AN ABSTRACT OF THE DISSERTATION OF

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Title: Using the Stock Market to Forecast Future Undesirable Outcomes

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Victor J. Tremblay

This dissertation focuses on the behavior of security returns around certain events that occurred in the Saudi stock market. In the first study, we measure and analyze the reaction of security returns around a major horizontal merger that occurred in the banking industry in Saudi Arabia. The objective of this study is to illustrate a method that can forecast the economic effect of a merger on market competition. We investigate whether the merger increases market power or economic efficiency using an event study methodology. Using the standardized cross-sectional test statistic, we test three hypotheses, namely the market power hypothesis, the productivity hypothesis, and the information hypothesis. When the actual merger date is chosen as the event date, the results support the productivity hypothesis. When the announcement date is chosen instead, we find that the results are consistent with the information hypothesis. The results did not show any support for the market power hypothesis. The overall results suggest that the merger is believed to increase the economic efficiency of the industry.

In the second study, we introduce a new technique that measures any misvaluation in the overall stock market. The objective of this study is to propose a method that can forecast financial bubbles. Various techniques have been used to identify the existence of stock market bubbles. All of them are based on the standard present value models. The success of those techniques in identifying bubbles depends on how good the underlying models are in detecting asset price misvaluation. In general, those techniques have not been satisfactory in detecting asset price bubbles. This study introduces a new technique that is based on a recently developed model called the composite-error model, which deviates from the traditional present value models. The approach generates a new index called “Market Valuation Index” - an index that measures the extent to which the overall stock market is over, under, or correctly valued. This new index helps identify financial bubbles and may help avoid financial crashes in the future. The capability of the new index to identify bubbles is tested on two historical crashes that occurred in the Saudi stock market during the years 2006 and 2008. In each case, this approach finds that the market was persistently overvalued during the pre-crash period, which indicates the existence of a bubble. The results also show that in each case the market was correctly valued during the post-crash period showing the disappearance of the bubble after the crash. In addition, this study runs various sensitivity analyses and finds that the results in general are not sensitive to changes in the length of estimation period, the level of significance, and the weighting scheme used to calculate the average of the estimated misvaluation.

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Using the Stock Market to Forecast Future Undesirable Outcomes

by

Assem S. Algursan

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APPROVED:

Major Professor, representing Economics

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Assem S. Algursan, Author

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CONTRIBUTION OF AUTHORS

Dr. Victor J. Tremblay provided ideas and assistance in all aspects of this dissertation.

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DEDICATION

This dissertation is dedicated to my beautiful wife, Ramia, and my children, Lara and Omar for all of their support, inspiration, and love.

I hope this work inspires and helps direct my children's lives no matter what they pursue.

Chapter 1

Using the Stock Market to Forecast Future Undesirable Outcomes

Introduction

The stock market has traditionally been viewed as forward looking, in that security prices reflect expectations of future profitability. By carefully analyzing these security prices and studying their reaction to economic events, we may be able to forecast undesirable outcomes that may affect the whole or certain segments of the economy. For this reason, the analysis of security prices and their reaction to economic events are of great importance.

In chapter 2, we focus on the reaction of security returns around a major horizontal merger. We show that by analyzing the reaction of security returns around a merger, we may be able to obtain important information regarding the economic effects of the merger on competition and efficiency. In Saudi Arabia, there has been an unprecedented increase in the number and value of announced mergers over the past decade. With this increase, it is important to ensure that regulatory policies are able to accurately distinguish between efficient and anticompetitive mergers. Therefore, our goal in this chapter is to illustrate how to obtain valuable information from the stock market that may increase the precision of antitrust policies in identifying anticompetitive mergers in Saudi Arabia. This is done by empirically investigating a case study of a merger event that occurred in the banking industry in Saudi Arabia. Using an event study methodology, we analyze the reaction of security returns of the acquirer and rival banks during the period surrounding the merger. We then examine whether the merger increases market power or economic efficiency.

In chapter 3, we present a method that can identify misvaluation in security returns. We construct an index that measures the extent to which the overall stock market is over, under, or correctly valued. By analyzing the pattern of this index, we can investigate the existence of a pre-existed bubble before a stock market crash. We focus on identifying stock market bubbles because they are of great concern to any economy since they can lead to a dramatic stock market crash and drop in wealth. During the last decade, the Saudi stock market has experienced two crashes, where the market index lost more than 50 percent of its value. This has led to substantial losses in investors' wealth and confidence in the stock market. Therefore, the purpose of this chapter is to introduce a method that can help identify financial bubbles and help avoid financial crashes in the future.

This dissertation can be of great importance to policy makers in Saudi Arabia. Chapter 2 is important because it provides a methodology that can increase the precision of antitrust policies in identifying anticompetitive mergers. Specifically, we believe that this study can be of great use to the Ministry of Commerce and Industry of Saudi Arabia since one of its goals is to ensure compliance with market competition laws. In addition, since the Saudi central bank, like any other central bank, is concerned with the level of competition and efficiency in the financial system, we believe that the content of this chapter can also be of great use.

Chapter 3 can also be important to policy makers who seek to insulate the economy from financial disturbances. Specifically, we believe that this chapter is vital to the Saudi central bank and the Saudi capital market authority since it provides analysis regarding two historical crashes that occurred in the Saudi stock market and suggests a mean that may help avoid similar crashes in the future. This chapter suggests an approach to increase information efficiency by raising the level of awareness between investors about the market misvaluation which can help avoid financial bubbles. In addition, the method in this chapter can also be used to set new polices that aim to eliminate potential financial bubbles.

Chapter 2

An Event Study Analysis of a Horizontal Merger: The Case of Saudi American Bank and United Saudi Bank

2.1 Introduction

Mergers and acquisitions, which will hereafter be called mergers, have long been a popular strategy used by firms in developed countries.[1] Over the last few years, this strategy has started to gain some popularity in developing countries as well. In Saudi Arabia, the number of mergers was relatively low during the 1990s through the mid-2000s. However, since 2006 the number and value of announced mergers have rapidly increased to record levels. To get a sense of the magnitude of this merger waves, Figure 2.1 depicts the number and value of the announced mergers from 1991 through 2011.

There are two lines of research that attempt to explain the driving forces of mergers. The first line focuses on the causes of merger waves. In this line, there are two main theories that can explain the causes of these merger waves. The first theory attributes merger waves to economic disturbances. Explained by Gort (1969) and examined by Mitchell and Mulherin (1996) and Harford (2005), this theory implies that mergers are an efficiency-improving response to various economic, regulatory, and technological shocks. The second theory attributes merger waves to stock market failure (inefficiency). This theory implies that stock market misvaluation impacts merger activities. According to Shleifer and Vishny (2003), mergers are a form of arbitrage by rational managers

[1] Mergers and acquisitions occur when two or more independent firms come under the control of a single firm. The terms “mergers” and “acquisitions” have slightly different meanings. A merger occurs when companies agree to go forward as a single new company rather than remain separately owned and operated. An acquisition occurs when one company takes over another.

operating in inefficient markets. A more recent paper by Rhodes-Kropf and Viswanathan (2004) shows that potential deviation between market values and fundamental values of both the bidder and target firms leads to a correlation between stock merger activities and market valuation.

The second line of research, which is most representative of the work undertaken in this study, focuses on the motivation behind mergers. In this line, studies are interested in the economic effects of these mergers on an industry. These types of studies are important because the economic effects of a merger depend on the motivation behind it. For instance, a merger can lead to realization of scale economies or other cost saving which leads to overall improvements in the industry's performance. On the other hand, a merger can also lead to a reduction in the number of competitors, an increase in entry barriers, elimination of potential competitors, and other factors that may lead to higher prices and loss of social welfare.[2]

There are two common methods used to investigate the economic effects of mergers. The first method is based on accounting data which analyzes the changes of firms' financial performance before and after a merger. Using financial statements, the method computes and compares the pre-merger and post-merger financial performance of merging and rival firms.[3] The advantage of this technique is that it measures the actual pre- and post- merger performance of firms.

[2] See Williamson (1968) for more information about economies and market power tradeoffs.

[3] Most common used financial ratios are Liquidity Ratios, Profitability Ratios, Solvency/Leverage Ratios, Return of Investment Ratios, and Market Stock Ratios (Kemal, 2011).

A drawback of this technique is that the measured changes between the pre-and post- merger period may not be solely due to the merger. Other events may occur during the same period that can also affect the performance of those firms. Thus, the *ceteris paribus* assumption is violated. Another drawback is that accounting data are based on historical expenditures which may not represent true opportunity costs.

The second approach is based on an event study methodology which measures the reaction of the financial market to the merger event. It measures the change in the firm's stock returns before and after a merger. This method avoids the problems that are associated with the accounting technique. In addition, assuming that the stock price of a firm reflects the discounted value of all expected future profits, this method can indirectly capture the impact of any unanticipated event on a firm's expected economic value. A weakness of this method is that its success depends on the assumption that financial markets are efficient.

The literature on the efficiency of financial markets can be divided into two main views. The first view is of those who support the efficient market hypothesis (EMH). [4] A strong form of this hypothesis says that security prices "fully reflect" all available information (Fama, 1970). A more realistic form of EMH allows for information and transaction costs and implies that a security price reflects information up to the point where the profits to be made by collecting and acting upon information are equal to zero (Jensen, 1978).

[4] For reviews and discussions of the efficient market hypothesis, see Fama (1970, 1991), and Malkiel (2003, 2011).

The second view, which is shaped by the work in market microstructures and the emerging work in neuroscience and behavioral finance, states that financial markets are not always efficient.[5] This view argues that various market frictions and constraints can distort market prices, which then can cause financial markets to behave inefficiently. This view also argues that some traders suffer from behavioral or cognitive biases that lead to a systematic misvaluation of security prices which again leads to market inefficiency.

This study adopts the first view and assumes that the Saudi stock market is efficient.[6] This assumption means that there is no misevaluation in security market prices (i.e., security prices are an unbiased estimates of the present value of expected future profits of a firm). There are two reasons to believe that the Saudi stock market is efficient during the period of study. First, Abraham, Seyyed, and Alsakran (2002) failed to reject the null hypothesis that the Saudi stock market is efficient during the period from October 1992 to December 1998. Second, since the Saudi stock market during the period under study did not experience any major event or financial volatility, we expect stock prices to represent their fundamental values.

The purpose of this study is to determine the economic impact of a single horizontal merger of two major banks in Saudi Arabia. In particular, we are going to investigate whether the merger is believed to increase the market power or economic

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[5] Market microstructure is a branch of finance that in part examines the ways in which market frictions, institutions, and information can affect security prices. For reviews of the market microstructure literature, see O'Hara (1995), Madhavan (2000), and Biais et al. (2005). For reviews of the behavioral finance literature, see Shiller (2003) and Barberis and Thaler (2003, 2005). For a review of the neuroscience evidence, see Coates (2012).

[6] Here, we are using the more realistic version of the EMH, which assumes the existence of information and transaction costs.

efficiency in the banking industry. The economic impact on the industry can be determined by analyzing the economic motivation behind this merger. We study whether the motivation behind the merger is believed to increase market power, productivity, or to signal information regarding the resources of merging and/or rival firms or regarding the possibility of future mergers. By using the event study methodology, we can determine investors' beliefs about the economic impact of this merger on the industry through analyzing the reaction of investors to the merger news.

