The Global Financial Crisis and Equity Markets in Middle East Oil Exporting Countries

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Abstract:
This paper employs extreme downside risk measures to estimate the impact of the global financial crisis in 2008/2009 on equity markets in major oil producing Middle East countries. The results in the paper indicate the spillover effect of the global crisis varied from a country to another, but most hardly affected market among the group of six markets was Dubai financial market in which portfolio loss reached about 42 per cent. This indicates that Dubai debt crisis, which emerged on surface in 2009, exacerbated the impact of the global financial crisis and prolonged the recovery process in these markets.

Keywords: **Value at risk, Fat-tails distribution; Expected Shortfall; Extreme losses**.

JEL classification: G3, F4, F3

1- Introduction

Despite financial crises are not a new phenomena, the global financial crisis in 2008/2009 differ from previous crises both in magnitude and globalization. Bartram et al (2009) indicate that by the end of February 2009, global equity market capitalization dropped to $22 trillion compared to $51 trillion at October 2007, realizing a drop of 56 per cent. However, the exposure of Middle East capital markets to the global financial crisis was at varying degrees, as some countries responded more stronger than others in the region. Stock markets in Gulf Cooperation

[1] The equity markets include Saudi, Kuwait, Dubai, Abu-Dhabi, Qatar, and Muscat stock market.

Countries (GCC), mainly Saudi Arabia, Kuwait, UAE, and Qatar reacted vigoursly to the downfall of stock markets in developed economies, as these countries held part of their financial wealth in foreign assets particularly in US bonds and other securities[2]. In the banking sector, only a few banks in GCC countries have publicly admitted they had losses due the spillover effect of the sub-prime crisis. These losses are believed to have taken the form of credit default risk and structured investment vehicles, and mortgage backed securities, as well as losses related to the sovereign wealth funds. It is becoming evident that the Middle East capital markets in general have overreacted to the events in US capital markets as the impact was quite substantial compared to the economic value of information transmitted to these markets. It is important to realize that the transmission effect of the global financial crisis on GCC capital markets was not limited to the direct effect from the global financial markets, but also included the negative impact of oil price fall from $120 per oil barrel to about $70 per barrel after the second half of 2008. Yet, another shock on GCC markets was in October 2009 when Dubai debt crisis came into surface and sent waves of shocks to the markets in the region. Share prices in Dubai financial market suffered their biggest fall amid fears that a debt crisis is looming as Dubai World, a giant conglomerate owned by Dubai government, asked its creditors for a six month debt payment delay. All GCC governments responded to the series of crisis by tightening even further credit at banks.

While the Middle East capital markets in the midst of a massive overhaul, due to increasing links with developed and other emerging markets, it should be admitted that, to my knowledge, no research published so far on the impact of the global financial crisis on the region's capital

[2] GCC markets responded sharply to the crisis by 15/Sept/2008, the day that Lehman filed for bankruptcy after failing to find a buyer.

markets. After the global financial crisis, and its ramification on emerging markets, the issue of risk transmission across capital markets expected to gain momentum and become the subject matter of more research in the coming years.

To assess the impact of the global financial crisis on portfolio returns in major oil producing GCC capital markets, we employed extreme risk measures of value- at-risk (VaR) and expected shortfall (ES). The value-at-risk (VaR) and the expected shortfall methods capture the likelihood of extreme losses that arise from extreme shocks that influence stock returns. VaR is defined as the maximum possible loss to a portfolio (or a security) with a given probability over a certain time horizon. In other words, VaR, reflects the likelihood of incurring a loss from investing in a portfolio over certain period of time, at a pre-specified probability level. However, ES measures the extreme losses that exceed VaR risk value. The major challenge in using VaR and ES approaches constitutes modeling the assets return distribution which is, according to the empirical research, characterized as fat tailed and skewed distribution. In this paper, following recent research papers we estimate VaR and the Expected Shortfall values using a fat-tail distribution, which is the Generalized Pareto Distribution (GPD). Extreme risk estimates using GPD models gained momentum in the past decade. McNeil (1997, 1998) investigates estimation of extreme risks in financial time series, using Extreme Value Theory (EVT), and Embrechts (1999, 2000a) show robustness of EVT in risk estimates. McNeil and Frey (2000) extend the analysis of extreme risk using heteroskedastic financial time series. Mullar et al (1998), and Pictet et al (1998) study extreme risk in foreign exchange markets using GARCH models. Gencay and Selcuk (2004) investigate the relative performance of VaR models using EVT, in a number of emerging markets after the Asian financial crisis of 1998. Giot and Laurent (2003) model VaR using a number of parametric univariate and multivariate models of ARCH class with skewed Student density. Tsafack (2009) explores VaR and ES on portfolios of U.S and Canadian stocks and bonds.

