to

understand the behavior of volatility in this sector in order to design new remedies in maintaining a stable financial sector. In this respect, the purpose of this study is modelling daily stock market return volatility of Jordanian commercial banks in addition to the three of the main indices in Amman stock exchange, by using Univariate GARCH framework for the period starting in 3rd January 2010 and ending in 31st December 2015. The objective of the study is to shed light on the distributional features of Jordanian bank returns and also investigate the risk, return relationship by employing GARCH and GARCH-M models.

2. Econometric Methodology

In the finance literature, risk of an investment in an asset is associated with its variance or volatility (Markowitz 1952; Tobin 1958). Therefore, it is of great concern in decision making for investors and portfolio managers alike (Poon and Granger, 2003). Finance practitioners typically use standard deviation or the variance of returns as a measure of historical volatility. However, estimation of return variations that do not change over time is not realistic, whereas, in contrary, we observe volatility to change over time, said to be time-dependent. Thus, in the present study, as proposed in recent financial literature, conditional variance has been used as a measure of the market return volatility (Tsay, 2010):

$$\sigma_t^2 = Var(r_t|\Omega_{t-1}) \quad (1)$$

where σ_t^2 is the conditional variance of the market returns series, r_t is the market returns at time t conditional on all available information set at time t-1, denoted as Ω_{t-1}.

In the literature, it is well documented that serial correlations in the second moments of the data are well captured by the general autoregressive conditional heteroscedasticity (GARCH) family of models. Therefore, we employ two specifications for the univariate GARCH type of models, specifically, the GARCH model of Bollerslev (1986) and GARCH in mean or GARCH-M model developed by Engle, Lilien, and Robins (1987). In presenting these models, there are two divergent equations, first, the conditional mean equation and second, the conditional variance equation. The following subsections will briefly overview the literature on volatility analysis and the models employed in the study.

2.1 ARCH model and testing ARCH effects

In classical econometric models, one important assumption is that error variance is assumed to be constant, or homoscedastic, $\sigma^2 = var(u^2)$. However, in real life this assumption seems not realistic as one observes changes in variance over time, thus heteroscedastic, $\sigma_t^2 = var(u^2)$. Asset returns also exhibit high volatility during some periods and low volatility over some other time periods. The Autoregressive Conditional

Heteroskedasticity (ARCH) model is first introduced by Engle (1982) that is able to model the time-varying volatility behavior of asset returns. The basic idea of Engle's model is that when modelling asset return behavior, the returns may not be serially correlated themselves, but may be correlated through their second moments, this feature captured by the conditional variance equation. Also, the model is superior in taking account of some important features of financial time series such as excess kurtosis, thick tails and volatility clustering and allows one to examine the impact of past market shocks on returns volatility at current time. According to the ARCH model, volatility can be modelled by admitting the conditional variance of the error term, σ^2_t, to rely upon past values of squared errors representing market shocks as shown in following conditional variance equation of q lags:

$$\sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \varepsilon^2_{t-2} + \ldots + \alpha_q \varepsilon^2_{t-q} + \varepsilon_t \tag{2}$$

The model presented by equation (2) is known as an ARCH (q) model, where error conditional variance also denoted as, h_t, depends upon q lags of squared errors. In order to test for existence of ARCH effect, the ARCH-LM test is employed, proposed by Engle (1982). Simply, the test may be conducted in four steps, first by obtaining the residual series, ε, from the conditional mean equation which might be modelled as any variant of autoregressive moving average ARMA (p,q) process[1]. Obtaining of the conditional mean equation will be as the following:

$$r_t = \emptyset_1 r_{t-1} + \emptyset_2 r_{t-1} + \ldots + \emptyset_p r_{t-1} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-1} + \varepsilon_t \tag{3}$$

The second step involves saving and squaring the residuals obtained from the estimation of the conditional mean equation. Then regress the predicted squared residuals on own lags and obtain the coefficient of determination from this regression represented in equation (4) below;

$$\varepsilon_t^2 = \delta_0 + \delta_1 \varepsilon^2_{t-1} + \delta_2 \varepsilon^2_{t-2} + \ldots + \delta_i \varepsilon^2_{t-i} + v_t \tag{4}$$

[1] According to ARMA (p,q) model the present value of returns depends upon its own past values and combination of present and past error terms.

