NONLINEARITY AND MARKET EFFICIENCY IN GCC STOCK MARKETS

BY

Abdullah M. H. Alharbi

Submitted to the Department of Economics and the
Graduate Faculty of the University of Kansas in
partial fulfillment of the requirement for
the degree of Doctor of Philosophy

William A. Barnett (Chair)

Ted Juhl

Paul Comolli

Shu Wu

Paul D. Koch

Date defended: April 27, 2009

The Dissertation Committee for Abdullah Alharbi certifies that
this is the approved version of the following dissertation:

NONLINEARITY AND MARKET EFFICIENCY IN GCC STOCK MARKETS

Committee:

William A. Barnett (Chair)

Ted Juhl

Paul Comolli

Shu Wu

Paul D. Koch

Date approved: April 27, 2009

ABSTRACT

Significant prediction of asset prices is of a great importance in financial economics. When studying economic and financial phenomena, it is essential to correctly specify the model. If the true dynamics are nonlinear, using linear methods will probably be irrelevant in doing empirical analysis. Existence of nonlinearity in financial markets has been argued by numerous studies. The main objective of this dissertation is to examine this issue in the six states of the Gulf Cooperation Council (GCC): Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates (UAE), using three robust and highly regarded nonlinearity tests. In addition, the Efficient Market Hypothesis (EMH) was tested in this dissertation for the GCC stock markets using both the standard linear approach and the more sophisticated nonlinearity tests. Since most of the empirical work was devoted to the advanced, well-organized stock markets, this study is a contribution to the limited literature on emerging markets in general and on the GCC markets in particular. Moreover, the findings of this study would contribute to future research on GCC stock markets by adding further insight into the dynamics underlying stock returns in these markets.

This dissertation consists of four chapters. Chapter one presents a general background on the economy and stock markets in the GCC region with more focus on the recent economic development and performance. The

second chapter is concerned with the literature on the EMH in financial markets including historical background, implications, and criticism of this hypothesis. In addition, this chapter provides literature review of nonlinear dynamics in the economy and financial markets. The third chapter deals with the methodology of the study and the analysis of the data. First, it starts with description of the data sample and preliminary analysis including descriptive statistics and unit root tests. Second, it presents a brief description of the three standards linear independence tests: Autocorrelation Function (ACF) test, Ljung-Peirce test, and the runs test. The theoretical aspects of the three nonlinearity tests are then discussed in details in this chapter. The last part of this chapter provides discussion and summary of the results obtained by linear and nonlinear serial dependence tests. Concluding remarks and findings of the study is provided in the last chapter.

Nonlinearity was tested in daily stock returns and the results indicate a strong evidence of nonlinearity in all of the six GCC markets. Using the nonlinearity tests, as well as the typical linear independence tests, the EMH was strongly rejected for the GCC stock markets. The study findings suggest using nonlinear paradigms instead of the simple linear methods to model financial relations. By doing so, the prediction of future stock prices would probably improve, benefiting both market practitioners and academic researchers.

DEDICATION

This dissertation is dedicated to:

My beloved mother and father, Hessah and Mohaimeed,

My wonderful wife, Reem

and

My lovely children: Milaf, Juri, Danah, and Ziyad

ACKNOWLEDGMENTS

First and foremost, I thank the Almighty God for giving me the opportunity and the ability to accomplish this work. Without God's help and guidance, I would not have reached to this point.

I would like to express my deep gratitude and appreciation to my advisor and committee chairperson, Dr. William Barnett, for his endless guidance and encouragement. I want also to extend my grateful thanks to the committee members for their great suggestions and generous support, and to the faculty and the staff in the Department of Economics, at the University of Kansas for their help and cooperation.

I am especially grateful to my sponsor, the Saudi Arabian Monetary Agency (SAMA), for their generous financial support. It is a great goal to invest in human resources, and I am extremely indebted to my country, the Kingdom of Saudi Arabia, and to those who put their trust in me. The pay back will never be enough, but doing my best for my country is my promise.

I would like to express my heartfelt thanks and gratitude to my dear parents, brothers, and sisters for their endless love, prayers, and encouragement. I am especially indebted to my brother, Zaid, for his unlimited support. I am also very grateful to my friends, especially Rakan and Mamdooh, for their moral support and sincere friendship. Last, but not least, my deepest thanks and appreciation go to my wife, Reem, for her understanding, patience, and sacrifices. Without her love and support this dissertation will never be possible.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION AND ECONOMIC OVERVIEW

1.1 Introduction to Study

When analyzing dynamical systems, traditional methods usually impose linearity for approximation purposes. But real dynamical systems are evolving by nature, and involve many forces and agents that interact in a sophisticated, more likely nonlinear, way rather than a simple linear one. When such complicated relations are linearly approximated, some important information may not be extracted from the original data, resulting in misleading results and conclusions. In economics, the early literature of studying economic relations was dominated by linear methods. However, there has been a rapid emergence of research in the area of nonlinear analysis over the last twenty years, greatly attributed to the significant development in computing and applied statistics. From the theoretical point of view, there is no strong reason to believe that underlying dynamics in economic relationships are linear. Furthermore, many empirical studies have documented a strong evidence of nonlinear structure in various economic relationships.

In the literature of financial economics, a rich volume of empirical research has been dedicated to testing the Efficient Market Hypothesis (EMH), or alternatively the random walk behavior, in financial markets. Typically, historical security prices or returns are tested for significant serial dependence and, if found, would result in rejecting the hypothesis of market efficiency. Some EMH implications are that security prices move randomly and follow normal distribution. It also implies the rationality of market participants. Initially, there was strong empirical support for the EMH in many financial markets. But historical records of unexpected market collapses as well as the increasing evidence of persistence volatility and market's irrationality have raised some doubts on the validity of the EMH. Moreover, most of the studies conducted in this literature have only examined the presence of linear serial dependence in financial time series. Knowing that these series are linearly independent does not, however, rule out the possibility of nonlinear dependence. In fact, there are a growing number of studies that argue for strong evidence of nonlinear serial dependence in security returns in many financial markets.

1.2 Motivation and Objectives

Existence of nonlinearity in financial markets is of a great importance for both market practitioners and academic researchers. For instance, if a security follows nonlinear behavior, it may not be profitable for investors to use linearity-based trading strategies. Similarly, specifying the true data-generating process is enormously important in academic research since the existence of nonlinearity would greatly affect modeling and analyzing any financial relations. In accordance with this, nonlinearity tests are very effective tools that can be used as diagnostic tests to explore and understand the nature of the underlying dynamics in stock returns. Thus, testing for nonlinearity should be a necessary step preceding any attempt to analyze financial markets. Being better-organized and more-regulated, stock markets across the Gulf Cooperation Council (GCC) countries have witnessed an extraordinary expansion over the last few years. These markets experienced historical growth from 2000 to 2005, and then started to go through high fluctuations, in the same time of the rapid growth in economic activity. Therefore, it is worth studying the dynamics underlying stock returns in the GCC region during this period of phenomenal growth.

The objective of this dissertation is twofold. First, it seeks to determine whether nonlinearity exists in stock returns, using three robust and highly regarded nonlinearity tests. Second, it attempts to assist on the issue of market efficiency in the GCC region by testing the serial dependence in stock returns, using both typical linear methods and the more sophisticated nonlinearity tests. On one hand, evidence of nonlinearity in GCC stock markets would support the argument that economic relations should be modeled and analyzed by nonlinear approaches. On the other hand, if stock returns exhibit significant serial dependence, the market efficiency hypothesis in GCC stock markets should be strongly rejected. Since most of the empirical work was devoted to the advanced, well-organized stock markets, this study is a contribution to the limited literature on emerging stock markets in general and GCC markets in particular. Moreover, the findings of this study would contribute to future research on GCC stock markets by adding further insight into the dynamics of these markets.

1.3 Outlines of Study

The dissertation is organized in four chapters. In the rest of this chapter, GCC economies and stock markets are briefly reviewed to provide the reader with a general background on this region with more focus on the recent development and performance. The second chapter is concerned with the literature on Efficient Market Hypothesis (EMH) in financial markets including historical background, implications, and criticism of this hypothesis. In addition, this chapter provides literature review of nonlinear dynamics in the economy and financial markets. The third chapter deals with the methodology of the study and the analysis of the data. First, it starts with description of the data sample and preliminary analysis including descriptive statistics and unit root tests. Second, it also presents a brief description of the three standards linear dependence tests: Autocorrelation Function (ACF) test, Ljung-Peirce test, and the runs test. The theoretical aspects of the three nonlinearity tests: Hinich bispectrum test (Melvin J Hinich, 1982), White's neural network test

(White, 1989a), and Kaplan's test (Kaplan, 1994), are discussed in details in this chapter. The last part of this chapter provides discussion and summary of the results obtained by linear and nonlinear serial dependence tests. Concluding remarks and findings of the study is presented at the last chapter.

1.4 GCC Economies: Brief Review

The Gulf Cooperation Council (GCC) was founded on May 1981 joining six of the Arabic Gulf states: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates (UAE). The aim of this council is to promote coordination, integration, and inter-connection between the member states in all fields including the economy. These countries share many geographic, demographic, social, and economic features. For instance, the Gulf region is rich of natural resources such as oil and gas where the combined GCC region accounts for 45% of the world's proven oil reserves and 17% of the world's proven natural gas reserves (Fasano & Iqbal, 2003). Four of the six nations, namely Saudi Arabia, Kuwait, UAE, and Qatar, are major members in the Organization of the Petroleum Exporting Countries (OPEC). Knowing that energy is vital to the world economic growth, the GCC bloc is a crucial player in the global economy as being the top energy producer and exporter. Except of Bahrain whose oil reserves is quite small, the high abundance of natural resources has led the GCC economies to be heavily dependent on hydrocarbon industries as major sources of economic growth and export revenues. This can be considered a big economic challenge for this region when considering the fact that oil and gas are depletable resources. In addition, energy prices, by their nature, are very volatile and this would obviously result in a non-sustainable economic growth. As a result, GCC policy makers have been targeting economic diversification in their economic plans for more than two decades. The GCC countries are also facing some other challenges such as the rapidly growing young population along with the heavy reliance of private sector on foreign labor.

Although natural resources are still dominating the GDP and export revenues, there has been a significant move toward economic diversification in these countries by reducing reliance on oil and increasing the share of non-oil private sector in the GDP. Furthermore, many political and economic reforms have taken place during the last two decades in this region. The GCC countries have also shown a considerable progress towards the liberalization and openness of their markets, resulting in the accession for all of the six nations to the World Trade Organization (WTO). The economic integration has been substantially strengthened by the GCC Customs Union, which was established in 2003 to facilitate intra-GCC flow of goods, and to create a collective negotiating power for the GCC members. The region has also enhanced its global trade position by signing free trade agreements with various countries and economic blocks while pursuing the ongoing negotiations with many others. Another big step towards economic unity was the GCC common market lunched in January 2008. This common market will allow free flow of capital, in addition to the freedom of movement, residency, employment (in both the private and public sectors), and real state ownership for the GCC nationals at any of the six states. Moreover, the region is looking forward to 2010, which is the planned date for the currency union that will be followed by series of steps to achieve the monetary union, and hence a higher level of economic integration.

1.5 Economic Growth

During the period of 1997-2007, the overall region has witnessed a strong economic growth, in the wake of booming oil prices. It can be noticed from Table 1 that the combined GCC economy has substantially increased by 70%, in real term. The individual economic growth records showed that Qatar has been experiencing an economic boom with an average annual growth rate of 11%, as being the fastest growing GCC country, and among the top expanding economies in the world. The other states have also showed significant economic performance reflected in the average annual growth rates of 6.7% (UAE), 6.5% (Bahrain), 5.6% (Kuwait), 4.6% (Oman), and 3.4% (Saudi Arabia). Following the sharp decline of oil prices in 1998, year 1999 registered the lowest economic performance relative to the whole period where real GDP slightly declined in Kuwait, Oman and Saudi Arabia while it was growing by rates more than 3% in the other states. As mentioned earlier, the rapid growth of population is one of the region's economic challenges knowing that the major source of the economic growth is the hydrocarbon industries, which are capital-intensive. Table 2 lists the growth rates of population in GCC countries during the same period. The whole region's population has been increasing by an average rate near to 3% annually. Among the six GCC states, UAE has witnessed the highest growth rate of about 5% each year, on average, followed by Qatar, 4.5%, and Kuwait, 4%. Oman has been the lowest growing country in terms of population, where it registered an average annual rate of about 1.4%.

Table 1: Real GDP Growth Rates (%) for GCC Countries

	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
1997	3.144	2.475	6.178	28.45	2.592	7.931
1998	4.812	3.663	2.713	9.031	2.835	0.123
1999	4.324	-1.779	- 0.238	5.504	- 0.748	3.139
2000	5.235	4.685	5.486	10.94	4.865	12.38
2001	15.14	0.22	7.509	6.318	0.547	1.695
2002	5.193	3.01	2.567	3.2	0.128	2.649
2003	7.245	17.33	2.005	6.323	7.659	11.89
2004	5.644	10.68	5.333	17.72	5.268	9.691
2005	7.853	11.4	6.015	9.24	6.062	8.192
2006	6.546	6.279*	6.785	10.34*	4.295	9.388
2007*	6.631	4.575	6.380	14.23	4.099	7.377

Source: IMF World Economic Outlook available at: http://www.econstats.com
*: IMF forecast.

Table 2: Population Growth Rates (%) for GCC Countries

	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
1997	2.42	4.81	2.34	2.58	2.60	5.92
1998	2.29	6.64	2.06	2.98	2.70	5.90
1999	2.24	6.73	1.73	3.63	2.71	5.76
2000	2.24	5.81	1.39	4.36	2.66	5.53
2001	2.25	4.83	1.02	5.14	2.61	5.31
2002	2.25	4.21	0.71	5.66	2.58	5.08
2003	2.21	3.69	0.62	5.64	2.54	4.77
2004	2.14	3.34	0.79	5.02	2.49	4.36
2005	2.03	3.12	1.14	4.09	2.42	3.90
2006	1.93	2.87	1.55	3.11	2.35	3.45
2007	1.84	2.58	1.90	2.33	2.29	3.06

Source: International Financial Statistics (IFS), IMF.

Table 3 presents the real GDP growth rates for GCC compared to some advanced, emerging, and regional economies for the period of 1999-2007. The region's economy has significantly grown by an average annual rate of 6.3%, compared to the global economic growth of 4.3%. This rate was also higher than that of some developed countries such as USA (2.8%), Japan (1.5%), and UK (2.8%). It can be noticed from this table that, over the nine-years period, major emerging economies such as China, India, Brazil, and Russia have outperformed the advanced ones. For instance, China has witnessed a substantial growth during this period with an annual growth rate of about 9%, and double digits rates since 2003. Similarly, this time has been a boom economic growth for some developing economies such as India and Russia that recorded an average annual growth rate near to 6%. Regionally, the GCC witnessed significant economic growth compared to the neighbor regions such as Middle East, Asia, and Africa. In addition, GCC, as an economic bloc, has experienced a higher growth rate than that of the European Union.

The nominal GDP pre-capita (see Table 4) has dramatically increased for the Gulf countries during 1996-2006. In fact, it was more than tripled in Qatar, placing it among the top wealthiest nations, and nearly doubled in the other GCC states. As a result of the long economic expansion, GCC region started to experience an increasing pressure on prices in the recent years. Inflation rates for GCC countries are listed in Table 5 for the period from 1997 to 2007. It can be recognized that inflation rates were relatively low prior to 2003. Since then, prices started to elevate rapidly, especially in the cases of Qatar and UAE that have recently experienced double digits inflation rates.

Table 3: Real GDP Growth (%) of GCC and World Economies

		1999	2000	2001	2002	2003	2004	2005	2006	2007
GCC		1.7	7.3	5.2	2.8	8.7	9.1	8.1	6.8	7.2
Developed Economies	USA	4.4	3.7	0.8	1.6	2.5	3.9	3.2	3.3	2.2
	Jap.	-0.2	2.9	0.2	0.3	1.4	2.7	1.9	2.2	2.3
	U.K.	3.0	3.8	2.4	2.1	2.7	3.3	1.9	2.7	2.9
	Europe Union	3.0	3.9	2.1	1.4	1.5	2.6	1.9	3.2	2.8
Emerging Economies	China	7.1	8.4	8.3	9.1	10.0	10.1	10.4	10.7	10.0
	India	7.0	5.4	3.9	4.3	7.3	7.8	9.2	9.2	8.4
	Brazil	0.8	4.4	1.3	2.7	1.1	5.7	2.9	3.7	4.4
	Russia	6.3	10.0	5.1	4.7	7.3	7.2	6.4	6.7	6.4
Africa		2.6	3.1	4.4	3.7	4.7	5.8	5.6	5.5	6.2
Asia		6.3	7.0	6.1	7.0	8.4	8.8	8.6	8.2	8.8
Middle East		2.0	5.4	3.0	3.9	6.5	5.5	5.4	5.7	5.6
World		3.7	4.8	2.5	3.1	4.0	5.3	4.9	5.4	4.9

Source: IMF World Economic Outlook available at: http://www.econstats.com.

Figure 1: Annual Real GDP Growth Rates for GCC and some Selected Economies

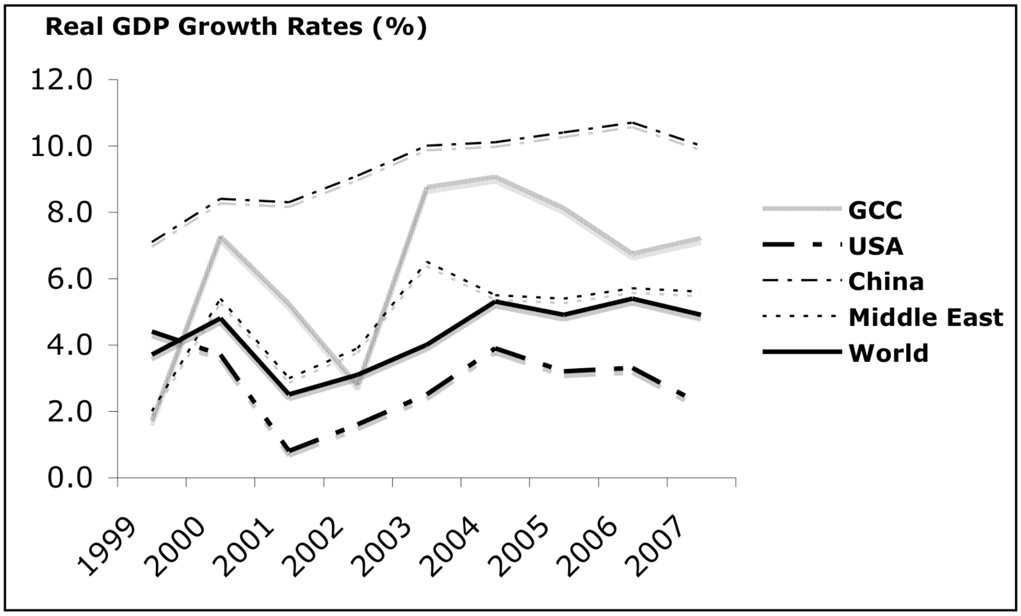


Table 4: GDP Per Capita, Current Prices (US$ thousands)

	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
1996	10.1	17.3	6.6	16	7.9	17.8
1997	10.2	18.5	7.2	17.4	8.5	19.7
1998	10.2	13.7	7.4	21.6	8.7	19.9
1999	10	13.4	7.1	21.1	8.1	18.2
2000	11.9	17	8.9	28.5	9.2	21.6
2001	11.7	15.1	8.8	27.3	8.7	19.7
2002	12.1	15.8	8.8	28.9	8.8	19.9
2003	13.7	18.1	9.3	33	9.8	21.8
2004	15.3	20.2	10.4	37.6	11.1	24.1
2005	18.4	26	12.7	43.1	13.4	27.7
2006	21.4	31.3	15.5	53.5	15.4	35.1

Source: Arab Monetary Fund (AMF).

Table 5: Inflation Rates in GCC Countries

	Bahrain	Kuwait	Oman	Qatar	Saudi Arabia	UAE
1997	2.05	0.81	-0.36	2.60	-0.43	2.95
1998	-0.86	0.60	0.43	2.92	-0.17	1.96
1999	-1.01	3.08	0.51	2.16	-1.31	2.10
2000	-0.95	1.57	-1.20	1.68	-1.10	1.36
2001	-0.84	1.45	-0.84	1.44	-1.14	2.74
2002	0.62	0.80	-0.33	0.24	0.23	2.93
2003	1.98	0.99	0.17	2.26	0.59	3.16
2004	2.42	1.26	0.67	6.80	0.36	5.02
2005	2.39	4.12	1.85	8.81	0.63	6.19
2006	2.80	3.09	3.20	11.83	2.31	9.27
2007*	3.36	4.98	5.50	13.76	4.11	11.03

Note: Inflation rates are computed as the annual percent change of average consumer prices.
Source: International Monetary Fund (IMF),
*: IMF forecasts

1.6 GCC Stock Markets

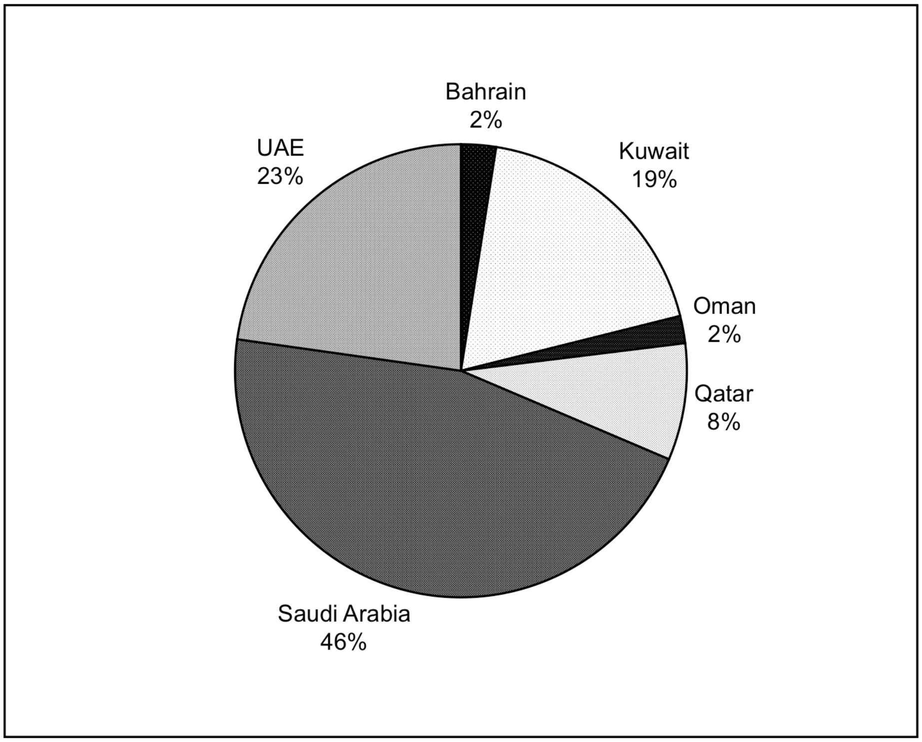
Stock market plays an important role in economy where it works as a channel to transfer money from savers (share holders) to borrowers (firms). In fact, it can increase the overall economic efficiency by mobilizing capital to productive investments. GCC stock markets have a short history relative to the world financial markets. In general, these markets have been in ongoing regulations and structural developments since late 1990s. Prior to 2000, most of the GCC markets were operating informally. As indicated in Table 6, GCC stock exchanges were established as early as 1977 when Kuwait Stock Exchange (KSE) were officially launched as the first regulated GCC stock market. Until 1999, Kuwait was the only market where stocks are traded electronically. In Saudi Arabia, the largest stock market in the GCC and Middle East regions, stock were traded over the counter until 2001, when the automated trading system was introduced. Saudi Arabia has the lion's share of the overall GCC stock market, where in 2007 it was accounted for 46% of the region's market capitalization, while Bahrain and Oman are the smallest markets with combined share of less than 5% of the whole market (see Figure 2).