The remaining parts of the paper includes the following. Section two illustrates descriptive statistic analysis. Section three present the methodology of the research. Section four includes discussion of results. The final section concludes the study.

2: Descriptive statistics

Table (1) present several desciptive statistics on stock returns defined as $\log(p_t / p_{t-1})$, where p_t is the log of daily price index[3]. The sample sizes differ from one market to another, depending on availability of the data at the stock markets' web sites[4]. The analysis presented in the table display positive mean returns, with skewness towards negative returns for all markets as reflected in the maximum and minimum statistics. The maximum and minimum statistics also reveal the likelihood of making extreme gains despite relatively higher extreme loss possibilities.

The negative skewness coefficients also suport such a possibility. The excess kurtosis coefficients, which exceeds 3 for all markets in the group strongly support the assumption of leptokurtotic (fat-tailedness). To verify this point we included QQ-plots of returns against two thin tailed distributions of the Exponential and Normal distributions. The QQ plots indicate departure of the return quantiles, from the thin tailed Normal

[3] The stock returns, as defined here, is not a total market return since dividends are not included. However, in empirical work on the S&P 500 index, by Gallant, Rossi, and Tauchen (1992) indicate results are invariant to inclusion or exclusion of dividends in stock returns.

[4] Stock indices extracted from the web sites of stock markets.The sample period for Saudi, Qatar, Dubai, and Abu-Dhabi markets extend from Jan/1/2004 to Feb/23/2010, for Muscat from Feb/1/2001 to Feb/23/2010, and for Kuwait from June/17/2001 to Feb/21/2010.

distribution for all markets[5] . The Ljung-Box Q-statistics of order 15 on the squared residual series reflect a high serial correlation in the second moments of stock returns for all markets in the group.This support the relevance of the hetroscedasticity assumption in modelling stock returns volatility in GCC markets.

Table (1): Descriptive Statistics

	Kuwait	Saudi	Ab.Dhabi	Dubai	Qatar	Muscat
Mean (%)	0.83E-2	0.29E-2	0.36E-2	0.41E-2	0.43E-2	0.68E-2
St.deviation	0.10	0.22	0.17	0.25	0.20	0.13
minimum	-0.63	-1.15	-1.08	-1.40	-1.12	-0.97
maximum	0.54	1.08	0.96	1.32	1.05	0.90
Jarque-Bera (p-value)*	1684 (0.00)	2133 (0.00)	2005 (0.00)	1219 (0.00)	1461 (0.00)	21125 (0.00)
skewness	-0.25	-0.70	0.18	-0.005	-0.12	-0.38
Ex.kurtosis	4.25	5.45	5.39	4.21	4.77	15.05
$Q^2(15)$ (p-value)*	877 (0.00)	1164 (0.00)	680 (0.00)	931 (0.00)	1050 (0.00)	3233 (0.00)
N	2220	1627	1663	1659	1549	2244

* Significant at 1% significance level. N=number of observations

Notes: $Q^2(15)$ is the Ljung-Box Q-statistic of order 15 on the squired series.

3. Methodology

3.1: VaR and ES

In financial literature, it is widely believed that returns of high frequency data, characterized with fatter tails than the Normal distribution returns. The fat tailedness of stock returns have attracted many researchers to use Extreme Value Theorem (EVT) that underlies the Generalized Pareto Distribution (GPD) model which designed to capture the influence of extreme losses on stock markets risk. The basic assumption underlying EVT is that the tails of every fat tailed distribution converge

[5] If the data is from an exponential distribution, the points on the graph would lie along positively sloped straight line. If there is a concave presence, it is an indication that of fat-tailed distribution, whereas a convex shape indicates short-tailed distribution.

asymptotically to the tails of Pareto distribution[6]. The estimation of tails in GPD specification can be expressed as:

$$F(x) = [1 - F(u)]G_{\omega,\beta}(x-u) + F(u) \qquad (1)$$

Where x is all points of returns above a threshold point, u, so that x>u, and $G_{\omega,\beta}$ (x) is the two parameters GPD distribution function:

$$G_{\omega,\beta}(x) = \begin{Bmatrix} 1-(1+\omega x/\beta)^{-1/\omega} & \omega \neq 0 \\ 1-e^{(-x/\beta)} & \omega = 0 \end{Bmatrix} \qquad (2)$$