In the next step, in order to verify the existence of any ARCH effect, we compute the test statistic prescribed as TR^2 (the number of observations, T, multiplied by the coefficient of determination) which is distributed as a chi-square with degrees of freedom equal to the number of lag length, $\chi^2_{(m)}$. The final step is testing of the null hypothesis against the alternative one, as the following:

$$H_0: \delta_1 = 0 \text{ and } \delta_2 = 0 \text{ and } \ldots \text{ and } \delta_i = 0$$
$$H_1: \delta_1 \neq 0 \text{ or } \delta_2 \neq 0 \text{ or } \ldots \text{ or } \delta_i \neq 0 \quad (5)$$

The null hypothesis refers to no ARCH effect in the residual series. Testing for ARCH effect is imperative before estimating any variant of volatility model to make sure that this type of models is appropriate for the data.[2] Findings of this examination for our returns series are presented in the last column of Table 1; the results indicate that all indices series exhibit ARCH effect except ABCO, CABK, BOJX, AHLI and SGBJ. The existence of the ARCH effect in the return series lays reasonable ground to estimate GARCH models.

2.2 GARCH model

The generalized conditional autoregressive heteroscedasticity (GARCH) model proposed by Bollerslev (1986) allows the conditional variance to be estimated by past own lags and squared values of errors. The model assumes that there is a linear relationship between current value of conditional variance as a dependent variable and its past values and squared values of errors as independent variables. The GARCH model superior than the ARCH model because it does not require many lags to capture the behavior in the data generating process also it can easily be estimated, that is successful in predicting conditional variances.

In this paper, in order to examine volatility in our return series we used GARCH (1,1) specification for the conditional variance equation. The model have two formulas, conditional mean and conditional variance, these two formulas are estimated concurrently. The GARCH (1,1) specifications are expressed as:

$$r_t = \mu(\theta) + \varepsilon_t \quad (6)$$

$$\varepsilon_t \sim (0, \sigma_t^2)$$

$$h_t = \omega + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1} \quad (7)$$

[2] The null hypothesis of ARCH-LM test is no ARCH effect in the returns series. Rejection H0 implies that those residuals variances are heteroscedastic.

where r_t is the return on asset at time t, $\mu(\theta)$ is the conditional mean equation with a residual term, ε_t defined as $\varepsilon_t = \sigma_t(\theta)z_t$ where z_t is *iid* standardized residuals with zero mean and unit variance. The dynamics of the conditional mean equation can be described by any ARMA type of model. In the conditional variance equation, h_t, ω is a constant term. α_1 is the ARCH term which measures the impact of market shocks on volatility at time t, while β_1 is the GARCH parameter which measures the effect of prior period's volatility on current volatility. A few of restrictions are wanted to make sure that h_t is positive during all t periods. Bollerslev (1986) argue that $\omega > 0, \alpha_1 \geq 0$ *and* $\beta_1 \geq 0$ that will be adequate for the conditional variance to be nonnegative. Also, for weak stationarity of the model it is required that $\alpha + \beta < 1$. The estimated results of GARCH (1,1) model for Jordanian data set are presented in the rest of this article at the empirical findings part.

2.3 GARCH-M model

One of the main considerable issues in the financial theory is the relationship between risks and returns. The financial and investment theories emphasize that investors should be compensated or

rewarded for suffering any additional unit of risk in order to make investment in that asset. In other words, this positive relationship between risk and asset returns is consistent with the spirit of financial and investment theories. In order to incorporate this concept into the model, Engle, Lilien and Robins (1987) proposed a model which called GARCH in mean (GARCH-M) model. According to this model, the rate of return of an asset is determined by its risk. The GARCH-M is the extended of the GARCH framework, this formulation allows the conditional variance of returns (or standard deviation) to step inside the conditional mean equation as:

$$r_t = \mu + \lambda h_{t-1} + \varepsilon_t \quad (8)$$

$$\varepsilon_t \sim N\ (0, \sigma^2 t)$$

$$h_t = \omega + \alpha_1 \varepsilon^2_{t-1} + \beta_1 h_{t-1} \quad (9)$$

where λ is the risk premium coefficient; it should have positive sign and be statistically significant at conventional levels. Consequently, the rate of return will increase in response to increasing levels of risk which will lead to an increase in the conditional variance at current period. In order to find risk premium coefficients for the returns data set of this study, we applied GARCH-M (1,1) specification for general index (G-index) of Amman stock exchange ASE , financial sector index (F-index) and banks sector index (B-index).

