Relationship Between Market Volatility and Trading Volume: Evidence from Amman Stock Exchange

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Abstract

Market expectations of future return volatility play a crucial role in finance; we investigate the empirical relationship between return volatility and trading volume using data from the Amman Stock Exchange (ASE) for 27 individual stocks, using daily data for the period 2002-2012. The results indicate that trading volume significantly contributes to the return volatility process of stocks in Amman stock Exchange, as suggested in many studies. On the other hand, the results also signify that the Trading volume has no significant effect on the reduction of the volatility persistence for majority of stocks in the sample, challenging the existence of "Mixed Distribution Hypothesis" in Amman stock Exchange.

Key Words: stock index returns, trading volume, emerging markets, volatility, GARCH

Introduction

Market expectations of future return volatility play a crucial role in finance; the volatility characteristics of stock returns have been one of the key topics examined in finance literature. The ARCH models – including GARCH, EGARCH, and so forth – forecast future return volatility given only information on lagged return innovations.
Results from previous articles suggest that in an ARCH model that already accounts for the impact of lagged return innovations on future volatility; lagged volume will have no marginal power to forecast future volatility. Although there is no a clear-cut consensus regarding the underlying rationale for the ARCH, and GARCH effect in stock returns, one of the predominant theoretical justifications has been the mixture of distributions hypothesis (MDH). MDH, as put forward by Clark (1973), Tauchen and Pitts (1983), and Lastrapes and Lamoureux (1990), alleges that the conditional heteroscedasticity in stock returns can be explained by a serially correlated mixing variable that measures the rate at which information is transmitted to the market.

These authors have shown that the information arrivals stemming from of exogenous variables can be identify by the mixture of distributions, and that variables exhibit time-varying ARCH effect. In many of the later studies the validity of MDH in various stock markets, the trading volume is taken as a proxy to represent the rate and bulk of information flow to the market. Volume as suggested by Morgan (1976) regarded as a major risk factor contributing to the volatility of returns, particularly in less liquid and thin markets including emerging markets. Most studies on the relationship between return volatility and trading volume applied on developed markets, there are a few studies in emerging markets. This paper aims to contribute to the literature by investigating the relationship between trading volume and stock return volatility in Amman Stock Exchange (ASE) by utilizing a relatively more recent database and extensive dataset including individual stocks instead of a general index which has been primarily used in previous studies.

This paper is structured as follows: Section 2 provides a brief review of literature, Section 3 discusses econometric methodology. The data set and empirical results are presented in Section 4. Finally Section 5 contains concluding remarks.

Literature Review

Market expectations of future return volatility play a fatal role in finance, the volatility of returns in financial assets exhibit time varying conditional variance characteristic, which is implied in a GARCH model set forth by Bollerslev (1986). Traditional ARCH models –including GARCH, EGARCH, and so forth – forecast future return volatility given only information on lagged return innovations, the power of GARCH modeling lies in its effectiveness in capturing volatility clustering and persistence. Furthermore, an ARCH specification not only allows the identification of volatility clustering in an autoregressive structure but also allows a mixture of distributions, such as daily stock returns, being generated by a dominant stochastic mixing variable. In many cases, the rate of information's flow is considered as the primary mixing variable. Depending on this basic premise, MDH in which the stochastic mixing variable is considered to be the rate of arrival of information flow into the market. The MDH implies that return volatility is proportional to the rate of information arrival, thus explaining the observed heteroskedasticity in returns. Brock and LeBaron (1996) finds that when demand diversity reflected in trading process and volume is stronger, the volatility persistence of returns arise from beliefs rather than fundamentals.