Where ω is the tail index, and $\beta > 0$ is the scale parameter. Following McNeil (1999), letting $F(u) = \frac{N-n}{N}$, where N is the total sample size, and n is the number of observations above the threshold level, then substituting $G_{\omega,\beta}(x)$ from (2) into equation (1), for $\omega > 0$, the tail estimate can be stated as:

$$\hat{F}(x) = 1 - \frac{n}{N}(1+\hat{\omega}\frac{x-\mu}{\hat{\beta}})^{-1/\hat{\omega}} \qquad (3)$$

for a given probability q, then VaR estimate is computed by inverting (3) to get:

$$\hat{VaR}_q = u + \frac{\hat{\beta}}{\hat{\omega}}\left\{\left(\frac{N}{n}(1-q)\right)^{-\hat{\omega}} - 1\right\} \qquad (4)$$

More vigilant determination of the threshold value is deemed necessary for more accurate estimates of GPD parameters. It is important to balance between setting a high threshold value that reduce the sample size to insufficient level, and setting a low threshold level that end up with sizable sample size but with less extreme values in the estimation process.

[6]In this paper we apply the "Peaks – Over – Threshold" (POT) model following McNeil and Frey, 2000). The POT model is based on the "Pickands – Balkema-de Haan Theorm" which state that the distribution of observations in excess of certain high threshold can be approximated by a Generalized Pareto Distribution (GDP).

Given that VaR represents a high quantile of the distribution of losses, i.e., 95th or 99th percentile, it stand for the maximum loss that is only exceeded on a small proportion of occasions.

Artzner, Delbaen, Eber and Heath (1997), have criticized VaR as a measure of risk on the basis that it fails to capture the potential losses that exceeds VaR value. They propose use of Expected Shortfall (ES) as a measure of the expected size of a loss that exceeds VaR. It should be realized that ES complement VaR estimates as it answer the question: When VaR values underestimate risk, what is the size of the expected loss ? Thus, ES is a measure of the likelihood of high unusual loss, or stock market crash. The Expected Shortfall can be estimated as:

$$ES_q = VaR_q + E(X - VaR_q) \setminus x > VaR_q \qquad (5)$$

Equation (5) can be simplified into (see McNeil (1998)):

$$\hat{E}S_q = \frac{V\hat{a}R}{1-\hat{\omega}} + \frac{\hat{\beta} - \hat{\omega}u}{1-\hat{\omega}} \qquad (6)$$

McNeil (1998), extend the above analysis to dynamic VaR and dynamic Expected shortfall estimates as in the following:

$$VaR_k^t = u_{t+k} + \sigma_{t+k} VaR(e_t)_q \qquad (7)$$

$$ES_k^t = u_{t+k} + \sigma_{t+k} ES(e_t)_q \qquad (8)$$

$$where\ k = 1,2,...$$

Where $VaR(e_t)_q$ denotes the qth-quantile of a noise variable e_t, and $ES(e_t)_q$ is the corresponding expected shortfall.

4. Results

To compute extreme portfolio losses we fit GPD to the returns of the six stock price indices to generate risk measures of VaR and ES, before and after the global financial crisis in 2008/2009. Like many emerging markets, the Middle East capital markets responded sharply to the crisis by 15/Sept/2008, the day that Lehman investment bank filed for bankruptcy after failing to find a buyer. As a result, in this study we considered this date as a distinctive date between the pre-crisis and post-crisis epochs. Since we are only interested in the extreme losses we only reported in table (2), the GPD parameters for the lower tails. A fundamental issue in GPD parameters estimation is the threshold value determination. To reduce estimation bias with regard to the threshold value determination in this paper we employed the so-called backtesting criteria[7]. Results in table (2) report the lower tail parameter and the scale parameter. The significance of the lower tail parameters confirm the negative skewness result reported in table (2), and also support the relevance of the Generalized Pareto Distribution in modeling the extreme loss events in GCC markets. In general, significant lower tail parameters imply the likelihood of incurring negative loss when investing in these markets. But to what extent the global financial crisis influenced dynamics of risk in GCC markets? To answer this question we need to divide the sample period into two sub- periods. As indicated in figures 1-3, the response of GCC markets to the global crisis as represented in the sharp downfall of S&P 500 index, started from 15/September/2008, the day when Lehman investment bank announced its bankruptcy. The period from Lehman fall to March/2009 was the crisis period across the global financial markets, including GCC markets. Although most developed and emerging markets started to recover from the crisis by the end of first quarter of 2009, the spillover effect of the crisis on GCC markets, continued till the end of 2009.There were two events contributed to such sluggish recovery process of GCC markets during this period. One of