Table 6: GCC Stock Exchanges

Country	Stock Exchange	Year of Commencement
Bahrain	Bahrain Stock Exchange (BSE)	1988
Kuwait	Kuwait Stock Exchange (KSE)	1977
Oman	Muscat Securities Market (MSM)	1988
Qatar	Doha Securities Market (DSM)	1997
Saudi Arabia	Saudi Stock Exchange (Tadawul).	1989
UAE	Abu Dhabi Securities Market (ADSM)	2000
UAE	Dubai Financial Market (DFM)	2000

Source: FINCORP(2005), and respective stock exchanges.

Figure 2: Country Shares in Combined GCC Stock Market (2007)



As the GCC was experiencing the recent economic expansion, a more explosive growth was taking place in the region's stock markets too. Table 7 lists some general indicators of GCC stock markets during 2000-2007. Between 2000 and 2005, the Gulf markets witnessed a sharp increase in market size and trading activity. For instance, the size of the overall GCC market, as measured by market capitalization, rose from $120 billions in 2000 to over a trillion in 2005, an increase by more than 800%. Individually, GCC stock markets grew at explosive rates ranging from 164% for Oman to 2004%

for UAE. Similarly, trading has tremendously increased in all GCC markets from 2000 through 2005. The number of trades and volume traded for the combined GCC market rose by more than 7000% and 1000%, respectively. Indeed, the Saudi market was ranked 16th in the world in terms of market capitalization and 14th in terms of number of trades by the end of 2005[1]. This region's substantial growth could be attributed to various factors. For instance, the significant structural development during this period resulted in more regulated and electronically traded markets and this might have boosted stocks trading in this region. In 2006, however, the total GCC market was dropped by 35%[2], but rose up again by 54% in 2007. With no considerable change in economic realties, this excess volatility raised questions about the rationality of these markets. Some argued that these markets seem to be very speculative and mainly driven by trading rather than market fundamentals. In fact, such irregular behavior may not be explained by simple linear paradigms. Also, it is more likely that stock returns in the GCC markets follow a nonlinear path. In assessing such arguments, we must first examine the existence of nonlinear serial dependence in GCC stock returns.

[1] ZAWYA, available at http://www.zawya.com/cm/profile.cfm/cid1000011
[2] This sharp drop was due to the 2006 collapse in three major markets: Saudi Arabia, UAE, and Qatar.

Table 7: GCC Stock Markets Indicators

		Transactions (thous)	Volume (mn Shares)	Value (US$ bn)	Market Cap (US$ bn)	No. of Companies	Index Gains
Bahrain	2000	N/A	420.3	0.2	6.6	39	-0.145
	2001	13.1	335.3	0.2	6.6	43	-0.027
	2002	13.0	353.1	0.2	7.6	41	0.003
	2003	14.6	405.6	0.3	9.7	44	0.274
	2004	15.8	335.8	0.5	13.5	45	0.321
	2005	22.5	458.3	0.7	17.4	47	0.227
	2006	21.7	727.6	1.3	21.1	50	-0.019
	2007	27.7	851.1	1.1	27.0	51	0.265
Kuwait	2000	171.0	6758.0	4.4	21.6	86	0.028
	2001	355.1	16299.0	12.1	28.2	88	0.288
	2002	521.3	27834.0	22.7	35.8	95	0.241
	2003	1081.7	49563.0	55.1	61.5	108	0.639
	2004	1056.9	33543.7	51.8	75.2	125	0.119
	2005	1964.2	52337.6	97.6	142.1	158	0.664
	2006	1486.2	37657.9	59.2	143.8	180	-0.092
	2007	2101.1	70432.8	135.5	210.5	196	0.300
Oman	2000	N/A	146.1	0.6	5.1	113	N/A
	2001	N/A	138.3	0.4	4.5	119	-0.244
	2002	92.9	191.8	0.6	5.2	127	0.262
	2003	179.1	315.2	1.5	6.6	139	0.421
	2004	255.0	345.4	1.9	7.6	166	0.238
	2005	394.0	512.2	3.6	12.7	176	0.444
	2006	312.4	925.5	2.3	12.9	180	0.145
	2007	564.2	2989.1	5.2	23.0	200	0.619

Table 7: GCC Stock Markets Indicators (Continued)

		Transactions (thous)	Volume (mn Shares)	Value (US$ bn)	Market Cap (US$ bn)	No. of Companies	Index Gains
Qatar	2000	12.2	31.6	0.2	8.2	22	0.082
	2001	15.8	51.0	0.4	9.0	23	0.429
	2002	29.8	79.6	0.9	10.6	25	0.373
	2003	134.7	190.0	3.2	26.7	28	0.566
	2004	290.3	316.6	6.4	40.4	30	0.476
	2005	1130.0	1033.1	28.3	87.1	32	0.835
	2006	1932.6	1865.4	20.5	60.9	36	-0.375
	2007	1811.8	3411.3	29.9	95.5	40	0.404
Saudi Arabia	2000	498.1	554.9	17.4	67.9	76	0.113
	2001	605.0	691.8	22.3	73.2	76	0.076
	2002	1033.7	1735.8	35.7	74.9	68	0.036
	2003	3763.4	5566.9	159.1	157.3	70	0.762
	2004	13319.5	10298.0	473.0	305.9	73	0.849
	2005	46607.9	12281.0	1103.7	646.0	77	1.037
	2006	96095.9	54439.7	1402.8	326.3	86	-0.525
	2007	65665.5	58862.0	682.1	519.0	111	0.409
UAE	2000	6.6	24.0	0.1	11.0	27	N/A
	2001	19.3	77.3	0.4	13.7	27	0.236
	2002	36.3	209.2	1.1	29.9	37	0.145
	2003	50.7	561.4	2.0	39.6	44	0.321
	2004	299.3	6069.3	18.2	82.3	53	0.884
	2005	2301.2	34145.6	140.6	231.4	89	1.029
	2006	3412.6	51355.6	120.4	168.7	102	-0.399
	2007	3354.6	157318.1	151.0	257.4	120	0.336

Source: Global Research-GCC, Jan 2008.

Figure 3: Stock market Capitalization ($US billions)

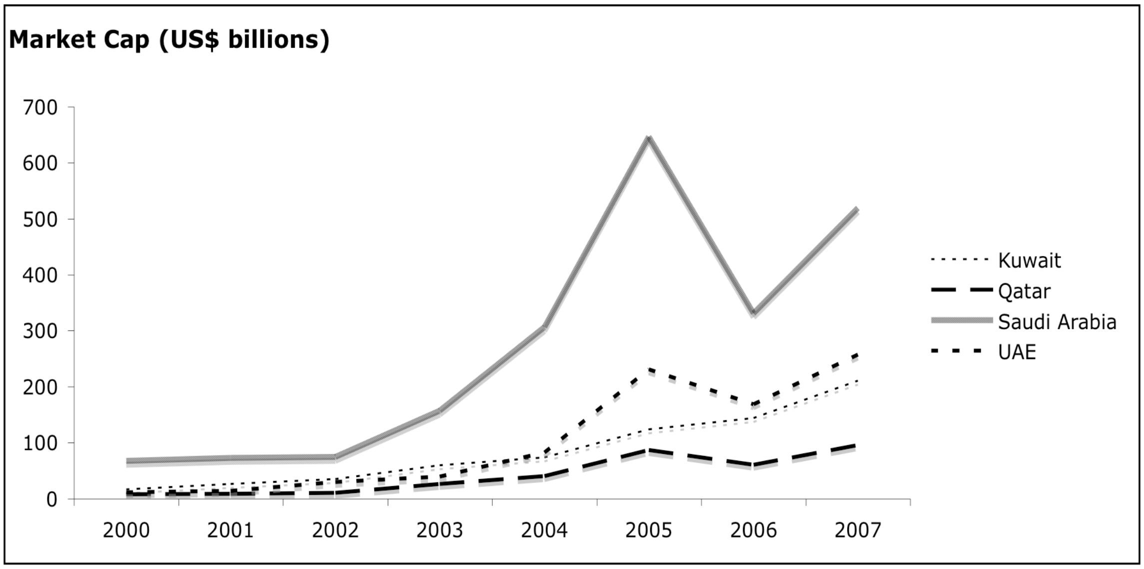
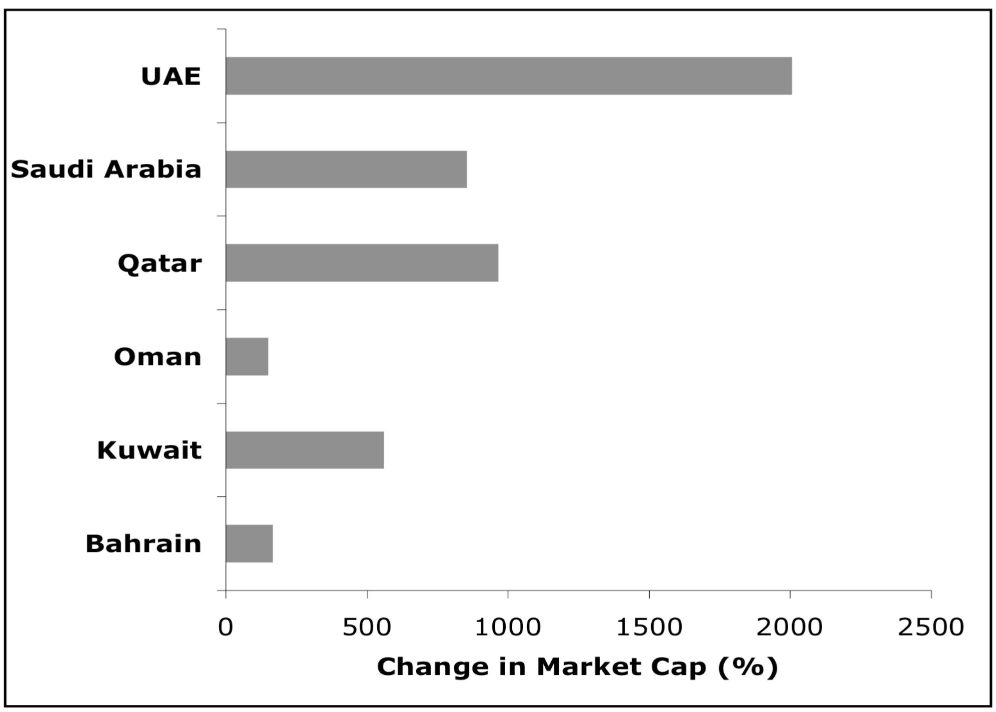


Figure 4: Change in GCC Market Capitalization between 2000 and 2005 (%)



CHAPTER TWO

EFFICIENCY OF FINANCIAL MARKETS AND NONLINEARITY

2.1 Introduction

The concept of market efficiency is considered central to finance and financial economics and one of the most controversial topics in these fields. In the last three decades, the issue of financial market efficiency has been widely investigated, with more emphasis on developed markets, to answer the question of whether these markets are efficient or not. The word “efficiency” is sometimes used ambiguously, and a clarification of this word would be helpful before moving to a further discussion. Economists are usually concerned with three types of efficiency in the capital market. These are allocational (Pareto) efficiency, allocating capital resources in the most productive manner; operational efficiency, conducting the transactions at competitive cost for market participants; and informational efficiency, the extent to which all available information is incorporated into the prices of securities[3]. Generally, the empirical works on financial market efficiency focus on the third type; that is, the informational market efficiency[4]. Most theoretical discussions and empirical studies of market efficiency are based on the proposition that asset prices follow a random walk behavior, which implies

[3] The degree of allocational efficiency depends on both operational and informational efficiency.
[4] One should be aware that financial market can be informationally efficient without being allocationally or operationally efficient.

that asset prices cannot be predicted. This framework is known as the Random Walk Hypothesis (RWH) or alternatively the Efficient Market Hypothesis (EMH). In such context, if the hypothesis that the asset's price moves randomly cannot be rejected, then it supports the market efficiency theory.

Initially, the EMH was widely accepted by academics and financial economists. Representing the view of many EMH proponents at that time, Michael Jensen once wrote "there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis. That hypothesis has been tested and, with very few exceptions, found consistent with the data in a wide variety of markets…." (Jensen, 1978, p. 95). However, with the increasing mixed results of EMH empirical testing, the initial confidence in this proposition has declined, and it has been a subject of intense and persuasive debate. The empirical validity of market efficiency has been questionable in the sense that financial markets cannot be efficient, and potential predictability of asset returns can never be ruled out. This argument can be assessed when considering the empirical findings that violate market efficiency throughout many studies on developed markets as well as some studies on developing ones. These studies have mainly focused on the appearance of some predictable patterns in financial markets and the excessive volatility that can never be explained within the context of market efficiency.

Some economists, however, took this debate a step further by arguing that economic relations, and hence the data generating processes, are inherently nonlinear; thus, it is inconsistent to use linear models for testing the market efficiency. As a result, an increasing number of studies have been conducted to test efficiency of financial markets using nonlinearity tests. Rather than testing for simple linear dependence, nonlinearity tests are able to detect a higher degree of dependence in the data that may never be detected by conventional linear tests. The recent literature asserts the presence of nonlinearity in various economic and financial time series.

This chapter will shed some light on the literature of the EMH and some of its empirical findings in both developed and less matured markets including the GCC markets. In addition, implications of the EMH and some of its critics will be overviewed in the second part of this chapter. The last part provides a brief review of the nonlinear dynamics literature in economics and financial markets with more emphasis on the empirical findings.

2.2 Efficient Market Hypotheses

2.2.1 Literature Review

The notion of market efficiency can be traced back to the French mathematician Louis Bachelier who submitted his Sorbon Ph.D. dissertation “Theory of Speculation” in 1900. In that theoretical work, he introduced some insightful ideas about the commodities prices arguing that prices fluctuate randomly, and hence speculators should consistently earn no extraordinary profits over the long term, describing this condition as a “fair game.” Unfortunately, Bachelier’s work was ignored for sixty years until it was reached to economists by Paul Samuelson in the late 1950s (Bernstein, 1992), and subsequently translated to English and published in 1964 by Cootner (Bachelier, 1964). Prior to that time, investment and financial analysis had been dominated by the two well-known techniques: the technical analysis and the fundamental analysis. The technical analysis, whose practitioners are usually called chartists, depends on using charts and analyzing past statistics such as price and volume to interpret market behavior and attempt to identify or predict some patterns. Chartists believe that market is ten percent logical and ninety percent psychological (Malkiel, 2003a). On the other hand, fundamental analysts are concerned with the underlying forces that affect the economy over all and the financial market in specific. Some of the issues fundamentalists may consider include economic growth, interest rates, dividends payout, balance sheet, income statement, cash flow statement and so on. Unlike technical analysts, fundamentalists believe that market is ninety percent logical and 10 percent psychological (Malkiel, 2003a). The term “Random Walk” was first introduced by Karl Pearson (1905) when he posed “The Problem of the Random Walk” which was concerned with the optimal search strategy to find a man (presumably very drunk) who started walking in a field with arbitrary directions. It was concluded that the man would most probably end up at or close to the position where he had already started (Dimson & Mussavian, 1998). The analogy of that problem has been then applied to finance and economics for series whose successive changes are serially independent. In financial markets, the random walk model asserts that all subsequent asset price changes represent random departures from previous prices. Usually, the hypothesis of random walk is associated with the concept of market efficiency in the sense that in efficient financial markets, asset prices confront the random walk behavior. The basis of the “market efficiency” argument is that in efficient market all information is already reflected in the asset price; therefore, the price movements do not follow any patterns or trends. Generally, this may imply that price changes are somehow unpredictable and investors cannot outperform the market and achieve superior profits.. Empirically, the application of random walk can be traced back as early as 1933 when Cowles (1933) published his article following the forecasting failures of 1929 crash of US stock market. In that study, Cowles analyzed forecasting performance of forty-five professional agencies that attempted to predict stock prices and found their performance, on average, is not any better than the performance of pure chance, concluding that stock market forecasters were unable to forecast. Indeed, many believe that the modern literature of market efficiency starts with the work of Samuelson (1965) whose contribution is neatly summarized by the title of his article: “Proof that Properly Anticipated Prices Fluctuate Randomly” (Lo Andrew & MacKinlay, 1999). Samuelson’s work is considered as the first formal economic argument for “efficient market” in which he explained market efficiency in terms of a less restricted martingale rather than a random walk.

In 1965, Fama published his doctoral dissertation, “The Behavior of Stock Market Prices,” suggesting that stock prices are unpredictable and follow a random walk. In that study, Fama (1965) established the basic principles of the EMH and provided this definition for efficient market:

> “An ‘efficient’ market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value.”

Since then, the interests have shifted heavily to this literature and voluminous empirical research has been dedicated to investigating the behavior of asset prices. One influential study was the early unpublished paper by Roberts (1967) who coined the term “Efficient Market Hypothesis” and introduced the classical taxonomy of information sets to distinguish between three forms of the market efficiency: weak-form where the information set includes only historical data, semi-strong form in which the information set includes publicly available information, and strong-form where information set includes all information that can be known to any market participant including private information (Campbell, Lo, & MacKinlay, 1997). Based on Samuelson’s work and the taxonomy of Roberts, Fama (1970) published his influential article in which he extended the discussion of “informational” market efficiency and provided a comprehensive review of the market efficiency literature. He proceeded from theory to empirical evidence covering most of the prior theoretical development and empirical work. In that article, Fama identifies three forms of capital market efficiency:

1) Weak-form market efficiency:

   This form states that all historical share prices and other financial data are fully reflected in the asset prices. That means no investor can earn excess returns by developing trading rules based on past price or return information. In another word, it implies that technical analysis techniques would not be able to outperform the market, whereas some forms of fundamental analysis could be used to provide excess returns.

It is the weak-form in a sense that asset prices are the most public and easily available information.

2) Semi Strong-form market efficiency:

This form asserts that all information available to the public is fully reflected in asset prices. In such market, publicly available information such as annual reports, financial statements of companies, historical data, and other relevant information can not be used by investors to get superior profits. This implies that neither technical nor fundamental analysis can be used to outperform the market.

3) Strong-form market efficiency:

This form of the EMH asserts that all information, whether public or private, is fully incorporated in asset prices. That means even insider information cannot be used for getting excess return. In fact, this is a very strong-form hypothesis which means prices will be fully and instantaneously adjusted to any possible information of any kind.

It can be noticed that a market that is strong-form efficient is semi strong-form efficient, and a market that is semi strong-form efficient is weak-form efficient, but not vice versa.

Testing weak-from efficiency requires testing whether changes in asset prices (or returns) resemble a random walk behavior. Statistically, it measures the independence of changes in prices or returns, and when significant independence is found, it would be evidence of market efficiency in the weak sense. In fact, this test form is the conventional approach where historical asset prices are the only needed information. Consequently, such form of efficiency has been widely examined in both developed and emerging markets. For instance, an early study conducted to analyze the behavior of 22 stocks and commodity prices in UK suggested that prices change randomly (Kendall, 1953). Similar inference was also claimed by Roberts (1959) who plotted a randomly generated sequence of time series and argued that it was indistinguishable from a record of US stock prices. In addition, Fama (1965) empirically tested the random walk behavior of stock prices using the serial correlation and runs tests on thirty stocks of the Dow Jones Industrial Average (DJIA). He used the data of daily stock prices for the period from 1957 to 1962 and concluded that the DJIA was efficient. Another study by Solink (1973) investigated a group of 234 common stocks from eight European stock markets and tested for serial correlation independence in daily, weekly, and monthly price changes. He documented very small dependency that cannot be significantly used for prediction. Spectral analysis technique was also employed by Granger and Morgenstern (1963) to examine the price movements of the New York Stock Exchange (NYSE) and could not find significant serial correlation in the NYSE returns. Further more, instances of weak-form efficiency in developed markets were reported by Cowles (1960), Osborne (1959, 1962), Cootner (1962), and Fama and Blume

(1966). Market efficiency has also been investigated in some less matured stock markets. For example, evidence of efficiency were concluded in stock markets of Singapore (Hong, 1978), Malaysia (Barnes, 1986), and Greece (Panas, 1990). In addition, random walk hypothesis couldn’t be rejected in financial markets of some Latin American countries (Ojah & Karemera, 1999) and Australia (Groenewold & Kang, 1993).