Accordingly, more investors have an incentive to trade the share based on diverse expectations on future returns. Based on this finding, GARCH behavior in stock's return is generated by a serially correlated news arrival process where arrivals can be proxied by the trade volume. Many studies have confirm that the trading volume significantly contributes to the time-series return process of stocks. Such as, McKenzie and Faff (2003); have shown that the presence of positive feedback trading induces autocorrelation in stock returns to be negatively related with the level of volatility, in other words, that the conditional autocorrelation in stock returns is highly dependent on trading volume for individual stocks but not for the index. Lamoureux and Lastrapes (1990, 1994) have concluded that volume has a positive effect on conditional volatility, Bohl and Henke (2003), Gallagher and Kiely (2005), Pyun, et al.(2000) , and Gallo and Pacini (2000) . have all concluded that trading volume serving as an appropriate proxy for information, significantly reduces the volatility persistence in those countries.

In other direction, Ahmed, et al.(2005), Huang and Yang (2001), Salman (2002) and Yuksel (2002, and Chen, et al. (2001) have all concluded that persistence in return volatility remains even after volume is included in conditional variance equation, results in conflict with MDH. Regarding other few studies including Turkish stock market, Guner and Onder (2002) have found out a significant relationship between volatility and trading volume. Sabri (2004) has discovered that trading volume represent one of the main factors in predicting return volatility using a modified MDH, Andersen (1996) finding out that the normality restriction imposed by standard MDH as well as finite sample biases might bias volatility persistence measures downward.

The impact of volume on return volatility through price formation process is also well documented in literature. Admati and Pfleiderer (1988) denote that when the liquidity traders choose to trade at the same time of the day, this pooling of trades attracts informed traders, this strategy minimizes the adverse selection costs reflected in bid-ask spreads. On the other hand, Foster and Viswanathan (1993) find that the effect of volume on return volatility exhibit a U-shaped pattern. Specifically, the effect is very high in the first half hour of trading, fall during the mid-day and then increases again towards the close of trading. Majority of the studies have confirmed the existence of a significant volume and return volatility relationship, even though there is a progress in recent years, the literature still suffers from the scarcity of studies investigate the return- volatility volume relationship in these market segments, particularly for MENA Markets which include our country Jordan. Besides, most of the existing studies on emerging markets have used solely stock index instead of individual stocks, this particular study aims to fill this gap by investigating the impact of trading volume on volatility persistence and the validity of MDH for 27 stocks traded in ASE.

Methodology and Data

The sample period in this study span from January 2002 to October 2012, the data set is comprised of daily return and volume series of 27 stocks traded in ASE.

The individual stocks in the sample are contain of firms selected randomly with different size and trading volume, the rationale behind mixing firms with different characteristic is to see if the results obtained from the return volatility-volume analysis vary across firms with different trading volume. The stock returns are calculated by the following formula:

$$R_t = Ln(P_t / P_{t-1}) \qquad (1)$$

Where t p represents the end-of-day closing price of the individual stock, the lists of firms included in the sample provided in *Appendix 1*.

Since the seminal work by Engle (1982) several hypotheses have been attempted to explain the behavior of asset returns , Engle(1982) introduced a model in which the variance at time t is modeled as a linear combination of past squared residuals and called it an ARCH (autoregressive conditionally heteroscedastic) process. Bolerslev (1986) introduced a more general structure in which the variance model looks more like an ARMA than an AR and called this a GARCH (generalized ARCH) process.

One hypothesis that has been successful in explaining the success of the GARCH class of models has been the mixture of distributions hypothesis (MDH) (Clark, 1973, Tauchen and Pitts, 1983, Lamoureux and Lastrapes, 1990). According the mixed distribution hypothesis (MDH), the innovation on returns R_t is a linear combination of intraday returns movements:

$$R_t = \sum_{i=1}^{n_t} \delta_{it} \qquad (2)$$

Where δ_{it} it is the intraday return increment in day t due to information flows arriving into the market and n_t is the number of information arrivals within a given day, each δ_{it} it is assumed to be an independent identically distributed random variable with mean zero and variance σ^2 , δ_{it} is N (0, σ^2). Since the number of intraday price increments is random, daily returns follow a mixture of normally distributed random variables with n_t as the mixing variable. Thus, according to equation (2) the daily return r_t is generated by a subordinate stochastic process in which r_t is dependent on δ_{it} and the mixing variable n_t is the directing process. For a sufficiently large sample where n_t and δ_i are independently and identically distributed, the Central Limit Theorem implies $r_t \mid n_t \sim (0, \sigma^2 n_t)$. Next, following Lamoureux and Lastrapes (1990), we assume that the number of information arrivals n_t follows an autoregressive process :

$$n_t = \phi_0 + \phi_1(L)n_{t-1} + \ell_t \qquad (3)$$

Where $\theta_1(L)$ is a polynomial in the lag operator L and ℓ_t an error term, the conditional variance of the daily returns can be represented as:

$$\sigma^2_{r_t|n_t} = E(r_t \mid n_t) \qquad (4)$$

Substituting the autoregressive process in equation (3) into equation (4) yields:

$$\sigma^2_{r_t|n_t} = \sigma^2(\phi_0 + \phi_1(L)n_{t-1} + \ell_t = \sigma^2\phi_0 + \phi_1(L)\sigma^2_{r_{t-1}|n_{t-1}} + \sigma^2\ell_t \qquad (5)$$

Eq (5) illustrate the fundamental feature of the MDH that represent the persistence in terms of conditional variance that can be estimating by a GARCH model, Since the relationship between daily return variance and the unobservable mixing variable cannot be easily estimated, a proper proxy is required.

The trading volume could serve as a proxy measure for the unobservable amount of information that flows into the market (see Andersen, 1996; Lamoureux and Lastrapes,1990).

The existence of autocorrelation in the volume time series is essential because the MDH implies that serial correlation in volume causes conditional heteroscedasticity in stock returns.

Following Bohl and Henke (2003), the serial correlation structure of trading volume is analyzed using autocorrelation coefficients and Ljung-Box statistics. Then the stationarity of trading volume is testing by using ADF test. Testing unit root is important because subsequent tests for the impact of trading volume on volatility may be invalid if the trading volume series are nonstationary.

Following model is used to test the impact of trading volume on volatility:

$$r_t = \phi_0 + \phi_1(L) r_{t-1} + \ell_t \qquad (6)$$

In addition:

$$\sigma_t^2 = \alpha_0 + \alpha_1(L)\ell_{t-1}^2 + \alpha_2(L)\sigma_{t-1}^2 + \alpha_3 V_t \qquad (7)$$

Where $\phi_1(L)$, $\alpha_1(L)$ and $\alpha_2(L)$ are polynomials in the lag operator L and V_t is the trading volume, as we seen in Eq. (6) an autoregression in the mean of returns is allowed.

Therefore, the possibility of a low-order linear autoregressive process in returns of the individual stocks is taken into account, the conditional variance is modeled in Eq. (7), including the daily total volume of stocks traded, V_t from close $t-1$ to close of t as a proxy of information arrivals. First, we estimated a restricted version of Eq (7) by setting the coefficient of the volume of trade to zero, $\alpha 3 = 0$. If the parameters of the lag polynomials. $\alpha 1(L)$, $\alpha 2(L)$ are positive, then volatility shocks persist over time where the degree of persistence is determined by the magnitude of these parameters. Second, we estimate the unrestricted version of Eq (7). If the trading volume represents a reasonable proxy for information arrival and is serially correlated,estimation based on Eq (6) and Eq (7) would yield $\alpha 3 > 0$ and values of $\alpha 1(L)$, and $\alpha 2(L)$ are significantly smaller than that when V_t is not included. Hence, the mixing variable is statistically significant in explaining the volatility of stock returns.

The aim of this article is to examine whether inclusion of serially correlated proxy, namely the trading volume, diminish the values of $\alpha 1(L)$, and $\alpha 2(L)$ significantly for a sample of stocks traded in the Amman stock Exchange.