[7] Some authors fit the GPD under different threshold values to assess their relative goodness of fit using the QQ plots. In the case of a good fit for GPD, the QQ plots expected to exhibit straight line tails.

these events was crude oil price fall from $120 per oil barrel before the crisis to about $70 per barrel through the whole period after the crisis. The other event, which even more important than the oil market effect, was Dubai debt crisis in 2009, which sent waves of shocks to the markets in the region. Both these events are linked with the global crisis in away, or another, therefore they cannot be considered as separate crisis. Thus, taking the date of Lehman investment bank failure (15/August/2008) as a distinctive date between pre and post crisis sample periods, results in table (3) present VaR and ES values for each of the two eras,. Estimated risk values of VaR and ES indicate the percentage of a portfolio value that can be lost when an asset held for a single day with a probability of 5 percent (or 95% confidence level)[8]. Both risk measures indicate the impact on GCC markets differ from one market to another, reflecting differences in the degree of openness of each capital market to international capital markets and foreign investments. Based on the expected shortfall (ES) values, it is evident that Dubai financial market was the most affected by the global financial crisis as portfolio losses increased from 18 percent at the pre-crisis era to 42 per cent at the post-crisis period. It is not a surprise to have such high level of risk for Dubai financial market which also hardly hit by Dubai debt crisis in October 2009. Share prices in Dubai financial market plummeted amid fears that Dubai World, a giant conglomerate owned by Dubai government, asked its creditors for debt rescheduling. It is also indicated in the table, in the normal situations (before the crisis) Saudi market is the riskiest in the group, as portfolio loss can reach up to 16 per cent in every 20 days (VaR at 5% significance level). However, Kuwait stock market is the least

[8] Commonly used significance levels are 1%, and 5%, . For example, BIS sets VaR values using significance level at 5% and holding period for 10 days when measuring the adequacy of banks capital. However, J.P.Morgan computes its daily VaR at significance level of 5%, with one day holding period, and Bankers Trust discloses its daily VaR at 1% significance level.

affected by the global crisis and Muscat market is the least riskier in the normal situations.

The backtesting results in table (3), indicate for most cases the violation rates are within the acceptable 5% tolerance level, and still less than 10% tolerance level.

The backtesting criteria compares out-sample forecast VaR values with the actual loss values from the data and compute the percentage of the actual losses that exceed the estimated forecast VaR values in every 100 trading days. If the number of failures (or violations) exceed the significance level, then the model under estimates VaR values, and the opposite is correct when the number of violations is significantly smaller than the expected level. In general, the ideal model yield estimates of failure rates close to stipulated significance level to pass the back-testing criteria.

Table (2): Parameters of GPD

	$\hat{\omega}_L$	$\hat{\beta}$
Kuwait (t-ratio)	0.50 (4.76)*	0.15E-3 (0.05)
Saudi (t-ratio)	0.47 (2.91)*	0.78E-3 (0.07)
Dubai (t-ratio)	0.43 (3.11)*	0.52E-3 (0.04)
Abu-Dhabi (t-ratio)	0.53 (6.12)*	0.86E-4 (0.03)
Qatar (t-ratio)	0.44 (2.25)**	0.8E-3 (0.04)
Muscat (t-ratio)	0.55 (7.97)	0.55E-3 (0.19)

*significant at 5% significance level.
** significant at 10% sig.level

Note: $\hat{\omega}_L$ is lower tail, and $\hat{\beta}$ is the scale parameter.