To our knowledge, there are no studies that investigate the economic impact of any merger in Saudi Arabia which makes this study the first to do so. In addition, this study contributes to the existing small body of literature that focuses on the Saudi stock market or on mergers that occurred in Saudi Arabia. Since the number of mergers in Saudi Arabia is growing and since mergers can sometimes be anticompetitive, we find it important to demonstrate how to use the event study methodology to investigate whether a merger will increase market power or economic efficiency. We believe that this study can be of importance to the Ministry of Commerce and Industry of Saudi Arabia since one of its goals is to ensure compliance with market competition laws, which as stated in article 1 aim to "protect and encourage fair competition and combat monopolistic practices that affect lawful competition".

The remainder of the chapter is organized as follows. In section 2.2, we will briefly review the history of the stock market and banking industry in Saudi Arabia. Section 2.3 provides an overview of merger motives and economic consequences. Section 2.4 reviews the literature on both event studies and mergers. Section 2.5 describes the event study methodology. Section 2.6 discusses the data and econometric issues. Finally, we discuss the empirical results on section 2.7 and then close the discussion with its conclusion on section 2.8.

2.2 A Brief History of the Stock Market and Banking Industry in Saudi Arabia

2.2.1 The Saudi Stock Market

This section provides a brief history of the Saudi stock market and its unique characteristics. This will give the reader a broader view of the environment surrounding the event and the market forces that affect the results.

The Saudi stock market is relatively young. The existence of the first publically traded company, Arab Automobile Company, dates back to mid-1930s. By the end of 1975, there were 14 publically traded companies. However, the shares of all companies were traded in an informal capital market.[7] The first appearance of a formal market was in 1984 when the ministerial committees consisting of the Ministry of Finance and National Economy, the Ministry of Commerce, and the Saudi Arabian Monetary Agency decided to regulate and develop this over-the-counter stock market.[8] Therefore, the share trading intermediation function that used to be the task of unofficial brokers was handed over to the banks.[9] During this period and until the establishment of an electronic trading system

[7] Informal capital market here means a market without a capital market law. Capital market law deals with laws regulating investments made by individuals or businesses in capital markets. In Saudi Arabia, the organization that issues the required rules and regulations for implementing the provisions of capital market law is the Capital Market Authority.

[8] For details on each ministry, see Aldukheil (2002).

[9] There were only 11 banks during that time.

in 1990, the amount of time needed to fully execute an order took from several days to over a week.[10]

The introduction of the electronic trading system, called Electronic Securities and Information System (ESIS), led to a more efficient market.[11] It reduced the cost and settlement time significantly from what it was before. With the new system, each commercial bank had to establish a trading division, called a Central Trading Unit (CTU), summing to a total of 12 CTUs in the country. All those units are connected to the Saudi Arabian Monetary Agency (the central bank of Saudi Arabia) through a central system. The system can be accessed either through the CTUs themselves or through some selected bank branches.[12] As a result, buy or sell orders can only be entered through those places. With this electronic trading system, most of the orders are executed on the same day of entering the orders with a confirmation slip delivered on the next day.[13] However, some orders are executed on the next day with confirmation slip delivered on the day after.[14] In mid-1997, a more developed version of ESIS made the execution and settlement times occur simultaneously.

[10] Al-Suhaibani and Kryzanowski (2000) explains that this long delay was due to the low volume and lack of coordination between the banks. Also, there were several other restrictions on banks such as the fact that banks could neither hold positions in stocks nor break up large blocks of shares to accommodate buyers.

[11] This system was replaced by a more advanced system called TADAWUL in 2001. To read more about ESIS, see Al-Suhaibani, and Kryzanowski (2000) and Al-Dukheil (2002).

[12] Information on the number of selected bank branches during the time of the merger is not available.

[13] Ownership is transferred on the date and time of execution. There were two types of ownership documents- Ishaar and certificates. When the paper says confirmation slip, it means Ishaar document. Certificates take about 2 days to one week or more to get issued.

[14] 95% of the transactions are executed on day T and delivered on day T+1, while the rest are executed on day T+1 and delivered on day T+2 (Al-Dukheil, 2002).

The Saudi stock market has a number of unique characteristics which distinguish it from other markets. We will only mention those characteristics that are believed to be important to this study when analyzing the results. First, the market is dominated by retail investors (i.e., individual investors who buy and sell securities for their personal account) and lacks the presence of institutional investors (i.e., financial institutions that buy and sell securities in large volume, such as investment banks, insurance companies, pension funds, and registered investment companies).[15] The lack of financial analysts who perform various financial analyses about stock performance and provide investment recommendations is another important characteristic of the Saudi stock market. In addition, even though listed companies meet the minimum accounting information disclosure requirements set by the Saudi Organization of Certified Public Accountants (SOCPA), the level of voluntary information disclosure is low (Naser, and Nuseibah, 2003).[16] Relative to other countries, the level of detail in companies' disclosed accounting information is low. Finally, the market witnessed cases where selective groups used insider trading information to affect a particular stock (Niblock and Malik, 2007).[17]

[15] During the time of the merger, institutional investors in Saudi Arabia were only banks (eleven banks) and three government institutions (Public Pension Agency, General Organization for Social Insurance, and Public Investment Fund).

[16] Accounting information here means companies' periodic financial reports such as financial statements, income statements etc. Naser, and Nuseibah (2003) paper classifies voluntary information disclosure into two categories: voluntary disclosure related to mandatory such as breakdown of assets (current and fixed assets) and voluntary disclosure unrelated to mandatory such as future expansion in a company's assets.

[17] Insider trading is the trading of securities by an individual with access to information that has not been disclosed to general public, and that is not otherwise available to the general public. In Saudi Arabia, insider trading is considered illegal.

2.2.2 Banking Industry in Saudi Arabia

Modern Banking in Saudi Arabia began in 1926. The industry started with few local money exchangers and one foreign based trading company to provide the very basic services for the community and pilgrims.[18] Money exchangers were only providing day to day banking services, which covered only some of the banking activities required in modern society. All banking services that were not provided by money exchangers were left to a foreign based trading company, the Netherlands Trading Society.[19]

The surge in oil demand and production in the late 1940s increased government revenues and expenditures and the financing of major infrastructure and industrial projects. This attracted foreign banks to enter the market; these included French Banque de L'lndochine, Arab Bank, British Bank of Middle East, National Bank of Pakistan, and Bank Misr of Egypt. By 1975, the number of foreign banks reached a total of ten banks.

On the other hand, the government was worried about its local money exchangers and how they would compete with those foreign banks. Therefore, in order to protect the local money exchangers the government encouraged local money exchangers (Al-Kaki

[18] Money exchangers are considered as traders. Based on the Saudi Arabian Monetary Agency (SAMA) law, money exchangers can only exchange currency, purchase and sell foreign currency, and purchase and sell traveler's checks and bank drafts. For more information about rules and regulation of money exchanging business, you can visit SAMA's website (http://www.sama.gov.sa). A trading company is a company that facilitates trade between a home country and foreign countries. It is an exporter, importer and a trader. It provides a wider range of services than a money exchanger can provide. A pilgrim is a traveler who is on a journey to a holy place. The holy place in Saudi Arabia is the city of Mecca. Pilgrims go to Mecca because pilgrimage is required for every Muslim who can afford it as one of the five pillars of faith.

[19] The Netherlands Trading Society was a private Dutch trading company that was not only providing trade services but also banking services. The company later became known as Algemene Bank Nederland.

and Bin Mahfouz Co.) to merge and form a local bank.[20] In 1953, the two money exchangers agreed to merge together to become the first local bank under the name of National Commercial Bank. This merger was the first merger that took place in the industry. In 1957, the government established a law that gives the Saudi Arabian Monetary Agency control over banks operating in the country (Reumann, 1995). In 1960, the Saudi Arabian Monetary Agency used its rights and forced two falling banks (Riyad and Al-watany) to merge.[21] In 1975, the government expressed its intention explicitly in its second five-year development plan that it would attempt to increase the participation of the Saudi nationals in the ownership and management of the country's banks. According to the Ministry of Economy and Planning (1975) "Increased Saudi participation in ownership and management of the Kingdom's banks will contribute to closer control of the Kingdom's financial resources". To achieve this goal, the government implemented a policy in 1976 that forces foreign banks to convert their branches into publicly traded companies with participation of Saudi citizens. The government was able to convert all foreign banks except three.[22]

In 1982, the remaining three banks were merged to establish the United Saudi Commercial Bank, becoming the third merger in the industry. The fourth merger that occurred in the industry was the merger of United Saudi Commercial Bank and Saudi

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[20] Local bank is defined here as a domestic bank that is fully or partially with majority owned by Saudi citizens, the government, or both.

[21] The two banks were having serious liquidity problems arising from mismanagement and improper loans. Board members in both banks had borrowed heavily and then defaulted on loan repayments. Because bank Al-watany at the time was technically insolvent coinciding with the fact that board members refuse to settle their debts, the central bank of Saudi Arabia had decided to liquidate the bank and merge its operations with Riyad Bank.

[22] The policy was implemented to encourage the participation of Saudi investors in an important sector and to increase the public participation in the stock market.

Cairo Bank to become the United Saudi Bank in 1997. According to the Saudi Arabian Monetary Agency (1999), this merger was part of their banking system restructuring.

Thus far, all mergers that occurred were motivated primarily by government policies.[23] However, the year of 1999 witnessed the last and the only merger with an ambiguous motive. It is the Saudi American Bank's (SAMBA) acquisition of the United Saudi Bank (USB).[24]

This is an interesting case because it is not clear whether the motive for the merger was to increase market power, productivity, or to send a signal to the market. On one hand, this merger reduced the number of competitors in the same industry which could lead to less competition. On the other hand, this merger made SAMBA the third largest bank in the Saudi Arabian banking industry and one of the largest banks in the Middle East in terms of total assets. If the merger led to lower costs, due to scale economics, then this increase in size leads to a more efficient bank which could increase competition.

In terms of market concentration, a study by Al-Muharrami et al. (2006) examines the market structure of the Saudi Arabian banking industry during the years 1993-2002 and shows that two of three concentration ratios are decreasing. Another study by Al-Muharrami (2009) shows that the trend of both k-Bank Concentration Ratio (CR_k) and the Herfindahl-Hirschman Index (HHI) during the period of 1993-2006 have decreased where

[23] The first and third mergers were due to the so-called saudization policy. The saudization policy is aimed to encourage the Saudi citizens to open their own businesses and to transfer the majority of ownership of previously non-Saudi firms to Saudi citizens. The fourth merger event was part of the Saudi Arabian Monetary Agency's attempt (influenced by the government) to restructure the banking industry. The only merger not influenced by government policy was the merger of two falling banks, Riyad and Al-watany banks in 1960. Manne (1965) classifies this merger under the so-called market for corporate control.