Generally speaking, most of the early empirical studies have shown corroborating evidence in favor of random walk behavior in mature stock markets, with few instances of efficiency in the developing markets. Nevertheless, increasing findings of recent empirical works indicate that the EMH does not always hold in stock returns even in its weak-form suggesting that asset prices are predictable to some extent. For instance, Lo and MacKinlay (1988) proposed the approach of variance ratio test which is based on comparing variance estimators derived from data sampled at different frequencies. Applying this test to US stock market for weekly returns, they strongly rejected the random walk hypothesis for the entire sample period of 1962 to 1985. Moreover, Poterba and Summers (1988) examined mean reversion in the US stock prices using the variance ratio test on monthly data. They found positive serial correlation in stock returns over short run (less than a year), and negative serial correlation in the longer horizon returns. Similar finding of autocorrelation patterns was also concluded by Fama and French (1988). Furthermore, some studies on the volatility of US stock and bond markets found evidence of significant excess volatility and concluded a rejection of market efficiency (LeRoy & Porter, 1981; Shiller, 1981). Evidence of non-random walk has also been reported in some emerging stock markets. For example, Wong and Kwong (1984) used runs test to examine the weak-form efficiency in Hong Kong stock market and concluded that it is inefficient. Another study by Urrutia (1995) employed the variance ratio test to investigate market efficiency in four major Latin American stock markets (Argentina, Brazil, Chile, and Mexico) and argued for the rejection of random walk hypothesis in these markets.

2.2.2 Efficiency in GCC Stock Markets

Few studies have been done on the stock market efficiency in GCC countries. Most of them were conducted to examine the presence of random walk behavior and hence to test for the conventional weak-form of the EMH. In the literature of stock market efficiency, it is generally believed that emerging markets is more likely to be inefficient since they are categorized as small-sized, thin trading, and less regulated markets. This prospective could be supported by the empirical findings of market inefficiencies in emerging markets including the GCC region. In the literature of GCC stock markets efficiency, empirical findings are mainly in favor of market inefficiency, with few instances of weak-form efficient markets. Efficiency of GCC financial markets was investigated by the early work of Gandhi et al. (1980) in which the Kuwaiti Stock Exchange (KSE) was analyzed during 1975 to 1978. They tested KSE for market efficiency using autocorrelation coefficients test, runs test, and simple volatility test finding that stock prices are highly serially correlated and volatile, and suggested that KSE is inefficient. Similar conclusion was also drawn by Bulter and Malikah (1992) who examined efficiency of Saudi and Kuwaiti stock markets using serial correlation and runs tests. The study was conducted on individual stock returns for the sample period from 1985 to 1989 and the results indicated significant serial correlation in both markets which can be considered clear evidence of market inefficiency. Similarly, other studies have reported instances of market inefficiency in stock markets of Saudi Arabia (Nourredine, 1998) , UAE (Ebid, 1990), and Kuwait (N. E. Al-Loughani, 1995). In `addition, a recent study by Elango and Hussein (2008) analyzed the stock markets in the six GCC countries and tested for random walk using runs test. Their results indicated that the weak-form efficiency was rejected for all GCC markets during the study period (from 2001 to 2006). Few studies, however, argued for week-form efficiency in some gulf stock markets. Among them was by Dahel and Labbas (1999) who examined the randomness behavior in stock markets of Saudi Arabia, Kuwait, Bahrain, and Oman. Using unit root, autocorrelation, and variance ratio tests, they couldn't reject the random walk hypothesis suggesting that these markets were characterized by weak-form efficiency. Another study by Abraham *et al.* (2002) examined efficiency in three GCC stock markets (Saudi Arabia, Kuwait, and Bahrain) using runs test and variance ratio test. The obtained results showed evidence of weak-form market efficiency in Saudi Arabia and Bahrain, but not Kuwait. In fact, the mixed results on GCC markets are not quite surprising knowing that similar inconsistency of results have been noted in many cases of developed and emerging markets.

2.2.3 Implications and Criticism

Despite the initial empirical support of the EMH, enormous empirical studies have argued for the existence of systematic patterns and historical anomalies in the movements of the stock prices. With the emerging literature of forecasting and nonlinear dynamical systems, questions are raised regarding the relevance of the EMH, or the methodologies used for testing this hypothesis. The recent stream of research has already cast some doubts on the validity of this preposition and argued that stock markets cannot be efficient, and prices predictability can never be ruled out, at least to some extent. The debate on the EMH and predictability of asset prices is extensive and a complete survey of this literature is beyond the scope of this dissertation. Yet, it is worth going through some of these arguments. As one of the most contested propositions in social sciences, the EMH has been a controversial issue in economics and finance. It has been challenged and criticized by many economists and statisticians. In an early argument, Grossman and Stiglitz (1980) assert that it is impossible to have perfectly informationally efficient market in which all available information is fully reflected in prices, and thus there will be no incentive to gather the costly information or even to trade at all, which may result in a collapse of such markets. Instead, some inefficiencies in stock markets are reasonable to compensate investors for the costs and efforts of gathering information and trading (Grossman & Stiglitz, 1980). Thus, a non-degenerate market equilibrium will not arise unless there are sufficient profit opportunities (A. Lo & MacKinlay, 1999).

The vast literature on stock market anomalies and relative predictability of stock prices is very supportive to the claim that financial markets cannot be efficient. For instance, stock market seasonalities such as calendar effects are among the most investigated anomalies in stock market returns. Such effects may include month-of-the-year, week-of-the-month, day-of-the-week, and hour-of-the-day effects. It has been notably recognized by many studies that the returns on common stocks in January tend to be much higher than in other months, especially for the smaller capitalization stocks (Keim, 1983; Lakonishok & Smidt, 1988; Reinganum, 1983). This anomaly is known as the turn-of-the-year or January effect. Also, week-end anomaly has been found evident in some stock markets by French (1980), and Gibbons and Hess (1981). Furthermore, some studies on firm characteristics argue that firm size can be associated with stock returns. For example, Banz (1981), Reinganum

(1981), Roll (1983) and others have documented the tendency of small-firm stocks to outperform large-firm stocks in the long run. The effects of some stock valuation ratios on future returns have been also examined in some studies. Basu (1977), for instance, conducted a study on 1400 firms over the period from 1956 to 1971 and reported a strong evidence that stocks of companies with low price-earning (P/E) ratios tend to provide higher rates of returns than stocks of companies with high (P/E) ratios. Similar findings on significant effect of (P/E) ratio in the long run were documented by Cook and Rozeff (1984), Jaffe et al. (1989), and Fuller *et al.* (1993). Price-to-book-value (P/BV) ratio is another valuation variable that has been empirically found associated with future returns. Fore instance, Fama and French (1992) documented the out performance of stocks with low P/BV ratios compared to stocks with high P/BV ratio in a study applied to US stock markets covering the sample period from 1963 to 1990. Similarly, effect of P/BV was found significant in many international stock markets (E. F. Fama & French, 1998). Fama and French (1992) argue that using P/VB and firm size together provides considerable prediction power for future returns. The dividend yield, defined as dividend-price ratio, has also showed some prediction ability for future stock prices. The relation between dividend yield and stock returns has been empirically tested by some studies such as Campbell and Shiller (1988) and Fama and French (1988) who concluded that dividend yield were able to explain much of the variation of future stock market returns. In addition, company’s cash flow, as seen by investment analysts as the health indicator for the company, can be successfully used in the prediction of returns. Some studies such as that by Chan et al. (1991), and Hawawini and Keim (1995) documented that higher returns are associated with high ratio of cash flow to price (C/P), and concluded that the (C/P) can be used as a fairly good predictor for returns.

The trade-off between risk and expected return is considered essential concept in modern financial economics, but some economists argue that risk is not considered in the EMH. Lo and MacKinlay (1999) pointed that a positive expected return of a stock my just reflect the reward of buying and holding such a stock with the associated risk, while some risk averse investors might be willing to pay in order to avoid holding stocks with unpredictable returns. Furthermore, they claim that the implicit link between the random walk and the efficient market hypotheses is incorrect, since they are not equivalent except in the case of risk neutrality. Moreover, LeRoy (1973) and Lucas (1978) argued that the RWH is neither a necessary nor a sufficient condition for rationally determined asset prices. Indeed, Lucas (1978) showed that in informationally efficient markets, rational asset prices may have a forecastable element that is associated with the forecastability of consumption, and hence the EMH hold, but prices do not confront the random walk behavior.

It is implicitly assumed by the EMH that all market practitioners have the same access to all available information. This seems to be a very strong and unrealistic assumption. But even if it holds, people are not endowed with identical cognitive and interpretive abilities. Simon (1955, 1957) pointed out that individuals have limited informational and computational knowledge; thus, he argues that rationality of an individual is constrained by human psychological limitations and instead of the full rationality he proposed the concept of “bounded rationality.” In fact, it can be argued that investors’ decisions may considerably be affected by some human behavior characteristics. For that reason, some economists and psychologists have introduced a new promising field of research, the behavioral finance, by incorporating the influence of human psychology on the behavior of financial practitioners to get better understanding of the price determination process of financial assets. It is usually assumed in the EMH that investors are rational profit maximizers. In the context of informationally efficient market, rationality involves using all available information and responding instantly to any new information in the best manner. However, financial behaviorists argue that the deviations of securities from their fundamental values may arise due to investors’ cognitive biases. Various studies have shown that market participants can be irrational when making their trading decisions and documented several behavioral biases that may result in market inefficiency. For instance, rationality assumption implies a risk aversion attitude of investors, which means that investors must be compensated with more return in order to accept more risk. However, Tversky and Kahneman (1979) conducted some experiments on investor's behavior and concluded that investors tend to be risk seeking when they face substantial loss. In particular, they observed that when faced with sure gain, most investors are risk averse, but when faced with sure loss, they become risk takers. To clearly illustrate this phenomena, Peters (1991) provides this simple example to explain such case:

Suppose an investor has been offered these two investment opportunities:

A) Sure gain of $85,000
B) 85 percent chance of receiving $100,000, and 15 percent chance of receiving nothing.

According to Tversky and Kahneman, most people would prefer the sure gain (choice A) even though the expected return is identical for both choices (i.e. $85,000). Typically, this behavior is characterized as risk aversion.

Now, suppose that investor has to choose between these two investment opportunities:

A) Sure loss of $85,000

B) 85 percent chance of loosing $100,000, and 15 percent chance of loosing nothing.

Similarly, both options would give the same expected loss of $ (85000); however it is now a worse scenario where the investor is loosing in both cases and has to choose the lesser of two evils. Choice (B) is riskier than choice (A), but the investor will more likely to be risk taker and choose the second option. Seemingly, such investor would not prefer the sure loss as long as there is any chance of positive return or at least zero, so when faced with this scenario he will more likely to gamble. This cognitive bias is argued by behavioral economists to be behind many of the poor investment decisions in financial markets.

Another challenging behavioral bias to the market rationality is the empirical evidence of short-term momentum and long run reversals in stock prices. Momentum is defined by the tendency of stock prices to move in and continue in the same direction for period of time. According to behavioral economists, momentum my result from prices that initially underreact to the new information and over time the gradual adjustment bring them back to their intrinsic values. As pointed by Barberis et al. (1998), a stock's underreaction to news would be detected if the average return on the stock in the period following good news is higher than the average return in the period following bad news. The higher average return is caused by the stock's correction process to the mistake of underreaction, which takes place gradually in the following period giving a higher return at that time. Several researchers have examined underreaction of security prices to good news and events. For instance, there has been statistical evidence of underreaction to earning announcements (Chan, Jegadeesh, & Lakonishok, 1996; Jegadeesh & Titman, 1993; Rouwenhorst, 1998), share repurchase announcements (D. Ikenberry, Lakonishok, & Vermaelen, 1995), dividend initiations and omissions (Michaely, Thaler, & Womack, 1995), and stock splits (D. L. Ikenberry, Rankine, & Stice, 1996). Another reason why momentum may occur is the stock's overreaction to new information. The overreaction takes place when the average return in the period following a series of good news is lower than the average return following a series of bad news (Barberis et al., 1998). After receiving series of good news, some investors would overweight that news and overreact pushing the stock price up too high. But in the long run, the subsequent news may reflect different facts about that stock, or they might even contradict the previous news, causing investors to revise their beliefs and hence the adjustment process will gradually drive the price down. De Bondt and Thaler (1985, 1987) ascribed this phenomena to the human psychology of investors and suggested that investors are uncertain about the stock intrinsic value, so they might become very optimistic about the stock value when the company is winning and very pessimistic when the company is loosing. Empirical evidence of overreaction was argued by numerous studies that documented existence of long-term return reversals in stock prices and attempted to predict the long run returns. For instance, studies by De Bondt and Thaler (1985), Chopra et al. (1992), and Zarowin (1989) have reported evidence of predicting stock returns over long horizon using the idea of “contrarian” strategy, which involves buying stocks that have been poorly performing for long time. These findings of underreaction and overreaction of stock prices to the market information raised serious doubts about the claim of instant adjustment of prices to new information as implied by the EMH. Moreover, such evidence suggests that sophisticated investors may earn superior returns by taking advantage of underreaction and overreaction without bearing additional risk; therefore, it presents a real challenge to the validity of the EMH (Barberis et al., 1998).

Underreaction and overreaction seem to coincide with the irrational behavior of “overconfidence”, which is a cognitive bias referred by financial behaviorists to describe investors who overestimate their abilities and beliefs to evaluate securities. This overconfidence may lead to irrational judgment and wrong financial decisions resulting in assets mispricing. Indeed, overconfidence can be found evident in financial markets as well as in many other fields of life. De Bondt and Thaler (1995) pointed that it might be the most robust finding in the psychology of judgment. In fact, not only typical individuals are subject to overconfidence, but even professionals such as security analysts can be overconfident. Evidence of the overconfidence bias has been documented in financial markets by several studies such as De Bondt and Thaler (1990), Chen and Jiang (2006), and Friesen and Weller (2006). Furthermore, overconfidence could lead to irrational investment behavior in the form of excessive trading when overconfident Investors think that they have reliable information to justify trades. By either misinterpreting or overweighting the information they have, overconfident traders would make too frequent unjustified trades leading to overwhelming trading and hence excessive volatility in the financial markets. Generally, trading volume were found higher than normal in financial markets and many argue that excessive trade by investors is too large to be justified on rational grounds. Various studies attempted to address overconfidence and excessive trading in financial markets. Odean (1999), for example, found that overconfident investors got gains less than what they anticipated, and that gain might not even offset the costs of trading. Another explanation for overconfidence is provided by Change and Lee (2006) who claim that overconfident investors may trade more aggressively in periods following market gains. Some argue that noise irrational trading may have resulted in the observed excessive trading, and this can be related to the excessive volatilities recognized in many financial markets. The high stock price volatility was questioned by Shiller (1981) who pointed that such high volatility is hard to be justified by some fundamentals change such as subsequent variations in dividend payment. In addition, Shleifer and Summers (1990) suggested that financial market participants are either rational arbitrageurs trading on the basis of information, or noise traders trading on the basis of imperfect information.

Despite the empirical evidence of patterns found in price movements, the persistence of these patterns is still quite questionable. Some argue that those patterns may not be sufficient to build reliable investment strategies that can be used consistently to earn significant profits. In fact, it was argued that many of these patterns are only chance events, better described by anomalies, that do not persist for too long (Roll, 1994). Some proponents of EMH such as Malkiel (2003b) claims that these violations of price change independence of past information are of small effect relative to transaction costs and not dependable from period to period. Malkiel also referred to the tendency of many of the predictable patterns to disappear once they are published and reached by large number of investors. It means new anomalies and price movement patterns would likely to keep appearing and be exploited by traders from time to time, in one market and another, but no forecasting model can be reliably used.

Initially, this may seem to be a further controversial issue in the EMH debate. On one hand, market efficiency along with the assumption of “full” rationality has been seriously challenged by evidence of inefficiency and irrationality in many financial markets. This was significantly contributed by the recent research on market psychology, and historically assessed by the various episodes of bubbles and subsequent crashes in many financial markets. On the other hand, the predictability of asset returns, although it is not completely ruled out, is still in question regarding its accuracy and reliability. One concern that may arise in such matters is questioning the theoretical framework used in those findings. Most empirical work in the literature of market efficiency is based on linear methodologies. These might be considered good approximation techniques when modeling simple relations, but not sufficiently able to explain irregular complicated relations which what we really observe in the real life. To provide a better explanation on behavior of financial markets, or probably bridge the gap in the EMH debate, an alternative theoretical paradigm can be considered. In fact, it is legitimate to hypothesize that the too complicated system such as financial markets might have been oversimplified by the linear approximation, which can cause misleading findings. The assumptions of linearity in the underlying financial system, or that financial time series can be well approximated by linear models, is only motivated by simplicity of linear paradigms, but not built on a solid theoretical base. It is strongly believed that nonlinear approaches fit the real world much better. Thus, linear approximation is expected to be irrelevant or misleading in modeling financial time series and instead, it is suggested to analyze such relations within the context of nonlinearity. This is due to the fact that many forces such as economic and social conditions, market psychology, institutional regulation, and the interaction of these forces and many other factors can drive financial systems. Therefore, it is intuitively appealing to think of the financial asset return as a relatively complicated process that needs to be examined in a broader rather than in a simple approach. Over-simplification may lead to inaccurate judgment about the structure and generating process of the data. In financial market, oversimplified linear models can result in poor investment decisions, even by professionals, producing more stock market volatility. In addition, the linear techniques are not able to intuitively explain the abnormal deviations frequently appear in stock prices as well as the observed historical financial crises.

The advance in fields of complexity and nonlinear dynamic systems attracted the interest of researchers to pay more attention to the nonlinear dynamics in financial markets. As mentioned earlier, the literature of stock market efficiency has been mainly focused on testing the week-form of market efficient hypothesis using the traditional tests for random walk behavior in stock prices such as runs, autocorrelation coefficients, and unit root tests. Technically, these tests are conducted to examine the linear serial independence in stock return movements, but cannot detect any nonlinear structure in the data. If independence is concluded by those tests, it will only reject the linear predictability of asset returns, but does not rule out the possibility of nonlinearity in the underlying structure of financial data and thus the possibility of forecasting the returns. If nonlinearity exists in stock market returns, it would obviously contradict the EMH since asset returns can be linearly uncorrelated and at the same time nonlinearly dependent. Moreover, the existence of nonlinear dependence will open a new door for the potential asset returns predictability and stimulate further research and efforts to look for profitable nonlinearity-based trading strategies. Hence, an overview of nonlinear dynamics in economics and the financial markets in particular is necessary before proceeding further to the nonlinearity tests.

2.3 Nonlinearity

2.3.1 Literature Review

The terms linearity and nonlinearity are usually associated, respectively, with simplicity and difficulty. By definition, the linear system is the one that has the property of simple proportion; that is: having an output that is proportional to its inputs. A simple straight line can graphically depict a linear function. Mathematically speaking, it is the function that has these properties:

$$f(x+y) = f(x) + f(y) \tag{1}$$

$$f(ax) = af(x) \tag{2}$$

On the other hand, a nonlinear system is the one in which properties (1) and (2) do not hold since its output is not proportional to its inputs. Nonlinear system can be illustrated graphically by a curve. To better understand the behavior of any system it is necessary to look at the way its variables interact and change over time; in other word, to understand the real dynamics of that system. Predictability of natural and social processes is of great importance in the history of science and it has been usually connected with theory of dynamical systems. In the context of system dynamics, the output of a linear system changes over time by constant amount, which is implied by the constant slope. On the other hand, we will probably recognize different proportional change in the output of a nonlinear system for each unit of time, which is implied by the variant slope. Such non-constant evolvement is argued by many to be what we actually observe in the real world. Linearity is usually imposed to approximate real dynamical systems that are, by their very nature, characterized as nonlinear systems. In real dynamical systems, nonlinearity arises as a result of the interaction of simple and complex forces that can affect the initial conditions and act on the evolvement of these systems. Indeed, nonlinearity is claimed to be a salient feature of many dynamical systems in natural and social sciences such as physics, chemistry, biology, meteorology, medicine, and economics. However, the empirical modeling of time series was dominated by linear methods for many years due to the fact that linear models can be analyzed much easier than nonlinear models; thus many nonlinear phenomena have been simplified and fitted by linear models. But exploiting linear approximation to predict a real system output may produce inaccurate results and incorrect conclusion. That is because linear models cannot adequately capture some irregular variation and nonlinearity-associated aspects in the underlying dynamics. The dissatisfaction with linear models accompanied by the substantial advances in computing and applied statistics has greatly contributed to the emerging research in the new era of nonlinear analysis. The last three decades have witnessed wide applications of the theory of nonlinear dynamical systems in many fields. Moreover, it is argued that nonlinear dynamical systems may exhibit some complex behavior such as chaos, bifurcation, and irregular oscillations that can never be captured by linear techniques.

2.3.2 Nonlinear Dynamics in Economics

Studying the dynamics of economic systems has a long history in economics. Back to the beginning of the twentieth century, economists were concerned with the fluctuations of economic activity around its long term growth path, what is known in the literature as “business cycles.” It has been noticed by many economists that economic variables such as gross domestic product (GDP), stock prices, inflation, interest rates, exchange rates, and unemployment exhibit persistent fluctuations over time. As pointed by Hommes (2004), in the context of business cycles there are two viewpoints provided by economists to explain these fluctuations. The first explanation is given by the new classical economists who believe that economy is inherently stable, often linear, and converges to unique steady state path. The source of fluctuations is argued by this group to be exogenous random shocks to economic fundamentals, such as preferences, endowments, technology, and others. On the contrary, the Keynesian viewpoint asserts that, even in the absence of external shocks to the fundamental of the economy, fluctuations in economic variables may arise due to volatile, self-fulfilling expectations. According to Keynesians, fluctuations should be explained by nonlinear economic laws of motion rather than attributing them to some external random events. The classical prospective on business cycles is empirically supported by the early work of Frisch (1933) and Slutzky (1937) who showed that simple, linear dynamic model with additive random term can generate cyclic processes similar to the actual observed business cycles. On the nonlinearity side, some attempts were made by Kaldor (1940), Hicks (1950), and Goodwin (1951) to develop nonlinear dynamical models with locally unstable steady states and stable limit cycles as an explanation for business cycles. But those models suffered from some shortcomings and hence didn't show sufficient success (Hommes, 2004). By the 1960s, modeling economic dynamics had been mainly conducted by linear methodologies, making use of the so-called Frisch-Slutzky paradigm. A tremendous stimulus to the linear framework was the wide range of computer software packages by which one can simply estimate a linear model using standard regression techniques. One example is the widely used autoregressive moving average models of Box and Jenkins (1976) in which dynamics of estimated models can be completely described by their impulse response functions and directly related to linear models of the macroeconomy (Pesaran & Potter, 1992). Moreover, Scheinkman (1990) argues that at least two reasons might have contributed to the dominance of Frisch-Slutzky linear paradigm. First, it was recognized at that time that nonlinear models seemed unable to produce the statistical aspects of the observed economic data, and hence there was no obvious gain in the introduction of nonlinearities. In addition, the relative empirical success of some linear models may have attributed to this dominance. Linear approaches, however, has been criticized by many economists since they do not provide sufficient economic explanation of the persistent fluctuations. Instead, they treat them as being exogenous shocks to the system for which no good explanations exist. Pesaran and Potter (1992) addressed the issue of nonlinearity existence in economics and argued that once curvature is introduced into utility and production functions in theoretical dynamical models, it becomes self-evident. Moreover, linearly approximated models seem to be incapable of addressing certain features of economic reality, and thus may not correctly specify the underlying dynamics of economic relations. Fore instance, linear approaches can be highly deficient when economic behavior is dominated by asymmetric costs of adjustments, irreversibilities, transaction costs, and institutional and physical rigidities (Pesaran & Potter, 1992). Presence of nonlinearity in economic systems is assessed by Campbell et al. (1997) who states that “many aspects of economic behavior may not be linear. Experimental evidence and casual introspections suggest that investors’ attitudes towards risk and expected return are nonlinear. The terms of many financial contracts such as options and other derivative securities are nonlinear. And the strategic interactions among market participants, the process by which information is incorporated into security prices, and the dynamics of economy-wide fluctuation are all inherently nonlinear.”