Our findings are totally consistent with the financial and investment theories. The findings are reported in empirical evidence section in the rest of this paper.

3. Empirical findings

This study employed GARCH (1,1) and its extension GARCH-M model on the data set of market return series for the Jordanian daily financial data. In the first part of this section we present the descriptive statistics for the data and the unit root test results. The second part will summarize the estimation results of the models.

3.1 Data and Descriptive Statistics

The sample includes thirteen conventional bank stocks traded on the Amman stock exchange (ASE) as well as the general index (G-Index), financial sector index (F-Index) and banking sector index (B-Index).[3]

The time period of the study covers 3rd January 2010 till 31st December 2015 inclusive, resulting in 1488 observations excluding holidays. Daily closing index values have been used which are gathered from the website of ASE. The continuously compounded daily returns (r_t) are calculated as the first difference of logarithm returns for each series individually as follows:

$$\boldsymbol{r_t = ln[(P_t / P_{t-1})]100} \quad (10)$$

where r_t is the continuously compounded daily returns. P_t and P_{t-1} are the closing index prices of each series at the present day and previous day, respectively. In equation (10), the first differences of nature logarithm of return series are expressed in percentages.

In order to present the distributional properties of the daily returns series (r_t) of the Jordanian commercial banks and financial market indices during the period considered, various descriptive statistics indicators (minimum, maximum, mean, standard deviation, skewness, excess kurtosis and Jarque-Bera) and ARCH-LM test statistics are presented in Table 1. As it can be observed from Table 1, seven banks have negative average returns and the remaining six banks have positive average returns. Among the sector indices, only the banking sector index (B-index) has positive average return. Columns six and seven presents the skewness and kurtosis, respectively, most series are negatively skewed and have relatively high value of excess kurtosis.[4] The Jarque-Bera (J-B) test statistic is used as a test for normality. These statistics clearly indicate deviation from normality at conventional significance levels.[5] ARCH-LM test results at lag (10) confirm the presence of volatility clustering for most of the series except ABCO, CABK, AHLI and SGBJ.[6]

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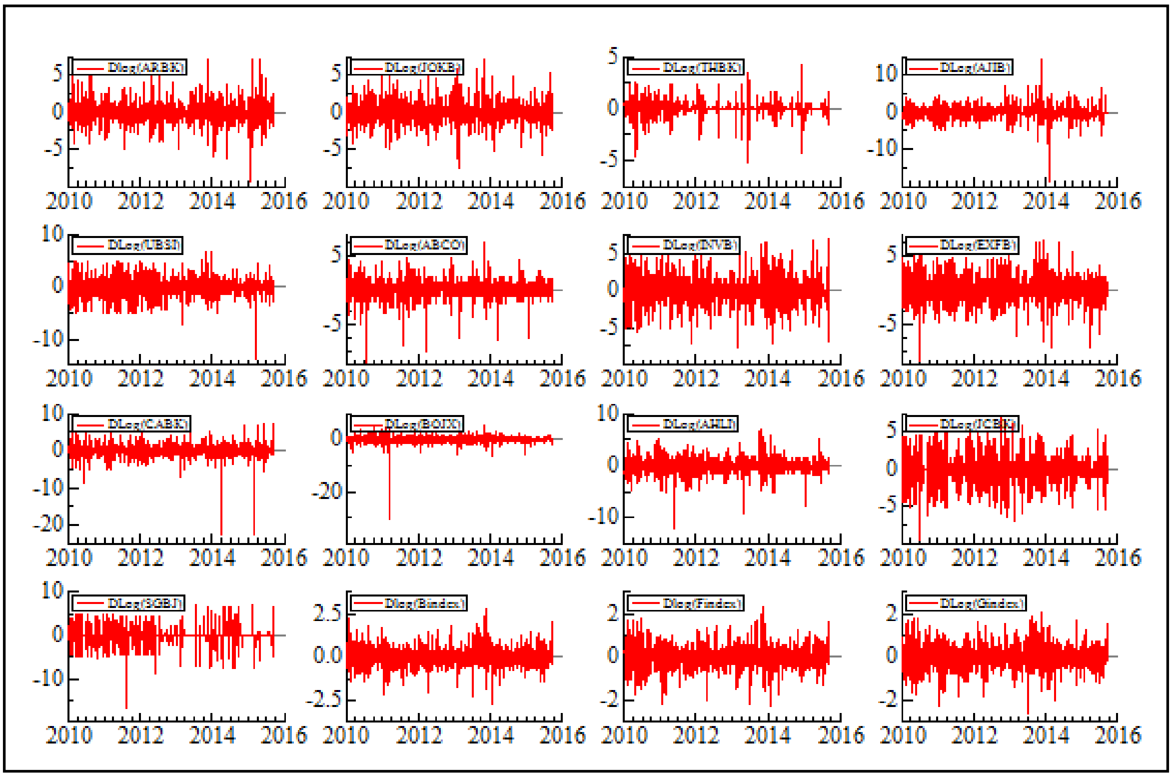
3 The banks' names are listed in the appendix.
4 Skewness values show asymmetry and kurtosis indicate flatness and peackedness, in the return series.
5 Under the null hypothesis for the Jarque-Bera test, the return series is normally distributed.
6 The reason of did not exist ARCH effect in these series of returns since it has many zeros during the period of study. The price was constant for the long period..

