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On the Asymmetric and Dynamic Price-volume Nexus: Sector-level Evidence

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Abstract

This study aims to provide an empirical analysis of the return-volume and volatility-volume linkages, using both market- and sector-level data from the emerging equity market of Qatar. The OLS and VAR modelling approaches are employed to explore the contemporaneous and dynamic relations, respectively, between index returns and trading volume, while the volatility-volume relation is examined using an EGARCH-X(1,1) model. The results suggest a positive contemporaneous return-volume relation across almost all sectors, and this relation is found to be asymmetric. Absence of a dynamic relation between returns and volume is detected for the aggregate market and for the majority of sectors. Further, most of the index series exhibit evidence of asymmetry and clustering in return volatility. Finally, lagged values of trading volume appear to supply information useful in forecasting the future dynamics of price variability in all sectors, with the transportation sector representing the sole exception. These results hold practical implications for investors trading on the Qatari market.

JEL classification numbers: C22, C58, D82, E44, G10
Keywords: Qatar Exchange; market sectors; asymmetry; trading volume; volatility; EGARCH.

1 Introduction

Research on the dynamics and consequences of the linkage between stock prices and trading volume has strikingly absorbed academicians and practitioners for decades. This renewed interest is justified by the essential roles that both variables play in financial markets, and by the practical implications derived from their respective behaviours during the alternating episodes of market tranquillity and market turmoil.

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Indeed, the information contained in stock prices typically reflects a vivid picture of many aspects of firms' profiles. In general, investors and fund managers draw upon daily stock price data to capture some vital corporate fundamentals such as earnings/price ratio, book/market ratio, and dividend yield, thereby making sensible investment decisions. Stock market prices can also be indicative of the economic prospects of a country. Moreover, monetary authorities and policymakers incessantly put the direction and magnitude of stock price changes under the microscope, given that such changes may influence the economy's fundamentals in subtle and complex ways over possibly long periods of time.

Equally important, trading volume data, viewed as a proxy variable for the flow of information into the market, can serve a useful function in ameliorating the prediction quality of future returns and return volatility which, in turn, constitute the foundation stones of risk management, equity valuation, and portfolio allocation and rebalancing decisions. Further, volume data are broadly employed to identify the status quo of the market and to help portray its behavior trend. Chordia *et al.* (2000) demonstrate that trading volume is a major determinant of bid-ask spreads. As pointed out by Gallant *et al.* (1992) and Hiemstra and Jones (1994), more knowledge on market microstructure can be acquired through examining the joint dynamics of stock prices and volume than studying only the univariate dynamics of prices.

The relevant research domain provides some theoretical interpretations for the observed price-volume linkage, with the mixture of distributions hypothesis (MDH, henceforth) (Clark, 1973; Harris, 1986; Anderson, 1996; Liesenfeld, 2001) and the sequential information arrival hypothesis (SIAH, henceforth) (Copeland, 1976; Morse, 1980; Jennings and Barry, 1983; Smirlock and Starks, 1985; Brooks, 1998) being the most commonly cited models accounting for such a relation.

The MDH posits that asset prices and trading activity (volume) tend to be positively related because they are together reliant on a common underlying driving factor, which is thought to be the rate of information flow. The joint distribution of trading volume and price is assumed to be bivariate normal conditional on the same underlying latent news arrival. Due to the fact that the random arrival of new pieces of information is unobservable, data on trading volume levels are used as a proxy for it. According to the MDH, all market traders react simultaneously to new information, causing the transition of prices toward new equilibria to occur instantly. This implies that the information content of past observations of trading volume has no significant predictive power for explaining asset price movements, and vice versa, since these two variables exhibit perfect synchronicity in their adjustment to new unexpected information signals (Bollerslev and Jubinski, 1999; Darrat *et al.*, 2003). Within the framework of SIAH, on the other hand, shifts to new equilibria are not of such an instantaneous nature. That is, the dissemination of new pieces of information into the hands of market traders takes place sequentially rather than synchronously and, as a result, the forces of demand and supply interpret and respond to these information signals at various speeds. There exist intermediate equilibrium processes culminating with a general condition of market equilibrium. Hence, the overall market equilibrium is supposed to evolve through a series of successive individual equilibria. Under this scenario, the information contained in past values of trading volume may have the ability to improve the prediction of price changes, and vice versa. This implies a positive causal relationship running from either trading volume or price changes to the other variable.

Despite the vast bulk of scholarly work addressing the relationship between stock prices and trading volumes, the predominant orientation in these studies remains entrenched in the developed capital markets of the US, Japan, and some European countries. Emerging and frontier markets have generally received meagre attention on this topic. Consequently, we contribute to the existing research by closely considering a burgeoning and lucrative emerging market that has been beyond the focus of attention in prior literature, the Qatar Exchange (QE, henceforth).

The main thrust of the current study is to revisit the price-volume relations. Of particular interest, the following issues are empirically examined within both the entire market and each sector of the QE:

i. Does any contemporaneous relation exist between trading volume and price changes (returns)?
ii. Does any causal (dynamic) linkage exist between trading volume and price changes (returns)? And which way is the direction of causality, if any?
iii. Does the volatility of index returns display persistence and asymmetric behavior?
iv. What does the relation between trading volume and price variability look like?

By developing evidence-based answers to these questions, this piece of work contributes to the existing body of research in at least two respects. First, there seems a dearth of studies exploring the stock price-volume relation in the context of emerging markets whose characteristics and dynamics are, in one way or another, dissimilar to those of their more developed counterparts. To date, this relation has not been examined using data from the emerging equity market of Qatar. To the author's best knowledge, the only exception is the work of Abdalla and Al-Khouri (2011), which focuses on the Gulf Cooperation Council (GCC) countries and utilizes only aggregate market data. The current study constitutes one such attempt. Second, the empirical investigation of the price-volume relation in previous studies has relied on either aggregate market- or firm-level data. Surprisingly, no research thus far has attempted to conduct a sector-level analysis on such a relation, an urgent void in the literature that provides a rationale for this study. On the one hand, market-level data may potentially introduce aggregation bias into the empirical analyses, given that it encompasses heterogeneous industries with rather disparate market capitalizations, divergent levels of trading activity, and different reactions to market cycles. On the other hand, the analysis of sample firm-level data may fall short of building up a complete picture of the market dynamics for a certain country. Arguably, the industry-based analysis of the price-volume linkage is expected to yield more accurate results and new insights that might otherwise be difficult to obtain with the other two approaches. It can also serve as a beneficial complement to the traditional analysis that depends on highly aggregated market data or firm-level data.