As in many other fields of science, economists' interest in nonlinear dynamical systems has considerably increased following the introductory of chaos theory in the 1970s. Deterministic chaotic system, which denotes the apparently random output of certain nonlinear dynamical systems, has two interesting properties:

1) Stochasticity is intrinsically generated in the system.
2) The system is highly sensitive to initial conditions.

Many economists have been inspired by chaos theory as a promising field that provides further insight into nonlinear dynamics of some economic systems. Basically, economists argue that if simple deterministic systems can produce random-looking results, then the seemingly random data that we observe in economic systems is not necessarily coming from random systems. If that is the case, then it is very possible to explain some economic irregularities by relatively simple nonlinear systems. For instance, the argument that asset prices have predictable, as well as some unpredictable (or random) components, can be supported by the theory of chaos. For that reason, chaos is considered as a nonlinear reconciliation which can potentially bridge the gap between the classical stochasticity considerations and the real-life observations. The recent trend of academic research reflects a substantial surge in the literature of nonlinear dynamics including chaos theory and, more recently, complexity theory[5]. Day (1992) argues for the potential presence of complex dynamic behavior in economic data throughout the irregular fluctuations in some economic aspects such as individual commodity prices and quantities, aggregate indices representing the whole economy, and economic growth. He also pointed that economic activity may follow overlapping waves of consumption, technology, and organization, and argued that any evidence that economic data converge to stationary states, to steady growth, or to periodic cycles would appear to be of a temporary kind. In simple stochastic models, Hsieh (1989) suggests two types of nonlinear dependence, additive nonlinearity and multiplicative nonlinearity. Also known as nonlinearity in the mean, additive nonlinearity enters a process through its mean or expected value, so that each element in the sequence can be expressed as the sum of zero-mean random element and a non-linear function of past elements. With multiplicative nonlinearity, each element can be expressed as the product of a zero-mean random element and a nonlinear function of past elements. This means nonlinearity affects the process through its variance and hence this type is alternatively described as nonlinearity in variance.

Empirically, many studies have been conducted to investigate the presence of nonlinearity in economic time series whether it is stochastic nonlinearity or deterministic chaos. Evidence of low dimensional deterministic

---

[5] For a good survey see Kiel and Elliott (1996), Arthur et al. (1997), Rosser (2004) and Perona (2005).

chaos in economic data is relatively weak; however, there is substantial empirical evidence of nonlinearity in many economic series. For instance, it has been noted that many economic variables and relations display asymmetry and nonlinear adjustment (Neftci, 1984; Rothman, 1988; Terasvirta & Anderson, 1992). Moreover, some studies showed that the internal dynamics of an economy may follow a very complex behavior that is endogenously generated (Arthur et al., 1997; Day & Chen, 1993; Rosser, 2004).

2.3.3 Nonlinear Dynamics in Financial Markets

As mentioned earlier, financial economics has been dominated for many years by linear models, and more specifically, by the random walk framework. With advances in theory of nonlinear dynamical systems, researchers attempted to analyze nonlinear dynamics and chaotic structure of financial time series. As a result, many theoretical and empirical works have been devoted to nonlinear phenomena in financial economics. Generally speaking, economists are aware of the necessity of nonlinear analysis in financial economics as briefly described by Campbell et al. (1997): "a natural frontier for financial econometrics is the modeling of nonlinear phenomena." Some researchers such as Savit (1988), Peters (1991), and Antoniou *et al.* (1997) argue for several reasons to believe that financial markets are characterized by nonlinear behavior. For instance, stock prices can be nonlinearly affected by various factors such macroeconomic variables, political conditions, whether, and many others. When underlying trends of these factors are subtracted out, the remaining random-looking price fluctuations can be a result of the inherent nonlinearity in the market (Savit, 1988). In addition, existence of nonlinearity can be attributed to one important feature in financial markets, the feedback mechanisms in asset price movements. That is, if asset price go up too high, self-regulating forces would drive this price down to the normal level (correct price), and vise-versa (Savit, 1988). These mechanisms can be linear if the corrective adjustment is proportional to the price deviation from the correct value, while it is not necessary for market correction to be proportional to the price deviation in case of nonlinear feedback mechanisms. Savit (1988) argues that these effects of feedback dynamics may be nonlinear since simple linear feedback dynamics cannot generally produce the observed random-looking fluctuations in asset prices. The nonlinear feedback effects, on the other hand, may arise due to some aspect in the market psychology such as overreaction to bad news. In fact, studies on cognitive bias and market psychology, reviewed in earlier section, provide supportive results that coincide with this argument. Overreaction and underreaction in financial markets may result in complex, nonlinear dynamics in terms of feed back mechanisms in asset price movements. Moreover, the presence of market imperfections such as transaction costs may contribute to nonlinearities in financial markets

(Antoniou et al., 1997). For instance, when market participants receive new information they may not immediately respond to it, considering the existence of transaction costs, and instead, they would wait until it confirms a change in recent trends, resulting in a nonlinear reaction (Peters, 1991). It is also argued that this delay of response may result in clustering of price changes (Antoniou et al., 1997). Another reason is related to the notion of “rational investors”, the assumption that has been used in most linear paradigms in the literature of capital markets. Investors may not necessarily be risk-averse when making their investment decisions since, as previously discussed, they tend to be risk-takers when faced with capital loss. Asset prices can be greatly affected by the behavior of market practitioners who usually place their investment decisions based on their expectations and beliefs. The rationality of investors has been questioned recently, with the growing evidence of irrational and irregular behavior of financial asset prices. In addition, linear frameworks such as the EMH assume that investors are unbiased when they set subjective probabilities (Peters, 1991). But the contrary can be noticed from the historical events like the sudden unpredicted crashes of some financial markets around the world, and the empirical counter examples documented by various studies in the context of market psychology. For instance, the case of overconfident investors who place too much faith in their prediction abilities is one possible bias that can be introduced to the subjective probabilities (Antoniou et al., 1997). Furthermore, market rationality is considered as a strong assumption that could be associated with problem of oversimplification in economic realties. This may explain the recent surge of interests in “bounded rationality” as an alternative approach to rational expectations. In fact, some nonlinear economic dynamical models have been recently developed based on the assumption of bounded rationality (Hommes, 2004).

Nonlinear dynamics in financial markets is argued in many studies, greatly motivated by the increased interest in deterministic nonlinear chaotic process. Existence of chaos in asset prices means the possible existence of profitable, nonlinearity-based, trading rules, at least in the short run, assuming the actual generating mechanism is known (Barnett & Serletis, 2000). Despite of the little evidence of chaos in financial markets, there is strong evidence of nonlinearity in both mature and emerging financial and capital markets. For example, Hinich and Patterson (1985) have concluded a strong evidence of nonlinearity in daily stock returns in a study on fifteen US common stocks. Savit (1988) suggests that asset returns may be generated by deterministic chaos. He argues that the process appears stochastic since the forecasting error grows exponentially. Moreover, evidence of nonlinearity has been documented in US weekly stock returns (D. A. Hsieh, 1991), and daily closing bid prices of some foreign currencies in terms of US dollars (David A. Hsieh, 1989). Scheinkman and LeBaron (1989) has also argued that nonlinear dependence is evident in weekly and daily US stock returns, while Peters

(1991) concluded a further evidence of a nonlinearity presence in currency, bond, and stock markets in the US. Nonlinear dependence is also found evident in some other developed financial markets such as UK (Abhyankar, Copeland, & Wong, 1995; Brooks, 1996; Opong, Mulholland, Fox, & Farahmand, 1999), Germany (Kosfeld & Robe, 2001), and Japan (Lim, Azali, Habibullah, & Liew, 2003). Literature on nonlinearity in emerging financial markets is relatively limited, but initial empirical findings suggest that nonlinearities can be evident even in the less matured markets. Several studies reported evidence of nonlinearity in financial markets of Turkey (Antoniou et al., 1997), Greece (Barkoulas & Travlos, 1998), several Asian countries (Lim & Hinich, 2005) and a group of Latin American countries (Bonilla, Romero-Meza, & Hinich, 2006). For the GCC stock markets, few studies have been conducted on the nonlinear dynamics in financial markets. Those studies put more emphasis on the volatility of stock market returns and interaction with other economic realties rather than directly testing for nonlinear dependence in stocks returns. In one study, Al-Loughani and Chappell (2001) investigate the day-of-the-week effect in the Kuwait Stock Exchange (KSE) using a nonlinear GARCH representation. In part of this study, Brock, Dechert and Scheinkman (BDS) test proposed by Brock *et al.*, (1987) was applied to the residuals of a linear basic model[6] of daily stock market returns, suggesting a presence a nonlinear structure in stock returns.

[6] In this model, daily stock return is regressed on five dummy variables representing the trading days.

They claim that GARCH (1,1) can adequately explain variations in daily returns and conclude that a day-of-the-week effect is evident in the KSE. Another study employs nonlinear cointegration analysis to examine the linkages between oil prices and stock markets in GCC countries and concludes that oil price affect the stock price indices in a nonlinear fashion (Maghyereh & Al-Kandari, 2007).

In conclusion, a great deal in financial research is concerned with the question of market efficiency, and more specifically the EMH. The recent emerging interest in nonlinear dynamics analysis has led to a further challenge to the validity of the EMH. Unlike traditional market efficiency tests for linear serial dependence, nonlinearity tests can be conducted on financial market data to examine the presence of nonlinear dependence, and hence to either reject or fail to reject the hypothesis of market efficiency. In the next chapter, three of the well-known nonlinearity tests will be applied on returns of the GCC stock markets looking for any nonlinear structure in the data. These tests are namely Hinich bispectrum test (Melvin J Hinich, 1982), White's neural network test (White, 1989a), and Kaplan's test (Kaplan, 1994).

CHAPTER THREE

EMPIRICAL ANALYSIS

3.1 Data Description

The stock markets' data of the six GCC members are used in this dissertation with different sample period due to the data availability. For UAE, which has two major stock exchanges: Dubai and Abu Dhabi Stock Exchanges, the stock market is represented by the general index of National Bank of Abu Dhabi (NBAD)[7]. Tadwul All-Shares Index (TASI), Kuwait Stock Exchange (KSE), Doha Stock Exchange (DSE), Muscat Stock Market (MSM), and Bahrain Stock Exchange (BSE) respectively represent stock markets of Saudi Arabia, Kuwait, Qatar, Oman, and Bahrain[8]. The obtained data set consists of the daily closing indices of TASI (from 13 March 1995 to 14 March 2007), KSE (from 17 June 2001 to 31 December 2007), UAE (from 23 January 1999 to 10 December 2007), MSM (3 May 1999 to 1 May 2008), DSE (1 February 2002 to 28 May 2008), and BSE (31 December 2002 to 19 May 2008). For each series, the daily return (R_t) of the Stock Exchange (SE) composite index will be calculated according to the following equation:

---

[7] It is a market capitalization weighted index that has 38 listed companies in both markets accounting for 75% of the overall active market. Dr. Shaukat Hammoudeh thankfully provided data for NBAD general index.
[8] Data for these markets were obtained from the corresponding stock exchange authorities.

$$R_t = \ln\left({SE_t}/{SE_{t-1}} \right) \times 100 \qquad (3)$$

where SE_t is the stock index closing price on day *t,* and SE_{t-1} is the stock index closing price on the previous trading day. Before applying the tests for linear and nonlinear serial dependence, each series will be tested for unit root. Employing the unit root tests is important to assure the stationarity of the underlying empirical variables and avoid any possible spurious regression that may be involved in the serial dependence tests. Therefore, this study employs three of the well known tests in the literature of unit root. These are Augmented Dickey and Fuller (ADF) test (1981), Phillips and Perron (PP) test (1988), and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test (1992).

3.2 Preliminary Statistics and Unit Root Tests

The daily GCC Stock markets indices and their returns are graphically depicted by figure 1 through figure12. Summary statistics for returns are computed and listed in Table 2. Before conducting the unit root tests, an optimal lag length needs to be determined as a prior step. For ADF, Hannan-Quinn (Hannan and Quinn, 1979)[9] criterion (HQC) is used for optimal lag length, while for PP and KPSS the bandwidth is selected using the Newey-West (1994) Bartlett kernel. The null hypothesis in ADF and PP tests is that a

[9] In a simulation study, Liew (2004) conducted a study on the performance of some commonly used selection criteria and he found that the HQC outperformed other criteria with relatively large sample (120 or more observations). Knowing that all of the six series samples used in this study are relatively large (1000 observations and above), I employed the HQC as an optimal lag selection criterion.

series has a unit root, which means a stationary series should have significant ADF and PP statistics. Unlike ADF and PP, the KPSS tests the null hypothesis that the series is stationary against the alternative hypothesis of having unit root and hence a stationary series would have insignificant KPSS statistics. ADF, PP, and KPSS were conducted on the first log difference of the stock market index for each of the GCC markets. These tests were employed with constant term and no time trend, and the resulted test statistics are reported in Table 1. The results of ADF and PP unit root tests show strong evidence that all series are stationary at ten, five, and even one percent significance levels. Similar results were concluded by the KPSS test for the GCC markets with the exception of UAE and MSM[10]. As a result, we can generally conclude that stock markets returns in GCC countries are stationary.

[10] To confirm the stationarity conclusion of UAE and MSM stock indices returns, I conducted a fourth unit root test (DF-GLS test) and obtain results with similar conclusion as that obtained by ADF and PP tests.

Table 8: Summary Statistics for GCC Stock Returns

Statistics	**TASI**	**KSE**	**UAE**	**BSE**	**DSE**	**MSM**
Mean	0.051	0.121	0.046	0.076	0.124	0.069
Median	0.084	0.134	0.013	0.046	0.082	0.035
Maximum	9.391	5.047	6.216	3.613	5.815	6.804
Minimum	-10.088	-4.777	-6.429	-2.587	-8.074	-8.699
Std. Dev.	1.225	0.854	0.864	0.558	1.345	0.781
Skewness	-1.011	-0.546	0.026	0.481	-0.174	0.212
Kurtosis	17.269	7.640	13.710	7.999	5.982	17.092
Jarque-Bera	30988	1570	12379	1437	598	18559
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Sum	182.460	201.404	118.974	100.783	196.681	155.449
Observations	3581	1659	2590	1331	1592	2241

Table 9: Unit Root Tests for GCC Stock Returns

Series	**ADF**	**PP**	**KPSS**
TASI	-19.623*	-55.915*	0.194
KSE	-17.810*	-34.011*	0.332
UAE	-13.290*	-40.575*	0.555**
BSE	-31.037*	-31.973*	0.223
DSE	-26.548*	-27.565*	0.328
MSM	-35.622*	-37.261*	0.970*

Note: The 1% and 5% critical values are -3.432, -2.862 for ADF, -3.433, -2.863 for PP, and 0.739, 0.463 for KPSS respectively. "*" and "**" denotes the rejection of the null at 1% and 5% level of significance, respectively.

Figure 5: Daily Index of Saudi Arabia Stock Market (TASI)

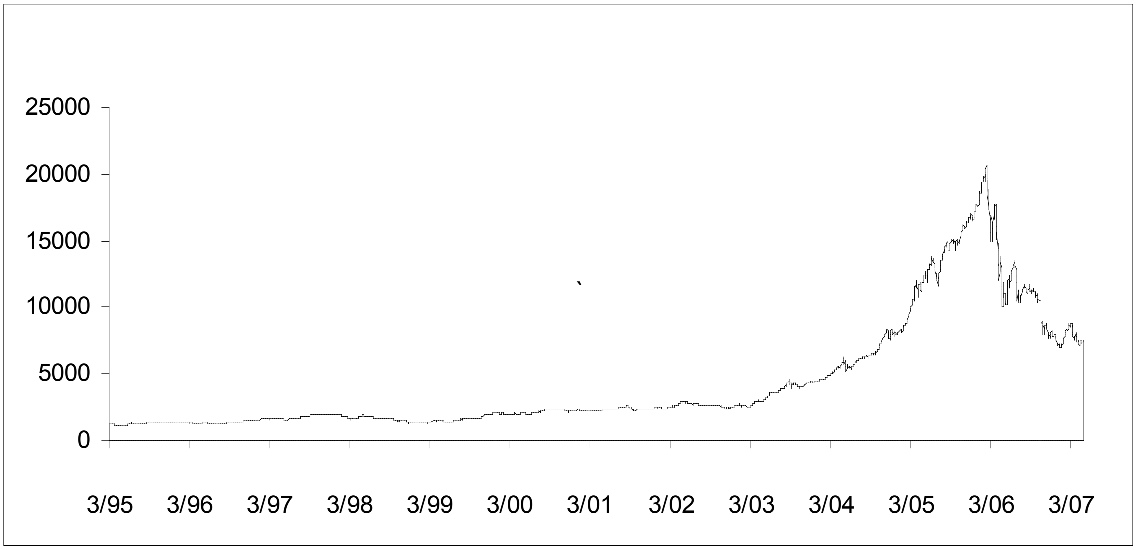


Figure 6: Daily Returns on TASI

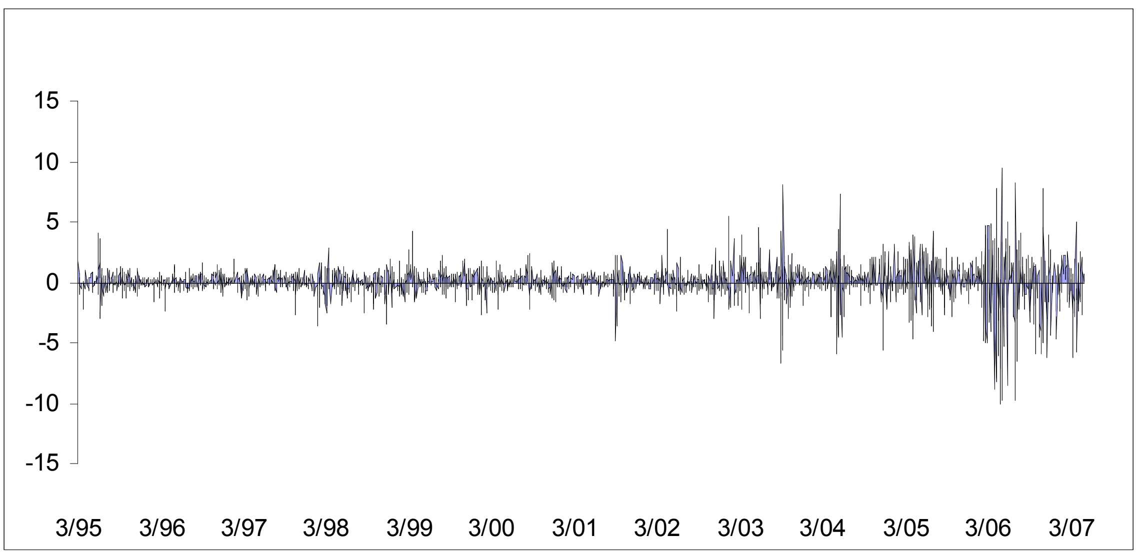


Figure 7: Daily Index of Kuwait Stock Exchange (KSE)