The daily logarithmic returns series used in the study are presented in Figure 1. The visual inspection of the series indicates that the returns series clearly exhibit volatility clustering (or sometimes called volatility pooling).

Table 1. Descriptive Statistics of the Returns Series and Test for ARCH Effect

Index Symbol	*Min*	*Max*	*Mean*	*SD*	*Skewness*	*E-Kurtosis*	*Jarque-Bera(P-value)*	*ARCH-LM(p-VALUE)*
ARBK	-9.32810	7.23210	-0.04344	1.34690	0.28728	5.64640	1997.2[0.0000]	62.973 [0.0000]
JOKB	-7.52230	7.15470	0.00388	1.32130	0.11317	3.99610	993.23[0.0000]	38.339 [0.0000]
THBK	-5.15870	4.25600	0.01874	0.58745	-0.97403	19.10600	22868[0.0000]	31.636 [0.0000]
AJIB	-18.53100	14.15600	0.02483	1.65930	-0.73978	17.36600	18834[0.0000]	19.062 [0.0000]
UBSI	-13.68600	6.85980	-0.01464	1.70780	-0.30394	4.30460	1171.7[0.0000]	17.536 [0.0000]
ABCO	-10.62900	6.89930	0.00117	1.26660	-0.87205	9.40250	5669.9[0.0000]	0.65879 [0.5176]
INVB	-7.66330	6.95260	-0.00622	1.74110	-0.00291	2.64220	432.83[0.0000]	35.625 [0.0000]
EXFB	-10.31800	7.21960	-0.02725	1.69720	-0.06793	3.55590	785.11[0.0000]	17.865 [0.0000]
CABK	-22.62600	7.21030	0.00214	1.64270	-3.19760	48.83500	150400[0.0000]	0.54205 [0.5817]
BOJX	-30.39000	5.44880	0.01215	1.32800	-8.09300	185.28000	2144600[0.0000]	0.010337 [0.9897]
AHLI	-12.15200	6.79510	-0.01314	1.37520	-0.60921	8.43670	4505.1[0.0000]	1.6808 [0.1361]
JCBK	-9.63920	6.83190	-0.02187	1.77600	-0.16086	2.88240	521.53[0.0000]	53.492 [0.0000]
SGBJ	-16.86200	7.21030	-0.02000	1.72760	-0.89808	11.16600	7929.8[0.0000]	2.6832 [0.0687]
Bindex	-2.74570	2.79780	0.00989	0.51960	0.21809	3.20140	647.25[0.0000]	60.569 [0.0000]
Findex	-2.29670	2.34540	-0.00343	0.51401	0.00664	2.22310	306.43[0.0000]	62.708 [0.0000]
Gindex	-2.64570	2.08540	-0.01218	0.51822	-0.04128	1.98480	244.67[0.0000]	22.457 [0.0000]



Note: P-values are displayed as [.]