The remainder of the study proceeds as follows. Section two sheds light on the Qatari capital market. Section three provides a succinct review of prior research. Data description and preliminary analyses are presented in Section four. In Section five, the contemporaneous and dynamic relations between stock index returns and trading volume are assessed. Subsequently, the relation between conditional return volatility and trading volume is examined in Section six. Finally, Section seven sums up and concludes.

2 The Qatari Capital Market

Over recent years, Qatar has emerged as one of the most rapidly growing economies around the globe, possessing the third-largest proven reservoir of natural gas in the world and is currently sitting atop one of the world's leading exporter of Liquefied Natural Gas (LNG). According to the IMF country report (2013), Qatar's Real Gross Domestic Product (GDP) is projected at 6.8% in 2014, fuelled mainly by a growth rate of 10.4% in the non-hydrocarbon sector. The overall fiscal surplus (% of the GDP) is expected to stand high at 9.3 in 2014, and the external current account (% of the GDP) is projected to show a surplus of 25.1 in 2014.

Commencing its activities in May 1997, the QE initially accommodated only 17 participant companies with an overall market capitalization of nearly $2.588 billion. By the end of 2015, this number rose to 45 companies, with a combined market capitalization hitting $151.555 billion, or as much as three-fourth of the country's GDP. The total volume of shares traded on the QE registered 2.302 billion shares worth $25.676 billion at the end of 2015, compared to 12.317 million shares exchanged at an aggregate value of $67.929 million recorded in 1997. The number of transactions executed during 2015 reached 1,190,807 as opposed to only 1,585 deals conducted in 1997.

Taking a quantum leap in developing the country's debt instruments market and expanding the variety of investment vehicles available to institutional investors in particular, Qatar's central bank approved the listing of Qatari government T-bills on the exchange in December 2011. There are also plans afoot to list government bonds as well as Sukuk (i.e., Islamic bonds) for trading on the Qatari market.

At the outset, the shareholding companies were categorized into four key sectors that include Insurance, Industrials, Banking and Financial Institutions, and Services. However, in April 2012 the QE reclassified the listed companies into seven sectors which are Banks and Financial Services (BFS, henceforth), Consumer Goods and Services (CGS, henceforth), Industrials (IND, henceforth), Insurance (INS, henceforth), Real Estate (RST, henceforth), Telecommunications (TLC, henceforth), and Transportation (TRP, henceforth), aiming to keep pace with world industry standards and to offer investors outstanding market visibility.

The diversity of these sectors is illustrated in Table 1, which displays a statistical snapshot of their key market indicators by the end of 2015.

Table 1: A snapshot of the QE market sectors during 2015

Sector	BFS	CGS	IND	INS	RST	TLC	TRP
Market capitalization	74.955	18.123	56.204	6.134	7.922	14.683	7.401
Trading value	19.083	5.289	11.887	1.479	10.686	3.856	2.319
Number of transactions	322,299	98,899	289,472	30,376	250,970	140,618	58,173
Weight in All Share Index (%)	39.31	5.38	22.28	5.80	17.10	3.97	6.16

Notes: This table reports some main market indicators for the various sectors of the QE for the year ended 2015. These sectors include Banks and Financial Services (BFS), Consumer Goods and Services (CGS), Industrials (IND), Insurance (INS), Real Estate (RST), Telecommunications (TLC), and Transportation (TRP). Figures of sector market capitalization and trading value are reported in billions of US$.

As can be seen from Table 1, the BFS sector appears to dominate the Qatari capital market, making up 40.42% of the QE total market capitalization worth $74.955 billion and 34.95% of the QE total trading volume worth $19.083 billion. At the opposite extreme, the INS sector seems to play a slight role in the QE, constituting merely 3.31% of the QE total market capitalization with a value of $6.134 billion and 2.71% of the market's total trading volume worth $1.479 billion. The IND ranks the second largest sector in terms of market capitalization and trading volume, respectively, accounting for 30.31% ($56.204 billion) and 21.77% ($11.887 billion) in relation to the QE total market capitalization and trading volume, respectively. Finally, with respect to the number of transactions executed by sector, the BFS comes first with 593,818 representing 28.85% of the total number of executed transactions, whilst the INS comes last with only 58,021 transactions making up 2.82% relative to the overall number of transactions during 2015.

3 Prior Research

This section provides a succinct review on the debate over the return-volume and volume-volatility relations during the past two decades and half. A broad review of earlier literature (before the 1990s) can be found in Karpoff (1987).

Using daily data on S&P composite index and total NYSE trading volume, Gallant *et al*. (1992) find a positive relation between conditional return volatility and trading volume. Their evidence is broadly consistent with the empirical findings in Lamoureux and Lastrapes (1990) and Schwert (1989).

Hiemstra and Jones (1994) explore the dynamic linkages between stock prices and trading volumes, employing daily Dow Jones stock prices and percentage changes in NYSE trading volume. They report evidence of nonlinear bidirectional causality between the two variables. Further, after controlling for volatility persistence in returns, the authors continue to find that volume has strong nonlinear explanatory power for stock returns.

Brailsford (1996) examines the relationship between three different measures of trading volume (i.e., number of share transactions, number of shares traded, and total dollar value of shares traded) and return volatility, using daily data from the Australian stock market. He finds that the relationship is positively significant across the alternative measures of volume. Further, the volume-price change relationship is found to be asymmetric.

Controlling for firm size effects and thin trading, Chordia and Swaminathan (2000) look into the impact of the magnitude of volume traded on the lead-lag relation of stock returns. They provide evidence that trading volume is a major determinant of the cross-autocorrelation patterns observed in stock returns.

Lee and Rui (2000) examine the contemporaneous and causal relationships between trading volume, stock returns and return volatility in China's four stock exchanges (i.e., Shanghai A Index, Shanghai B Index, Shenzhen A Index, Shenzhen B Index). They provide evidence of a positive contemporaneous correlation between returns and volume in all four markets. Likewise, using 5-minute intraday transaction data for all DJIA stocks, Darrat *et al.* (2003) report weak evidence of contemporaneous relations and robust evidence of significant causality between volume and return volatility, thus providing strong support for the SIAH but not the MDH.

Kim *et al.* (2005) look into the dynamic causal relations between equity volatility and trading volume for the Korean market. They find, among other things, that stock price volatility is only related to domestic investors' trading volume prior to the 1997 financial crisis, whereas a feedback relation between foreign investors' trading volume and volatility is detected after the crisis.