Table (3): Risk estimates

	VaR	ES	Back testing VaR	Back testing ES
Kuwait				
Pre-crisis	0.074	0.127	0.04	0.02
Post-crisis	0.113	0.162	0.08	0.06
Saudi				
Pre-crisis	0.16	0.23	0.03	0.03
Post-crisis	0.19	0.27	0.03	0.02
Dubai				
Pre-crisis	0.138	0.187	0.05	0.03
Post-crisis	0.315	0.422	0.06	0.06
Abu-Dhabi				
Pre-crisis	0.10	0.164	0.06	0.03
Post-crisis	0.185	0.242	0.08	0.07
Qatar				
Pre-crisis	0.124	0.195	0.06	0.04
Post-crisis	0.211	0.299	0.06	0.05
Muscat				
Pre-crisis	0.06	0.112	0.04	0.02
Post-crisis	0.17	0.250	0.06	0.05

Note1: VaR and ES values estimated using nonlinear MLE method. Numbers in the back-testing columns indicate the percentage of the actual losses that exceed estimated VaR and ES values, at significance level of 0.05.

Note2: 15/Sept/2008, the day that Lehman filed for bankruptcy, is taken as the date of the crisis eruption.

5: Concluding remarks

Taking into account empirical regularities of fat-tailedness and skewness that characterize asset returns in emerging markets, in this paper we modeled the impact of the global financial crisis in 2008/2009 on capital markets of the major oil producing Gulf Cooperation Council (GCC) countries. Our findings indicate the increasing openness of GCC capital markets to foreign investments and vulnerability to crude oil market shocks, exacerbated exposure of GCC capital markets to external shocks. To assess the impact of the global crisis on GCC markets we estimated extreme risk values of VaR and ES before and after Lehman investment bank failure at (15/August/2008). Both risk measures indicate the impact on GCC capital markets differ from one market to another, reflecting the degree of openness and type and nature of the internal factors characterizing each market. Based on the expected shortfall (ES) values it is clear that Dubai financial market was the most affected by the global crisis, as portfolio loss jumped from 18 percent at the pre- crisis period to 42 per cent at the post-crisis period. It is not a surprise to come up with such high level of risk for Dubai financial market which hardly hit in October 2009, by Dubai debt crisis[9]. Share prices in Dubai financial market plummeted amid fears that Dubai World, a giant conglomerate owned by Dubai government, asked its creditors for a six month debt payment delay. In the normal situations (before the crisis) Saudi market is the highest in term of losses likelihood, as portfolio loss can reach up to 16 per cent in every 20 days (VaR at 5% significance level). However, Kuwait stock market is the least affected by the global crisis in the group, whereas Muscat market is the least riskier in the normal situations.

[9] Dubai debt crisis should not be viewed as independent from the Global financial crisis.