Empirical Results

We started our investigation with some basic descriptive analysis of the time series of stock returns and trading volume which are shown on Table 1; table 1 shown that the mean returns of all individual stocks are positive except Arab Union International Insurance, and Jordan Investment Trust. The mean returns ranges between 0.028% and 5.17% , 0.028%, and the standard deviation between 2.235% and 11.290%. The Jarque–Bera statistic indicates that the distribution of returns of all sample stocks has fat tails and sharper peaks than the normal distribution. In addition, all return series exhibit excess kurtosis, which is consistent with the presence of GARCH effects.

Table 1: Descriptive statistics for stock returns of individual firms

Stock	Mean%	Stdev%	Skewness	Excess Kurtosis	JB	Q(12)
ARBK	0.1517	3.010	0.324	4.622	760.87 *	0.654*
THBK	0.135	3.121	0.227	7.545	493.76 *	0.432*
AHLI	0.146	3.622	-0.313	7.654	765.32 *	0,321*
MEIN	0.0495	5.031	0.112	5.543	623.93*	0.454*
JOFR	0. 113	3.326	0.232	11.654	734.66*	0.635*
HOLI	0.0914	3.034	0.113	6.345	987.32*	0,576*
AIUI	-0.0183	5. 327	0.135	7.654	675.87*	0.465*
ARAS	0.0325	3. 294	0.139	4.430	1134.43*	0.034*
AAFI	0.0032	6.0250	0.123	6.987	634.77*	0.256*
INVH	0.1233	4. 314	0.258	5.765	733.66*	0.332*
AMWL	0.1423	3.027	0.098	6.876	699.65*	0.662*
JOMC	0.1235	3. 441	1.078	8,546	654.99*	0.234*
DARA	0.0122	11. 290	0.190	5.765	564.45*	0.498*
JOIT	-0.0327	4. 254	1.000	8.000	1828.21*	0.582*
UINV	-0.034	4.030	0.165	7.321	1234.09*	0.376*
ULDC	0.108	3. 454	0.409	6.654	1453.65*	0.522*
SPIC	0.025	5.017	0.234	7.654	765.11*	0.481*
REDV	0.156	3.032	0.123	7.543	567.34*	0.430*
PETT	0.1429	3. 456	0.409	6.998	943.34*	0.651*
JIIG	0.171	4.254	0.086	22.765	675.98*	0.234*
ITSC	0.028	3.304	0.345	4.654	786.43*	0.577*
JETT	0.0194	5.037	0.156	7.223	543.21*	0.287*
JTEL	0.001	4.020	0.213	8.543	1345.87*	0.651*
PRES	0.0014	3.135	-0.067	4.345	876.77*	0.541*
JOPT	0.00248	3.409	0.0321	6.765	765.09*	0.432*
JPHM	0.0066	2.235	0.0112	5.654	1232.87*	0.388*
APHC	-0.00735	3.137	0.143	7.654	432.98*	0.053*

Note: The table reports mean, standard deviation, skewness, kurtosis, the Jarque-Bera (JB) is the test statistic for the null hypothesis of normality in sample returns distributions. **Q (12),** Ljung-Box statistic up to 12 lags measures serial correlation in series. *, **, and *** refer to 1, 5, and 10 percent statistical significance levels respectively.

Table 2 reports augmented Dickey-Fuller test statistics, and KPSS unit root test statistics for the individual trading volume series, the KPSS test complements the Augmented Dickey–Fuller test and concerns regarding the power of either test can be addressed by comparing the significance of statistics from both tests. A stationary series has significant Augmented Dickey–Fuller statistics and insignificant KPSS statistics. According to Kwiatkowski et al. (1992), as shown in the table, all series exhibit significant serial correlation. Hence, for the sample stocks the rate of information arrival measured by the trading volume is significantly serially correlated, the test statistics of both unit root tests are statistically significant at one percent level, indicating that all sample series are stationary**.**