Using intraday data for E-mini S&P 500 index futures and Japanese Yen Foreign Exchange (FX) Futures, Chen *et al.* (2008) provide evidence of a significant bidirectional relationship between return volatility and trading imbalances, where the latter is used as a proxy for private information incorporating net of buy and seller orders. These findings correspond to those of Sarwar (2003) and Fung and Patterson (1999).

Focusing on the UK market, Ané and Ureche-Rangau (2008) look into the degree to which the temporal dependence of returns volatility and trading volume is compatible with an MDH model. The results indicate, *inter alia*, that although the two variables may share common short-term movements, they exhibit substantially dissimilar behaviours in the long run. This evidence lends support to the specification of Liesenfeld (2001), which differentiates volume and volatility for their long-run behavior.

Girard and Omran (2009) investigate the interaction of volatility and volume, using daily data from the Egyptian equity market over the period January 1998-May 2005. The results indicate that the incorporation of lagged volume traded into the conditional variance specification does not alter the persistence of GARCH effects. Nevertheless, when the trading activity is partitioned into expected and unexpected components, GARCH effects become smaller as proposed by the MDH.

Analysing monthly S&P 500 stock market data for the period from February 1973 to October 2008, Chen (2012) provides evidence of an asymmetric contemporaneous linkage between equity returns and trading volume. Moreover, employing a joint two-state Markov-switching model, the author demonstrates the ability of equity returns to predict trading volume in both bear and bull markets.

Jena and Dash (2014) examine the relationship between volatility and two trading activity variables, open interest and trading volume, with a view to unveiling the sources of uncertainty in India’s Nifty index futures price. They find that contemporaneous open interest and lagged trading volume play a significant role in explaining the volatility of the Nifty index futures return.

Using data from the Australian stock market, Shahzad *et al*. (2014) investigate the impact of institutional and individual trading on volatility. They generally find that the trades conducted by individual investors are more significant in explaining volatility than the trades carried out by institutional investors. They also find that absolute order imbalance has a marginal role in driving volatility.

More recently, Bose and Rahman (2015) explore the linkage between return volatility and trading volume for 15 selected stocks from the Dhaka Security Exchange in the emerging Bangladesh economy. They report compelling evidence that, in almost all cases, neither contemporaneous nor lagged volume provides important information that may motivate investors to trade. Umutlu and Shackleton (2015) report evidence that net sales of foreign investors have an increasing impact on volatility in the Korean stock market.

In addition to these one-country studies, there exists a strand of the literature that looks into the relations between stock prices, volume of trading, and volatility on a regional or even multi-country scale. For instance, Saatcioglu and Starks (1998) employ monthly aggregate data for a set of six Latin American stock markets. They find that the vast majority of these markets exhibit significant contemporaneous correlation between returns and volume. The

Granger causality tests yield some evidence supporting volume leading returns but not vice versa, a result in sharp contrast to the findings of some earlier studies (e.g., Smirlock and Starks, 1988; Bhagat and Bhatia, 1996).

Investigating the equity markets of New York, Tokyo, and London, Lee and Rui (2002) find that trading volume helps to forecast the return volatility but not the level of returns in all three markets. This evidence seems to be in line with Clark (1973) mixture model in which trading volume does not yield a better forecast of future stock returns.

Employing data from the GCC equity markets, Abdalla and Al-Khouri (2011) find that returns lead volume in five out of the seven markets. Further, the EGARCH model indicates that lagged volume has a positive impact on return volatility in four out of the seven markets.

Applying a bivariate GJR-GARCH specification on datasets from ten Asian equity markets, Chuang *et al.* (2012) provide evidence of dynamic relations between lagged equity returns and current trading volume for all sample equity markets. The results also show a strong asymmetric effect on return volatility across all sample equity markets.

In sum, notwithstanding its abundance, the repository of empirical research appears to be silent on unravelling the price-volume nexus at the sector level. Consequently, the current paper sets out to address this void in the literature.

4 Data and Exploratory Analysis

4.1 Data Description

The dataset includes daily stock index prices and the corresponding trading volumes for the entire market and the individual seven sectors. The sample period begins 1 April 2012 and ends on 29 January 2015, totalling 705 daily observations for each variable. The newly reclassified seven sectors made their formal debut on 1 April 2012, thereby dictating the start date of the sample period. The dataset is retrieved from the QE website. Because the QE maintains an array of market-wide indices for stock prices, the All Share Index (ASI, Henceforth) price series is specifically used to represent the entire market. A free-float market capitalization-weighted index, the ASI tracks the performance of all listed stocks with a minimum velocity of 1%. Velocity is the percentage of total shares that exchange hands over a one-year period. Constituent stocks of the ASI are further uniformly subsumed into the seven sector indices.

4.2 Preliminary Statistics

As a prelude to the empirical analyses, a series of daily index returns is generated for the market as well as for each sector. Daily index returns are computed as the natural logarithm of the ratio of consecutive closing index levels, $\ln (P_{i,t} / P_{i,t-1}) \times 100$. In addition, following some relevant research works (e.g., Gallant *et al.*, 1992; Kim *et al.*, 2005; Ané and Ureche-Rangau, 2008), this study employs the total Qatari riyal value of shares as a measure of trading volume. A major advantage of this measure is that it is not affected by such events as stock dividends and stock splits.

Table 2 displays some statistical characteristics and diagnostic test statistics relating to the index return and trading volume series of the aggregate market as well as the various sectors of the QE. As seen from Table 2, all index series display positive mean returns over the sample period. The CGS sector achieves the highest average daily return of 0.083, while the lowest average daily return of 0.026 is earned by the BFS sector. Compared to the other indices, the IND appears to experience the largest degree of return variability with a standard deviation of 4.461. The empirical return distribution is positively skewed for ASI, BFS, IND, TLC, and TRP, but negatively so for the remaining indices. With no exception, all index return series show excess kurtosis, confirming that the distributions of these series are far from being normal. As corroborating evidence, the Jarque-Bera test rejects the null hypothesis of normality for all index return distributions at 1% significance level. The null hypothesis of no serial correlation up to lag order 10 is rejected for the return series of ASI, BFS, IND, and TLC, as shown by the statistics of the Ljung-Box (L-B) test. The ARCH Lagrange Multiplier (LM) test rejects the null hypothesis that the error terms are conditionally homoscedastic up to lag order 10 for all return series, except for those of the INS and RST sectors. This finding points to the presence of a time-varying second moment in the return series.