Figure 2. Logarithmic Daily Returns of the Jordanian Commercial Banks and General Index, Financial Index and Banking Index Series (1.Jan.2010 - 31.Dec.2015)

3.2 Unit Root Tests

Table 2 gives ADF, PP[7] and KPSS[8] unit root test results for the returns series of the sample data. The purpose of employing the unit root tests is to detect whether the series are weakly stationary or not. In particular, it is important to determine whether the series are I(0) or I(1). In order to determine the order of integration of the data Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1981) Phillips–Perron (PP) (Phillips and Perron,1988) and Kwiatkowski Phillips, Schmidt, and Shin's (1992) (KPSS) unit root tests have been applied. According to these tests results logarithmic price indices are found to be nonstationary except in some cases which confirmed stationarity but only marginally. However, when applying the same test for the first difference of the logarithm return series, the findings show strong evidence of stationarity at 1% level of significance in most cases. And therefore, we conclude that the returns series are stationary.

Table 2. ADF, PP and KPSS Unit Root Tests Output for the Returns Series

Tests	*Log(ARBK)*	*Log(JOKB)*	*Log(THBK)*	*Log(AJIB)*	*Log(UBSI)*	*Log(INVB)*	*Log(EXFB)*	*Log(JCBK)*	*Log(Bindex)*	*Log(Findex)*	*Log(Gindex)*
t_T (ADF)	-2.812968	-1.642342	-2.563404	-2.955853	-2.750108	-2.779991	-0.906081	-1.226404	-1.511772	-1.674966	-2.002208
t_m (ADF)	-2.247422	-1.663451	-1.315604	-1.678242	-2.328002	-2.221597	-0.87064	-1.736257	-0.897668	-1.546471	-2.463163
t (ADF)	-1.295791	0.018601	2.258611	-0.1153	-0.926824	-1.01889	-1.160863	(-1.802306)***	0.680849	-0.240585	-0.817448
t_T (PP)	-2.480592	-1.701967	(-3.625003)**	-2.828077	-2.664983	-2.614648	-1.111972	-1.246636	-1.489649	-1.608417	-1.944582
t_m (PP)	-2.150926	-1.726307	-1.303022	-1.56112	-2.328002	-2.02756	-1.081829	-1.737456	-0.835918	-1.370179	-2.430028
t (PP)	-1.583993	-0.021357	2.251057	-0.021422	-0.908692	-0.921769	-1.200189	(-1.829974)***	0.672165	-0.254248	-0.844286
t_T (KPSS)	(0.547672)*	(0.555426)*	(0.24725)*	(0.329348)*	(0.662868)*	(0.510189)*	(0.434639)*	(1.064514)*	(0.682038)*	(0.916000)*	(0.923156)*
t_m (KPSS)	(2.90711)*	(0.565092)*	(4.289799)*	(3.318381)*	(1.842032)*	(2.414121)*	(0.415271)***	(2.735838)*	(2.085276)*	(0.972248)*	(1.460349)*
Tests	*Dlog(ARBK)*	*DLog(JOKB)*	*DLog(THBK)*	*DLog(AJIB)*	*DLog(UBSI)*	*DLog(INVB)*	*DLog(EXFB)*	*DLog(JCBK)*	*Dlog(Bindex)*	*Dlog(Findex)*	*Dlog(Gindex)*
t_T (ADF)	(-34.99328)*	(-46.22132)*	(-23.07871)*	(-40.8043)*	(-40.3704)*	(-44.26213)*	(-23.2824)*	(-22.04319)*	(-34.44167)*	(-32.38130)*	(-33.69012)*
t_m (ADF)	(-34.99496)*	(-46.2284)*	(-23.07675)*	(-40.81733)*	(-40.38368)*	(-44.27627)*	(-23.27187)*	(-22.0052)*	(-34.44298)*	(-32.33396)*	(-33.63936)*
t (ADF)	(-34.97475)*	(-46.2432)*	(-22.92735)*	(-40.8206)*	(-40.39282)*	(-44.29069)*	(-23.25845)*	(-21.99778)*	(-34.44215)*	(-32.34354)*	(-33.63426)*
t_T (PP)	(-35.12295)*	(-46.23956)*	(-56.97044)*	(-40.87356)*	(-40.46947)*	(-46.16809)*	(-44.57822)*	(-48.49493)*	(-34.38511)*	(-32.34675)*	(-33.60225)*
t_m (PP)	(-35.10881)*	(-46.24326)*	(-56.84863)*	(-40.88678)*	(-40.48318)*	(-46.17759)*	(-44.58027)*	(-47.85497)*	(-34.39038)*	(-32.32805)*	(-33.56486)*
t (PP)	(-35.01811)*	(-46.25788)*	(-55.05135)*	(-40.88419)*	(-40.49205)*	(-46.18731)*	(-44.53564)*	(-47.67654)*	(-34.38258)*	(-32.33849)*	(-33.5709)*
t_T (KPSS)	0.061874	0.068991	0.037518	0.036115	0.038331	0.057911	(0.1721)**	0.067778	0.105768	0.097356	0.055495
t_m (KPSS)	0.125346	0.114331	0.063479	0.041795	0.038792	0.068527	0.19611	0.317719	0.172341	(0.402826)***	0.32021