Table 2: Results of unit root tests

Stock	ADF	KPSS
ARBK	**-3.436**	**1.433**
HBK	**-3.453**	**0.985**
AHLI	**-4.657**	**1.765**
MEIN	**-7.654**	**2.321**
JOFR	**-5.234**	**3.091`**
HOLI	**-3.876**	**1.432**
AIUI	**-7.321**	**1.234**
ARAS	**-4.321**	**0.977**
AAFI	**-5.456**	**2.320**
INVH	**-5.543**	**1.345**
AMWL	**-7.342**	**2.009**
JOMC	**-6.876**	**1.876**
DARA	**-4.321**	**2.654**
JOIT	**-3.654**	**0.876**
UINV	**-5.345**	**0.854**
ULDC	**-6.432**	**1.432**
SPIC	**-4.345**	**0.749**
REDV	**-7.897**	**2.543**
PETT	**-4.231**	**0.965**
JIIG	**-3.436**	**0.882**
ITSC	**-6.121**	**0.722**
JETT	**-5.987**	**1.987**
JTEL	**-6.732**	**2.998**
PRES	**-4.234**	**1.443**
JOPT	**-4.675**	**0.811**
JPHM	**-3.432**	**0.955**
APHC	**-6.765**	**2.218**

Note: The ADF and KPSS tests contain a constant term and augmentations of DF tests are determined according to the AIC. Critical values of ADF and KPSS tests at one percent level are -3.433 and 0.739, respectively.

Table (3) report the results of GARCH (1,1) models, Eq. (7) is estimated excluding the trading volume and using GARCH (1,1) the parameterization.

Table 3: Results of GARCH (1, 1) models

Stock	ϕ	α	$\phi+\alpha$	AIC
ARBK	0.062*	0.864*	0.926	-3.69
THBK	0.132*	0.522*	0.654	-3.77
AHLI	0.207*	0.556**	0.763	-3.89
MEIN	0.176*	0.885*	1.061	-3.31
JOFR	0.132*	0.636*	0.768	-3.77
HOLI	0.107*	0.759*	0.866	-3.49
AIUI	0.145*	0.886*	1.031	-3.99
ARAS	0.054*	0.876*	0.93	-3.75
AAFI	0.165*	0.881*	1.046	-3.59
INVH	0.297*	0.632*	0.929	-3.89
AMWL	0.169*	0.712*	0.881	-3.63
JOMC	0.198*	0.698*	0.896	-3.99
DARA	0.202*	0.665*	0.867	-3.79
JOIT	0.098*	0.743*	0.841	-3.39
UINV	0.175*	0.654*	0.829	-3.99
ULDC	0.143*	0.789*	0.932	-3.59
SPIC	0.234*	0.671*	0.905	-4
REDV	0.127*	0.539*	0.666	-3.51
PETT	0.034*	0.913*	0.947	-3.99
JIIG	0.189*	0.698**	0.887	-3.85
ITSC	0.113*	0.809*	0.922	-3.49
JETT	0.219*	0.608*	0.827	-3.97
JTEL	0.104*	0.711*	0.815	-3.8
PRES	0.116*	0.776*	0.892	-3.59
JOPT	0.145*	0.803*	0.948	-3.92
JPHM	0.227*	0.678*	0.905	-3.71
APHC	0.081*	0.832*	0.913	-3.79

Note: . *, **, and *** refer to 1, 5, and 10 percent statistical significance levels respectively.

The estimated parameters $\hat{\alpha}_1$ and $\hat{\alpha}_2$ are reported in Table 3, to valuate the degree of persistence in volatility we also report $\hat{\alpha}_1+\hat{\alpha}_2$.Table 3 also contains Akaike Information Criterion (AIC) to provide the basis for a comparison of the GARCH models with and without trading volume. All estimated coefficients are statistically significant at one percent level, results also indicate a high degree of persistence in most stocks volatility.