With respect to the univariate properties of trading volume, some observations from Table 2 stand out. In terms of market trading activities, the BFS seems to be the leading sector in the Qatari market, registering a mean daily volume traded of QR85.44 million, while the INS comes bottom of all the seven sectors with a mean daily volume traded of only QR4.14 million. The RST sector appears to exhibit the highest level of trading volume fluctuations, recording a standard deviation of QR184.28 million which is about 2.5 times its mean trading volume. Analogous to the index return distributions, all trading volume series appear to be much leptokurtic, with the Jarque-Bera test providing overwhelming evidence of non-normality of the individual volume series at the 1% significance level.

Table 2: Descriptive statistics of the ASI and sector indices.

Index	ASI	BFS	CGS	IND	INS	RST	TLC	TRP
Returns								
Mean	0.043	0.026	0.083	0.069	0.044	0.032	0.040	0.037
SD	0.408	0.474	0.731	4.461	0.989	0.839	0.860	0.649
Skewness	0.376	0.731	-0.945	0.302	-0.301	-0.142	0.405	0.886
Kurtosis	4.450	5.297	22.074	156.079	5.051	9.646	5.091	6.689
J-B	36.058	100.359	497.285	317.3	61.865	599.320	68.072	226.901
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L-B (10)	22.658	22.647	5.627	40.018	7.372	7.376	16.838	5.042
	(0.007)	(0.007)	(0.777)	(0.000)	(0.598)	(0.598)	(0.051)	(0.831)
ARCH (10) LM	30.449	57.096	26.601	34.464	15.827	6.878	21.903	16.737
	(0.007)	(0.000)	(0.003)	(0.000)	(0.104)	(0.737)	(0.015)	(0.080)
Trading Volume								
Mean	276.261	85.449	32.475	55.087	4.142	79.254	13.781	15.969
SD	210.356	54.501	22.425	38.081	5.343	184.284	11.374	12.006
Skewness	2.886	3.585	1.525	1.984	3.354	4.466	2.043	2.028
Kurtosis	11.902	26.812	5.954	8.084	17.559	21.629	8.353	8.719
J-B	152.878	840.261	244.806	565.003	349.784	579.686	615.954	667.783
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
L-B (10)	36.431	51.912	19.006	22.081	14.937	36.327	39.459	32.713
	(0.000)	(0.000)	(0.025)	(0.009)	(0.073)	(0.000)	(0.000)	(0.000)
ARCH (10) LM	19.714	2.899	15.965	37.722	31.801	32.637	14.463	30.178
	(0.032)	(0.984)	(0.101)	(0.000)	(0.000)	(0.000)	(0.153)	(0.001)

Notes: This table reports summary statistics (the first four moments) of stock returns and trading volume for the aggregate market and the various sectors of the QE. It also reports the results of some diagnostic checks. The indices are All Share Index (ASI), Banks and Financial Services (BFS), Consumer Goods and Services (CGS), Industrials (IND), Insurance (INS), Real Estate (RST), Telecommunications (TLC), and Transportation (TRP). SD is the standard deviation. The first and second moments of trading volume are expressed in millions of Qatari riyals. J-B is the Jarque-Bera test for normality. L-B (10) is the Ljung-Box statistic that tests the null hypothesis of no autocorrelation up to lag order 10 in return and trading volume series. ARCH (10) LM is the χ^2 statistics of the Lagrange Multiplier (LM) test for the presence of ARCH effects in the first 10 lags, with the null hypothesis of no heteroskedasticity. *P*-values are provided in parentheses.

The results of the Ljung-Box (L-B) test on the first 10 lags suggest the existence of serial correlation in all volume series. ARCH effects appear to be substantially present in the volume series of ASI, IND, INS, RST, and, TRP sectors, as indicated by the statistics of the ARCH Lagrange Multiplier (LM) test. However, ARCH effects are not very strong for BFS, CGS, and TLC sectors.

4.3 Trend and Stationarity Analyses

It is well documented that many financial time series tend to reveal signs of trending behavior or nonstationarity in the mean. The trend analysis aims to ascertain whether the observations of a series show a pattern of sustained upward or downward movement over time, while the stationarity analysis is used to determine if a series has time-dependent moments (Mills and Markellos, 2008; Kantz and Schreiber, 2004). There exists ample evidence that trading volume series show linear and nonlinear time trends (e.g., Chen *et al*., 2001; Lee and Rui, 2002; Chuang *et al*., 2012). As such, a preliminary econometric task is to detect the presence of such time trends in each trading volume series. For this purpose, the following regression specification is estimated:

$$V_t = \alpha + \beta_1 t + \beta_2 t^2 + \varepsilon_t \tag{1}$$

where V_t is the raw observations of trading volume for each index, t and t^2 denote linear and quadratic time trend variables, respectively.

As shown in Equation (1), trend stationarity in volume series is tested through regressing the series on a deterministic function of time. A quadratic time trend term is also included to capture a potential nonlinear time trend in volume data. Panel A of Table 3 lists the estimates of the regression model described by Equation (1).

Table 3: Trend and unit root tests

Panel A. Linear and nonlinear time trends in trading volume series

Index	ASI	BFS	CGS	IND	INS	RST	TLC	TRP
α	372.14 [10.838]***	122.208 [14.484]***	53.624 [15.330]***	66.877 [11.153]***	4.159 [4.979]***	78.956 [2.603]**	25.631 [14.700]***	20.485 [11.208]***
β_1	-1.512 [-3.098]***	-0.749 [-6.246]***	-0.286 [-5.758]***	-0.349 [-4.096]***	-0.029 [-2.522]**	0.212 [3.910]**	-0.178 [-7.201]***	-0.137 [-5.287]***
β_2	0.004 [2.923]***	0.002 [6.746]***	0.001 [4.858]***	0.001 [5.019]***	0.001 [3.887]***	-0.001 [-0.979]	0.001 [6.588]***	0.001 [6.525]***
F-T	4.846**	23.399***	20.650***	17.236***	19.819***	3.139**	27.092***	29.726***

This panel displays the coefficient estimates resulting from regressing volume trading series on linear as well as nonlinear time trend variables. F-T is the F test for the overall goodness of fit of the regression model for each index. The *t*-statistics are provided in square brackets. *** and ** denote statistical significance at the 1% and 5% levels, respectively.

Panel B. Results of ADF and PP tests for stationarity.