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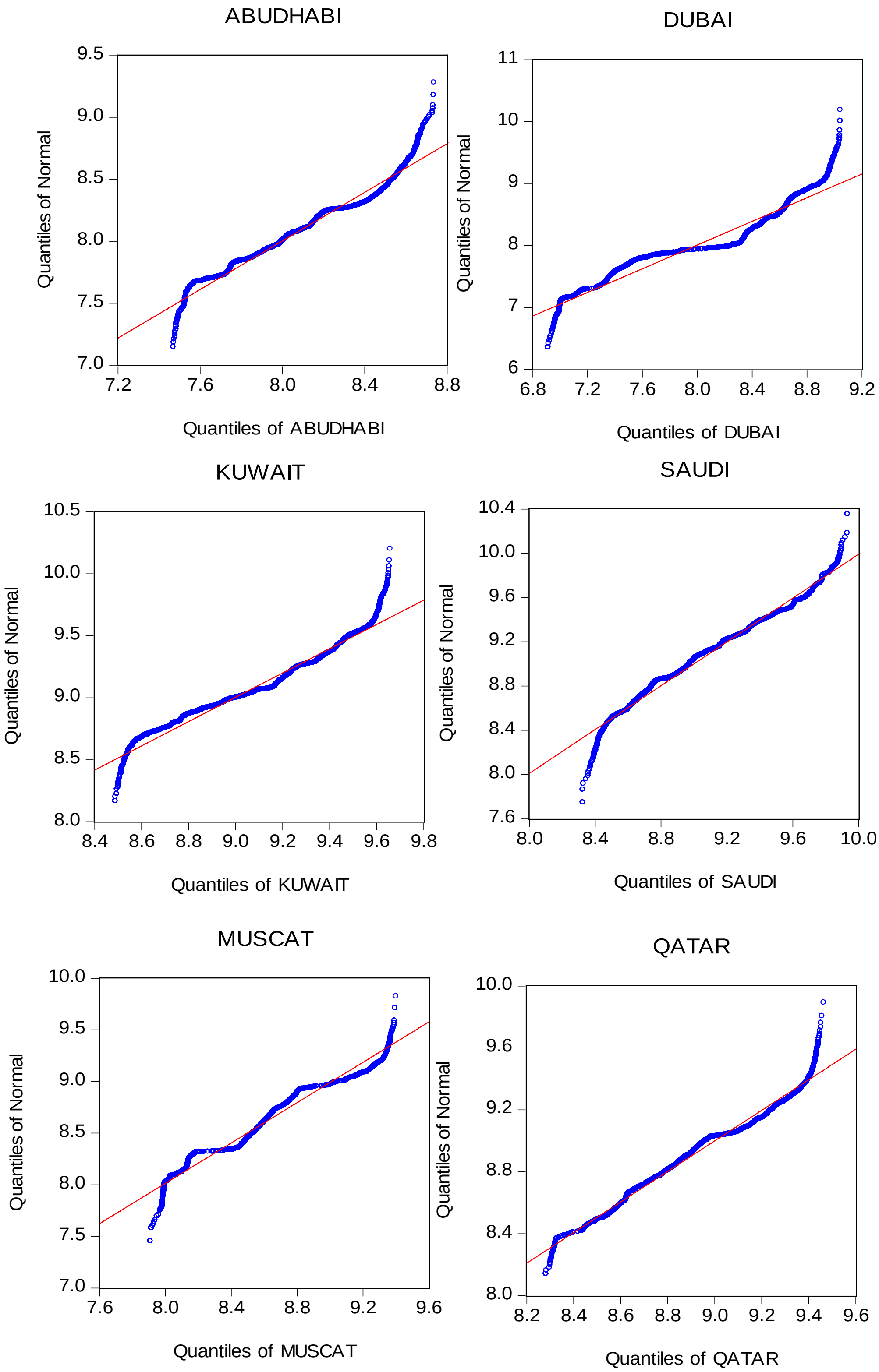
Plots (A) QQ-plots against the Normal distribution



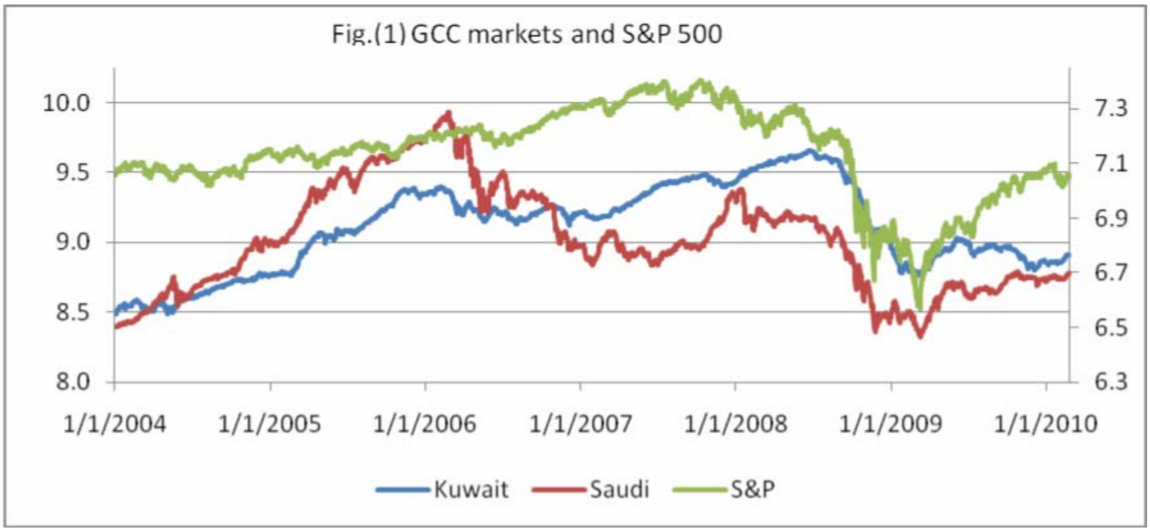


Fig.(1) GCC markets and S&P 500
10.0
9.5
9.0
8.5
8.0
7.3
7.1
6.9
6.7
6.5
6.3
1/1/2004
1/1/2005
1/1/2006
1/1/2007
1/1/2008
1/1/2009
1/1/2010
Kuwait
Saudi
S&P