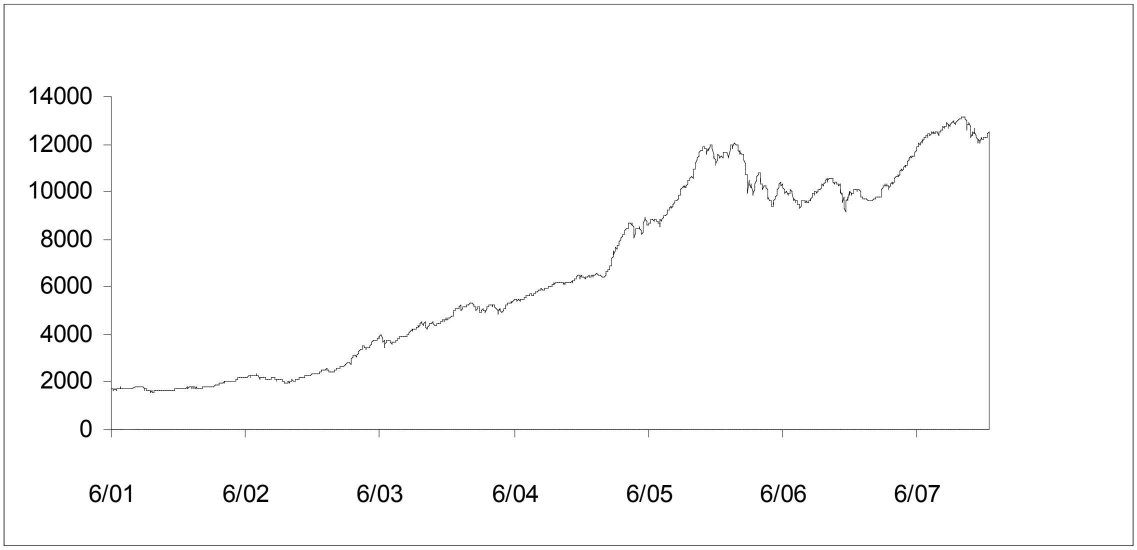


Figure 8: Daily Returns on KSE

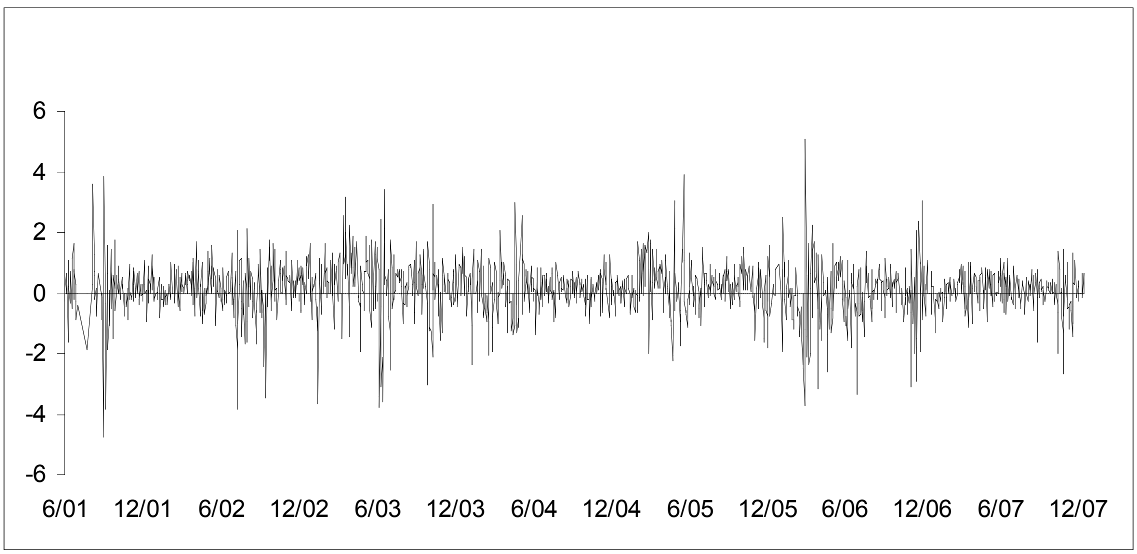


Figure 9: Daily Index of UAE Stock Market

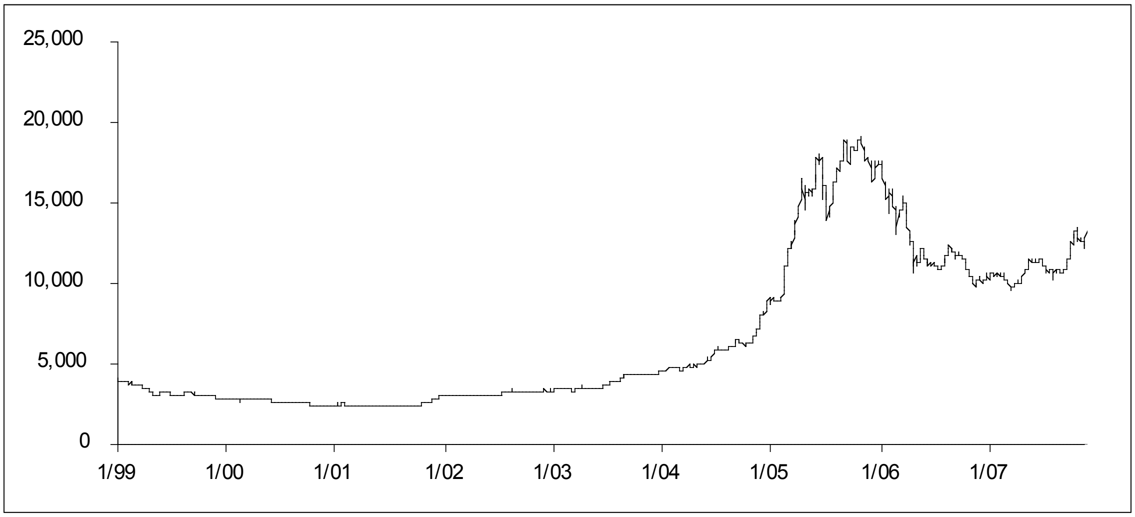


Figure 10: Daily Returns (%) on UAE

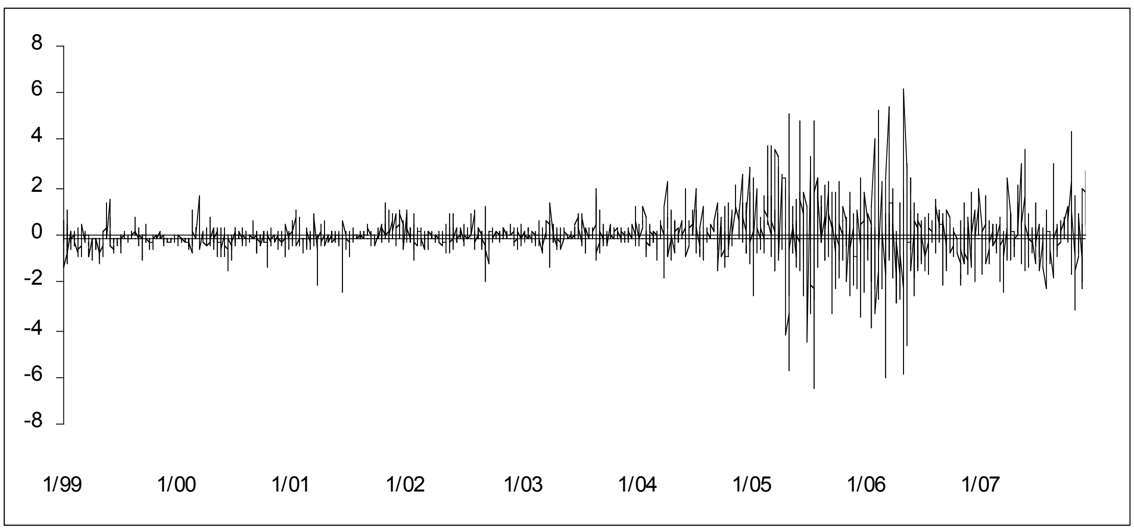


Figure 11: Daily Index of Muscat Stock Market (MSM)

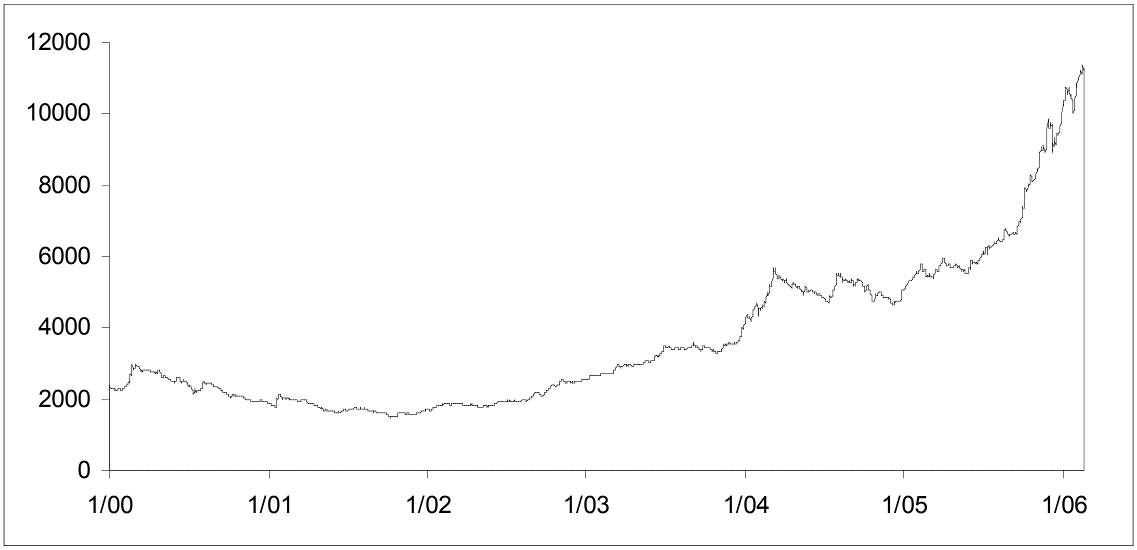


Figure 12: Daily Returns on MSM

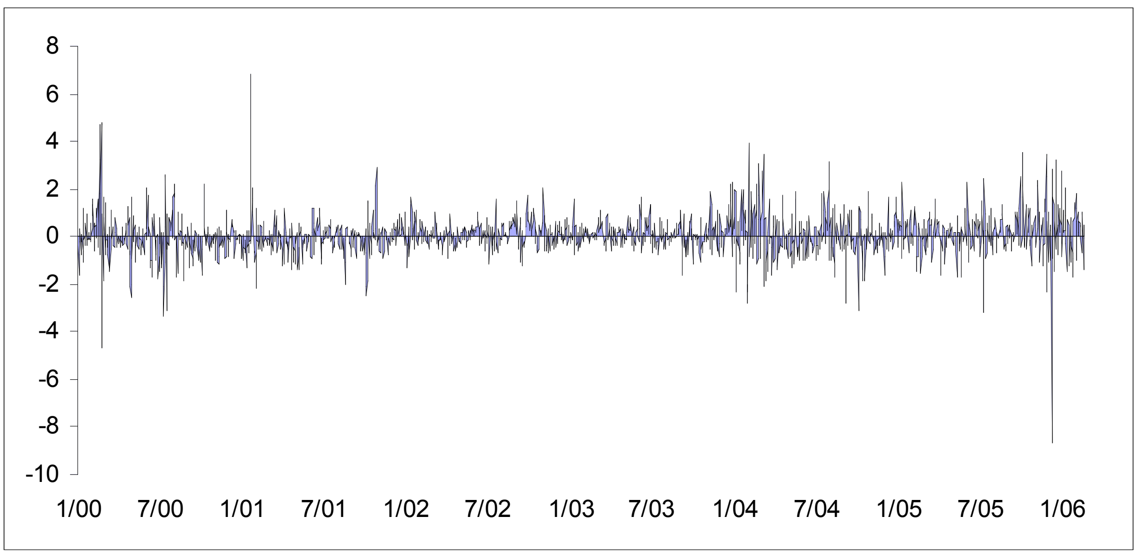


Figure 13: Daily Index of Doha Stock Exchange (DSE)

Figure 14: Daily Returns on DSE

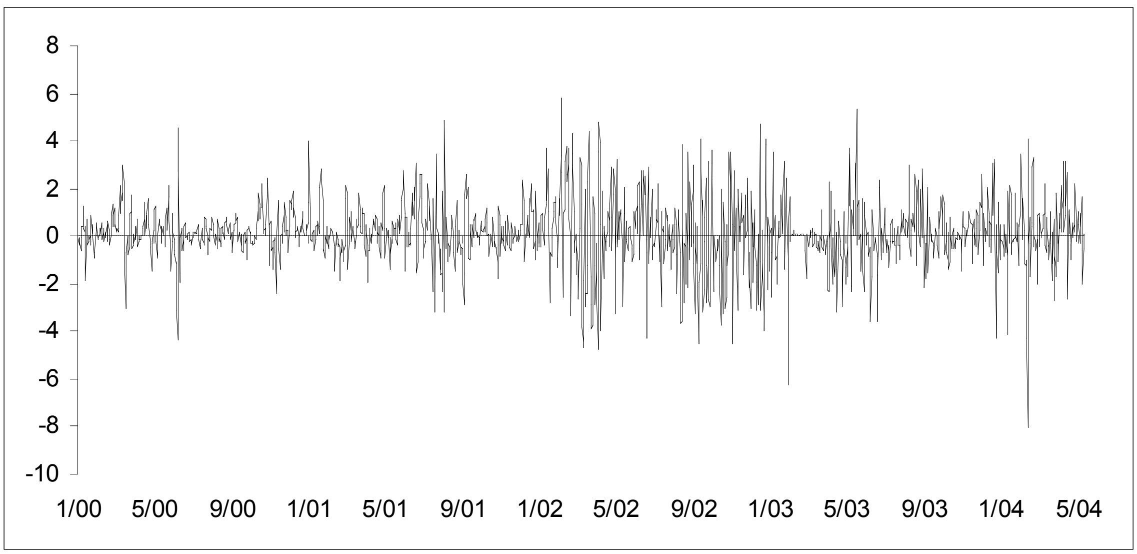


Figure 15: Daily Returns on Bahrain Stock Exchange (BSE)

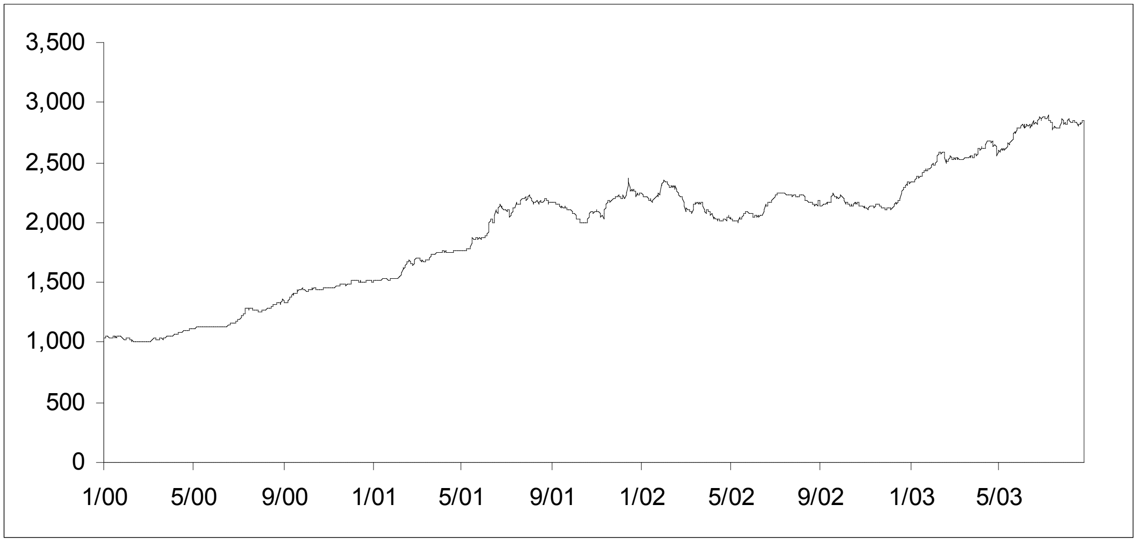
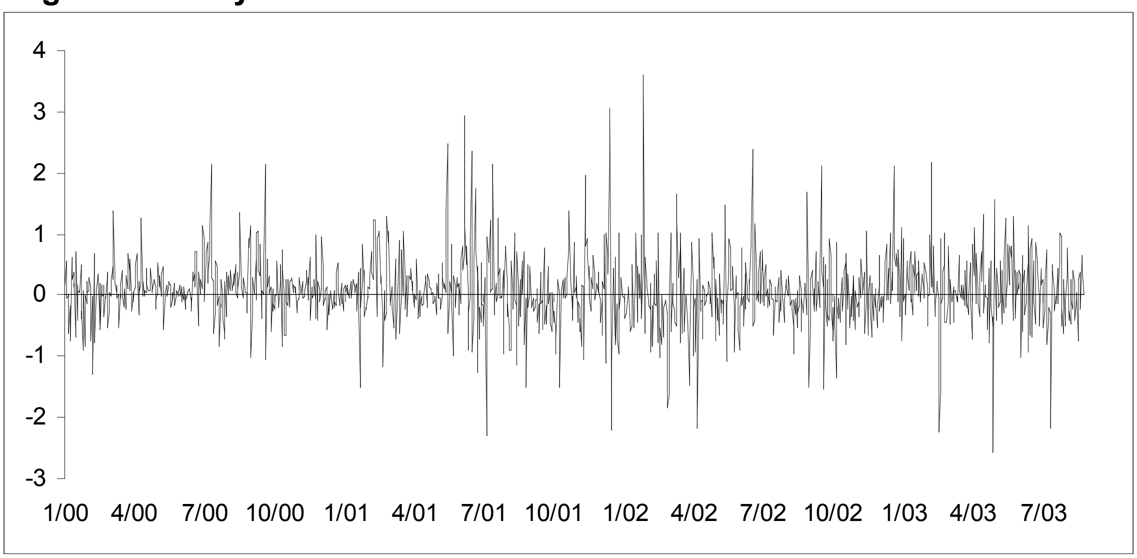


Figure 16: Daily Returns on BSE



3.3 Methodology

This study mainly aims at exploring the nonlinear dynamics in stock returns and examine if they exhibit nonlinear serial dependence, and hence a violation of market efficiency theory. Serial dependence is also examined using the conventional linear approach by applying some standards tests for linear serial dependence. Therefore, the test for serial dependence in the stock returns will be carried out through both linear and the nonlinear approaches to test the random walk behavior in these markets. This will provide conclusive results on the issue of stock market efficiency in the GCC region. In the literature of market efficiency, there are many traditional linear tests that can either directly or indirectly examine the random walk model. The focus will be on tests that particularly used to test the linear dependence of time series. Among the widely used methods of testing the linear dependence are the Autocorrelation Function (ACF) test, Ljung-Peirce test, and the runs test. In the nonlinear approach, three of the highly regarded nonlinearity tests will be applied on the daily returns to further explore the nature of the stock return dynamics in the GCC markets and look for any nonlinear structure in the data. These tests are: Hinich bispectrum test (Melvin J Hinich, 1982), White's neural network test (White, 1989a), and Kaplan's test (Kaplan, 1994). Before applying the three nonlinearity tests on stock returns, some considerations need to be mentioned regarding the implementation of those tests. First of all, it should be recognized that Hinich test is conducted without prewhitening or using any linear filtering for the data. As pointed by Ashley, Patterson, and Hinich (1986), hinich test is invariant to linear filtering because nonlinearity, if found in the original data, would pass any way to the residuals through the linear filter. White test and Kaplan test, on the other hand, require using lagged stock returns to implement those tests. Therefore, choosing the optimal lag length is a prior step needed before conducting the neural network test and Kaplan test, and to do so, I employed the HQC as an optimal lag for these tests. Second, as mentioned earlier, Kaplan's test is better used for testing nonlinearity in general. Hence, it might be beneficial to run it first to rule out the narrowest null of exact linearity (Barnett et al., 1997) and then proceed to the other two tests.

3.4 Tests for Serial Independence: Linear Approach

3.4.1 Autocorrelation Function Test

The autocorrelation coefficient ρ_k measures the degree of correlation between the current stock return R_t and the return separated by *k* lags, R_{t-k}.

It can be computed as the ratio of the covariance between R_t and R_{t-k} to the product of their standard deviations:

$$p_k = \frac{\operatorname{cov}(R_t, R_{t-k})}{\sigma(R_t)\sigma(R_{t-k})} = \frac{E[(R_t - \mu)(R_{t-k} - \mu)]}{E[(R_t - \mu)^2]}$$

If the stock returns follow a random walk, there will be no significant serial dependence. However, if significant serial correlation found evident in the stock returns, it is a clear contradiction to the hypothesis of market efficiency since information of past stock returns are able to explain a significant amount of the observed variation in stock returns. It also implies a predictability power of past stock returns in predicting future returns. Under the null of random walk, the autocorrelation coefficients will not be significantly different than zero.

Autocorrelation coefficient at lag *k* can be estimated as:

$$\hat{p}_k = \frac{\sum_{t=1}^{n-k} (R_t - \overline{R})(R_{t+k} - \overline{R})}{\sum_{t=1}^{n} (R_t - \overline{R})^2},$$

where $\overline{R}$ is the sample mean of stock returns.

3.4.2 Ljung-Box Q test

The Ljung-Box Q test (Ljung & Box, 1978) is a modification of the original Box-Pierce Q test (Box & Pierce, 1970) which is a portmanteau test that examine the overall randomness of data based on selected lags. In other word, it is used to test a set of k serial correlation coefficients simultaneously for the hypothesis of no serial correlations up to k lags. Therefore, it tests the following joint null hypothesis:

$$\rho_1 = \rho_2 = ... = \rho_k = 0$$

As pointed by Campbell et al.(1997), the Q-statistic test has power against many alternative approaches when testing the RWH since this hypothesis implies that all autocorrelations are zero. Rejecting the null hypothesis means that at least one autocorrelation is not zero. The original Box-Pierce statistic is defined as:

$$Q_k = N\sum_{j=1}^{k}\rho_j^2$$

where N is the sample size, and ρ_j is the autocorrelation coefficient at lag j.

One of the shortcomings of this test is the weak performance with short sample. As a result, Ljung and Box (1978) suggested a modified test that provides a substantial improved statistic, denoted as QLB, that is robust for both short and large samples. Hence, QLB is a preferred test in the literature and can be computed as:

$$QLB_k = N(N+2)\sum_{j=1}^{k}\frac{\hat{\rho}_j^2}{N-j}$$

Where $\hat{\rho}_j$ is the sample autocorrelation coefficient at lag j.

For a large sample, Q_k follows approximately a chi-square distribution with k degrees of freedom (Box and Pierce, 1970).

3.4.3 Run Test

The run test is one of the standard non-parametric tests for serial dependence of time series. In runs test, the number of sequences of consecutive positive and negative returns is tabulated and compared against its sampling distribution under the random walk hypothesis (Campbell *et al.* 1997). Unlike the previous linear tests, runs test has a considerable advantage that it doesn't require the stock returns to be normally distributed. Thus, this test can be employed as an alternative test for serial dependence considering the possibility of non-normal distribution of stock returns. As reported in Table 3, the Jarque-Bera test for normality rejects the normality of all GCC stock returns, and hence runs test might detect serial dependencies that cannot be captured by the autocorrelation tests. For daily data, a run is defined as a sequence of days in which the stock return changes in the same direction. Let r be the actual runs, N be the number of observations, and N_a and N_b are respectively the number of observations above and below the sample mean. Under the null hypothesis that successive returns are independent, the total expected number of runs is distributed as normal with the following mean:

$$\mu = E(r) = \frac{N + 2N_a N_b}{N} \tag{11}$$

and the following standard deviation:

$$\sigma = \left[\frac{2N_a N_b (2N_a N_b - N)}{N^2 (N-1)} \right]^{\frac{1}{2}} \tag{12}$$

The test for serial independence can be implemented by comparing the actual number of runs in stock returns, *r*, to the expected number of runs μ.