Notes:

τ_T represents the most general model with a drift and trend; τ_μ is the model with a drift and without trend; τ is the most restricted model without a drift and trend.

For ADF, PP and KPSS: ***, ** and * denote rejection of the null hypothesis at the 1%, 5% and 10% levels respectively.

Tests for unit roots have been carried out in E-VIEWS 7.1.

[7] The null hypotheses of ADF and PP tests, return series has a unit root [$r_t \sim I(1)$].

[8] The null hypotheses of KPSS test, return series is stationary [$r_t \sim I(0)$].

3.3 Estimates of The GARCH models

Based on the test results in the above section, we proceed to estimate GARCH models for the series after excluding the five series, namely, ABCO, CABK, BOJX, AHLI and SGBJ from our sample. The estimations of the GARCH and GARCH-M models are presented in the following subsections.

3.3.1 GARCH (1,1) model

Estimates of the GARCH (1,1) model are presented only for the conditional variance equation to save space as observed in Table 3. Both the estimated ARCH parameter (α_1) and the GARCH parameter (β_1) shown in the third and fourth columns, respectively, are all highly significant at least at the 1% level of significance. These results indicate that today's conditional variance significantly is affected from the shocks to the market in the previous day (ε^2_{t-1}) and from yesterday's volatility (h_{t-1}). High values of these coefficients are also indicative of strong response of today's volatility to yesterday's market shocks and volatility. For the weak stationarity condition of the estimated model, the sum of both ARCH and GARCH coefficients have to be less than unity (i.e ($\alpha_1 + \beta_1) < 1$) When sum of these coefficients are less than 1 but close to unity, it indicates that

their impact is persistent, i.e impact does not die out quickly. As shown clearly in the fifth column in Table 3 all of the return series have a reverting variance process except for ABCO, JOKB and THBK for which the estimates for ($\alpha_1 + \beta_1$) are 1.085, 1.049 and 1.048 respectively.

This implies that the process is not weakly stationary as explained in Bollerslev (1986), Engle, Ng & Rothschild (1990). The other series have the summation of these parameters to be less than unity and indicate that impact is highly persistent. These results also certify the existence of volatility clustering in the return series which is an important matter for the investment decision makers; volatility clustering hint that low fluctuation periods mingle with high fluctuation periods. The diagnostics tests are applied to make sure that our estimation models have no remaining ARCH effects and the conditional mean and conditional variance innovations are not correlated. For this end, model diagnostic results are reported at the last three columns in Table 3 which are ARCH-LM, Q-statistic and Q2-statistic are at lag 10. The test results indicate that the estimated models do not suffer from misspecification.

3.3.2 GARCH-M (1,1) model

The GARCH-M model is estimated to check the positive relationship between risk and return for risk-averse investors. Consequently, the GARCH-M (1,1) specification has been estimated for core index returns which are general index of the Amman stock exchange (G-Index), financial sector index (F-Index) and banking sector index (B-Index) for the sample period. The estimation results are presented in Table 4. Table 4 shows ω, α_1, and β_1 at the second, third and fourth columns, respectively, all these parameters are nonnegative and significant, the sum of the estimated α_1 and β_1 coefficients are less than one for the all of the cases. The added parameter of this specification is λ which refers to the risk premium coefficient. As observed from column six, the estimated risk premium coefficient has a positive sign and is highly statistically significant in the all cases which implies that mean returns are affected by previous conditional variance. In this regard, our result not contradicts with spirit of the positive relation between risk and return, and the conditional variance can be used as a measure of return risk. Consequently, the results suggest that as the degree of risk (volatility) increases, the rate of return will increase by 19.64%, 24.84% and 45.45% for general market returns, financial sector returns and banking sector returns, respectively. The results clearly indicate that banking sector has the highest premium coefficient comparing with the other sectors since the banking sector is highly sensitive to uncertainty leading to high premium demanded from the risk-averse investors. In other words, we found enough evidence for existence of feedback from conditional variance to the conditional mean equation.