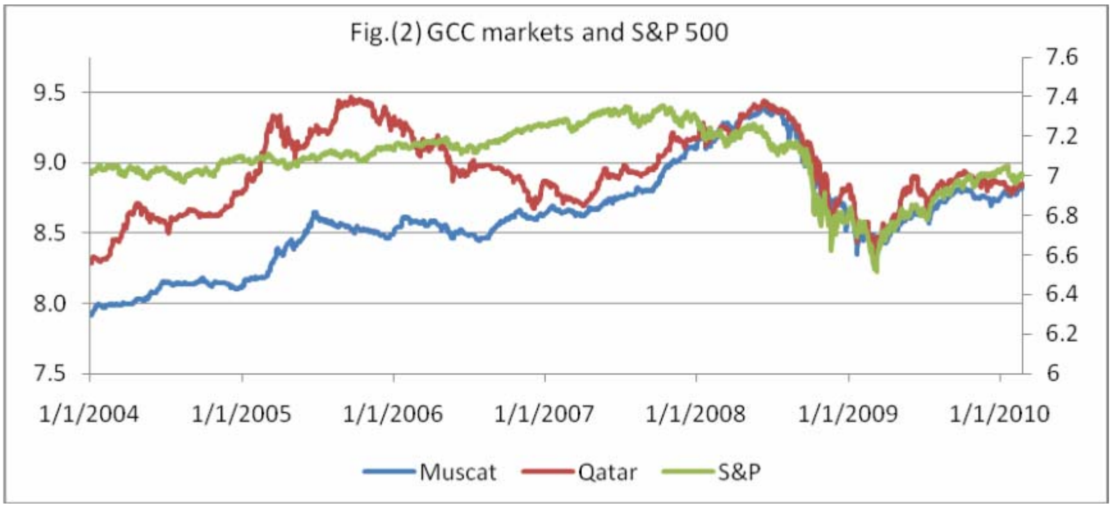


Fig.(2) GCC markets and S&P 500
9.5
9.0
8.5
8.0
7.5
7.6
7.4
7.2
7
6.8
6.6
6.4
6.2
6
1/1/2004
1/1/2005
1/1/2006
1/1/2007
1/1/2008
1/1/2009
1/1/2010
Muscat
Qatar
S&P

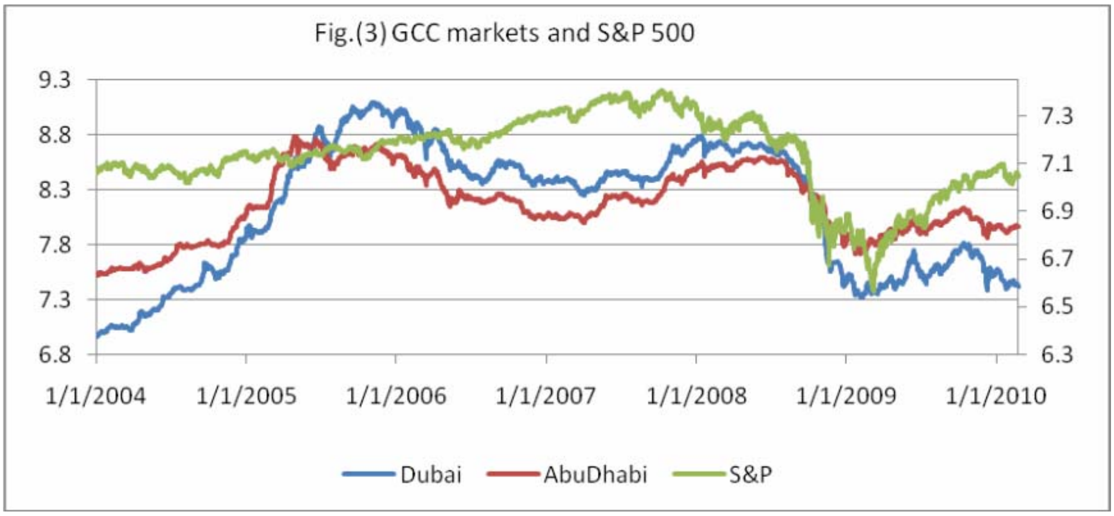


Fig.(3) GCC markets and S&P 500
9.3
8.8
8.3
7.8
7.3
6.8
7.3
7.1
6.9
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1/1/2004
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Dubai
AbuDhabi
S&P