The null hypothesis of independence implies that *r* does not significantly differ from μ. If actual number of runs is less than expected, then it would imply a positive serial correlation in the data while the opposite case would imply a negative serial correlation. The asymptotic Z-statistic can then be computed as:

$$Z = \frac{r - \mu}{\sigma}$$

3.5 Results of Linear Approach

3.5.1 Autocorrelation Coefficients and Q-Statistics

The autocorrelation coefficients for the GCC markets are reported in Table 1 for the first 10 lags. The results indicate a strong evidence of positive first-order correlation where the null of no first-order serial dependence was rejected for all GCC markets except of KSE. There is no evidence of negative serial correlation in the GCC markets where TASI was the only case in which a weak evidence of negative correlation is found. This might be supportive to the argument that GCC stock markets exhibit momentum effect, but it is not likely to be characterized by mean reverting behavior. The ACF statistics suggest a strong evidence of serial correlation in the first 10 lags for UAE, TASI, and MSM, a weak evidence for BSE and DSM, and almost no evidence for KSE. For UAE, nine of the autocorrelation coefficients are significant at the five percent level, and for TASI and MSM, the autocorrelation coefficients for each market found to be statistically significant at seven out of the ten cases. In addition, there is evidence of higher degrees of serial correlation, five lags and more, in TASI, UAE, BSE, and MSM. Generally, the results of autocorrelation test in Table 1 indicate a strong evidence of serial correlation in the GCC daily stock returns.

Table 10: Tests for Serial Correlation in Daily GCC Stock Returns.

	Lags (k)	1	2	3	4	5	6	7	8	9	10
TASI	AC(k)	**0.07***	**-0.09***	**0.07***	**0.08***	**0.06***	**-0.01**	**-0.05***	**0.04***	**0.03**	**-0.02**
	Q(k)	**19.57**	**50.42**	**66.80**	**87.10**	**100.01**	**100.46**	**109.56**	**116.12**	**119.48**	**121.23**
UAE	AC(k)	**0.29***	**-0.05***	**0.03**	**0.09***	**0.11***	**0.12***	**0.09***	**0.08***	**0.04***	**0.04***
	Q(k)	**222.74**	**228.26**	**231.22**	**250.85**	**283.65**	**318.21**	**339.46**	**355.69**	**359.56**	**364.10**
KSE	AC(k)	**0.18***	**-0.02**	**0.03**	**0.09***	**0.06***	**0.01**	**-0.01**	**0.05**	**0.01**	**0.02**
	Q(k)	**56.38**	**56.76**	**57.89**	**69.84**	**75.08**	**75.25**	**75.48**	**78.84**	**78.89**	**79.58**
DSE	AC(k)	**0.34***	**-0.02**	**-0.01**	**0.00**	**0.03**	**0.01**	**0.00**	**0.03**	**0.06***	**0.06***
	Q(k)	**179.30**	**179.67**	**179.95**	**179.95**	**181.30**	**181.38**	**181.38**	**183.28**	**188.17**	**193.72**
BSE	AC(k)	**0.16***	**0.03**	**0.04**	**0.04**	**0.06***	**0.05***	**0.03**	**0.03**	**0.07***	**0.05**
	Q(k)	**33.79**	**34.96**	**37.34**	**38.99**	**43.10**	**46.98**	**48.52**	**50.04**	**56.31**	**59.45**
MSM	AC(k)	**0.28***	**0.09***	**0.03**	**0.06***	**0.08***	**0.06***	**0.06***	**0.03**	**0.03**	**0.05***
	Q(k)	**171.39**	**191.06**	**193.28**	**201.98**	**214.67**	**223.31**	**231.80**	**233.80**	**235.22**	**239.95**

(*):Significant at 5% level

This conclusion can be supported by the Ljung-Box Q statistics for the first ten lags where the null hypothesis is rejected at even one percent for all the GCC markets. As a result, one can strongly rejects the null of no serial correlation in the GCC stock returns.

3.5.2 Run Test

The run test statistics are listed in Table 11 for the daily GCC stock returns. As reported in this table, run test of serial independence provided very significant Z-statistics with extremely low p-values for each of the six GCC markets. That means the deference between the expected number of runs and the actual one is statistically significant at all levels which strongly suggests the rejection of the independence null in the stock returns for the GCC markets. These results are consistent with the previous findings of serial correlation tests that the GCC stock return series are not following random walk model. For each market, the statistics showed that actual number of runs is significantly lower than expected number of runs indicating a positive serial correlation in the daily returns. This evidence of positive correlation is supportive the earlier results obtained by the autocorrelation test.

Table 11: Run Test for GCC Daily Stock Returns

	Obs. (N)	n(above)	n(below)	Expected runs (m)	Actual runs (R)	Z	P-value
TASI	3581	1872	1709	1788	1511	-9.27	0
UAE	2590	1295	1295	1296	999	-11.67	0
KSE	1659	829	830	830	709	-5.97	0
DSE	1592	796	796	797	550	-12.38	0
BSE	1331	666	665	666	571	-5.24	0
MSM	2241	1120	1121	1121	830	-12.32	0

3.5.3 Summary of Results

To test the EMH in the GCC markets, three of the widely used standard tests were employed to examine the linear dependence in the daily stock returns. Both ACF and Ljung-Box tests provided a strong evidence of serial correlation in all of the GCC markets. Similarly, a strong evidence of serial dependence was concluded by the run test for each series. The results of ACF and run tests suggested that stock returns are positively correlated. In addition, ACF showed a strong presence of first-order correlation in all markets. It also indicated that higher-degree of serial correlation (five days and more) is significantly evident in some GCC markets. As a result, the null of linear serial independence of daily stock returns is rejected for all GCC markets and hence we rejected the hypothesis of market efficiency in its weak form.

3.6 Tests for Serial Independence: Nonlinear Approach

In the field of financial economics, there has been emerging interest in examining uncovered nonlinearities in stock market returns by using various nonlinearity tests. Among these tests, three highly regarded and significant tests are employed in this study to investigate the presence of nonlinearity in daily stock market returns of the GCC countries. These tests are Hinich bispectrum test (Melvin J Hinich, 1982), White neural network test (Lee, White, & Granger, 1993), and Kaplan test (Kaplan, 1994). They were chosen due to their good repute and relatively high performance[11] in detecting nonlinear structure in the economic data based on the extensive review and evaluation study conducted by Barnett *et al.* (1997) on a group of nonlinearity tests. In that study, Barnett et al. designed and ran a single-blind controlled competition among five of the most widely used tests for nonlinearity or chaos to explore the relative power of those tests. The five tests involved in that competition includes the three tests to be used in this study besides the BDS test (Brock et al., 1987) and NEGM (Nychka, Ellner, Gallant, and McCaffrey) test proposed by Nychka *et al.* (1992). Hinich bispectrum test is regarded as one of the best available tests for nonlinearity in economic data. As pointed by Barnett *et al.* (1997), hinich bispectrum approach has the advantage of providing direct tests for both nonlinearity and Gaussianity, since the test statistics have known asymptotic sampling distribution under the null hypothesis of either linearity or Gaussianity. Another well known test is the White's neural network which provides a test for nonlinearity in the mean. It has been reported by some simulation studies that whit's test against nonlinearity in the mean has power against various types of nonlinear processes (Barnett et al., 1997). The third test, Kaplan's test, is relatively less popular than the other two tests, but nevertheless it has been very successful in detecting nonlinearities in the competition conducted by Barnett et al.

[11] In fact, Dr. William Barnett has highly recommended these three tests for their robustness.

(1997). Both bispectral and neural network approaches provide test for specific type of nonlinearity while Kaplan's method test linearity against all possible alternatives to exact linearity and hence Kaplan's test can be used to test for general nonlinearity.

3.6.1 Kaplan Test

This test was initially proposed by Kaplan (1994) for the detection of determinism in the underlying dynamics of a time series. With the emerging interest in nonlinear dynamics, Kaplan's test has been recently used in several studies as a test of linear stochastic process against general nonlinearity, whether it is chaotic or noisy. In the chaos literature, the output of a chaotic system is indistinguishable visually from that of a stochastic process when plotting a time series. Nevertheless, plots of the solution paths in phase space (x_{t+1} plotted against x_t and lagged values of x_t) would usually reveal deterministic structure that was not evident in plot of x_t versus t (Barnett et al., 1997). Kaplan's test for nonlinearity is based on examining the continuity of dynamical maps using the fact that deterministic solution paths, unlike stochastic process, have the property that if two points are very close together, then their images are also close together. That is, if the underlying function linking images and pre-images is continuous, it is expected when x_t and y_t (the pre-images) are close to each other to have x_{t+1} and y_{t+1} (the images) close to each other too. Based on this fact, Kaplan has produced a test statistic, which has a strictly positive lower bound for a linear stochastic process, but not for a nonlinear deterministic solution path (Barnett et al., (1997). The test statistic can be computed from an adequately large number of linear processes that plausibly might have produced the data using the method of “surrogate data”. Surrogate data refers to random data generated with the same mean, variance, autocorrelation function and histogram as the original data. This approach can be used to test for linearity against the alternative noisy nonlinear dynamics. The null hypothesis for Kaplan’s test is that the process is stochastic linear. Implementing this test requires to compute a test statistic from the produced linear stochastic process surrogates and then compare it to that computed from the observed data in order to determine which one would better describe the data, the surrogates or the noisy continuous nonlinear dynamical solution path. As explained by Barnett et al. (1997), the test procedure can be formally stated as the following:

If we have a vector $x_t = (x_t, x_{t-\tau}, x_{t-2\tau}, \ldots., x_{t-(m-1)\tau})$ that is embedded in m-dimensional phase space and obtained from the observed data set $\{x_i\}_{i=1}^{T}$, then there is a recursive function $f(x_t)$ such that $f(x_t) = x_{t+\tau}$, where τ is a fixed positive integer time delay and $x_{t+\tau}$ is called the image of the point x_t in phase space. By the analogy of the well known delta-epsilon definition of continuity, distance in phase space plays the role of delta (δ) whereas distance of their images plays the role of epsilon (ε). Hence, for a given embedding dimension m, the distance in phase can be represented as $\delta_{ij} = \left|x_i - x_j\right|$ and the distance in images can be represented as $\varepsilon_{ij} = \left|x_{i+1} - x_{j+1}\right|$ for all pairs of time subscripts (i, j), and the time delay $\tau = 1$ (for simplicity). Let $\mathrm{E}(r)$ denotes the average of the values of ε_{ij} over those (i, j) satisfying $\delta_{ij} < r$. That means $\mathrm{E}(r)$ computes the average distance between images whose pre-images are r-close. In case of deterministic system with continuous $f(.)$, the average distance of the images is expected to decline as their corresponding pre-images are very close. Furthermore, it is expected that $\mathrm{E}(r) \to 0$ as $r \to 0$ for a perfectly deterministic system, where this convergence is not expected for stochastic system in which the nearby pre-images may have very distinct images.

The statistic for Kaplan's test, *K* is defined as:

$$K \equiv \lim_{r \to 0} E(r). \qquad (4)$$

Since the available data cannot be practically adequate to take the limit of $\mathrm{E}(r)$ as $r \to 0$, the analysis here would resemble the approach of Kaplan (1994) and Barnett et al. (1997), so a finite r is implicitly selected by averaging ε_{ij} over the 200 pairs of (i, j) that produce the smallest values of δ_{ij}.

The nonzero value of *K* can be interpreted as the "goodness of fit" measure from fitting a continuous model of some fixed order to an infinite amount of data (Barnett et al., 1997). Another way of interpreting the nonzero value of *K* is as the level of non-determinism (i.e. the amount of noise) in the data (Matilla-Garcia, 2007). When K is smaller for the observed data than for the surrogate data produced by a model that satisfies the stated null hypothesis, then the null hypothesis should be rejected. The level of non-determinism, or simply *K,* is expected to be higher for stochastic system than for deterministic ones, and hence we should reject the null hypothesis when *K* on the observed stock returns is smaller than K on the surrogates. Following Kaplan's approach, the time series will be embedded in 2, 3, 4, and 5 dimensional spaces.

In order to test for linear dynamics, one needs to compare the value of the test statistic, *K*, obtained from the original observed data to the minimum value of *K* obtained from the surrogates. The minimum *K* can be chosen in different ways. One simple approach is to compute the minimum value of *K* directly from the finite number of surrogates, and imputes that to the population of surrogates consistent with the procedure. Another method is to compute the mean and the standard error of the values of *K* from the finite sample of surrogates and then subtract a multiple (2 or 3) of the standard error from the mean to get an estimate of the population minimum. Finally, the null hypothesis of linearity will be rejected if the value of the test statistic from the surrogates (denoted as KS) is never small enough relative to the value of the test statistic computed from the original data (denoted as K). That is, when K<KS, the null hypothesis will be rejected.

3.6.2 Hinich Bispectrum Test

Based on earlier work of Subba Rao and Gabr (1980), Hinich (1982) has developed a statistical test for the detection of nonlinearity in time series based on the estimated bispectrum of the observed time series – that is the double Fourier transform of the third-order cumulant function. In this test, two hypotheses can be tested: Linearity and Gaussianity. Hinich linearity test would test for the existence of third-order nonlinear dependence. In other words, it tests the flatness of skewness function (or lack of third-order nonlinear dependence). If linearity is tested, then the null hypothesis would be 'skewness function is flat' or 'No third-order nonlinear dependence' and If Gaussianity is tested then the null hypothesis would be 'time series is Gaussian' or 'skewness function is flat and equal to zero'. Flatness of the skewness function is necessary but not sufficient condition for general linearity and Gaussianity. However, flatness of the skewness function is necessary and sufficient condition for the lack of third-order nonlinearity (Barnett et al., 1997). Therfore, failing to reject the null hypothesis of linearity does not mean that the series is linear; it only means that the series is not third-order nonlinear.

Let $\{x(t)\}$ represent a third-order stationary time series with zero-mean.

The autocovariance function of $\{x(t)\}$ is given by:

$$C_x(n) = \mathrm{E}[X_{t+n}X_t]. \quad (5)$$

The spectrum of $\{x(t)\}$ is defined as the Fourier transform of $C_x(n)$:

$$S(f) = \sum_{n=0}^{\infty} C_x(n)\exp\{-2\pi ifn\} \quad (6)$$

Then, the third-order cumulant function of $\{x(t)\}$ is defined as:

$$C_{xxx}(m,n) = \mathrm{E}[\mathrm{X}_{t+m}X_{t+n}X_t] \quad (7)$$

The bispectrum at frequency pair (f_1, f_2) is the double Fourier transform of $C_{xxx}(m,n)$:

$$B(f_1, f_2) = \sum_m \sum_n C_{xxx}(m,n)\exp\{-i2\pi(f_1 m + f_2 n)\} \quad (8)$$

Given the symmetries of $B(f_1, f_2)$, its principle domain is the triangular set

$$\Omega = \{0 < f_1 < 1/2, f_2 < f_1, 2f_1 + f_2 < 1\}. \quad (9)$$

Suppose $\{x(t)\}$ is linear time series that takes this form:

$$x(t) = \sum_{n=0}^{\infty} a(n)u(t-n), \quad (10)$$

where $\{u(t)\}$ is a purely random process and the weights $\{a(n)\}$ are fixed. If so, the bispectrum of $\{x(t)\}$ is:

$$B_x(f_1, f_2) = \mu_3 A(f_1)A(f_2)A^*(f_1 + f_2), \quad (11)$$

where $\mu_3 = E[u^3(t)]$, $A^*(f)$ denotes the complex conjugate, and

$$A(f) = \sum_{n=0}^{\infty} a(n)\exp(-i2\pi fn). \quad (12)$$

Since the spectrum of $\{x(t)\}$ is:

$$S_x(f) = \sigma_u^2 \left| A(f) \right|^2 \tag{13}$$

it follows that:

$$\Psi^2(f_1, f_2) \equiv \frac{\left| B_x(f_1, f_2) \right|^2}{S_x(f_1) S_x(f_2) S_x(f_1 + f_2)} = \frac{\mu_3^2}{\sigma_u^6} \tag{14}$$

for all f_1 and f_2 in Ω where $\Psi(f_1, f_2)$ is called the skewness function of $\{x(t)\}$. $\{x(t)\}$ can be tested for linearity through the null hypothesis that the squared skewness function, $\Psi^2(f_1, f_2)$, is constant over all frequency pairs (f_1, f_2). For Gaussianity test the null hypothesis would be that $\Psi^2(f_1, f_2)$ is zero over all frequencies.

The estimated bispectrum will not be significantly different from zero under the null hypothesis of Gaussianity and linearity. The test statistics for both hypotheses[12] is then reduced to:

$\hat{H} = 2\left| \hat{X}(f_m, f_n) \right|^2$ at the frequency pair (f_m, f_n), where

$$\hat{X}(f_m, f_n) \equiv \frac{\hat{B}_x(f_m, f_n)}{[N / M^2]^{1/2} [\hat{S}_x(f_m) \hat{S}_x(f_n) \hat{S}_x(f_{m+n})]^{1/2}}, \tag{15}$$

[12] In other words, the statistics of nonzero bispectrum.

$\hat{S}_x(.)$ is the estimator of the power spectrum of $\{x(t)\}$, $f_m = \frac{(2m-1)M}{2N}$ for each integer m = 1…n, and M is the frame size, which is a parameter need to be chosen a priori.[13]

Hinich (1982) shows that under the null hypothesis of Gaussianity, the estimated standardized bispectrum, $\hat{H}$, is approximately chi-squared with 2P degrees of freedom, where P denotes the number of squares whose centers are in the principal domain.

If $\{x(t)\}$ is linear but not Gaussian, then $\hat{H}$ is asymptotically distributed as independent, non-central chi-squared with 2 degrees of freedom. The non-centrality parameter is consistently estimated by:

$$\hat{\lambda} = \left\{ 2\sum_m \sum_n \left| \hat{X}(f_m, f_n \right|^2 / P \right\} - 2, \qquad (16)$$

If the null hypothesis of linearity test is true, then the sample dispersion of the estimators $\hat{H}$ should be consistent with the population dispersion of $\chi^2(2, \hat{\lambda})$. In contrast, if $\{x(t)\}$ is nonlinear, then the sample dispersion would exceed that expected under the null hypothesis of linearity (Ashley and Patterson, 1989). The dispersion can be measured in many ways, and based on the simulation results reported by Ashley, Patterson, and Hinich (1986) they suggest the use of the 80% quantile of the empirical distribution. David

[13] Hinich showed that consistency of the standardized bispectrum estimator requires that M to be chosen such $M = N^c$ for $.5 < c < 1$, where the choice of c governs the trade-off between the bias and variance of the estimator.

(1970), shows that the sample 80 percent quantile, $\hat{\xi}_{.8}$, is asymptotically distributed as $N(\xi_{.8}, \sigma^2)$, where σ^2 is estimated by

$$\hat{\sigma}^2 = .8(1-.8)f^{-1}(\hat{\xi}_{.8})P^{-1}, \tag{17}$$

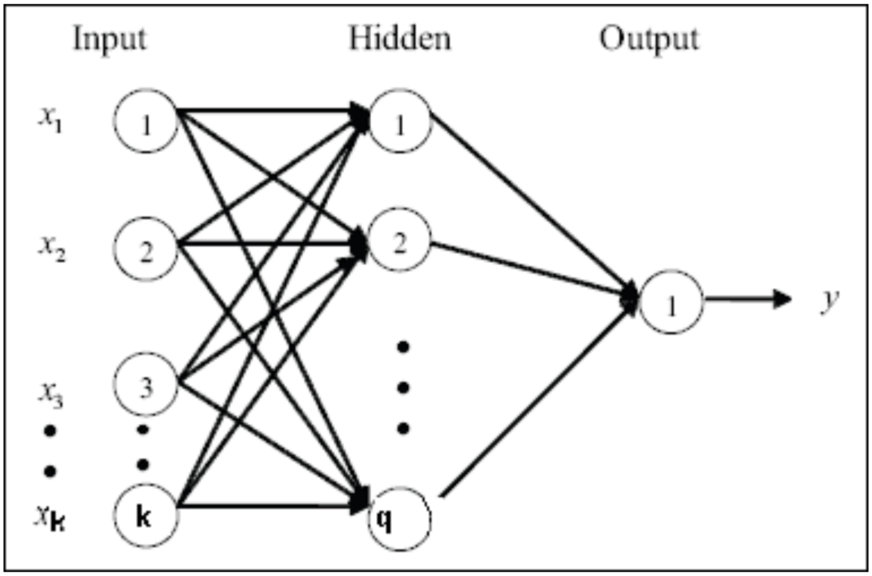
$\xi_{.8}$ is the population 80 percent quantile of $\chi^2(2,\hat{\lambda})$, and $f(.)$ is the density function of $\chi^2(2,\hat{\lambda})$. Hence, to examine whether the sample dispersion of the estimated standardized bispectrum, $\hat{H}$, is significantly grater than the population dispersion, Ashley and Patterson (1989) define this test

$$Z \equiv \hat{\xi}_{.8} / \hat{\sigma} \sim N(0,1) \tag{18}$$

3.6.3 White's (Neural Network) Test

Based on the workings of the human brain, cognitive scientists have introduced a class of models called Artificial Neural Networks (ANN) which has been motivated by certain features of the way of processing information inside the brain (Lee et al, 1993). The most interesting feature of neural networks is the capability to approximate any nonlinear function with significant precision. Hence, if ANN is applied to a time series that is characterized by truly nonlinear dynamic relationships, it will detect these relationships and provide a superior fit compared to linear time series models, without the need to construct a specific parametric nonlinear time series model (Franses & van Dijk, 2000). Recently, there has been a growing interest in neural networks in finance and economics. As cited by Franses and van Dijk (2000), many applications of neural networks have been used in financial analysis for modeling and forecasting some financial series such as stock prices (Gencay, 1996; Gencay & Stengos, 1998; Haefke & Helmenstein, 1996; Qi & Maddala, 1999), exchange rates (Franses & van Griensven, 1998; Gençay, 1999; Kuan, Liu, College of, Business, & University of Illinois at, 1995), interest rates (Swanson & White, 1995) and option pricing (Hutchinson, Lo, & Poggio, 1994). Moreover, neural networks can be employed to test for nonlinearity existence in time series due to their ability to provide good approximation. Fore example, White (1989a), and Lee *et al.* (1993) developed a nonlinearity test based on neural network approach to detect neglected nonlinearity in the mean. In this test, the time series is fitted by a single hidden-layer feed-forward neural network augmented by connections from input to output to determine whether any nonlinear structure remains in the residuals of an AR model fitted to the same data (Barnett et al., 1997).