[24] The name of the Saudi American Bank (SAMBA) was changed to become SAMBA Financial Group in 2003.

total deposits and total loans have been taken as a measure of bank size. [25] Both studies covered all banks in the industry except United Saudi Bank, which is considered the target bank in our case. Both studies examine the overall market concentration trends of a long period. However, they did not discuss the short term trend movement during the period of study. The trends in concentration in the deposits and loans markets found in Al-Muharrami (2009) and duplicated in Table 2.1 show that when total deposits are used as a measure of bank size, the CR_2, CR_3 and HHI are found to be larger in the year of 1999 and 2000 from what it was in 1998. However, when the total loans are used as a measure of bank size, CR2, CR3 is found to be smaller in the year of 1999 and 2000.[26]

2.3 Merger Motives and Economic Consequences

The motivation behind mergers can vary. All those motivations can be sorted under three general classifications. The first classification is those mergers that are induced by financial consideration. This type of merger occurs only when firms are profit maximizers. In this category, firms engage in merger activity simply to maximize their profits by taking advantage of the synergy created, whether it is cost or revenue synergy. This synergy means that the value of the combined firms is higher than the sum of the values of the separate firms. Good examples of this category are the market power and efficiency motives.

The second classification includes those mergers that are induced by non-profit motives. In this category, firms engage in mergers based on three motives found in

[25] CR_k is defined as the sum of market shares of the k largest banks in the market. HHI is defined as the sum of the squares of the market shares of all banks included in the sample.

[26] HHI was not calculated when total loans was used as a measure of size.

financial, managerial and behavioral economics. The first motive comes from firms' eagerness to reduce the risk of doing business. Firms may engage in a merger in order to diversify (reduce) their risk by targeting different markets. The second motive results from the principle-agent problem that can occur when stockholder ownership is separate from managerial control. When principle-agent problem is present, firms may have managers who take on a merger to increase their own personal wealth or utility, even though it is not the firms' best interest to do so. The final motive is a psychological motive and is found in firms that are operated by managers who may have their own psychological motives to engage in mergers. Some managers may suffer from overconfidence, over-optimism, or have a desire for empire building which can motivate them to engage in merger activities.

The third classification is those mergers and acquisitions that are motivated by government policies. Those policies can take the form of deregulation policies or tax policies. Deregulation can increase merger activities because it can create new investment opportunities for the deregulated industry and at the same time can remove barriers to merging (Andrade et al., 2001). In addition, certain types of tax policies may enable a firm to avoid taxes by merging with another firm.

There are three types of mergers. The first type is called a horizontal merger. This type includes all mergers that occur between firms that compete in the same market. The second type is the vertical merger, which includes any merger between two or more firms that produce different goods or services, yet share the same final product. The final type is the conglomerate merger, which includes all mergers that are not classified under the above two types.[27] The merger that this study is investigating is of the first type (horizontal merger).

Since a horizontal merger reduces the number of competitors, firms that engage in this type of merger may increase market power. If firms merge to increase their market power, then the market power hypothesis states that the merger will result in higher prices and lead to higher profits for all firms including rival firms, which in turn will lead to higher market values for all firms in the industry. However, the predatory pricing hypothesis states that it is also possible that the new merged firm engages in predatory conduct. If investors believe that the merger will lead to such behavior, then the market value of the new merged firm will increase while the market value of rival firms will decrease even though the merger increases market power. However, Eckbo and Wier (1985) report that antitrust enforcement agencies view predation as highly unlikely to occur.

Firms that engage in a horizontal merger can also increase the economic efficiency in an industry. A merger that increases the economic efficiency can have two economic effects: a productivity effect and an “information” effect (Eckbo and Wier, 1985).[28] If a merger allows the new merged firm to adopt a new technological innovation that leads to realization of scale economies or other cost saving, then the merger is said to have a productivity effect. This productivity effect will reduce the costs of the new merged firm alone which will make it a tougher competitor and harm rival firms. As a result, the

[27] For more information about all the three types of mergers, see Tremblay & Tremblay (2012).

[28] The term “information effect” was used in Eckbo and Wier (1985). Other studies sometimes call it “precedent effect” instead.

productivity hypothesis states that the market value of the new merged firm will be higher while the market value of all rival firms will be lower. If a merger signals an increase in demand for resources owned by the merging firms or even by rival firms, or if the merger sends a signal to the market of the potential productivity gains associated with the merger that are also available to rival firms, then the merger is said to have an information effect. In this case, the market value of merging firms will be higher while the market value of rivals will be unchanged or higher.[29] This is called the information hypothesis.

In order to empirically test for the net effect of a merger and whether it increases market power or economic efficiency, all one needs to do is to use the event study methodology to test for the wealth net effects of the merger on merging and rival firms.[30] The market power hypothesis is consistent when a horizontal merger increases the market value of merging and rival firms and inconsistent otherwise. The productivity hypothesis is consistent when a horizontal merger increases the market value of merging firms but decreases the market value of rival firms and inconsistent otherwise. The information hypothesis is consistent when the market value is higher for the merging firms and unchanged or higher for rival firms and inconsistent otherwise. Therefore, a merger is said to increase market power if the market power hypothesis is consistent. If either the productivity hypothesis or the information hypothesis is consistent then the merger is said to increase economic efficiency (see Table 2.2).

[29] The market value of rival firms will not change in the case when the merger signals an increase in demand for resources owned by merging firms only.

[30] We are testing for the net effects because the effects of a merger are not mutually exclusive, which means that it is possible for a merger to increase both market power and efficiency.

2.4 A Review of the Literature

The event study methodology was formally developed by Ball and Brown (1968) and Fama et al. (1969). According to Binder (1998), the methodology was originally introduced by Fama et al. (1969) and then used by Ball and Brown (1968), yet due to unexpected change in the journal process the Ball and Brown paper appeared in print first.[31] However, Mackinlay (1997) reports that there were several event studies in earlier papers, including Dolley (1933), Myers and Bakay (1948), Barker (1956, 1957, 1958), and Ashley (1962).

From the time it was introduced and until now, the event study method has been and continues to be a popular tool in empirical studies. One of the reasons the method is popular is its applicability. Initially used in accounting and finance, event studies are found to be useful in other disciplines as well, such as economics, law, management, and marketing.[32] Since event study research is highly interdisciplinary, a review of all important works is beyond the scope of this chapter. The purpose of this review is to summarize the main historical development of the event study methodology and its application to mergers. This review will also summarize all event studies that use Saudi Arabian stock market data. Other reviews of the literature of event studies include

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[31] According to Michael Jensen at a conference held in honor of Lawrence Fisher in April 1996, the Fama et al. paper was rejected three times before it was accepted by the *International Economic Review* (Binder, 1998).

[32] For reviews on the use of event studies on accounting and capital market, Management, marketing, law, analysis of antitrust, transport research, and information system research, see Lev and Ohlson (1982), Bernard (1989) and Kothari (2001) , Mcwilliams and Siegel (1997), Johnston (2007), Bhagat and Romano (2002,2002), Cichello and Lamdin (2007), Gong (2009), and Roztocki and Weistroffer (2009), respectively.

Henderson (1990), MacKinlay (1997), Binder (1998), McWilliams and McWilliams (2000), Serra (2002), Korthi and Warner (2005), and Corrado (2011).

2.4.1 Advancements in the Event Study Methodology

An event study method is a technique that estimates the impact of a specific event such as a merger, earnings announcement, or stock split on the stock price of a firm. The method first identifies the event of interest and the event window, the period over which security prices are expected to be influenced by an event. Then, the method uses data from an estimation window, which is prior to the event window, to estimate an empirical model of normal returns.[33] The model is then used to forecast normal returns during the event window, assuming that the event had never taken place. Once the normal returns of the event window are estimated, the abnormal returns of a security are calculated as the actual *ex-post* returns minus the estimated or forecasted normal returns of that security. If the researcher is interested in analyzing the impact of an event on stock returns of a security for an event window with a single period, then abnormal returns are used. On the other hand, if the researcher is interested in examining the impact of an event over an event window with multiple periods, then the researcher must use the cumulative abnormal returns which can be calculated by simply summing up the abnormal returns for each period. [34]

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[33] Examples of empirical models used in estimating the normal returns are the mean-adjusted returns model, the market-adjusted returns model, the market model, the market and risk adjusted returns models, and the multifactor models.

[34] All event study method steps will be discussed in detail in section 2.5.

Soon after the event study methodology was introduced, a number of studies came out examining the validity of the technique. The best known among these are Brown and Warner (1980, 1985). Using monthly security return data, Brown and Warner (1980) examine three general models used in event studies to estimate abnormal returns. The paper concludes that beyond a simple one factor market model, there is no evidence that more complicated models provide any added benefit. In Brown and Warner (1985), the properties of daily security return data and their effects on event study methodologies are examined. Their results reinforce the conclusions of their previous work with monthly data. Other studies such as Dyckman et al. (1984), Brown and Weinstein (1985), and Jain (1986) generally conclude that the market model works as well as the other alternatives.[35]

Other studies have focused on statistical issues that are associated with the method. They investigated the validity of the statistical assumptions that the regression model residuals are normally distributed, are not serially correlated, have a constant variance, and are not correlated with the explanatory variables. In particular, these studies evaluate how serious the problems in inferences are when 1) Stock returns are not normally distributed; 2) The return on a security and the return on the market index are measured over a different trading interval; 3) The variance estimates of the regression model's residual are different across firms; 4) Stock returns data are cross-sectionally dependent or have event clustering.

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[35] Examples of other alternatives are the mean-adjusted returns model, the market-adjusted returns model, the market and risk adjusted returns models, and the multifactor models.

When looking at non-normality of the stock returns, studies such as Brown and Warner (1985) and Berry et al. (1990) find that daily returns are non-normal. However, as pointed out by Brown and Warner (1985), departures from normality are less pronounced for cross-sectional average abnormal returns. Brown and Warner (1985) conclude that non-normality of daily returns has no obvious impact on event study methodologies while Berry et al. (1990) could not reject the null hypothesis that the distribution of the residuals is normal. On the other hand, McWilliams and Siegel (1997) recommend not imposing normality assumption when relatively small sample portfolios ($N \leq 22$) are used. However, McWilliams and McWilliams (2000) disagree with their recommendation and are comfortable recommending the use of the normal distribution with sample size as small as 5. Corrado (2011) reports that while several studies show that the assumption of normality is not a concern when returns data are taken from the New York Stock Exchange, other studies state that the assumption is of a concern when return data are taken from other exchanges such as the Nasdaq stock exchange, Toronto stock exchange, Copenhagen stock exchange, and Asia-Pacific stock exchanges.

Given that the assumption of normality may be a concern, several studies have developed non-parametric tests. Based on a recent review by Corrado (2011), the most successful tests are the non-parametric sign and rank tests advanced in McConnell and Muscarella (1985), Corrado (1989), Lummer and McConnell (1989), Zivney and Thompson (1989), and Corrado and Zivney (1992). Kolari and Pynnonen (2011) develop a generalized rank test (GRANK) and show that their new test outperforms popular parametric tests. They also show that their test outperforms previous rank tests of cumulative abnormal returns. In general, these studies found that the non-parametric sign and rank tests are well specified and provide an improvement in test power over the standard parametric tests.

Non-synchronous trading occurs when the return on a security and the return on the market index are calculated for different time periods. Scholes and Williams (1977) and Dimson (1979) show that the non-synchronous trading of securities can cause the OLS parameter estimates of the market model to be biased and inconsistent. A simple method to correct the problem is to exclude the non-synchronous observations from the sample (Brown and Warner, 1985). Two other widely recognized techniques are the Scholes and Williams method and the Dimson aggregated coefficients method.[36] However, several studies show that adjusting for non-synchronous trading using these two methods does not significantly improve the results. These studies include Reinganum (1982), Theobald (1983), and Brown and Warner (1985).