Index	**ASI**	**BFS**	**CGS**	**IND**	**INS**	**RST**	**TLC**	**TRP**
Returns								
Lags	0	9	0	5	0	0	6	0
ADF	-16.224 (0.000)	-5.134 (0.000)	-21.039 (0.000)	-11.495 (0.000)	-19.211 (0.000)	-16.526 (0.000)	-6.038 (0.000)	-14.725 (0.000)
PP	-16.275 (0.000)	-16.907 (0.000)	-20.916 (0.000)	-82.764 (0.000)	-19.215 (0.000)	-16.561 (0.000)	-17.706 (0.000)	-14.876 (0.000)
Trading Volume								
Lags	2	2	3	0	0	1	1	2
ADF	-3.870 (0.000)	-5.790 (0.000)	-5.545 (0.000)	-10.339 (0.000)	-10.192 (0.000)	-4.146 (0.001)	-8.447 (0.000)	-6.470 (0.000)
PP	-6.584 (0.000)	-12.953 (0.000)	-10.109 (0.000)	-10.371 (0.000)	-10.370 (0.000)	-5.574 (0.000)	-13.469 (0.000)	-11.859 (0.000)

This panel reports the results of the Augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit root tests. Both tests are applied to return and detrended trading volume series relating to the whole market and each sector. The null hypothesis in ADF and PP tests is that the time series is nonstationary. The appropriate lag order is chosen by the Akaike Information Criterion (AIC). *p*-values are provided in parentheses. The critical values for either ADF or PP test, with a constant term, are -3.450 and -2. 870 at the 1% and 5% levels of significance, respectively. The critical values are obtained from MacKinnon (1996).

The results indicate that the coefficient estimates for both linear and nonlinear time trends in each index regression are statistically significant at the 5% level or better, with the RST sector being the only exception. Specifically, the quadratic term coefficient for the RST is insignificant. In addition, the bottom row of Panel A of Table 3 provides the *F*-test statistics that show that the explanatory variables in each index regression are jointly statistically significant at the conventional levels. Hence, a trading volume series adjusted solely for a linear time trend is employed for the RST sector in the subsequent analysis. For the remaining indices, the trading volume series with linear and nonlinear time trends removed are used. These detrended volume series are represented by the residuals of regression Equation (1). For expositional purposes, detrended trading volume series for each index is henceforth referred to as trading volume or volume.

The next procedure is to verify that the individual series of index returns and detrended trading volume are stationary. To this end, the Augmented Dickey-Fuller test (ADF) (Dickey and Fuller, 1979, 1981) and the nonparametric Phillips-Perron test (PP) (Phillips and Perron, 1988) are considered in the analysis. Alexander (2001) indicates that the PP test is more useful when the dataset under investigation exhibits GARCH effects.

Panel B of Table 3 reports the results of the ADF and PP tests. The ADF and PP tests consistently reject the null hypothesis of a unit root for each series of the index returns and detrended trading volume at the 1% significance level, suggesting that all series are stationary processes.

5 Index Returns and Trading Volume

5.1 Contemporaneous Relation

The first issue to consider is the contemporaneous relation between stock index returns and trading volume across the entire market and the separate market sectors, and whether or not the nature of such a relation is asymmetric. In this context, the following OLS regression model is estimated:

$$DV_t = \alpha + \psi_1 R_t + \psi_2 M_t R_t + \varepsilon_t \quad (2)$$

where DV_t is the detrended trading volume on day t, R_t is the index return, and M_t is a dummy variable that takes on the value of one if $R_t < 0$ and zero otherwise.
The statistical significance of the coefficient ψ_1 is indicative of a contemporaneous relation between index returns and trading volume, whereas the asymmetry of the relation is captured by the coefficient ψ_2. Brailsford (1996) points out that if the estimate value of ψ_2 is found to be statistically significant and negative, this would indicate that the response slope for negative returns is smaller than that for non-negative returns, which corresponds with the asymmetric behavior of return-volume relation.
Table 4 presents the parameter estimates of the regression model in Equation (2). At the aggregate market level, there exists a positive contemporaneous relation between the ASI returns and trading volume, as shown by the significant coefficient ψ_1, a result consistent with those of most previous research (e.g., Saatcioglu and Starks, 1998; Lee and Rui, 2000; Darrat *et al*., 2003; Chen, 2012; Chuang *et al*., 2012). Nonetheless, this relation appears not to be asymmetric, as demonstrated by the statistical insignificance of the coefficient ψ_2.

Table 4: Relationship between stock index returns and detrended trading volume

Index	**ASI**	**BFS**	**CGS**	**IND**	**INS**	**RST**	**TLC**	**TRP**
α	-7.833 [-0.450]	-8.381** [-2.049]	-2.557* [-1.718]	-1.156 [-0.576]	-0.495 [-1.275]	-20.801 [-1.503]	-2.445*** [-2.969]	-3.669*** [-4.535]
ψ_1	82.587** [2.803]	41.970*** [4.631]	8.643*** [3.441]	0.665 [1.068]	1.258** [2.556]	67.391*** [3.460]	4.055*** [3.810]	11.544*** [8.735]
ψ_2	-34.362 [-0.394]	-46.087** [-2.582]	-9.552** [-2.357]	-3.032*** [-3.365]	-1.391* [-1.769]	-69.013** [-2.084]	-8.093*** [-4.164]	- 14.957*** [-5.819]
F-T	3.039**	11.898***	6.045***	7.359***	3.434**	6.546***	9.056***	39.062***

Notes: This table displays the coefficient estimates resulting from regressing detrended trading volume on index returns. ψ_1 captures the contemporaneous association between the two variables. ψ_2 allows for asymmetry in the relation. F-T is the F test for the overall goodness of fit of the regression model for each index. The indices under study are All Share Index (ASI), Banks and Financial Services (BFS), Consumer Goods and Services

(CGS), Industrials (IND), Insurance (INS), Real Estate (RST), Telecommunications (TLC), and Transportation (TRP). *The t*-statistics are provided in square brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

At the sector level, the results of Table 4 show that the estimates of ψ_1 are significantly positive across the individual sectors, with the exception of the IND sector, suggesting the existence of a positive contemporaneous relation between stock returns and trading volume. Ciner (2002) indicates that, in the realm of MDH, the contemporaneous return-volume relation implies that the two market variables are endogenously determined and react to the same exogenous variable couched in the rate of information flow into the market.

Further, the slope coefficients ψ_2 for all sectors are significantly negative, providing evidence of asymmetric contemporaneous relations between returns and volume. Compatible with the findings reported by Smirlock and Starks (1985), Brailsford (1996), and Ratner and Leal (2001), such a result implies that the response of trading volume of the Qatari market sectors to an upward momentum in stock prices seems to be more intense than to a downward momentum.