Figure 17: Single Hidden Layer Feed-Forward Network



As depicted in Figure 17, neural networks are parallel distributed processors consist of artificial neurons, usually called “nodes”. Those nodes are classified as input nodes, some intermediate “hidden” nodes, and an output node. A simple and leading class of ANN is the “single hidden layer feed-forward network” (See Fig 1). In this model, the network is constructed by a layered mapping of the three nodes with connections (weights) between them. As described by Lee et al. (1993), the input units in this network would work as sensors that send signals x_i, where $i = 1,....,k$ and integer *k* denotes number of inputs units. These signals would be either attenuated or amplified by a weight factor γ_{ji} where j refers to the hidden processing unit j. The intermediate hidden unit j would receive signals $x_i \gamma_{ij}$ $i = 1,....,k$, and process them in a specific way. Simply, the hidden processing units sum the arriving signals yielding $\tilde{x}'\gamma_j$ where $\tilde{x} = (1, x_1, \ldots\ldots, x_k)'$, $\gamma_j \equiv (\gamma_{j0}, \gamma_{j1}, \ldots., \gamma_{jk})'$ and then produce an output activation $\psi(\tilde{x}'\gamma_j)$ where ψ refers to the activation (or squashing) function which is a given nonlinear mapping from $\Re$ to $\Re$. ψ can be chosen as a cumulative distribution function (c.d.f), such as the commonly used logistic function, $\psi(\lambda) = (1 + e^{-\lambda})^{-1}$, $\lambda \in \Re$. The hidden unit signals (or output activation)$\psi(\tilde{x}'\gamma_j)$ would then be passed to the output after summing all signals over q hidden units to produce an output:

$$f(x, \delta) = \tilde{x}'\theta + \sum_{j=1}^{q} \beta_j \psi(\tilde{x}'\gamma_j), \qquad q \in \mathrm{N}, \tag{19}$$

Where $\beta_1, \ldots, \beta_q$ are hidden-to-output weights, $\gamma_1, , \ldots., \gamma_q$ are input-to-hidden weights, and $\delta = (\theta, \beta_1 \ldots, \beta_q, \gamma_1', \ldots, \gamma_q')'$.

As discussed by White (1989a, 1990) and Lee et al. (1993), functions of the form (19) can produce arbitrarily accurate approximation to arbitrary functions in a variety of normed function spaces; therefore, this form of functions has the capability of approximating an arbitrary nonlinear mapping. In practice, it has been shown that tractable values for the number of hidden unites (q) can provide good approximation when the mapping is fairly smooth (Lee et al., 1993). For instance, the deterministic chaos of the logistic map was well approximated by Lapedes and Farber (1987) using five hidden units, while Gallant and White (1992) used the same number of hidden unites to well approximate the Mackey-Glass chaos (Lee et al., 1993).

White's test for neglected nonlinearity (Lee et al., 1993) uses a single hidden layer network augmented by connections from input to output. Given input $x_t = (1, y_{t-1}, y_{t-2}, ..., y_{t-p})'$, the ANN(p,q) model for output y_t, with q hidden units and p lags is determined by:

$$y_t = x_t'\theta + \sum_{j=1}^{q} \beta_j \psi(x_t'\gamma_j) + \varepsilon_t, \qquad \text{t=1, …,n,} \tag{20}$$

$\beta_1, ..., \beta_q$ are hidden-to-output weights, $\gamma_1, ,...., \gamma_q$ are input-to-hidden weights, and Ψ is a nonlinear activation (squashing) function.

In this test, the null hypothesis would be that the series is linear in the mean.

If the null is true, i.e. :

$H_0 : P[\mathrm{E}(y_t \mid x_t) = x_t'\theta^*] = 1$ for some θ^*,

then, the optimal network weights, β_j^*, are zero for j=1…,q, yielding an affine network. Hence, the test of neural network would involve testing the hypothesis: $\beta_1^* = \beta_2^* = .. = \beta_q^* = 0$. (21)

It should be noticed from (20) that when the null hypothesis is true, the parameters γ_j are not identified, and hence γ_j has to be chosen a priori as suggested by white (1989a) to fix this identification problem by, for example, drawing them randomly from some distribution (Franses & van Dijk, 2000). To implement this test as a Lagrange multiplier test, the following hypothesis needs to be tested:

$H_0 : \mathrm{E}(\Psi_t e_t^*) = 0$ vs $Ha : \mathrm{E}(\Psi_t e_t^*) \neq 0$, where $e_t^* = y_t - x_t'\theta^*$, $\Psi_t = (\psi(x_t'\Gamma_1),...,(x_t'\Gamma_q))'$, $\Gamma = (\Gamma_1,.....,\Gamma_q)$ is the hidden unit activation vector, which is chosen a priori and independently of the sequence $\{x_t\}$ for given $q \in \mathrm{N}$, and ψ is the activation function, the logistic $\psi(\lambda) = (1+e^{-\lambda})^{-1}, \lambda \in \Re$ will be used here following the approach of Lee et al. (1993).

Performance of white test depends on the following M test:

$$M_n = \left(\left(n^{1/2}\sum_{t=1}^{n}\Psi_t\hat{e}_t\right)\hat{W}_n^{-1}\left(n^{1/2}\sum_{t=1}^{n}\Psi_t\hat{e}_t\right)\right),$$

where $\hat{W}_n$ is a consistent estimator of: $\overset{*}{W} = \mathrm{var}\left(n^{-1/2}\sum_{t=1}^{n}\Psi_t \overset{*}{e}\right)$, and $\overset{\wedge}{e_t}$ denote the estimated residuals for the linear model, given by:

$$e_t^{\wedge} = y_t - x_t^{'}\theta^{\wedge},$$

It follows that under the null hypothesis, an asymptotic chi-square statistic can be formed as: $M_n \xrightarrow{d} \chi^2(q)$ as $n \to \infty$.

Lee et al. (1993) pointed to the two practical difficulties that would exist when implementing this test. First, elements of Ψ_t tend to be collinear with x_t and with themselves. Therefore, Lee et al. (1993) recommended to conduct the test on $q^* < q$ principal components of Ψ_t not collinear with x_t, denoted Ψ_t^* as a remedy for this problem. The second drawback of implementing this test is the tedious computation of $\hat{W}_t$. Thus, Lee et al. (1993) suggested to use an the following equivalent test statistic that avoids explicit computation of $\hat{W}_t$:

$$nR^2 \xrightarrow{d} \chi^2(q^*),$$

Where R^2 is the uncentered squared multiple correlation from a standard linear regression of $\hat{e}_t$ on x_t and Ψ_t^*.

3.7 Results of Nonlinear Approach

3.7.1 Kaplan Test

As mentioned earlier, the null hypothesis for Kaplan's test is the stochastic linearity of the process generating the daily stock returns. The test is applied to the six GCC markets[14] for embedding dimensions (m) of 2, 3, 4, and 5. Using twenty surrogates, the mean, minimum, standard deviations are computed over those surrogates for each series in addition to K statistic on returns. When implementing the test, the null of stochastic linearity will be rejected when the computed K for stock returns (K) is less than, at least, one of the two measures of minimum K statistics from surrogates (KS_{min}), that is when $K < KS_{min}$. As a handle on the results significance, Kaplan suggested the use of t-statistic: $t = \frac{K - KS_{mean}}{KS_{sd}}$, where KS_{mean} and KS_{sd} are respectively the mean and standard deviation for KS values from surrogates.

The test statistics are reported for all of the GCC stock markets in Tables ranging from (Table 12) to (Table 17). As it can be seen from the results, the null of stochastic linearity in the daily stock returns should be rejected for

[14] Test statistics were computed using MATLAB source code provided thankfully by Kaplan in his website.

each series at all embeddings except of KSE at embedding m=4, and BSE at embedding m=2. Hence, one can conclude strong evidence of nonlinearity existence in the stock returns for the GCC markets. The test results are consistent with the theory of nonlinear dynamics in financial markets as well as the other results by previous studies in the literature. As mentioned earlier, this finding will be an evidence of general nonlinearity in those series. Hence, it will motivate to proceed with further specific-nonlinearity tests and examine the existence of third order nonlinearity using Hinich's bispectrum test, in addition to the existence of nonlinearity in the mean using White's test.

Table 12: Kaplan Statistics in Stock Returns of TASI Under the Null of Linearity

Embedding Dimension	KS_{mean}	KS_{sd}	KS_{min}	K	t-statistics
2	1.39	0.10	1.22	0.68	-6.80
3	1.32	0.18	0.78	0.69	-3.62
4	1.37	0.24	0.77	0.63	-3.06
5	1.31	0.21	0.89	0.57	-3.47

Note: The test statistic (K) is conducted using 7 lags and 20 surrogates.

Table 13: Kaplan Statistics in Stock Returns of KSE Under the Null of Linearity

Embedding Dimension	KS_{mean}	KS_{sd}	KS_{min}	K	t-statistics
2	0.94	0.11	0.74	0.55	-3.37
3	0.93	0.14	0.70	0.62	-2.74
4	0.92	0.13	0.63	0.70	-2.92
5	1.03	0.16	0.83	0.43	-3.04

Note: The test statistic (K) is conducted using 3 lags and 20 surrogates.

Table 14: Kaplan Statistics in UAE Stock Returns Under the Null of Linearity

Embedding Dimension	KS_{mean}	KS_{sd}	KS_{min}	K	t-statistics
2	0.89	0.08	0.74	0.32	-7.19
3	0.96	0.11	0.73	0.31	-6.03
4	0.95	0.10	0.81	0.26	-6.61
5	0.91	0.16	0.47	0.17	-3.72

Note: The test statistic (K) is conducted using 7 lags and 20 surrogates.

Table 15: Kaplan Statistics in DSE Stock Returns Under the Null of Linearity

Embedding Dimension	KS_{mean}	KS_{sd}	KS_{min}	K	t-statistics
2	1.41	0.12	1.12	0.81	-4.85
3	1.43	0.23	1.06	0.31	-4.92
4	1.38	0.19	1.10	0.15	-6.39
5	1.46	0.36	0.34	-0.02	-4.10

Note: The test statistic (K) is conducted using 1 lag and 20 surrogates.

Table 16: Kaplan Statistics in BSE Stock Returns Under the Null of Linearity

Embedding Dimension	KS_{mean}	KS_{sd}	KS_{min}	K	t-statistics
2	0.61	0.05	0.53	0.55	-1.28
3	0.63	0.07	0.52	0.46	-2.44
4	0.64	0.09	0.42	0.33	-3.47
5	0.61	0.1278	0.39	0.34	-2.10

Note: The test statistic (K) is conducted using 7 lags and 20 surrogates.

Table 17: Kaplan Statistics in MSM Stock Returns Under the Null of Linearity

Embedding Dimension	KS_{mean}	KS_{sd}	KS_{min}	K	t-statistics
2	0.86	0.07	0.77	0.48	-5.32
3	0.78	0.11	0.48	0.46	-3.04
4	0.81	0.11	0.61	0.43	-3.48
5	0.88	0.16	0.57	0.40	-2.99

Note: The test statistic (K) is conducted using 7 lags and 20 surrogates.

3.7.2 Hinich Bispectrum Test

Hinich bispectrum test for linearity and Gaussianity is applied to the daily stock returns of the six GCC markets. The results of the test are reported in Table 2 where Gaussianity and linearity statistics is respectively listed in the second and third columns with the associated p-values in parentheses. The results of Gaussianity test indicate extremely small p-values for all of the GCC markets and hence the null hypothesis of Gussianity in daily stock returns should be strongly rejected even at the 1% significance level for each GCC market. This rejection of Gaussianity is consistent with the result of Jarque-Bara normality test reported earlier in Table1. On the other hand, Hinich's linearity test yields very significant results concluded by the very small p-values for the 80 percent quantile bispectrum linearity test for five GCC stock markets, namely TASI, KSE, UAE, BSE, and MSM. As pointed by Barnett et al. (1997), the rejection of the null of linearity is a strong evidence for the presence of third order nonlinearity in the in the data generation mechanism. Therefore, the null of linearity in daily stock returns is strongly rejected in these markets using Hinich's bispectral test. For DSM, the null of linearity could not be rejected at 5 percent significance level. It should be noticed, however, that this does not mean the series is linear, but it only means "the lack of third order nonlinearity" in that series. In addition, this rejection might be resulted from the relatively small number of observations (1592) for DSM that might lead to less robustness of Hinich's bispectrum test, which is one slight drawback of this test. As a result, we can generally conclude a strong evidence that the daily stock returns in GCC markets fallow a non-Gaussian, non-linear process. The results of Hinich's test are consistent with other findings of earlier empirical studies on stock markets using same methodology such as the early work by Hinich and Patterson (1985). Furthermore, these results confirm what have been concluded by studies on emerging markets using Hinich's bispectrum test such as Antoniou *et al.* (1997), Lim *et al.* (2003) and others, supporting the claim that nonlinearity can also be evident in the less developed stock markets that usually characterized as small-sized, thin-trading markets.

Table 18: Hinich Bispectrum Test for Daily Stock Returns in GCC

Series	Gaussianity Test Stat. (Pvalue)	Linearity Test Stat. (P-value)
TASI	2475.52 (0.0000)	13.65 (0.0000)
KSE	5066.63 (0.0000)	31.41 (0.0000)
UAE	4495.28 (0.0000)	63.47 (0.0000)
BSE	727.10 (0.0000)	13.35 (0.0000)
DSE	769.26 (0.0000)	1.03 (0.150958)
MSM	2521.07 (0.0000)	28.973 (0.0000)

Notes: for Gaussianity, the test statistic has an asymptotic central chi-square distribution with 2p degrees of freedom. For linearity, the test statistic is distributed as standard normal distribution Z(0,1) and taken as one-sided test. The associated p-values are listed in parenthesis.

3.7.3 White's (Neural Network) Test

Following the approach of Lee *et al.* (1993), and the test implementation by Franses and van Dijk (2000)[15], the neural network test is applied to the daily stock index returns for all GCC markets. For each series, the test is computed for lagged returns as inputs with ten hidden units (q=10). The parameters (weights) γ_{ji} are sampled from a uniform distribution on [-2, 2]. For the choice of principal components as an alternative to the original activation function, Franses and van Dijk (2000) suggest to set the number of principal components fairly small (i.e. q^* = 2 or 3), where they should also be orthogonal to the inputs X_t. As implemented in Franses and van Dijk (2000), the largest principal component is disregarded, and the second and third largest components are used in the auxiliary regression of $\hat{e}_t$. Since the value of the test depends on randomly chosen values for γ_{ji}, the decision to reject the null hypothesis could be, to some extent, attributed to chance (Franses & van Dijk, 2000). Thus, Lee *et al.* (1993) proposed an alternative method, where the test is computed for several different draws (replications) of γ_{ji} (or Γ) and use the Bonferroni inequality to get an upper bound on the p-value of the test. Let p(1), …, p(k) denote the ascending-ordered p-values obtained from the asymptotic $\chi^2(q)$ distribution and corresponding to k

[15] The test was implemented using the GAUSS code provided by Franses and van Dijk (2000).

draws for Γ. The standard Bonferroni inequality implies rejection of the null of linearity at the 100α% level if p(1)< α/k. Thus, the simple Bonferroni p-value is given by kp(1) which can be interpreted as the overall p-value of the k tests. To improve the power of the test, Lee *et al.* (1993) employ the modified Bonferroni bound method that is suggested by Hochberg (1988). This method allows the consideration of the p-values rather than just the smallest observed one. The improved Bonferroni bound is then given by $\min_{j=1,\ldots,k}$ (k-i+1)p(i). The test statistic is computed for each return series x_t as n times the R^2 generated from a regression of the residuals from AR(p) model on x_t and two principal components. Repeating this procedures 10 times, the p-value is computed for both Chi Square and F tests using the standard as well as the improved Bonferroni methods.

White's test is applied to the daily stock returns of the six GCC markets, and the results are reported for in Table 3.2.3. By looking at those results, it is obvious that the hypothesis of linearity should be rejected for the GCC stock markets of TASI, KSE, UAE, MSM, and DSE at five percent significance level. For the BSE, the linearity hypothesis cannot be rejected though. As a result, one can conclude a strong evidence of neglected nonlinearity in the mean of the daily stock returns for the GCC markets with the exception of the BSE. This also confirms the earlier conclusions obtained by the other two tests, Kaplan's test and Hinich's bispectrum test.

Table 19: White's NN test for GCC Stock Markets Returns (p-values)

Series	Chi Sq (Std Bonf)	F (Std Bonf)	Chi Sq (Improved Bonf)	F (Improved Bonf)
TASI	0.022	0.023	0.022	0.023
KSE	0.001	0.001	0.001	0.001
UAE	0.000	0.000	0.000	0.000
MSM	0.000	0.000	0.000	0.000
DSE	0.000	0.000	0.000	0.000
BSE	4.438	4.461	0.455	0.457

Notes: The test was conducted on every series with 10 hidden units and 10 replications. Optimal lag lengths were chosen as 7 lags for TASI and UAE, 1 lag for MSM, DSE, and BSE, and 3 lags for KSE.

3.7.4 Summary of Results

Nonlinear dependence in stock markets returns was examined in the six GCC countries using Kaplan test, Hinich bispectrum test, and White neural network test. The obtained results by these tests are summarized in Table 3.4. From that table, it can be recognized that null hypothesis of linearity is rejected in most of the cases. In fact, linearity was rejected for each series by at least two of the three tests, which generally supports the presence of nonlinearity in the GCC stock market returns. For TASI, UAE, and MSM, linearity is significantly rejected by all of the three tests, and that means nonlinear dependence can be strongly concluded in these three markets. Moreover, the findings of this study will point to some interesting facts about the nature of the data generating process for stock market returns in the GCC region. First, it can be argued that nonlinearity, in general, is evident in these markets by the results of Kaplan test which tests for stochastic linearity against all other kinds of nonlinearity. Second, the significant results of white test suggest that the GCC stock market returns are more likely to exhibit nonlinearity in the mean. Third, results of Hinich bispectrum test indicate a strong evidence of the existence of a higher degree of nonlinearity in the underlying dynamics for these markets. In conclusion, evidence of nonlinearity in GCC stock markets can be strongly claimed and hence this can clearly be considered a contradiction to the EMH in its weak form. The findings of this study will contribute to the literature of the GCC financial markets by providing a preliminary diagnostic tool to determine the nature of the data generating process before any further empirical work. More specifically, the results of this study insist on the fact that it would be inappropriate to employ linear methods when dealing with such financial data knowing that the underlying generating process is non-linear in nature. One implication is that modeling GCC financial markets has to be based on nonlinear paradigms instead of the conventional linear methodologies. In addition, it is possible, not easy though, to predict the GCC stock markets returns using nonlinear-based trading strategies.

Table 20: Results Summary of Testing the Null of Linearity

Series	Kaplan 's Test	Hinich's Test	White's Test
TASI	Reject at all m	Reject	Reject
KSE	Reject at m=2,3,5	Reject	Reject
UAE	Reject at all m	Reject	Reject
BSE	Reject at m=3,4,5	Reject	Fail to Reject
DSE	Reject at all m	Fail to reject	Reject
MSM	Reject at all m	Reject	Reject

CHAPTER FOUR

CONCLUSION

This dissertation mainly aims at exploring nonlinear dynamics in stock markets returns in the six GCC countries using Kaplan test, Hinich bispectral test, and White neural network test. In addition, this study employs these nonlinearity tests, as well as the conventional linear approach, using the Autocorrelation Function (ACF) test, Ljung-Peirce test, and the runs tests, to examine the Efficient Market Hypothesis (EMH), in the GCC markets.

The obtained results of nonlinearity tests indicate that null hypothesis of linearity is strongly rejected for each series, which generally supports the presence of nonlinearity in the GCC stock market returns. These results of nonlinearity tests can point to some interesting facts about the nature of the data generating process for stock market returns in the GCC region. First, it can be argued that nonlinearity, in general, is evident in these markets by the results of Kaplan test which tests for stochastic linearity against all other kinds of nonlinearity. Second, the significant results of white test suggest that the GCC stock market returns are more likely to exhibit nonlinearity in the mean. Third, results of Hinich bispectrum test indicate a strong evidence of the existence of a higher degree of nonlinearity in the underlying dynamics for these markets. It should be also noticed that even in the absence of linear dependence, by using optimal lag selection, the nonlinear dependence is strongly evident in the GCC daily stock returns.

When testing the EMH, both linear and nonlinear methods indicated a significant serial dependence in daily stock returns. This can clearly be considered a contradiction to the EMH in its weak form, and hence an evidence of market inefficiency in GCC countries.

The findings of this study are consistence with that of previous empirical studies on the existence of nonlinearity in financial markets. Furthermore, the concluded evidence of nonlinearity will support the argument that nonlinearity can be present even in the less developed, small financial markets. These findings will contribute to the literature of the GCC financial markets by providing a preliminary diagnostic tool to determine the nature of the data generating process before any further empirical work. More specifically, the results of this study insist on the fact that it would be inappropriate to employ linear methods when analyzing such the GCC stock markets, knowing that the underlying generating process is more likely to be nonlinear. One implication is that modeling GCC financial markets has to be based on nonlinear paradigms instead of the conventional linear methodologies. In addition, the evidence of nonlinearity concluded in this study means that it is possible, not easy though, to predict the GCC stock markets returns using nonlinear-based trading strategies.

The presence of nonlinearity in GCC stock markets is a first step that can promote a new line of research to better understand the nonlinear dynamics in these markets. Knowing that stock returns in GCC are inherently nonlinear, the unpredicted sharp motions in returns might indicate a complex behavior such as a chaotic process in these markets. In fact, it can be argued that GCC markets are overvalued and influenced by nonlinear speculative bubble. Chaos theory would provide a good explanation to such kind of complexity in GCC stock markets. Hence a further research is recommended to examine if these markets exhibit low deterministic chaotic processes. This may require more detailed information on GCC financial markets and economic fundamentals, which has been one of the main obstacles to academic research in the region. The recent development in GCC financial market calls for the necessity of having professional institutes that can provide a wider range of economic and financial data.

REFERENCES

Abhyankar, A., Copeland, L. S., & Wong, W. (1995). Nonlinear Dynamics in Real-Time Equity Market Indices: Evidence from the United Kingdom. *The Economic Journal, 105*(431), 864-880.

Abraham, A., Seyyed, F. J., & Alsakran, S. A. (2002). Testing the Random Walk Behavior and Efficiency of the Gulf Stock Markets. *The Financial Review, 37*(3), 469-480.

Al-Loughani, N., & Chappell, D. (2001). Modelling the day-of-the-week effect in the Kuwait Stock Exchange: a nonlinear GARCH representation. *Applied Financial Economics, 11*(4), 353-359.