Beaver (1968), Patell and Wolfson (1979), Kalay and Lowenstein (1985), and Rosenstein and Wyatt (1990) provide evidence of heteroscedasticity, which can be a problem with cross-sectional data of different stocks. Aktas et al. (2007) and Harrington and Shrider (2007) argue that cross-sectional variation in the effects of an event leads to an increase in cross-sectional variance. Well known solutions include the use of a generalized least squares model (Collins and Dent, 1984), a method of moments estimator

[36] In the Scholes and Williams method, consistent estimators are calculated as a combination of OLS estimators that are obtained by regressing the return on a security against returns on the market from previous, current, and subsequent periods. In Dimson's aggregated coefficients method, consistent estimators are obtained from a multiple regression model of security returns against previous, current, and subsequent market returns.

(Froot, 1989), the test statistic proposed by Boehmer et al. (1991), and a generalized autoregressive conditional heteroskedasticity approach (GARCH) (Brockett, Chen, and Garven, 1999). Several studies have suggested the cross-sectional variance adjustment procedures developed by Boehmer et al. (1991).

When pooling data from firms in related industries, market model residuals are found to be cross-sectionally correlated (King, 1966). Tests procedures that ignore this correlation can lead to unwarranted statistical inferences (Gonedes and Dopuch, 1974). Several procedures that account for cross-sectional correlation were introduced. These procedures are Jaffe's (1974) and Mandelker's (1974) portfolio method, Patell's (1976) test statistic, the crude dependence adjustment (Brown and Warner, 1980), and generalized least squares (Collins and Dent, 1984). However, Brown and Warner (1985) report that "adjustment for cross-sectional dependence is not always necessary for reasonable test statistic specifications. If the degree of dependence is small, as in studies where event dates are not clustered, ignoring the dependence induces little bias in variance estimates". In their event study methodology reviews, both Henderson (1990) and Binder (1998) reach a similar conclusion.

2.4.2 Mergers and Event Studies

Numerous studies have used the event study method to investigate a number of important questions that arise in mergers. These questions can be placed under two general categories. The first category includes studies that are concerned about the shareholders' value gains from mergers and the distribution of that gain. The second category includes studies that investigate the sources of the value gains resulted from mergers. Since this study falls under the second category, this section will focus more on reviewing studies that attempt to explain the sources of the value gains.

Studies that fall under the first category mostly attempt to answer the following two questions; Do corporate takeovers generate positive gains? How large are the gains to shareholders of bidding and target firms? Examples of such studies are Mandelker (1974), Eller (1976), Langetieg(1978), Dodd (1980), Asquith (1983), Asquith et al (1983), Malatesta (1983), Tse and Soufani (2001), Choi and Russell (2004), Yuce and Ng (2005), Campa and Hernando (2006), and Ma et al. (2009).[37] These studies examine the effect of mergers on the value of merging firms. In general, evidence on the impact of mergers on target firms is consistent and suggests that target firms gain positive abnormal returns from mergers. However, the results of the impact of mergers on acquiring firms are mixed.[38]

Studies that investigate the sources of the value gains resulted from mergers are mainly concerned with two questions; Do mergers create market power or do they create efficiency? Does antitrust enforcement affect the value of merging firms? These studies analyze the impact of mergers not only on merging firms but also on rivals. In theory, mergers that increase market power by, for example, reducing the number of competitors will increase the profits and market values of all firms in the industry. On the other hand, mergers that increase the efficiency of the merged firm will increase the profitability and

[37] Mandelker (1974), Eller (1976), and Langetieg (1978) are examples of studies that use the actual merger date as their event date.

[38] For reviews on the impact of mergers on shareholder's wealth, see Jenson and Reuback (1983), Halpern (1983), Bruner (2002), Tuch and O'Sullivan (2007), Ismail et al. (2011).

value of the merged firms but reduce the value of competitors. Eckbo (1983) and Stillman (1983) were the first to empirically test these theories using the event study method. Based on this method, if a merger increases the value of merging and rival firms, this implies that the merger increases market power. If a merger increases the value of merging firms but decreases the value of rivals, then increased efficiency is implied.[39]

Eckbo (1983) examines 259 horizontal and vertical mergers in mining and manufacturing industries between 1963 and 1978, of which 76 were challenged by either the Federal Trade Commission (FTC) or the Antitrust Division of the Department of Justice (DOJ) under section 7 of the Clayton Act. He tests the market power hypothesis which implies that merging firms as well as their rivals benefit from the merger. He finds that the overall results are inconsistent with the market power hypothesis.

Stillman (1983) examines 11 horizontal mergers attempted between 1964 and 1972 that were challenged by antitrust enforcement agencies. Stillman tests the market power hypothesis to verify whether the decision to file a complaint against horizontal mergers is socially beneficial. His results show that from the 11 mergers, one was found to be consistent with the predictions of the market power hypothesis while another merger was found to have mixed results. The remaining nine mergers were inconsistent with the market power hypothesis, implying that they improved efficiency.

Another well-known study by Eckbo and Weir (1985) tests the proposition that the Hart-Scott-Rodino (HSR) Antitrust Improvements Act, which relaxes some legal

[39] In the case of antitrust enforcement, if an antitrust complaint decreases the value of merging and rival firms, this implies that the merger increases market power. If an antitrust complaint decreases the value of merging firms but increases the value of rivals, then increased efficiency is implied.

constraints found in Section 7 of the Clayton Act, has improved the FTC and DOJ selection processes in filing a complaint against a merger. Eckbo and Weir examine 82 horizontal mergers challenged under section 7 of the Clayton Act between 1963 and 1981. Their sample includes the 65 horizontal mergers used in Eckbo (1983) and an additional 17 horizontal mergers that occurred after the introduction of the HSR act. Eckbo and Weir conclude that the challenged horizontal mergers in their sample were not anticompetitive, and therefore reject the proposition that the HSR act has enhanced the agencies' precision in filing a complaint against only truly anticompetitive mergers.

Schumann (1993) updates and re-examines the conclusions and methodology of Eckbo (1983) and Eckbo and Wier (1985). Schumann examines the effect on rival firms of 37 horizontal mergers that were challenged by the FTC from 1981-1988. Like the previous two studies, he finds that, on average, rivals benefit from merger announcement but are unaffected by the antitrust complaints. When he examines the differential effects of antitrust complaints on rivals of different size, he finds that the value of small rivals increased significantly.

Song and Walkling (2000) develop and test a new hypothesis called the acquisition probability hypothesis. This hypothesis asserts that the source of rivals' positive abnormal returns is the increased probability that they will be targets themselves. This gives another explanation to the observed positive value gains in rival firms. Using a sample of 141 mergers and 2459 rival firms over the period between 1982 and 1991, they find evidence that supports their hypothesis.

A recent study by Duso et al. (2010) tests the usefulness of event studies for merger analysis. They test the ability of event studies to infer a merger's effect on profits for merging firms and their rivals. They estimate the *ex-ante* announcement effects of mergers on both merging and rival firms using an event study and then compare it with the estimated *ex-post* balance sheet profit effects of these mergers on merging and rival firms as measured by accounting data. They find that the estimated abnormal returns and *ex-post* profitability of mergers are positively and significantly correlated for merging firms and their competitors. They find that using a long pre-announcement period (25-50 days) increases the correlation between the two methods. They concluded that the event study methodology can be a useful technique in obtaining an *ex-ante* competitive analysis of mergers, which is consistent with Eckbo (1983) and Stillman (1983).

There are three important critiques to the Eckbo-Stillman methodology. First, McAfee and Williams (1988) argue that the power of event studies to detect anticompetitive mergers is low. They examined a challenged horizontal merger that was anticompetitive, yet failed to support the market power hypothesis. They argue that their failure to support the market power hypothesis is likely because the percentage of rival firms' revenue driven from the affected market is small. While this can be true, several studies show also that the power of detecting an event depends on the type of statistical test used. Second, as we mentioned earlier, efficient mergers can have both a productivity effect and an information effect. If the information effect is larger than the productivity effect, then rival firms can experience positive abnormal returns even though the merger is efficient. Third, the existence of behavioral agents, who suffer from cognitive or psychological weakness that causes them to make systematic errors in their investment decisions, can prevent event studies from detecting anticompetitive mergers (Tremblay and Tremblay, 2012). For instance, the uncertainty increase due to a merger announcement can make behavioral agents become overly pessimistic about the future of rival firms. As a result, rival firms may experience negative abnormal returns even though the merger is anticompetitive.

2.4.2.1 Bank Mergers and Event Studies [40]

Most of the empirical studies on bank mergers that use the event study approach examine the wealth effects of the merging banks. Those studies examine whether bank mergers benefit targets, bidders, or combined entities. The evidence indicates that, on average, stockholders of targeted firms benefit from mergers, while stockholders of acquiring firms marginally lose from mergers (Pilloff and Santomero, 1996; DeYoung et al., 2009). The evidence is less clear in terms of the overall stockholder value gains from bank mergers. Studies that examine North American bank mergers show that the results on the wealth effects are mixed (DeYoung et al., 2009). That is, while several studies find evidence that bank mergers benefit stockholders (e.g., Becher, 2000; Hart and Apilado, 2002; Al-Sharkas and Hassan, 2010), other studies find that bank mergers have no effect or sometimes negative effect on the wealth of stockholders (e.g., Houston and Ryngaert, 1994; Pilloff, 1996; Delong, 2001; Houston et al., 2001; Knapp et al., 2005; and Becher

[40] For a broader view on the consolidation of the financial services industry, see Berger et al. (1999).

and Campbell 2005). In contrast, evidence from studies that examine European bank mergers suggests that stockholders benefit from mergers (DeYoung et al., 2009).

There are few studies that use the Eckbo-Stillman methodology (using event study to examine merging firms and their rivals) to test the market power and efficiency hypotheses in the banking industry. However, there are other studies that use the same Eckbo-Stillman methodology to test other hypotheses. The most popular hypotheses used in these studies are 1) The information hypothesis, which states that merger announcements signal valuable information relevant to the merging and rival firms; 2) The takeover premium hypothesis, which states that a firm's value changes when its probability of being a future takeover target changes; 3) The acquisition probability hypothesis, which asserts that the source of rivals' positive abnormal returns is the increased probability that they will be targets themselves.

James and Wier (1987) attempt to analyze the source of acquisition related gains by examining the relation between returns to acquirers and competition in the acquisition market. Using a sample of 60 bank acquisitions during the years 1972-1983, they examine three hypotheses, one of which is the market power hypothesis. From their sample, only 21 bank acquisitions were used to test the market power hypothesis using the Eckbo-Stillman methodology. They find no evidence that supports the market power hypothesis.

In an attempt to explain why targets in bank acquisitions gain while bidders do not, Baradwaj et al. (1996) proposed a hypothesis called ”Takeover Premium Hypothesis” which states that a firm's value changes when its probability of being a future takeover target changes. Under this hypothesis, the defensive acquirers will have negative abnormal returns around the time of the announcement, smaller competitors have positive abnormal returns, and larger competitors will not be affected.[41] They looked at bank mergers during 1982 to 1993 and selected a sample of 19 defensive acquisitions which are defined as takeovers made by a firm as to become so large that it becomes an unattractive target itself. They find that their results are consistent with the takeover premium hypothesis.