Table 3. Estimation results of GARCH (1,1) Model and Diagnostic Tests

	GARCH(1,1) Coefficients				*Model Diagnostic*		
Index Symbol	***ω***	***α₁***	***β₁***	***α₁+β₁***	***ARCH-LM(10)***	***Q-Statistic(10)***	***Qsqu-Statistic(10)***
ARBK	0.422294	0.544063	0.54182	1.085883	0.58947	17.1721	5.83604
t-ratio	{3.222}	{3.532}	{7.318}		[0.8237]	[0.0706412]	[0.6655918]
p-value	[0.0013]	[0.0004]	[0.0000]				
JOKB	0.123885	0.189803	0.859673	1.049476	1.1779	4.08036	11.9574
t-ratio	{1.96}	{4.615}	{13.87}		[0.3012]	[0.9060441]	[0.1019685]
p-value	[0.0502]	[0.0000]	[0.0000]				
THBK	0.0001907	0.365153	0.68286	1.048013	0.32203	15.1922	3.1613
t-ratio	{2.625}	{3.842 }	{16.71 }		[0.9756]	[0.0555146]	[0.9238311]
p-value	[0.0088]	[0.0001]	[0.0000]				
AJIB	0.310925	0.159868	0.718513	0.878381	0.58542	11.5399	2.93219
t-ratio	{1.332 }	{2.428 }	{4.650 }		[0.7112]	[0.1729453]	[0.4021992]
p-value	[0.1829]	[0.0153]	[0.0000]				
UBSI	0.163999	0.138249	0.815667	0.953916	0.35666	10.4959	3.4792
t-ratio	{1.545}	{2.862}	{0.070571}		[0.9646]	[0.3118474]	[0.9007981]
p-value	[0.1225]	[0.0043]	[0.0000]				
INVB	0.273364	0.128597	0.783348	0.911945	0.80627	12.8448	7.90933
t-ratio	{1.648}	{3.479}	{9.255}		[0.6227]	[0.1173033]	[0.4423766]
p-value	[0.0995]	[0.0005]	[0.0000]				
EXFB	0.83078	0.125107	0.57531	0.700417	0.96228	9.6054	9.38222
t-ratio	{1.465}	{2.464}	{2.336}		[0.4747]	[0.2938209]	[0.3110853]
p-value	[0.1431]	[0.0138]	[0.0196]				
JCBK	0.376555	0.178842	0.705055	0.883897	0.35704	9.17746	3.88792
t-ratio	{2.195}	{4.374}	{8.71}		[0.9645]	[0.3275479]	[0.8670912]
p-value	[0.0283]	[0.0000]	[0.0000]				
B-index	0.060916	0.198561	0.588614	0.787175	0.55771	8.80702	5.32665
t-ratio	{2.018}	{3.098}	{3.695}		[0.8491]	[0.4552755]	[0.7221603]
p-value	[0.0438]	[0.002]	[0.0002]				
F-index	0.021467	0.162021	0.765586	0.927607	0.96625	11.1307	8.77222
t-ratio	{2.286}	{3.061}	{9.905}		[0.4711]	[0.2668556]	[0.3618741]
p-value	[0.0224]	[0.0022]	[0.0000]				
G-index	0.022222	0.170733	0.760517	0.93125	0.61212	6.48056	5.52415
t-ratio	{2.197}	{3.098}	{9.700}		[0.8046]	[0.6910233]	[0.7003632]
p-value	[0.0282]	[0.002]	[0.0000]				

Notes: *1. t-ratio* reported {.}. 2. *P-values reported* [.]. 3. *ARCH-LM*, *Q-Statistic* and *Qsqu-Statistic* until lag 25 have been calculated, the results confirm that estimation models has no remaining ARCH effect and residuals of conditional mean and variance are uncorrelated.

As in GARCH model reported in the previous section, the diagnostic test results are reported at the last three columns in Table 4. All of the test results indicate the adequacy of the estimated models.