Finally, the *F*-test statistic for the null hypothesis of joint insignificance of the regression coefficients (i.e., $\alpha = \psi_1 = \psi_2 = 0$) is strongly rejected across all indices, confirming the goodness of fit of the regression model.

5.2 Dynamic Relation

The second issue under scrutiny is whether the information inherent in past observations of trading volume is able to enhance the predictability of stock returns, and vice versa. The vector autoregressive (VAR) modelling approach fits well for this analysis. In particular, this approach gives the opportunity to investigate the dynamic relation between index returns and trading volume using the analysis of Granger causality (Granger, 1969, 1988). As the individual return and detrended trading volume series of each index turn out to be *I*(0) processes, the Granger causality test involves estimating the following bivariate VAR model with lag order *p*:

$$DV_t = \varphi_0 + \sum_{j=1}^{p} \varphi_1 DV_{t-j} + \sum_{j=1}^{p} \varphi_2 R_{t-j} + \varepsilon_{DV,t}$$

$$R_t = \delta_0 + \sum_{j=1}^{p} \delta_1 R_{t-j} + \sum_{j=1}^{p} \delta_2 DV_{t-j} + \varepsilon_{R,t} \qquad (3, 4)$$

where φ_0 and δ_0 represent constant terms. φ_2 (δ_2) is the parameter of R_{t-j} (DV_{t-j}) which shows how much the past values of index returns (trading volume) explain the current value of trading volume (index returns). $\varepsilon_{DV,t}$ and $\varepsilon_{R,t}$ denote the stochastic error terms assumed to be serially uncorrelated with zero mean and finite covariance matrix.

In Equation (3), if a standard *F*-test fails to reject the null hypothesis that all the estimated coefficients on lagged returns are statistically equal to zero (i.e., $\varphi_2 = 0$ for all *j*), then returns do not Granger-cause trading volume. Likewise, in Equation (4), if the estimated coefficients on lagged volume are jointly equal to zero (i.e., $\delta_2 = 0$ for all *j*), then trading volume does not Granger-cause returns. If both φ_2 and δ_2 are statistically different from zero, then a bidirectional relation exists between returns and volume.

The optimal lag order (p) in the VAR model for each index is selected based on the Akaike Information Criterion (AIC). The OLS technique is employed to estimate the VAR system, and the standard errors of the parameter estimates are adjusted for heteroskedasticity and autocorrelation using the Newey-West procedure (1987). The above equations are applied to the aggregate market and the various sectors separately. Panels A and B of Table 5 display causality test results obtained from the estimation of Equations (3) and (4), respectively.

Table 5: Test results of dynamic relation between index returns and detrended trading volume

Index	**ASI**	**BFS**	**CGS**	**IND**	**INS**	**RST**	**TLC**	**TRP**
lags	2	2	1	1	2	2	2	2
Panel A.								
H0: φ_2 = 0 for all *j*	0.105 (0.901)	0.378 (0.685)	7.944 (0.005)	6.367 (0.000)	0.186 (0.666)	0.383 (0.682)	3.511 (0.031)	2.217 (0.111)
Panel B.								
H0: δ_2 = 0 for all *j*	0.152 (0.859)	0.196 (0.822)	0.549 (0.459)	0.577 (0.796)	0.657 (0.448)	1.512 (0.222)	3.428 (0.034)	0.209 (0.811)

Notes: This table presents the results of Granger causality test within the context of VAR modeling. Panel A provides the results of testing the null hypothesis that returns do not Granger-cause trading volume, while Panel B provides the results of testing the null hypothesis that trading volume does not Granger-cause returns. The cells in Panels A and B contain the F-statistics as well as corresponding significance levels given in parentheses. The indices under study are All Share Index (ASI), Banks and Financial Services (BFS), Consumer Goods and Services (CGS), Industrials (IND), Insurance (INS), Real Estate (RST), Telecommunications (TLC), and Transportation (TRP). The appropriate lag lengths are identified using the Akaike Information Criterion (AIC). Standard errors are corrected for heteroskedasticity and autocorrelation using the Newey-West procedure (1987).

At the aggregate market level, the *F*-statistics in Panels A and B seem to be highly insignificant, providing evidence of no causal linkage between the ASI returns and volume in either direction. Thus, in the spirit of Granger causality, past information of the ASI returns or trading volume cannot be employed to forecast the behavior of the other variable. As such, it appears that the MDH is more relevant than the SIAH to explain the return-volume linkage in the Qatari market. This result is in line with that reported in Blasco *et al*. (2005), but at odds with the ones obtained by Gallant *et al*. (1992), Ratner and Leal (2001), and Chen (2012).

As for the lead-lag linkage at the sector level, the results shown in Panels A and B of Table 5 reveal some salient observations. First, for the TLC sector, a significant feedback relation is detected between returns and volume at the 5% level, demonstrating that the information contained in lagged values of trading volume can be used to improve the forecastability of returns in this sector in the short run, and vice versa. Second, there exists a significant unidirectional causality running from returns to volume in the CGS and IND sectors at the 1% level. This finding implies that returns have important information content for upcoming trading activities in the two sectors, with the reverse case being denied. Third and last, for the rest of sectors (i.e., BFS, INS, RST, and TRP), the *F*-statistics seem to be considerably insignificant in either direction, suggesting the presence of an independence relation between returns and volume in these sectors.

To sum up, the empirical examination of the return-volume relation in the Qatari market reveals that the nature of this relation seems to be contemporaneous and asymmetric, albeit not dynamic in the sense of Granger causality, in the majority of cases. The results based on market-level data are strongly in favour of the theoretical framework of the MDH, but those derived from sector-level data provide only partial support for the MDH.

6 Trading Volume and Conditional Volatility

The last objective of this study is to characterize the nature of the relationship between trading volume and price variability in the Qatari market. To accomplish this objective, an Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) specification is employed. This class of GARCH family models enjoys the advantage of tackling some observed time series properties of asset returns such as volatility clustering (i.e., high [low] price variations are more likely to be followed by high [low] price variations of either sign) and asymmetry in volatility (i.e., negative price innovations tend to trigger more volatility than do positive innovations of equal magnitude). In particular, unlike conventional GARCH frameworks such as the ARCH by Engle (1982) and GARCH by Bollerslev (1986), the EGARCH model, introduced by Nelson (1991), averts potential misspecification in the conditional volatility process through not imposing a symmetrical response of volatility towards negative and positive price shocks, thus capturing the stylized fact of asymmetry in asset return volatility (Glosten *et al*., 1993; Vanden, 2005).