Table 4: Results of GARCH (1,1) models with trading volume

Stock	$\hat{\phi}$	$\hat{\alpha}$	$\hat{\delta} \times 10000$	$\hat{\phi}+\hat{\alpha}$	AIC
ARBK	0.362*	0.342*	2.121*	0.704	-3.65
THBK	0.432*	0.292*	1.541*	0.724	-3.73
AHLI	0.377*	0.326*	0.754*	0.703	-3.85
MEIN	0.346*	0.655*	0.897*	0.939	-3.25
JOFR	0.302*	0.406*	0.008	0.708	-3.73
HOLI	0.277*	0.529*	-0.098**	0.806	-3.45
AIUI	0.315*	0.656*	0.138*	0.971	-3.95
ARAS	0.224*	0.543*	0.798*	0.767	-3.66
AAFI	0.335*	0.651*	-0.104**	0.986	-3.55
INVH	0.054*	0.402*	0.324*	0.456	-3.85
AMWL	0.234*	0.482*	0.265*	0.716	-3.59
JOMC	0.123*	0.397*	0.136	0.520	-3.95
DARA	0.256*	0.435*	4.654*	0.891	-3.75
JOIT	0.268*	0.513*	0.0543*	0.781	-3.35
UINV	0.345	0.424*	7.987*	0.769	-3.95
ULDC	0.313*	0.559*	0.543*	0.872	-3.55
SPIC	0.098*	0.441*	0.008	0.539	-3.96
REDV	0.297*	0.309*	0.035	0.606	-3.47
PETT	0.204*	0.683*	0.876*	0.887	-3.95
JIIG	0.098*	0.468*	0.554*	0.566	-3.81
ITSC	0.283*	0.579*	0.103**	0.862	-3.45
JETT	0.076*	0.378*	0.876*	0.454	-3.93
JTEL	0.274*	0.481*	6.435*	0.755	-3.76
PRES	0.286*	0.546*	0.039**	0.832	-3.55
JOPT	0.315*	0.573*	0.765*	0.888	-3.88
JPHM	0.11*	0.008	0.342*	0.558	-3.67
APHC	0.251*	0.602*	0.643*	0.853	-3.75

Note: *, **, and *** refer to 1, 5, and 10 percent statistical significance levels respectively.

Table (4) report the result of estimation unrestricted version of Eq. (7) including trading volume. The 23 out of 27 cases, the coefficients on trading volume are statistically significant at least at five percent level. These results imply a strong correlation between return volatility and trading volume, which is well documented in previous studies. However, the results also show that in the majority of cases, there is a very small reduction in the volatility persistence. Only for seven stocks in the sample, namely JORDAN PHARMA,JORDAN CONSULTING,SPCZ.INVST.COMD,REAL ESTATE DV,NTERNATIONAL INV,JORDAN EXPRESS, and INV HOUSE, we can observe a relative decrease in volatility persistence. Hence, including trading volume in the conditional variance equation does not result in a significant reduction of volatility persistence for most sample stocks. As we seen in Table 4, the sums of $\hat{\alpha}_1+\hat{\alpha}_2$ are fairly close to unity, and do not undergo noticeable change when compared to the model without the trading volume variable (As seen in Table 3 and Table 4, the AIC measures are lower in all cases for the model with trading volume variable.). These findings are consistent with findings of a number of studies in emerging markets Huang and Yang (2001) in Taiwan have found similar results. including Salman's findings on volume-return relationship for ISE.

Bohl and Henke (2003), and Pyun (2000), however, confirmed that persistence in return volatility tends to disappear when volume is included in conditional variance equation in Polish and Korean stock markets, respectively.Lamoureux and Lastrapes (1990) suggest that after including the proxy for daily information arrivals (trading -volume), the ARCH effect vanishes.