Table 4. Estimation results of GARCH-M (1,1) Model and Diagnostic Tests

	GARCH-M(1,1) Coefficients					*Model Diagnostic*		
Index Symbol	ω	α_1	β_1	$\alpha_1+\beta_1$	λ	*ARCH-LM(10)*	*Q-Statistic(10)*	*Qsqu-Statistic(10)*
G-index	0.031825	0.188986	0.701841	0.890827	0.196405	0.45004	8.75289	4.24153
t-ratio	{1.999}	{2.822}	{6.352}		{3.819}	[0.9217]	[0.4603900]	[0.8347004]
p-value	[0.0458]	[0.0048]	[0.0000]		[0.0001]			
F-index	0.032074	0.187749	0.693894	0.881643	0.248426	0.72443	13.0035	6.75461
t-ratio	{2.884}	{3.774}	{8.776}		{5.54}	[0.7020]	[0.1624474]	[0.5633250]
p-value	[0.004]	[0.0002]	[0.0000]		[0.0000]			
B-index	0.08266	0.211217	0.476414	0.687631	0.454513	0.41754	15.5761	4.25147
t-ratio	{4.033}	{5.771}	{5.328}		{3.756}	[0.9388]	[0.1124265]	[0.8337524]
p-value	[0.0001]	[0.0000]	[0.0000]		[0.0002]			

Notes:1. *t-ratio* reported {.}. 2. *P-values reported* [.]. 3.*ARCH-LM*, *Q-Statistic* and *Qsqu-Statistic* until lag 25 have been calculated, the results confirm that estimation models has no remaining ARCH effect and residuals of conditional mean and variance are uncorrelated.

4. Conclusions

This study applied the GARCH framework on the set of the market return series of the conventional Jordanian banks. This attempt to model the volatility that is one of the key issues in the financial life, volatility terminology indicates to uncertainty in the assets returns over time. The descriptive statistics display that the return series considered in this paper have positive skeweness and relatively high kurtosis which are against the evidence of normality. The Jarque-Bera (J-B) test has been used to check the normality of the series. The results of the tests indicate that the return series considered depart from normal distribution. The ARCH-LM test has been used to examine the heteroscedasticity of residuals; the results gave evidence for existence of ARCH effects in the residuals in most of the returns series taken into account in the study. The GARCH (1,1) models have been estimated for all the series used in the model. All the estimated parameters are positive and highly statistically significant. The obtained results found enough evidence for dependency of current volatility to the previous conditional variance and previous squared error; current volatility can be explained through past values of the conditional variance and market shocks. The findings confirm the existence of volatility clustering in the returns series; which means high volatility of returns followed by high volatility and low volatility of returns followed by low volatility. In order to examine the availability of risk premium for investors' in Amman stock exchange, the GARCH-M has been estimated for the three key indices investigated which are G-Index, F-index and B-Index. Consequently, the results provide evidence with positive sign and significant coefficient of the risk premium that the conditional mean can be determined by conditional variance that is also consistent with the financial theory. The results of the article confirm high sensitivity of the banking sector as compared with the others, since the risk premium parameter of the model estimated for the banking sector was the highest one. The diagnostic tests are applied confirm that the models do not suffer from misspecification.

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Appendix A. List of Names of Sample Series:

#	Code	Symbol	Bank Name
1	113023	ARBK	ARAB BANK
2	111002	JOKB	JORDAN KUWAIT BANK
3	111004	THBK	THE HOUSING BANK FOR TRADE AND FINANCE
4	111005	AJIB	ARAB JORDAN INVESTEMENT BANK
5	111007	UBSI	UNION BANK
6	111009	ABCO	ARAB BANKING CORPORATION /(JORDAN)
7	111014	INVB	INVEST BANK
8	111017	EXFB	CAPITAL BANK OF JORDAN
9	111021	CABK	CAIRO AMMAN BANK
10	111022	BOJX	BANK OF JORDAN
11	111033	AHLI	JORDAN AHLI BANK
12	111003	JCBK	JORDAN COMMERCIAL BANK
13	111020	SGBJ	SOCIETE GENERALE DE BANQUE - JORDANIE
14	......	G-index	GENERAL MARKET INDEX
15	......	F-index	FINANCIAL SECTOR INDEX
16	......	B-index	BANKS SECTOR INDEX