The volume-volatility linkage is examined using an EGARCH-X(1,1) model that accommodates lagged values of volume as an exogenous parameter in the conditional variance equation. In this context, trading volume is employed as a proxy variable reflecting the rate of information flow into the market to explain current price variability. The EGARCH-X(1,1) model is expressed as follows:

$$R_t = \alpha_0 + \sum_{j=1}^{p} \alpha_i R_{t-j} + \varepsilon_t \tag{5}$$

where $\varepsilon_t | \Omega_{t-1} \sim N(0, \sigma_t^2)$

$$\ln(\sigma_t^2) = \beta_0 + \beta_1 \frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} + \beta_2 \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \xi DV_{t-1} \tag{6}$$

where R_t is the daily index return, α_0 and β_0 are constant terms, and ε_t is the residual error term assumed to follow a Gaussian distribution with a zero mean and time varying variance σ_t^2, conditional on the information set Ω_{t-1} up to day t-1.

As shown in the conditional mean Equation (5), a statistically significant α_i would indicate the impact of own lagged returns. For consistency purposes, the appropriate lag orders identified in Section IV for the bivariate VAR system of equations are employed in the

AR(p) conditional mean equation. Specifically, one lag is used for the return series of CGS and IND, while two lags are used for the remaining series.

In the conditional variance Equation (6), β_1 represents the parameter coefficient of the ARCH term (i.e., ε_{t-1}), which measures the impact of preceding error terms (i.e., innovations) on the contemporaneous volatility. β_2 is the parameter coefficient of the GARCH term (i.e., σ^2_{t-1}) which measures the effect of the information contained in past conditional volatility values on the contemporaneous volatility. A significantly positive β_2 is indicative of volatility clustering or persistence. The coefficient γ captures the presence of asymmetric effect, which, if negative and statistically significant, gives an indication that negative price shocks (bad news) have a stronger impact on conditional volatility than do positive shocks (good news) of the same size. $\varepsilon_{t-1} / \sqrt{\sigma^2_{t-1}}$ denotes the standardized residuals at day t-1. The parameter coefficient ξ measures the impact of lagged detrended trading volume on the contemporaneous conditional volatility.

The parameter estimates of Equations (5) and (6) are obtained by maximizing the conditional normal log-likelihood function. The Quasi Maximum Likelihood Estimation (QMLE) method of Bollerslev and Wooldridge (1992) is utilized to compute the standard errors of the estimated coefficients. As indicated by Lumsdaine (1996), the QMLE procedure generates standard errors robust to any deviation from the Gaussian assumption. In addition, the relative importance of asymmetry, suggested by Booth *et al*. (1997), in each index return is constructed using the following formula:

$$RA = |-1+\gamma_i| / (1+\gamma_i) \tag{7}$$

A resulting relative asymmetry value equal to one signifies the absence of asymmetric effect, but greater (lower) than one indicates a negative (positive) asymmetry. If the coefficient of the asymmetric term, γ , for index i is statistically insignificant, then the asymmetry ratio is set to a value of one.

The QMLE estimates of Equations (5) and (6), along with the associated p-values, are presented in Panels A and B of Table 6, respectively. A perusal of the results shown in panel A unveils that the first order autoregressive coefficient is statistically significant for the return series of INS, RST, and TRP sectors at the 5% level or better, implying that returns in these sectors are dependent on their respective values of the previous day. However, the second order autoregressive coefficient is statistically insignificant for all return series, except for that of the INS sector.

With regard to the estimation results of the conditional variance equation, several observations can be inferred from Panel B of Table 6.

Table 6: Parameter estimates of the EGARCH (1,1) model with detrended trading volume

Index	**ASI**	**BFS**	**CGS**	**IND**	**INS**	**RST**	**TLC**	**TRP**
Panel A: Conditional Mean Equation Coefficients								
α_0	0.055 (0.037)	0.002 (0.956)	0.049 (0.103)	0.219 (0.053)	0.037 (0.194)	0.022 (0.681)	0.050 (0.336)	-0.002 (0.959)
α_1	0.086 (0.169)	0.025 (0.689)	-0.012 (0.924)	-0.062 (0.562)	0.106 (0.032)	0.082 (0.002)	-0.016 (0.801)	0.179 (0.002)
α_2	0.054 (0.365)	0.030 (0.594)			0.064 (0.043)	0.022 (0.748)	0.061 (0.327)	0.033 (0.592)
Panel B: Conditional Variance Equation Coefficients								
β_0	-1.686 (0.023)	-0.158 (0.066)	-0.534 (0.053)	-1.558 (0.024)	-0.008 (0.867)	-0.349 (0.404)	-0.318 (0.102)	-0.219 (0.024)
β_1	0.345 (0.022)	0.162 (0.025)	0.408 (0.033)	0.138 (0.167)	0.011 (0.874)	0.146 (0.359)	0.162 (0.270)	0.201 (0.006)
β_2	0.226 (0.573)	0.976 (0.000)	0.660 (0.000)	0.885 (0.000)	0.913 (0.000)	-0.196 (0.791)	0.399 (0.343)	0.930 (0.000)
γ_1	-0.001 (0.989)	-0.029 (0.005)	-0.137 (0.000)	-0.287 (0.000)	-0.151 (0.028)	-0.236 (0.000)	-0.008 (0.317)	-0.039 (0.005)
ξ_1	-0.046 (0.008)	-0.033 (0.000)	-0.011 (0.006)	-0.025 (0.005)	-0.010 (0.027)	-0.071 (0.000)	-0.021 (0.009)	-0.001 (0.804)
RA	1.000	1.059	1.317	1.805	1.355	1.617	1.000	1.081
Wald Test	480. 248	496.134 (0.000)	535.458 (0.000)	66.769 (0.000)	529.932 (0.000)	24.002 (0.000)	18.217 (0.003)	5127.03 (0.000)
Panel C: Residual Diagnostics								
J-B	27.499 (0.000)	27.504 (0.000)	622.3 (0.000)	37.865 (0.000)	37.439 (0.000)	822.507 (0.000)	111.253 (0.000)	48.865 (0.000)
L-B (10)	7.012 (0.314)	8.536 (0.318)	8.714 (0.464)	3.553 (0.895)	5.940 (0.654)	7.567 (0.477)	6.145 (0.440)	3.466 (0.902)
ARCH (10) LM	12.390 (0.259)	11.474 (0.209)	0.707 (1.000)	0.075 (1.000)	7.289 (0.550)	2.059 (0.996)	9.234 (0.269)	5.235 (0.875)