Al-Loughani, N. E. (1995). Random Walk in Thinly Traded Stock Markets: The Case of Kuwait. *Arab Journal of Administrative Sciences, 3*, 189-209.

Antoniou, A., Ergul, N., & Holmes, P. (1997). Market efficiency, thin trading and non-linear behaviour: evidence from an emerging market. *European Financial Management, 3*(2), 175-190.

Arab Monetary Fund (AMF). from http://www.amf.org.ae

Arthur, W. B., Durlauf, S. N., & Lane, D. A. (1997). *The Economy As an Evolving Complex System II*: Perseus Books Group.

Ashley, R. A., Patterson, D. M., & Hinich, M. J. (1986). A diagnostic test for nonlinear serial dependence in time series fitting errors. *Journal of Time Series Analysis, 7*(3), 165-178.

Bachelier, L. (1964). Theory of speculation (1900), reprinted in The random character of stock market prices [edited by Cootner, P.]: MIT Press, Cambridge, USA.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9*(1), 3-18.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics, 49*(3), 307-343.

Barkoulas, J., & Travlos, N. (1998). Chaos in an emerging capital market? The case of the Athens Stock Exchange. *Applied Financial Economics, 8*(3), 231-243.

Barnes, P. (1986). Thin trading and stock market efficiency: the case of the Kuala Lumpur Stock Exchange. *Journal of Business Finance and Accounting, 3*, 609–617.

Barnett, W. A., Gallant, A. R., Hinich, M. J., Jungeilges, J. A., Kaplan, D. T., & Jensen, M. J. (1997). A Single-Blind Controlled Competition Among Tests for Nonlinearity and Chaos. *Journal of Econometrics, 82*(1), 157-192.

Barnett, W. A., & Serletis, A. (2000). Martingales, nonlinearity, and chaos. *Journal of Economic Dynamics and Control, 24*(5-7), 703–724.

Basu, S. (1977). Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios. *Journal of Finance, 32*(3), 663–682.

Bernstein, P. L. (1992). Capital Ideas: The Improbable Origins of Wall Street: Free Press, New York.

Bonilla, C. A., Romero-Meza, R., & Hinich, M. J. (2006). Episodic nonlinearity in Latin American stock market indices. *Applied Economics Letters, 13*(3), 195-199.

Box, G. E. P., & Jenkins, G. M. (1976). Time Series Analysis: Forecasting and Control, rev. ed. *San Francisco*.

Box, G. E. P., & Pierce, D. A. (1970). Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *Journal of the American Statistical Association*, 1509-1526.

Brock, W., Dechert, W. D., & Scheinkman, J. (1987). A test for independence based on the correlation dimension, University of Wisconsin. *Economics Working Paper SSRI-8702*.

Brooks, C. (1996). Testing for non-linearity in daily sterling exchange rates. *Applied Financial Economics, 6*(4), 307-317.

Bulter, K. C., & Malaikah, J. (1992). Efficiency and Inefficiency in Thinly Traded Stock Markets: Kuwait and Saudi Arabia. *Journal of Banking and Finance, 16*, 197-210

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). The Econometrics of Financial Markets: Princeton University Press.

Campbell, J. Y., & Shiller, R. J. (1988). Stock Prices, Earnings, and Expected Dividends. *The Journal of Finance, 43*(3), 661-676.

Chan, L. K. C., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and Stock Returns in Japan. *The Journal of Finance, 46*(5), 1739-1764.

Chan, L. K. C., Jegadeesh, N., & Lakonishok, J. (1996). Momentum Strategies. *The Journal of Finance, 51*(5), 1681-1713.

Chen, Q., & Jiang, W. (2006). Analysts' Weighting of Private and Public Information. *The Review of Financial Studies, 19*(1), 319-355.

Chopra, N., Lakonishok, J., & Ritter, J. R. (1992). Measuring abnormal performance: Do stocks overreact? *Journal of Financial Economics, 31*(2), 235-268.

Chuang, W. I., & Lee, B. S. (2006). An empirical evaluation of the overconfidence hypothesis. *Journal of Banking and Finance, 30*(9), 2489-2515.

Cook, T. J., & Rozeff, M. S. (1984). Size and Earnings/Price Ratio Anomalies: One Effect or Two? *The Journal of Financial and Quantitative Analysis, 19*(4), 449-466.

Cootner, P. H. (1962). *Stock Prices: Random Vs. Systematic Changes*: Industrial Management Review.

Cowles, A. (1933). Can stock market forecasters forecast. *Econometrica, 1*(3), 309–324.

Cowles, A. (1960). A Revision of Previous Conclusions Regarding Stock Price Behavior. *Econometrica, 28*(4), 909-915.

Dahel, R., & Laabas, B. (1999). *The Behavior of Stock Prices in the GCC Markets*: Economic Research Forum for the Arab Countries, Iran & Turkey.

Day, R. H. (1992). Complex Economic Dynamics: Obvious in History, Generic in Theory, Elusive in Data. *Journal of Applied Econometrics, 7*, 9-23.

Day, R. H., & Chen, P. (1993). *Nonlinear dynamics and evolutionary economics*: Oxford University Press.
De Bondt, W. F. M., & Thaler, R. (1985). Does the Stock Market Overreact?". *Journal of Finance, 40*, 793-805.
De Bondt, W. F. M., & Thaler, R. (1987). Further evidence on investor overreaction and stock market seasonality. *Journal of Finance, 42*(3), 557-581.
De Bondt, W. F. M., & Thaler, R. H. (1990). Do Security Analysts Overreact? *The American Economic Review, 80*(2), 52-57.
De Bondt, W. F. M., & Thaler, R. H. (1995). Financial Decision-Making in Markets and Firms: A Behavioral Perspective," in Jarrow, R., V. Maksimovic and WT Ziemba (eds.), Finance, Series of Handbooks in Operations Research and Management Science, Elsevier-North Holland.
Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica, 49*(4), 1057-1072.
Dimson, E., & Mussavian, M. (1998). A brief history of market efficiency. *European Financial Management, 4*(1), 91.
Ebid, S. (1990). Characteristics and behavior of UAE stock market. *Journal of Economic and Administrative Sciences, 6*, 19–61.
EconStats. *IMF World Economic Outlook*, from http://www.econstats.com
Elango, R., & Hussein, M. (2008). An Empirical Analysis on the Weak-Form Efficiency of the GCC Markets Applying Selected Statistical Tests. *International Review of Business Research Papers, 4*(1), 140-159.
Fama, E. F. (1965). The Behavior of Stock-Market Prices. *The Journal of Business, 38*(1), 34-105.
Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance, 25*(2), 383-417.
Fama, E. F., & Blume, M. (1966). Filter rules and stock market trading profits. *Journal of Business, 39*(1), 226-241.
Fama, E. F., & French, K. R. (1988). Permanent and Temporary Components of Stock Prices. *The Journal of Political Economy, 96*(2), 246-273.
Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance, 47*(2), 427-465.
Fama, E. F., & French, K. R. (1998). Value versus Growth: The International Evidence. *The Journal of Finance, 53*(6), 1975-1999.
Fama, E. F., & Kenneth, R. (1988). French, 1988, Permanent and temporary components of stock prices. *Journal of Political Economy, 96*(2), 246-274.
Fasano, U., & Iqbal, Z. (2003). *GCC countries: from oil dependence to diversification*: International Monetary Fund.
FINCORP, G. M.-A. s. r., November 10, 2005.
Franses, P. H., & van Dijk, D. (2000). *Nonlinear Time Series Models in Empirical Finance*: Cambridge University Press.
Franses, P. H., & van Griensven, K. (1998). Forecasting exchange rates using neural networks for technical trading rules. *Studies in Nonlinear Dynamics and Econometrics, 2*(4), 109-114.

French, K. R. (1980). Stock Returns and the Weekend Effect. *Journal of Financial Economics, 8*(1), 55-69.
Friesen, G., & Weller, P. A. (2006). Quantifying Cognitive Biases in Analyst Earnings Forecasts. *Journal of Financial Markets, 9*(4), 333-365.
Frisch, R. (1933). *Propagation Problems and Impulse Problems in Dynamic Economics*: G. Allen & Unwin.
Fuller, R. J., Huberts, L., & Levinson, M. (1993). Returns to E/P Strategies, Higgledy-Piggledy Growth, Analysts' Forecast Errors and Omitted Risk Factors. *Journal of Portfolio Management, 19*(2), 13–24.
Gallant, A. R., & White, H. (1992). On learning the derivatives of an unknown mapping with multilayer feedforward networks. *Neural Networks, 5*(1), 129-138.
Gandhi, D. K., Saunders, A., & Woodward, R. S. (1980). Thin Capital Markets: A Case Study of the Kuwaiti Stock Market. *Applied Economics, 12*(3), 341–349.
Gencay, R. (1996). Non-linear Prediction of Security Returns with Moving Average Rules. *Journal of Forecasting, 15*(3), 165-174.
Gençay, R. (1999). Linear, non-linear and essential foreign exchange rate prediction with simple technical trading rules. *Journal of International Economics, 47*(1), 91-107.
Gencay, R., & Stengos, T. (1998). Moving Average Rules, Volume and the Predictability of Security Returns with Feedforward Networks. *Journal of Forecasting, 17*, 401-414.
Gibbons, M. R., & Hess, P. (1981). Day of the Week Effects and Asset Returns. *The Journal of Business, 54*(4), 579-596.
Global Research-GCC. (2008). GCC Market Review: Global Investment House.
Goodwin, R. M. (1951). The Nonlinear Accelerator and the Persistence of Business Cycles. *Econometrica, 19*(1), 1-17.
Granger, C., & Morgenstern, O. (1963). Spectral Analysis of New York Stock Prices. *Kyklos, 16*, 1-27.
Groenewold, N., & Kang, K. C. (1993). The Semi-Strong Efficiency of the Australian Share Market*. *The Economic Record, 69*(4), 405-410.
Grossman, S. J., & Stiglitz, J. E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review, 70*(3), 393-408.
Haefke, C., & Helmenstein, C. (1996). Forecasting Austrian IPOs: An Application of Linear and Neural Network Error-Correction Models. *Journal of Forecasting, 15*, 251.
Hicks, J. R. (1950). *A contribution to the theory of the trade cycle*: Clarendon Press Oxford.
Hinich, M. J. (1982). Testing for Gaussianity and linearity of a stationary time series. *Journal of Time Series Analysis, 3*(3).
Hinich, M. J., & Patterson, D. M. (1985). Evidence of Nonlinearity in Daily Stock Returns. *Journal of Business & Economic Statistics, 3*(1), 69-77.

Hochberg, Y. (1988). A sharper Bonferroni procedure for multiple tests of significance (Vol. 75, pp. 800-802): Biometrika Trust.
Hommes, C. H. (2004). Economic Dynamics. *Encyclopedia of nonlinear science, Routledge, London*, 245–248.
Hong, H. (1978). Predictability of Price Trends on Stock Exchanges: A Study of Some Far Eastern Countries. *The Review of Economics and Statistics, 60*(4), 619-621.
Hsieh, D. A. (1989). Testing for Nonlinear Dependence in Daily Foreign Exchange Rates. *Journal of Business, 62*(3), 339-368.
Hsieh, D. A. (1991). Chaos and Nonlinear Dynamics: Application to Financial Markets. *The Journal of Finance, 46*(5), 1839-1877.
Hutchinson, J. M., Lo, A. W., & Poggio, T. (1994). A nonparametric approach to pricing and hedging derivative securities via learning networks. *Journal of Finance, 49*(3), 851-889.
Ikenberry, D., Lakonishok, J., & Vermaelen, T. (1995). Market underreaction to open market share repurchases. *Journal of Financial Economics, 39*(2-3), 181-208.
Ikenberry, D. L., Rankine, G., & Stice, E. K. (1996). What Do Stock Splits Really Signal? *The Journal of Financial and Quantitative Analysis, 31*(3), 357-375.
International Monetary Fund. International Financial Statistics (IFS). Washington,: International Monetary Fund.
Jaffe, J., Keim, D. B., & Westerfield, R. (1989). Earnings Yields, Market Values, and Stock Returns. *The Journal of Finance, 44*(1), 135-148.
Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance, 48*(1), 65-91.
Jensen, M. C. (1978). Some Anomalous Evidence Regarding Market Efficiency. *Journal of Financial Economics, 6*(2/3), 95-101.
Kaldor, N. (1940). A Model of the Trade Cycle. *The Economic Journal, 50*(197), 78-92.
Kaplan, D. T. (1994). Exceptional events as evidence for determinism. *Physica D, 73*(1-2), 38-48.
Keim, D. B. (1983). Size related anomalies and stock return seasonality: Further evidence. *Journal of Financial Economics, 12*, 13-32.
Keim, D. B., & Hawawini, G. (1995). On the predictability of common stock returns: World-wide evidence. *Finance, Handbooks in Operations Research and Management ScienceElsevier, Amsterdam*.
Kendall, M. G. (1953). The Analysis of Economic Time Series. *Journal of the Royal Statistical Society, 96*, 11-25.
Kiel, L. D., & Elliott, E. W. (1996). *Chaos Theory in the Social Sciences: Foundations and Applications*: Univ of Michigan Pr.
Kosfeld, R., & Robe, S. (2001). Testing for nonlinearities in German bank stock returns. *EMPIRICAL ECONOMICS, 26*, 581-597.

Kuan, C. M., Liu, T., College of, C., Business, A., & University of Illinois at, U.-C. (1995). Forecasting exchange rates using feedforward and recurrent neural networks. *Journal of Applied Econometrics, 10*(4), 347-364.
Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: how sure are we that economic time series have a unit root. *Journal of Econometrics, 54*(1-3), 159-178.
Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective. *Review of Financial Studies, 1*(4), 403-425.
Lapedes, A., & Farber, R. (1987). Nonlinear signal processing using neural networks: prediction and system modeling. *1. IEEE international conference on neural networks, 21*.
Lee, T. H., White, H., & Granger, C. W. J. (1993). Testing for Neglected Nonlinearities in Time Series Models. *Journal of Econometrics, 56*, 269-290.
LeRoy, S. F. (1973). Risk Aversion and the Martingale Property of Stock Prices. *International Economic Review, 14*(2), 436-446.
LeRoy, S. F., & Porter, R. D. (1981). The Present-Value Relation: Tests Based on Implied Variance Bounds. *Econometrica, 49*(3), 555-574.
Lim, K. P., Azali, M., Habibullah, M. S., & Liew, V. K. S. (2003). ARE NON-LINEAR DYNAMICS A UNIVERSAL OCCURRENCE? FURTHER EVIDENCE FROM ASIAN STOCK MARKETS. *Proceedings of the 1st International Conference of the Asian Academy of Applied Business*, 10-12.
Lim, K. P., & Hinich, M. J. (2005). Cross-temporal universality of non-linear dependencies in Asian stock markets. *Economics Bulletin, 7*(1), 1-6.
Lo, A., & MacKinlay, A. C. (1999). A Non Random Walk Down Wall Street: Princeton University Press. Princeton New Jersey.
Lo Andrew, W., & MacKinlay, A. C. (1999). A Non-Random Walk Down Wall Street: Princeton University Press, Princeton NJ.
Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: evidence from a simple specification test. *Review of Financial Studies*.
Lucas, R. E. (1978). Asset Prices in an Exchange Economy. *Econometrica, 46*(6), 1429-1445.
Maghyereh, A., & Al-Kandari, A. (2007). Oil prices and stock markets in GCC countries: new evidence from nonlinear cointegration analysis. *Managerial Finance, 33*(7), 449-460.
Malkiel, B. G. (2003a). *A Random Walk Down Wall Street: The Time-Tested Strategy for Successful Investing*: WW Norton & Company.
Malkiel, B. G. (2003b). The Efficient Market Hypothesis and Its Critics. *The Journal of Economic Perspectives, 17*(1), 59-82.
Matilla-Garcia, M. (2007). Nonlinear dynamics in energy futures. *The Energy journal(Cambridge, MA), 28*(3), 7-29.
Michaely, R., Thaler, R. H., & Womack, K. L. (1995). Price Reactions to Dividend Initiations and Omissions: Overreaction or Drift? *The Journal of Finance, 50*(2), 573-608.

Neftci, S. N. (1984). Are Economic Time Series Asymmetric over the Business Cycle? *The Journal of Political Economy, 92*(2), 307-328.
Nourredine, K. (1998). Behavior of Stock Prices in the Saudi Arabian Financial Market: Empirical Research Findings. *Journal of Financial Management and Analysis, 11*, 48-55.
Nychka, D., Ellner, S., Gallant, A. R., & McCaffrey, D. (1992). Finding chaos in noisy systems. *Journal of the Royal Statistical Society B, 54*(2), 399-426.
Odean, T. (1999). Do Investors Trade Too Much? *American Economic Review, 89*(5), 1279-1298.
Ojah, K., & Karemera, D. (1999). Random Walks and Market Efficiency Tests of Latin American Emerging Equity Markets: A Revisit. *The Financial Review, 34*(2), 57-72.
Opong, K. K., Mulholland, G., Fox, A. F., & Farahmand, K. (1999). The behaviour of some UK equity indices: An application of Hurst and BDS tests. *Journal of Empirical Finance, 6*(3), 267-282.
Osborne, M. F. M. (1959). Brownian Motion in the Stock Market. *Operations Research, 7*(2), 145-173.
Osborne, M. F. M. (1962). Periodic Structure in the Brownian Motion of Stock Prices. *Operations Research, 10*(3), 345-379.
Panas, E. (1990). The behaviour of Athens stock prices. *Applied Economics, 22*(12), 1915-1727.
Pearson, K. (1905). The problem of the random walk. *Nature, 72*(1865), 294.
Perona, E. (2005). Birth and Early History of Nonlinear Dynamics in Economics. *Revista de Economía y Estadística, 43*, 2.
Pesaran, M. H., & Potter, S. M. (1992). Nonlinear Dynamics and Econometrics: An Introduction. *Journal of Applied Econometrics, 7*, 1-7.
Peters, E. E. (1991). A chaotic attractor for the S&P 500. *Financial Analysts Journal, 47*(2), 55-62.
Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika, 75*(2), 335-346.
Poterba, J., & Summers, L. (1988). Mean Reversion in Stock Returns: Evidence and Implications. *Journal of Financial Economics, 22*(1), 27–59.
Qi, M., & Maddala, G. S. (1999). Economic factors and the stock market: a new perspective. *Journal of Forecasting, 18*(3), 151-166.
Reinganum, M. R. (1981). Misspecification of capital market equilibrium: Empirical anomalies based on earnings' yields and market value. *Journal of Financial Economics, 9*, 19-46.
Reinganum, M. R. (1983). The anomalous stock market behavior of small firms in January: Empirical tests for tax-loss selling effects. *Journal of Financial Economics, 12*(1), 89-104.
Roberts, H. (1967). Statistical versus Clinical Prediction of the Stock Market. *unpublished paper presented to the Seminar on the Analysis of Security Prices, University of Chicago*.

Roberts, H. V. (1959). Stock-Market" Patterns" and Financial Analysis: Methodological Suggestions. *The Journal of Finance, 14*(1), 1-10.
Roll, R. (1983). Vas ist das? The turn-of-the-year effect and the return premia of small firms. *Journal of Portfolio Management, 9*(2), 18–28.
Roll, R. (1994). What Every CFO Should Know about Scientific Progress in Financial Economics: What Is Known and What Remains to Be Resolved. *Financial Management, 23*(2), 69-75.
Rosser, J. B. (2004). *Complexity in Economics*: Edward Elgar Pub Northampton, Ma.
Rothman, P. (1988). *Further Evidence on the Asymmetric Behavior of Unemployment Rates Over the Business Cycle*: CV Starr Center for Applied Economics, New York University, Faculty of Arts and Science, Department of Economics.
Rouwenhorst, K. G. (1998). International Momentum Strategies. *The Journal of Finance, 53*(1), 267-284.
Savit, R. (1988). *Nonlinearities and Chaotic Effects in Options Prices*: Center for the Study of Futures Markets, Columbia Business School, Columbia University.
Scheinkman, J. A. (1990). Nonlinearities in Economic Dynamics. *The Economic Journal, 100*(400), 33-48.
Schekman, J. A., & Lebaron, B. (1989). Nonlinear dynamics and stock returns. *Journal of Business, 62*, 311-317.
Shiller, R. J. (1981). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *The American Economic Rivew, 71*(3), 421-436.
Shleifer, A., & Summers, L. H. (1990). The Noise Trader Approach to Finance. *Journal of Economic Perspectives, 4*(2), 19-33.
Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics, 69*(1), 99-118.
Simon, H. A. (1957). *Models of man: social and rational: mathematical essays on rational human behavior in a social setting*: Wiley.
Slutzky, E. (1937). The Summation of Random Causes as the Source of Cyclic Processes. *Econometrica, 5*(2), 105-146.
Solnik, B. H. (1973). Note on the Validity of the Random Walk for European Stock Prices. *The Journal of Finance, 28*(5), 1151-1159.
Subba Rao, T., & Gabr, M. M. (1980). A test for linearity of stationary time series. *Journal of Time Series Analysis, 1*(2), 145-158.
Swanson, N. R., & White, H. (1995). A Model-Selection Approach to Assessing the Information in the Term Structure Using Linear Models and Artificial Neural Networks. *Journal of Business and Economic Statistics, 13*(3), 265-275.
Terasvirta, T., & Anderson, H. M. (1992). Characterizing Nonlinearities in Business Cycles Using Smooth Transition Autoregressive Models. *Journal of Applied Econometrics, 7*(0).
Tversky, A., & Kahneman, D. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263-292.
Urrutia, J. L. (1995). Tests of random walk and market efficiency for Latin American emerging markets. *Journal of Financial Research, 18*(3), 299-309.

White, H. (1989a). *An additional hidden unit test for neglected nonlinearity in multilayer feedforward networks.* Paper presented at the The International Joint Conference on Neural Networks Washington, DC.

White, H. (1990). Connectionist nonparametric regression: multilayer feedforward networks can learn arbitrary mappings. *Neural Networks, 3*(5), 535-549.

Wong, K. A., & Kwong, K. S. (1984). The Behaviour of Hong Kong Stock Prices. *Applied Economics, 16*(6), 905-917.

Zarowin, P. (1989). Does the Stock Market Overract to Corporate Earnings Information? *The Journal of Finance, 44*(5), 1385-1399.

ZAWYA. from http://www.zawya.com/cm/profile.cfm/cid1000011