Akhigbe and Madura (1999) test the information hypothesis which states that merger announcements signal valuable information relevant to the merging firms and their rivals as well. One of their three main questions is whether bank acquisition announcements convey intra-industry signals. They find that, on average, bank acquisition announcements generate significant positive intra-industry effects. Their overall results indicate that bank acquisitions signal information to investors which depends not only on event-specific characteristics but also on rival bank-specific characteristics.

Bendeck and Waller (2007) also examine the information hypothesis by studying target banks, bidding banks, and rivals of target banks. Following DeLong (2001), they define rivals as banks located in the same geographical area as the target bank. Like Akhigbe and Maura (1999), they find significant positive information effects at acquisition announcements for targets and rival banks. Their overall results suggest that the positive information effects for targets and rival banks are due to geographically specific industry information rather than expectations of increased efficiencies.

Weiss and Neumann (2010) jointly test several popular hypotheses, including the market power, efficiency and acquisition probability hypotheses. Analyzing a sample of

[41] A defensive acquirer is a firm that takes over another firm to become so large that it becomes an unattractive target itself.

425 bank mergers between 2000 and 2008, they find that the majority of the merger activities can be explained by at least one of their selected hypotheses. They also find that the market power and efficiency hypotheses can best explain the wealth effects found in merging and rival banks.

Bendeck and Waller (2011) examine the market power hypothesis, the efficiency hypothesis, and the information hypothesis. By disaggregating the sample of rival banks on the basis of whether the bidder and target banks operate in overlapping deposit markets prior to the merger announcement, Bendeck and Waller were able to test the hypotheses by examining the effects of mergers on the value of targets and their geographic rivals. Their results are inconsistent with the market power and efficiency hypotheses, yet consistent with the information hypothesis. Similar to Akhigbe and Madura's (1999) finding, they conclude that the gains in wealth from bank mergers are due to information signaling that may be affected by event-specific or bank-specific characteristics.

Hankir et al. (2011) test the market power hypothesis and four other hypotheses. Their sample consists of 600 intra-industry mergers by public banks in North America and Europe in the period from 1990 to 2008. They find that 10.8 percent of all mergers are consistent with the market power hypothesis, whereas the other control hypotheses together can explain only 21.3 percent of all merger actions.

Two important conclusions are reached from studies that examine bank mergers. First, the results are mixed for studies that investigate the sources of the value gains resulting from mergers. Second, when rival banks gain positive abnormal returns due to a merger, the source of this gain is still unknown.

2.4.3 Event Studies in Saudi Arabian Markets

One purpose of this section was to review studies that use the event study approach to examine mergers that occurred in Saudi Arabia. However, no such studies were found. In fact, I was able to find only five studies that use the event study approach to issues related to the Saudi Arabian economy: two studies test the efficiency of the Saudi Arabian stock market, two examine stock returns around earning announcements, and one tests the effect of dividend announcements on shareholders' value. Since only five studies were found, this section will review these studies and focus on the methodology used.

Jefry and Soufi (1993) test the informational efficiency of the Saudi stock market by examining the stock market reaction to government budget announcements.[42] They examine how long it takes for the Saudi stock market to react and fully adjust to the information contained in the government budget announcements. Their data consist of the weekly stock prices of 44 companies, which represent about 85 percent of the Saudi Arabian stock market, for the period between May 1985 and January 1989. They choose the market model as their normal return estimation model and use the entire sample period (May 1985 to January 1989) as their estimation window.[43] They used a 21 event window and test the null hypothesis of no abnormal returns using the traditional t-test (Brown and

[42] Jefry and Soufi (1993) define the government budget announcement as the government public announcement of the next year's budget for the kingdom of Saudi Arabia. The government budget content as described by Jefry and Soufi is based on several macroeconomic variables (e.g. the country's actual (forecasted) surplus/deficits for the previous (following) year, inflation rate, unemployment rate, etc.), several government policy decisions (e.g. spending levels for public health programs, public education programs, etc.), various income sources (crude oil sales, petrochemical sales, taxes, tariffs, investment income, etc.), and various spending units (e.g. Ministries, Municipalities, other agencies, etc.).

[43] Jefry and Soufi (1993) do not mention the exact number of weeks used in the estimation window. However, since their paper states that they use the whole sample period and since the paper does not state any omitted observations, it is likely that the length of the estimation window is about 200 weeks.

Warner, 1980). Their t-test statistics show that they failed to reject the null hypothesis at the 5% level of significance. They concluded that this shows that the market anticipates the budget information before the announcement and fully adjusts to reflect such information. Therefore, they suggested that the Saudi stock market is informationally efficient.

Uddin and Osman (2008) examine the effect of dividend announcements on shareholders' value in the absence of income taxes. They examine 178 dividend announcements made by 28 companies during the period from 2001 to 2005. They used the market-adjust return model, which assumes that the *ex-ante* expected returns are equal across securities, but not necessarily constant over time. When using this model, one can simply calculate an abnormal return as the difference between the return on a security *i* and the return on the market portfolio. Uddin and Osman use a 61-day event window, starting at day -30 and ending at day +30 for an event at time 0.[44] They find evidence that shareholders do not gain value from the announcements of dividends, which means that these announcements do not signal any new information about the firm's future earnings. However, when they divide their sample into sub-samples based on whether dividends increased, decreased, or distributed for the first time, they find mixed results. They find that the announcement that dividends increased may not signal any new fundamental information while the announcement that dividends decreased or that dividends are distributed for the first time do signal some information.

[44] Since the coefficients of the market-adjusted return model are pre-specified, there is no estimation period.

Alzhrani and Skerratt (2010) test the informational efficiency of the Saudi stock market by examining the market reaction to earnings announcements. They examine how long it takes for the Saudi stock market to react and fully adjust to the information contained in the earnings announcements. They use daily stock prices of 89 companies, which represent the whole market, and document 1667 earnings announcements during the period 2001-2007. They use the market-adjusted return model as their normal return estimation model. They calculate abnormal returns over a 40-day event window, starting at day -19 and ending at day +20 for an event at time 0. When they test the null hypothesis of no abnormal returns using the traditional t-test**,** they find evidence of a post-earnings announcement drift (a continuous upward (downward) drift in prices after positive (negative) news). They also find evidence of informed trading and leakage of information. They show that the market is slow in adjusting to new information when it is good news and overreacts when it is bad news. They suggest that the main explanation for investors over and under reaction to new information is due to the absence of analysts' forecasts and to the market being dominated by individual investors who are inexperienced.

Alzahrani (2010) extends the study done by Alzhrani and Skerratt (2010). He investigates whether it is possible to predict future returns by exploiting the documented inefficiency of the Saudi stock market found in previous work. After using the event study approach to document the post-earnings announcement drift, he applies a cross-sectional regression using pre-announcement cumulative abnormal returns, trading volume, and company size as dependent variables and post-announcement cumulative abnormal returns as an independent variable. He finds evidence within the event window that the pre-announcement returns and trading volume are good predictors for post-announcement returns or returns drift in the market.

Alzahrani and Gregoriou (2010) examine stock returns, trading activity, volatility, levels of stock liquidity, information asymmetry, and investor trading behavior around earnings announcements. They use 2170 earnings announcements of 95 listed companies covering the period between 2002 and 2009. They use both the market-adjusted return model and the market model to estimate the normal returns. They use an 89-day estimation window, starting at day -100 and ending at day -11, and three different event windows starting at day -10, -5, and -1 and ending at +10, +5, and +1 for an event at time 0, respectively. When they test the information content of the earnings announcements to see whether they convey important information, they find evidence in stock returns and trading volume that suggests that earnings announcements are important and highly informative. They also find evidence of information leakage before the release of earnings announcements. They also document a significant increase in volatility, liquidity, and information asymmetry. Finally, they find, in general, that large investors are more sophisticated and more informed around earnings announcements, while small investors tend to have stronger reactions.

In conclusion, all documented event studies for Saudi Arabia seem to ignore several statistical issues that are associated with the method, which can cause inference problems. For example, most of these studies use the market-adjusted return model, which does not handle calendar clustering well (Henderson, 1990). This model was also found to be less powerful than the market power in detecting abnormal returns (Dyckman et al., 1984). Moreover, all of these studies test the null hypothesis using a t-test, which does not take into account the possible change in variance. Finally, none of these studies discuss or deal with any of the other common statistical issues that may exist in event studies such as the non-synchronous trading problem or cross-sectional dependence.

2.5 Event Study Methodology

An event study method is used to estimate and draw inferences about the impact of an unanticipated event on the performance of stock market security prices. This method is based on the efficient market hypothesis (EMH). Generally, any event study must identify the event of interest, an event window, an estimation window, the normal return estimation model, and the null hypothesis.[45]

Defining the event of interest is the initial task of conducting any event study. It depends on what the researcher is investigating. For instance, if someone is interested in examining the effect of stock splits on security prices, then the event of interest is the announcement of the stock splits (Fama et al., 1969), or if he or she is interested in the information content of earnings, then the event of interest is the earnings announcement (Ball and Brown, 1968).

After defining the event of interest, the researcher must determine the event date. An event date is the date when the event of interest occurs. In merger event studies, an event date is usually defined as the announcement date of an event. Alternatively, an event date can be defined as the actual merger date (effective date) at which all uncertainty can

[45] The normal return estimation model (normal performance model) is a method to estimate a security's normal returns or what sometimes is referred to as expected returns.

be resolved (Halpern 1983). Once the event date is defined, it is important to specify the length of observation interval a researcher is using, which depends on the type of data used in an event study. If the length is one day, then the researcher defines the event date to be day ‘0’, which is the day when the event of interest occurs. If the length is one month, then month ’0’ is assigned to be the event date.

An event window is defined to be the period over which the security prices of firms involved in an event will be examined. Theoretically, an event window is defined to be the event date on which the event of interest occurs. However, since in practice information about an event can be leaked to traders before the event date or lags can exists in response to new information, it is common to define the event window to be larger than the event date. By doing so, the researcher can examine not only the period of interest, but also the periods surrounding the event.

The estimation window is the period where the researcher can estimate the normal return (the expected return conditional on the event never taking place) by using one of the normal return estimation models. This estimation window must not overlap with the event window in order to prevent the event from influencing the parameters’ estimates of a normal return estimation model. The most common choice of the estimation window is using the period prior to the selected event window, yet sometimes the post-event window is included as well in attempt to increase the robustness of the normal return estimation model (Mackinlay, 1997).

Figure 2.2 and 2.3 depict the theoretical and empirical time line for an event study. In theory, the event data is a particular point in time $t \simeq T_E = 0$ as in Figure 2.2. $W_{est} \in [T_0,$

T_E) represents the estimation window. $W_{post} \in (T_E, T_1]$ represents the post event window. The length of the estimation window is $L_1 = T_E - T_0$. The length of the post-event window is $L_2 = T_1 - T_E$. In practice, the impact of an event may take multiple periods and may not be fully captured in one period. Thus, an event window is introduced to include more than one period (day), as described in Figure 2.3. In this case, $T_E = 0$ is defined as the event date and $W \in [T_1, T_2]$ is defined as the event window. $W_{est} \in [T_0, T_1)$ and $W_{post} \in (T_2, T_3]$ represent the estimation and the post event windows, respectively. The length of the estimation window is $L_1 = T_1 - T_0$. The length of the event window is $L_2 = T_2 - T_1$. The length of the post-event window is $L_2 = T_3 - T_2$.