Notes: This table displays the estimation results of the EGARCH model. β_1 is the ARCH coefficient, β_2 is the GARCH coefficient, and γ_1 is the asymmetric coefficient in the EGARCH(1,1) model. The coefficient of lagged detrended trading volume, ξ_1, captures the impact of trading volume on the conditional return volatility. For consistency purposes, the optimal lag lengths identified for the VAR estimation are used in the AR(p) conditional mean specification. Specifically, one lag is used for the return series of CGS and IND, while two lags are used for the remaining series. RA represents the relative asymmetry ratio that is defined as $\left|-1+\gamma_{1,i}\right| / \left(1+\gamma_{1,i}\right)$. A Wald test is applied to test for the joint significance of the EGARCH model. J-B is the Jarque-Bera test for normality of the standardized residual series. L-B (10) is the Ljung-Box statistic that tests the null hypothesis of no autocorrelation in the standardized residual series up to tenth-order serial correlation. ARCH (10) LM is the χ^2 statistics of the Lagrange Multiplier (LM) test for the presence of ARCH effects in the first 10 lags, with the null hypothesis of no heteroskedasticity. *P*-values are reported in parentheses.

First, the coefficient of the ARCH component, β_1, appears to be statistically significant at the 5% level for the index series of ASI, BFS, CGS, and TRP. Thus, the contemporaneous return volatility of each of these indices is remarkably affected by their respective lagged innovations.

Second, the coefficient of the GARCH term, β_2, appears to be statistically significant at the 1% level for the index series of BFS, CGS, IND, INS, and TRP sectors. Further, the estimated values of these GARCH coefficients are, for the most part, close to one, implying an overwhelming degree of clustering in return volatility. The return series of the BFS sector shows the largest magnitude of volatility persistence, followed by those of the TRP, INS, IND, and CGS.

Third, the asymmetric coefficient, γ, is found to be negative and statistically significant for all return series, with those of the ASI and TLC being the exceptions. Moreover, the asymmetry ratio, RA, is higher than one for the return series of BFS, CGS, IND, INS, RST, and TRP, reflecting the stylized fact that negative information induces a larger increase in the return volatility than does positive information. For example, an RA of 1.805 implies that the impact of a negative shock on the current conditional variance of the IND sector is 1.805 times as large as that of a positive shock of the same size. Likewise, the magnitude effect of unfavourable news on the conditional variance of the RST sector is 1.617 times more than that of favourable news.

Fourth, with the exception of the TRP sector, the coefficient of lagged detrended volume, ξ, is negative and significant at the 5% level or better for all index series, implying that the lagged volume variable provides valuable information that contributes to the prediction of the future dynamics of price variability. Thus, in almost all volume-volatility relation cases, there exists substantial support for the implications of the SIAH. On the other hand, the finding that volume is negatively related to volatility seems to be at odds with those reported by several studies (i.e., Brailsford, 1996; Daigler and Wiley, 1999; Chen *et al*., 2001; Sabbaghi, 2011). A plausible explanation for this negative association could be that the equity market of Qatar is characterized by the phenomenon of thin trading where a good few stocks in various industries are not actively traded. Unlike mature ones, financial markets with thin trading are more likely to experience large return fluctuations, on the grounds that infrequent trading may push prices away from their true worth and exacerbate market volatility. Consequently, rising levels of trading activity may actually help alleviate mispricing of securities and market volatility.

Fifth and last, the null hypothesis that the EGARCH parameters are jointly equal to zero is rejected at the 1% significance level, on the basis of an F-version of the Wald test.

Finally, Panel C of Table 6 presents some diagnostic tests based on the standardized residuals. The Jarque-Bera test statistics show marked departures from the Gaussian distribution for all residual series. The results of the Ljung-Box test provide evidence against the presence of autocorrelation in all residual series for the first 10 lags. Thus, the EGARCH-X(1,1) model sounds highly efficient in capturing linear dependencies detected in the return series of ASI, BFS, IND, and TLC (see Table 2). The ARCH-LM test results are statistically insignificant, suggesting that the standardized residuals for all series are free from ARCH effects. Taken together, these findings demonstrate the adequacy of the EGARCH-X(1,1) specification in modelling return volatilities in the Qatari market.

7 Summary and Concluding Remarks

The present study revisits the stock price-volume relation, based on market- and sector-level data from the stock market of Qatar. In particular, three main issues are examined within both the aggregate market and each sector of the QE. First, the contemporaneous and dynamic relations between trading volume and price changes (returns). Second, the common characteristics of return volatility; and third, the asymmetric relation between trading volume and price variability. Daily historic data on stock index prices and corresponding trading volumes are collected for the period from 1 April 2012 to 29 January 2015.

At the aggregate market level, there exists a positive contemporaneous relation between the ASI returns and trading volume. However, the results of the VAR model provide evidence for the absence of a dynamic linkage between returns and volume in either direction. Consequently, past information of market-wide trading activity or returns cannot be used to predict the behavior of the other variable. In addition, the EGARCH-X(1,1) analysis demonstrates that return volatility is negatively related to trading volume. The conditional volatility of market returns shows no clear evidence of asymmetric response to new information.

At the sector level, returns and volume are found to be contemporaneously positively associated in all sectors except for the IND. Unlike that of the aggregate market, these individual associations appear to be asymmetric. With respect to the lead-lag linkage, an independence relation between returns and volume is detected for the BFS, INS, RST, and TRP sectors. A unidirectional causality running from returns to volume is observed for the CGS and IND sectors, while a bidirectional one is found for the TLC sector. A substantial degree of persistence in return volatility is detected for the BFS, CGS, IND, INS, and TRP sectors. Further, lagged values of trading activity appear to provide information useful in forecasting the future dynamics of price variability in all sectors, with the TRP representing the sole exception.

Overall, these results provide critical insights for fund managers and other investors trading on the Qatari market, considering that the volume of transactions is generally found to be informative about the price movement of sector indices. Specifically, tracking the behavior of trading volume over time can give a broad portrayal of the future direction of market prices and volatilities of equity, thereby enriching the information set available to investors for decision making. In fact, market participants can utilize volume as a harbinger of a market rally or decline and adjust their expectation on the future prices accordingly. Additionally, the nature and dimensions of the volume-volatility dynamics established for each sector must be taken account of by international portfolio managers contemplating sector diversification strategies in the Qatari market. In this respect, Galati and Tsatsronis (2003) find evidence that sector/industry effects have substantially become more important in explaining total variation in the European capital markets since the inauguration of the euro in 1999, while the contribution of country factors seems to be less important.

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