At least part of the persistence of stock volatility can be explained away by information arrivals. In this respect, compared with the empirical evidence on the return-volume relationship for the developed markets, the findings on Jordan stocks do not fully support the existence of Mixed Distribution Hypothesis (MDH) (Gallo and Pacini, 2000; Omran and McKenzie, 2000). These papers among the others, have found a high degree of volatility persistence for the US and UK stocks, there might be several reasons leading to this outcome.

First, the pattern of daily information arrivals and the information content of trading volume may be different in the Jordan stock market than those observed in developed markets. Particularly, as witnessed in many emerging markets majority of stock market participant in Jordan are short-term myopic investors, who frequently engage in speculative activities. Thus, their behavior can be characterized by overreaction to new information and announcements lacking fundamental analysis. Second, the price limits imposed by ASE. Third, the number of transactions rather than the trading volume might be a better proxy to represent daily information arrivals. (see Jones, Kaul and Lipson, 1994).

Conclusion

This paper has investigate the relationship between trading volume and return volatility for 27 individual stocks in Amman Stock Exchange by testing the validity of Mixed Distribution Hypothesis (MDH), when volume is taken as the proxy for the rate of daily information arrivals.
The empirical results verify that there is significant interaction between trading volume and return volatility when volume is entered into variance equation of GARCH-M model, the results of our study are supported by previous empirical evidence by Doe et al. (2008) for Asia Pacific market, and Mustafa and Nishat (2006) for Pakistani market. Thus, these findings provide strong evidence against the validity of MDH in Amman stock Exchange.

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Appendix (1): List of Company's Included in the Sample:

COMPANY'S NAME	COMPANY'S SHORT NAME	SYMBOL
ARAB BANK	ARAB BANK	ARBK
THE HOUSING BANK FOR TRADE AND FINANCE	HOUSING BK TRD FIN	THBK
JORDAN AHLI BANK	JORDAN AHLI BANK	AHLI
MIDDLE EAST INSURANCE	MIDDLE EAST INS	MEIN
JORDAN FRENCH INSURANCE	JOR FRENCH INS	JOFR
THE HOLY LAND INSURANCE	HOLY LAND INS	HOLI
ARAB UNION INTERNATIONAL INSURANCE	ARAB INT UNI INS	AIUI
THE ARAB ASSURERS	ARAB ASSURERS	ARAS
AL-AMIN FOR INVESTMENT	AL-AMIN FOR INV	AAFI
INVESTMENT HOUSE FOR FINANCIAL SERVICES	INV HOUSE	INVH
AMWAL INVEST	AMWAL INVEST	AMWL
JORDANIAN MANAGEMENT AND CONSULTING COMPANY	JORDAN CONSULTING	JOMC
DARAT JORDAN HOLDINGS	DARAT	DARA
JORDAN INVESTMENT TRUST	JOR INV TRUST	JOIT
UNION INVESTMENT CORPORATION	UNION INV	UINV
UNION LAND DEVELOPMENT CORPORATION	UNION LAND DEV	ULDC
SPECIALIZED INVESTMENT COMPOUNDS	SPCZ.INVST.COMD	SPIC
REAL ESTATE DEVELOPMENT	REAL ESTATE DV	REDV
THE REAL ESTATE & INVESTMENT PORTFOLIO CO.	RE ES & INV PORT C	PETT
JORDAN INTERNATIONAL INVESTMENT CO.	INTERNATIONAL INV.	JIIG
ITTIHAD SCHOOLS	ITTIHAD SCHOOLS	ITSC
JORDAN EXPRESS TOURIST TRANSPORT	JORDAN EXPRESS	JETT
JORDAN TELECOM	JORDAN TELECOM	JTEL
JORDAN PRESS FOUNDATION/AL-RA'I	J. PRESS FOUNDAT	PRES
JORDAN PETROLEUM REFINERY	JOR PETROLM REF	JOPT
THE JORDANIAN PHARMACEUTICAL MANUFACTURING	JORDAN PHARMA	JPHM
ARAB CENTER FOR PHARM.& CHEMICALS	ARAB PHARMA CHEM	APHC