A normal return estimation model is a model that uses the estimation window to estimate securities' normal returns. Various models have been used in previous work to estimate normal returns.[46] The most common is the market model.[47] The model is simply relating the return of any given security to the return of a market portfolio. A security's return (R_{it}) is defined as the percentage change in the company's security value. The return of the market portfolio (R_{mt}) is defined as the return on a weighted sum of all securities in the market. Those securities can be weighted either equally or by their respective market shares.

Using stock prices and dividends, stock returns for firm i at time t can be constructed as:

$$R_{it} = [P_{it} + D_{it} - P_{i,t-1}] / P_{i,t-1} \tag{2.1}$$

where P_{it}, $P_{i,\,t-1}$, are stock prices for firm i at the end of the day t and $t-1$, respectively.

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[46] Several normal return estimation models will be viewed later.
[47] See Fama (1976, chapter 3 and 4) to learn more about the market model.

D_{it} is dividend per share of a common stock of company *i* at time *t*.[48] For security *i*, the market model is written as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{2.2}$$

$$\varepsilon_{it} \sim N(0, \sigma^2)$$

where the lower script *t* in this model refers to the estimation window ($t \in W_{est}$). R_{it} and R_{mt} are the period *t* returns on security *i* and on the market portfolio, respectively.[49] α_i, β_i, and σ^2 are the parameters of the market model that measures the mean returns, the sensitivity of security *i* to the market (a measure of risk), and the variance of the disturbance term, respectively. Finally, ε_{it} is a normally distributed disturbance term with zero mean and variance σ^2.

The market model is widely used because it is simple and because it represents a potential improvement over the Mean Adjusted Returns model and frequently yields results similar to those of more sophisticated models (Brown and Warner 1980, 1985). The improvement of the market model over the constant mean model is represented by the extraction of the portion of the return that is related to variation in the market's return. This extraction leads to a reduction in the variance of abnormal returns which increases the power of the test. There are other normal return estimation models that can be used as well to measure the normal returns. In general, those models are the Mean-Adjusted Returns Model, the Market-Adjusted Returns Model, the Market and Risk Adjusted

[48] There were no dividends distributed during the sample period.

[49] The model's linear form follows from the assumed joint normality of asset returns. Appendix A shows how the linear relationship between security returns and the returns of the market Index is derived.

Returns Models, and the Multifactor Models.[50] According to Brown and Warner (1980, 1985), the first three models yielded similar test power for a well-specified test statistic when comparing to the market model. However, when event month clustering was introduced, the market model substantially performed better. Mackinlay (1997) reports that in general "the gains from employing multifactor models for event studies are limited". Thus, because of its simple form, a market model is preferred.

The abnormal return due to an event is defined as the actual *ex-post* return minus the normal return of a security over the event window. Thus, once the normal return for company i is estimated for the event window, the abnormal return can be calculated as follows:

$$AR_{it} = R_{it} - E(R_{it}|X_t) \tag{2.3}$$

where lower script t is referring to the event window ($t \in W$). AR_{it} is the period t abnormal return for security i. R_{it} is the period t actual *ex-post* return for security i. $E(R_{it}|X_t)$ is the period t estimated normal return for security i. It is the expected return conditional on the event never taking place. X_t is the pre-event conditioning information for the normal return estimation model (i.e. the information used to forecast the expected return assuming the event had never taken place).

Given the assumptions that stock returns are jointly multivariate normal, independently and identically distributed through time, the model's parameters can consistently and efficiently be estimated using ordinary least squares (OLS) regression.

[50] See Brown and Warner (1980, 1985), Henderson (1990), and McKinlay (1997) for more discussion about those types of models.

Using $\hat{\alpha}_i$ and $\hat{\beta}_i$ to represent the OLS estimates of the parameters α_i and β_i , abnormal returns can be calculated as follows:

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \tag{2.4}$$

Abnormal returns measure the impact of an event on stock returns of a security *i* at a single period $t \in W$. To examine the impact of an event on stock returns of a security *i* for multiple periods, one must calculate the cumulative abnormal returns. If the multiple periods are from t_1 to t_2, where $T_1 \leq t_1 \leq t_2 \leq T_2$, then the cumulative abnormal returns (CAR_{it}) are calculated by adding up the abnormal returns of each period as follow:

$$CAR_{it} = \sum_{t=t1}^{t2} AR_{it} \tag{2.5}$$

There are many statistical significance tests that can be used to test the null hypothesis that (cumulative) abnormal returns are zero over any event window.[51] Commonly used tests are the traditional test (Brown and Warner 1980, 1985), the standardized-residual test (Patell, 1976), the ordinary cross-sectional test (Charest, 1978), the standardized cross-sectional test (Boehmer et al., 1991), the method-of-moment test (Froot, 1989), the maximum-likelihood test (Ball and Torous, 1988), the sign test (Dixon and Mood, 1946), and the rank test (Corrado, 1989).

The statistical test used in this study is the standardized cross-sectional test (Boehmer et al., 1991). Unlike most commonly-used methods, the standardized cross-sectional test avoids overly frequent rejections of the null hypothesis when it is true, while maintaining an equally-powerful test when the null hypothesis is false. Like most tests, this test statistic assumes the null distribution (the probability distribution of the test

[51] Section 2.6 explicitly outlines all the null hypotheses used to make inferences.

statistic when the null hypothesis is true) is normally distributed with zero mean and variance equal to one.[52]

2.6 The Case under Study (Data and Econometric Issues)

2.6.1 Data

On January 6, 1999, SAMBA announced its intention to merge with the USB by an exchange of shares. The deal was agreed upon and carried on in July 3, 1999. The two banks form one of the largest banks in the Middle East. The merger did not change the name of the company or the composition of the board of directors. The exchange of shares agreement was done by exchanging 1 new share in SAMBA for each 3.25 existing shares in USB.[53] The merger reduced the number of banks from 11 to 10.[54] Eight out of the ten banks are studied in this merger case. Data are unavailable for the other two banks.[55] All related data were gathered from the official website of the Saudi Stock Exchange Company (TADAWUL).[56]

Because the event of interest is a merger event, the event date can be defined as either the announcement date (i.e., this is the date when both banks publicly announced

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[52] In order for this test to be correctly specified, abnormal returns must be cross-sectionally uncorrelated. This assumption must be satisfied when cross-sectional events are included in a study. However, this assumption should not be a concern in this study, since this study is dealing with time series data with one event.

[53] The source is SAMBA's official website (www.samba.com).

[54] Those banks are Al Rajhi Bank, Aljazira Bank, Arab National Bank, Banque Saudi Fransi, Riyad Bank, SAMBA financial group, Saudi Hollandi Bank, Saudi investment Bank, The Saudi British Bank, and Alahli Bank. Currently, there are twelve banks in the industry. The names of the other two banks are Al Bilad Bank and Alinma Bank.

[55] Those two banks are National Commercial Bank and Saudi Hollandi Bank. The former is not included in our study since it is not publicly traded. The latter is not included because it has too many untraded days during the studied windows.

[56] The name of the company "TADAWUL" is the Arabic word for "Trading". The official website of Tadawul is (www.tadawul.com.sa).

their intention to merge on Jan 6, 1999) or the actual merger date (i.e., the is the date when each outstanding share of the merging banks was converted into one share of the surviving bank on July 3, 1999).[57] Furthermore, based on the characteristics of the Saudi stock market and its large uncertainty during the announcement date, this study chooses the event date to be the actual merger date.[58] The focus will be on this event date. However, in an attempt to support the results, this study will also perform some comparisons between the results found when using both dates (the actual and announcement dates).

Since this study is going to compare results using both the actual and announcement dates, the estimation window will be chosen such that there is no overlap between the observations of the two events. For instance, looking at Figure 2.4, if the size of the estimation window is chosen to be more than 105 trading days, then there will be an overlap between the estimation window of the merger event case and the event window of the merger announcement case. If the selected size is between 90 and 105, then the observations of some companies will overlap. If the size of estimation window is chosen to be 90 trading days or less, then there will be no overlapping between the observations in all companies.

This study selects the size of the event window based on three reasons. The first is to capture any leaked information or any lags that might exist as a response to the release of the new information. To be able to capture the reaction of investors to new information when they have access to information that is not available to general public, the event

[57] The actual date can be selected as the event date only in the case of acquisitions.
[58] The causes of the market uncertainty will be discussed later.

window must start before the event date (*t=0*). When investors' evaluation of the economic consequences of an event is slow, then the event window must end after the event date (*t=0*). Second, when a market is volatile, a longer window will affect the power tests of the cumulative abnormal returns. Finally, Figure 2.4 shows that there are only a limited number of observations between the two event dates, which means that there will always be a tradeoff between the sizes of the event windows of the first and second event and the estimation window of second event. Given the previous selection criteria, this study uses a sample size of 8 securities with 111 observations for each security. The observations represent the period around the event, starting at day -100 and ending at day +10. The event date is defined as day 0. The estimation window is chosen to be 90 days, starting at day -100 and ending at day -11.[59] The event window is constructed to be 21 days, starting at day -10 and ending at day +10.[60] The market model is applied, and the National Center for Financial Economic Information NCFEI All-Share Index is used as the model's market index. This NCFEI All-Share Index is a capital weighted index on all share prices on the Saudi stock market.[61]

2.6.2 Econometric Issues

The first econometric challenge is the presence of a non-synchronous trading problem. Non-synchronous trading occurs when someone measures the return on a security and the return on the market index over a different trading interval. One situation

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[59] The length of the estimation window varies in the literature and ranges from 100 days to 300 days (Peterson, 1989; Armitage, 1995).

[60] There is still no agreement on the choice of the size of the event window among economists. In general, the size of the event window depends on each study.

[61] In 2000, the name of the market index was changed to Tadawul All-Share Index (TASI).

where non-synchronous trading can exist is when the data show that there are a number of days of untraded stocks in either or both of the period-windows and for some or all securities. In Saudi Arabia, banks used to hold their stocks from being traded whenever they go through, for instance, an important corporate action, an important business agreement, or unexpected board of directors' meeting. In this case, because the study is using the market model, a date matching between a security stock price and NCFEI All-Share Index must be done or otherwise a non-synchronous trading problem may occur. When a non-synchronous trading problem occurs, the estimates of the market model parameters are biased and inconsistent (Scholes and Williams (1977) and Dimson (1979)). To address this problem, the observations of the security and the market index on the day of the missing return and on the subsequent day are both removed (Brown and Warner, 1985).[62]

A second possible econometric challenge that may occur is when the parameters during the estimation window are unstable due to the occurrence of other unanticipated events or when the event window is contaminated. An event window is contaminated when other unrelated events occurs during that window and influence the results. Fortunately, there are no unanticipated events during the estimation windows used in this study. On the other hand, an event window contamination may exist due to earnings announcements during the last three days of the event window.[63] However, these earnings

[62] The subsequent day also must be dropped in order to keep the same unit interval throughout the sample.

[63] The number and days of banks announcing their earnings announcements was as follow: Two banks on Day 7, three banks on day 8, and then two banks on day 10.

announcements will not affect the paper's conclusion since these earnings announcements are far off from the event date.

Another possible complexity that may arise here is the possibility of having a thin market due to the size of the market and the industry in particular. A market is thin when it has a low number of buying and selling offers. However, considering the influence of thin trading on the distribution of the abnormal returns, Prem Jain (1986) finds that the OLS method of estimating market model parameters is as good as other popular methods. This suggests that, in general, the adjustments for thin trading are not important. Therefore, this paper will focus on more important challenges.

In particular, this study pays attention to the fact that all events induce an increase in the abnormal returns' variance. Beaver (1968) and Patell and Wolfson (1979) provide evidence of variance increase in abnormal returns. This variance increase is due to an event-day increase in the market model disturbance variance and /or cross-sectional variation in the true abnormal returns (the event's underlying economic effect).[64] Since those two are qualitatively equivalent, detecting one of them is sufficient to state that an event induces variance increase. Not adjusting for this variance increase will lead to a type I error (rejecting the null hypothesis when it is in fact true). To avoid this problem this study will use a test statistic that uses standard errors that are robust to cross-sectional variation in the true abnormal returns. A good candidate for that is the standardized cross-sectional test statistic known as the BMP test statistic by Boehmer et al. (1991).[65] This test

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[64] To see the mathematical representation and derivation of this distinguishes, see Harrington and Shrider (2007).

[65] This test was suggested by Harrington and Shrider's paper (2007).

uses the estimated cross-sectional variance of the standardized abnormal returns, which captures the event-induced increase in return volatility.

In order to be able to test the null hypothesis of no cross-sectional average (cumulative) abnormal returns around the event date using the BMP test, the paper must first define all the null hypotheses that are going to be tested. There are three hypotheses to be tested and these are the market power hypothesis, the productivity hypothesis, and the information hypothesis. As mentioned earlier, the market power hypothesis is consistent when a horizontal merger increases the market value of merging and rival firms and inconsistent otherwise. The productivity hypothesis is consistent when a horizontal merger increases the market value of merging firms but decreases the market value of rival firms and inconsistent otherwise. The information hypothesis is consistent when the market value is higher for the merging firms and unchanged or higher for rival firms and inconsistent otherwise. Assuming all null hypotheses are true, four null hypotheses are defined as follows:

A) Null hypotheses that test abnormal performance on a single period

1) Test for Abnormal Returns for SAMBA

H_o: AR $_{(SAMBA)} = 0$

H_1: AR $(_{SAMBA)} \neq 0$

And

2) Test for Average Standardized Abnormal Returns for Rival Banks

$\overline{H}_o$: $AR^*_{(Rival\ Banks)} = 0$

$\overline{H}_1$: $AR^*_{(Rival\ Banks)} \neq 0$

where $AR_{(SAMBA)}$ is SAMBA's abnormal return and $AR^{*}_{(Rival\ Banks)}$ is the average standardized abnormal return of rival banks.

The first null hypothesis (H_o) states that SAMBA's stock returns experience no abnormal returns or SAMBA's abnormal returns equal zero for any given day during the event window. The alternative hypothesis (H_1) states that SAMBA's stock returns do experience either positive or negative abnormal returns or SAMBA's abnormal returns do not equal zero for any given day during the event window. The second null hypothesis ($\overline{H}_o$) states that the average standardized abnormal returns of rival banks is zero for any given day during the event window. The alternative hypothesis ($\overline{H}_1$) states that the average standardized abnormal return of rival banks is different from zero for any given day during the event window. If the merger produces market power, then $AR_{(SAMBA)} > 0$ and $AR^{*}_{(Rival\ Banks)} > 0$. If the merger increases SAMBA's productivity, then $AR_{(SAMBA)} > 0$ and $AR^{*}_{(Rival\ Banks)} < 0$. If the merger signals positive information, then $AR_{(SAMBA)} > 0$ and $AR^{*}_{(Rival\ Banks)} \geq 0$.

B) Null hypotheses that test Abnormal performance over multiple periods:

3) Test for Cumulative Abnormal Returns for SAMBA

$\widetilde{H}_o$: $CAR_{(SAMBA)} = 0$

$\widetilde{H}_1$: $CAR_{(SAMBA)} \neq 0$

And

4) Test for Average Standardized Cumulative Abnormal Returns for Rival Banks

$\overline{\overline{H}}_o$: $CAR^{*}_{(Rival\ Banks)} = 0$

$\overline{\overline{H}}_1$: $CAR^{*}_{(Rival\ Banks)} \neq 0$

where CAR $_{(SAMBA)}$ is SAMBA's cumulative abnormal return and $CAR^*_{(Rival\ Banks)}$ is the average standardized cumulative abnormal return of rival banks.

The third null and alternative hypotheses ($\tilde{H}_o$ and $\tilde{H}_1$) test whether SAMBA's cumulative abnormal returns for multiple periods during the event window are equal or different from zero. Finally, the fourth null hypothesis and its alternative ($\bar{\bar{H}}_o$and $\bar{\bar{H}}_1$) test whether the average standardized cumulative abnormal returns of the rival banks for multiple periods during the event window are equal or different from zero. If the merger increases market power, then $CAR_{(SAMBA)} > 0$ and $CAR^*_{(Rival\ Banks)} > 0$. If the merger increases SAMBA's productivity, then $CAR_{(SAMBA)} > 0$ and $CAR^*_{(Rival\ Banks)} < 0$. If the merger signals information to rivals, then $CAR_{(SAMBA)} > 0$ and $CAR^*_{(Rival\ Banks)} \geq 0$. If information about the merger leaks before the event date, then $CAR_{(SAMBA)} \neq 0$ and $CAR^*_{(Rival\ Banks)} \neq 0$ before the event date. Finally, if investors' evaluation of the economic consequences of an event is slow (lag exists), then $CAR_{(SAMBA)} \neq 0$ and $CAR^*_{(Rival\ Banks)} \neq 0$ after the event date.

Stating all four null hypotheses, we will now proceed to test all these null hypotheses by using the BMP test. In order to do that, we first need to calculate the standard deviation, and then use it to standardize the abnormal return, and finally divide the average standardized abnormal returns of all securities over the estimated cross-sectional standard deviation of the standardized abnormal returns. A similar procedure can be followed when using cumulative abnormal returns instead of abnormal returns.

Differentiating between the variation in the market during the event window and the estimation window, and adjusting for the number of observations in the estimation window, we calculate the adjusted standard deviation estimate following Patell (1976) and Dodd and Warner (1983) as follows:

$$\check{S}_i = \hat{S}_i \sqrt{1 + \frac{1}{T_i} + \frac{(R_{m,e} - \bar{R}_m)^2}{\sum_{t=1}^{T_i} (R_{m,t} - \bar{R}_m)^2}} \tag{2.6}$$

where $\hat{S}_i$ is security i's non-adjusted standard deviation estimate of abnormal returns during the estimation period. This non-adjusted standard deviation estimate assumes that variation in the market during the event period is essentially the same as it was during the estimation period and does not adjust for the number of observation in the estimation window. T_i represents number of days in security i's estimation period. The term $(\frac{1}{T_i})$ adjusts for the number of observation in estimation window. $R_{m,e}$, $R_{m,t}$ and $\bar{R}_m$ are the market returns during the event window, the market returns during the estimation window, and the average market returns during the estimation window, respectively. The last term under the radical accounts for the market induced variance caused by the event. As mentioned earlier, failing to adjust the estimated standard deviation will lead to a type I error (rejecting the null hypothesis when it is true). Once the adjusted Standard deviation is calculated, standardized abnormal returns can be obtained as follows:

$$SAR_{it} = AR_{it} / \check{S}_i \tag{2.7}$$

There are two reasons for standardizing the abnormal returns. The first reason is to permit the cross-sectional distribution of abnormal returns to be compared to a unit normal distribution. The second reason is to prevent securities with large variances from dominating the test statistic. In other words, standardization gives you a weighted average of abnormal returns that puts a lower weight on abnormal returns with a high variance.

Finally, the BMP test statistic can be calculated as follows:

$$Z_{BMP} = \frac{\frac{1}{N}\sum_{i=1}^{N} SAR_{it}}{\sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}(SAR_{it} - \sum_{i=1}^{N}\frac{SAR_{it}}{N})^{2}}} \quad (2.8)$$

The numerator represents the average standardized abnormal returns for all *i* securities at a given day *t* during the event window. The denominator represents the estimated cross sectional standard deviation of the standardized abnormal returns for all *i* securities at a given day *t* during the event window.

The BMP test statistic assumes that the null distribution is normally distributed with zero mean and variance equal to one as mentioned earlier. If this assumption is not met (i.e., when the assumed sampling distribution of the test statistic is different from the actual distribution), then false inferences could be obtained. Tables 2.3 and 2.4 provide descriptive statistics of returns and abnormal returns during the estimation window; and Figure 2.5 depicts their distributions. The properties and distributions of abnormal returns show that the there are differences between the assumed null distribution and the actual distribution of the abnormal returns. These differences become smaller as the size of the estimation window and the sample size become larger. Finally, because the data of this study experience some degree of skewness and kurtosis, the stated significance levels in our results may not be valid.[66]

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[66] Skewness is a measure of the degree and direction of the asymmetry of the probability distribution of a real-valued random variable. A normal distribution has a skewness of 0. Kurtosis is a measure of the heaviness of the tails of the probability distribution of a real-valued random variable. Heavy

2.7 The Empirical Results

2.7.1 Empirical Results when Using the Effective Merger Date as the Event Date

In this section, we will present the results obtained when the effective merger date is used as the event date. The market model coefficients were obtained by using the Ordinary Least Squares method. The regression estimates of the market model for the acquirer and rival Banks are reported in Table 2.5. By using the market model estimates, the normal returns were predicted, and then abnormal returns were calculated. When looking individually at the effect of the merger event on each bank (i.e., this is done by looking at the abnormal returns of each bank), it was found that the merger event has differing effects on banks. Thus, the cross-sectional variation in the true abnormal returns is found to be present. This supports the paper's argument for its selection of the BMP test statistic since a paper by Harrington and Shider (2007) shows that cross-sectional variation in an event's impact on value causes the standardized prediction error and traditional tests for nonzero mean abnormal returns to be biased toward rejecting the null hypothesis of no mean effect.

Next, the paper discusses the abnormal and cumulative returns for SAMBA. Figure 2.6 shows some important observations. First, there is a positive spike the day after the event date. Notice that the impact of the merger event took place on day 1 instead of day 0. This study can present two possible scenarios to explain the reason behind the event effect taking place on day 1. It could be that the merger event occurred after the closing

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tailed distributions will have Kurtosis greater than 3 while light tailed distributions will have Kurtosis less than 3.

bell or at the end of the trading session on the event date such that investors didn't have the chance to react to the event on the same day. As a result, their reaction was carried on to the next day. Another possible explanation is that the reaction of investors is slow.

The second observation is the fact that there is a slight positive abnormal return before the event date. This may be due to information leakage that sometimes happens before any event. As the paper illustrated before, one of the characteristics of the Saudi stock market is its weak level of compliance, which would encourage the presence of insider trading. In addition, the information leakage phenomenon in emerging markets is well documented in the literature. A review paper on emerging markets by Bekaert and Harvey (2002) states that evidence from previous work suggests that many emerging markets experience informational leakages before event announcements. This study in fact expects such behavior because the market at the time was still new, and regulations were still not fully developed and not very restrictive.

When looking at Table 2.6, one can see that while all positive abnormal returns before and on the event date are all statistically not different from zero, day 1 is the only day during the event window that experiences abnormal return with 10 percent statistical significance. This abnormal return is strong enough to be detected at the 10 percent significance level, but not strong enough to be detected at the 5 percent or 1 percent significance levels. This could be due to the fact that the Saudi stock market is dominated by retail investors who may not be as sophisticated as institutional investors. In addition, if information leakage is assumed to be the reason for the slight positive abnormal return that occurred before the event date, then this information leakage can also explain the low level of power in the test statistics. Finally, a market dominated by retail investors can be volatile, which may lower the probability of detecting such event. The same analysis can be said to explain the slight volatility that occurred from day 2 through day7.

Looking at the cumulative abnormal return in Figure 2.7, the reader can notice the sharp positive jump in the cumulative abnormal return the day after the event occurred and then a somewhat steady line thereafter. The sharp increase in the cumulative abnormal return is due to the spike in abnormal returns that we saw previously in Figure 2.6. The cumulative abnormal return then starts gradually decreasing from day 1 and continues to decrease until day 6. This could mean that there was a slight overreaction by investors which was then corrected fairly quickly. From day 6 and on, the cumulative abnormal return becomes almost a flat line, which means that the abnormal return is statistically not different from zero.

The reader can also notice that the cumulative abnormal return starts rising three days before the event date. This may simply reflect the pre-event positive abnormal returns that we saw in the previous graph due to informational leakage. However, based on Table 2.6, this information leakage is not significant. Table 2.6 also shows that the cumulative abnormal returns are only statistically significant during days 1 through 5. The decrease in the level of significance during these days reflects the correction in investors' overreaction to the event.

Moving on to the rival banks, Figures 2.8 and 2.9 depict the average standardized abnormal returns (AR^*) and the average standardized cumulative abnormal returns (CAR^*), respectively. Looking at the AR^* line in Figure 2.8, it is very clear that on day 1, there was a negative spike in AR^*. This means that, on average, banks were losing .62 percent on their stock value due to the merger event. However, AR^* was experiencing instability from day - 2 and on. This could be due to the fact that the market is dominated by individual investors who may not always act rationally and who can sometimes make the market volatile. However, when it comes to which day AR^* experiences a statistically significant shift, Table 2.7 shows that day -4, day -1, day 1, day 3, and day 8 all experience a statistically negative shift. Based on the BMP test, this study can say with a high degree of confidence (99 percent confidence level) that AR^* were affected negatively on day 1 due to the two banks merging together. The table shows that the effect of the event was spread through the whole window starting before the event date. In addition to the individual dominated market factor, this could also reflect the lack of sophisticated institutional investors.

Looking at Figure 2.9, we can see that the CAR^* is negative during the event window. It started to show a gradual decrease 6 days before the event occurrence. On Day 1, a steep negative decrease occurred, indicating the average reaction of rival banks in the market, which again supports the efficiency hypothesis. The negative slope starts to flatten by the end of the event window. Not like SAMBA's cumulative abnormal return, the CAR^* took almost 10 days to absorb the event's information. This shows that the Saudi stock market in this particular industry does not react quickly to news.

In short, when the actual merger date is used as the event date, we find that the new merged bank has a statistically significant positive increase in its security value while the average of rival banks witnesses a statistically significant decrease on their stock values. This shows that the results are consistent with the productivity hypothesis.

2.7.2 Comparison between the Results when Using Actual and Announcement Event Dates

In this section, we will first summarize the results obtained when the announcement date is used as the event date. Then, we will compare the results found in this section to those found in the previous section. Finally, the researcher will attempt to justify any differences between the two results and then make an overall conclusion.

The calculation of abnormal returns and cumulative abnormal returns in this section will be the same as before except that the event date now is the announcement date. The regression estimates are reported in Table 2.8.

Next, Table 2.9 and Table 2.10 list the abnormal and cumulative abnormal returns and their test statistics for SAMBA and rival banks, respectively. When looking at Table 2.8, one can see a large and statistically significant positive abnormal return on day -1, which may indicate that the information about the announcement of the merger was leaked. In addition, the cumulative abnormal returns were positive and statistically significant at the 1 percent level on the day before the event, the day of the event, and the day after the event. On the other hand, Table 2.10 shows that abnormal returns were unstable and indicate a large volatility in the abnormal returns. Even with this large volatility, we can still see, on day 2, a relatively large negative abnormal return that is significant at the 1 percent level. However, the overall results on AR^* show no clear pattern on how the merger announcement affected the rival banks. When looking at CAR^*, we see that it is negative but statistically not different from zero in the days from day -5 until day 1. On day 2, CAR^* is found to be negative and statistically significant at the 10 percent level. From day 2 and on, CAR^* is found to be statistically not different from zero.

This study suggests two possible explanations as to why the results differ when using announcement date and when using actual date. First, it is possible that the merger has not only a productivity effect, but also an information effect. Investors might have believed that the merger would not only increase the productivity of the new merged bank, but also show rival banks the potential productivity gains associated with the merger that are also available to them. If investors believed that the merger would produce both productivity and information effects, then it is possible that the two effects might have cancelled out each other during the period surrounding the announcement date and led CAR^* to be statistically not different from zero. As for why CAR^* is significantly negative during the period surrounding the actual date, it is possible that the productivity effect dominated during that period.

Second, by looking at Figures 2.10, 2.11, 2.12, and 2.13, one can notice another difference between the two results: the level of volatility in both abnormal and cumulative abnormal returns. While abnormal and cumulative abnormal returns are found to be volatile during the time surrounding the announcement date, the level of volatility is found to be reduced when the actual date was used. The differences in the level of volatility in abnormal and cumulative abnormal returns can be due to the differences in the level of uncertainty.

This study provides three factors that could explain the reasons behind the high volatility of abnormal returns. The first factor is the implicit level of uncertainty about the completion of the merger process that is associated with each event. The announcement date may represent an early step in the level of completion of the merger process which gives a positive probability that the merger event may not take place in the future. This will increase the level of uncertainty between investors and therefore affect their investment decisions. On the other hand, the actual date represents a very late stage in the merger process. In fact, by using this date, the level of uncertainty regarding whether the merger event will occur becomes zero.

The second factor is the health of the economy of the country. While the economy of Saudi Arabia was doing well during the occurrence of the actual date based on the country's economic indicators such as the Gross Domestic Product (GDP) and many others, the announcement date occurred at the end of a bad economic year which was reflected on the stock market through large stock value losses. This can increase the level of uncertainty between investors about the reasons behind the merger event which could lead to more volatile abnormal returns.

The last factor is the lack of active presence of financial analysts who perform variance financial analysis about the performance of stocks of listed companies, provide investments' recommendations, and make future forecasts. This can potentially affect the results when using the announcement date. With a stock market that is dominated with retail investors and lacking sophisticated institutional investors, the low number of financial analysts can also lead to a high level of uncertainty. Since the time difference between the date when the two banks announced their intention to merge and the date when they actually merged together is 6 months, the level of uncertainty was reduced when the actual date was chosen. A six-month period can give enough time for investors to gather some information about the event and its implications. This can be done by following more experts' analysis on TV interviews or by reading their analysis in the newspapers.

Even though the results using both event dates are found to be different, they have something in common. Figure 2.13 shows that the cumulative abnormal returns using both event dates are negative from day -10 through day 5. In addition, Tables 2.7 and 2.10 show that during both event windows, no statistically significant positive values are found. This means that the merger did not produce any positive wealth effect on rival banks (i.e. the merger did not increase the market value of rival banks).

In short, when the announcement date is used as the event date, we find that the new merged bank has a statistically significant positive increase in its security value while the average of security values of rival banks is statistically not different from zero. This shows that the results are consistent with the information hypothesis.

The overall results show consistency with the economic efficiency hypotheses and no support for market power hypotheses. This suggests that investors believe that the merger will improve the economic efficiency of the industry.

2.8 Conclusion

The main goal of this study is to determine the economic impact behind the merger between SAMBA and USB in the banking industry in Saudi Arabia. We are interested in determining whether the merger is believed to increase market power or economic efficiency. Our analysis is based on the event study methodology.

When the effective date is chosen as the event date, the results support the productivity hypothesis. However, when the announcement date is chosen, the results are found to be consistent with the information hypothesis. In both cases, the results are found to be consistent with the economic efficiency hypotheses but not the market power hypotheses. The overall results show that investors believe that the merger is going to increase the overall economic efficiency of the banking industry.

This study suggests two possible explanations to why the results when using announcement date are different from those found when using actual date. First, it is possible that the merger has both the productivity and information effects. Those two effects can cancel each other, which could explain what happened during the period surrounding the announcement date, or one effect can dominates the other, which could explain what happened during the period surrounding the actual date. Another possible explanation for the different results is the greater uncertainty surrounding the announcement date.

To be able to accurately forecast the impact of a merger on competition and efficiency, antitrust agencies should not only rely on companies' documents, the testimony of economic experts, consumers, and companies' executives, but also on other economic approaches such as the event study approach presented in this chapter. Therefore, we suggest that this approach should always be used by the Ministry of Commerce and Industry of Saudi Arabia along with other approaches to detect the economic impact of a merger.

In future research, this study can be improved by using a statistical test that takes into account any deviation from normality in stock returns, and/or deals with a contaminated event window. In addition, taking into account the thin market may also improve the results. Finally, the presumption that all traders are rational can be relaxed by using the Composite-Error Model (Gokhale et al., 2014). This model can be used to estimate and adjust for any deviation from market efficiency.

Table 2.1: Trends in Concentration in Deposits and Loans Market

	Concentration in Deposits			Concentration in Loans	
Year	CR_2	CR_3	HHI	CR_2	CR_3
1993	0.38	0.55	1,455	0.39	0.57
1994	0.39	0.56	1,466	0.40	0.57
1995	0.38	0.54	1,468	0.40	0.57
1996	0.37	0.53	1,424	0.39	0.59
1997	0.38	0.53	1,447	0.41	0.60
1998	0.38	0.53	1,383	0.45	0.55
1999	0.41	0.56	1,420	0.39	0.51
2000	0.41	0.55	1,429	0.40	0.50
2001	0.39	0.53	1,403	0.39	0.51
2002	0.38	0.51	1,298	0.35	0.52
2003	0.37	0.50	1,307	0.39	0.52
2004	0.36	0.48	1,273	0.37	0.51
2005	0.35	0.48	1,236	0.36	0.50
2006	0.34	0.46	1,226	0.35	0.49

Source: Al-Muharrami (2009).

Table 2.2: Abnormal Returns Predictions under the Market Power and Economic Efficiency Hypotheses

	Abnormal Returns	
Hypotheses	Merging Firms	Rival Firms
Market Power:		
Market Power Hypothesis	Positive	Positive
Predatory Pricing Hypothesis	Positive	Negative
Economic Efficiency:		
Productivity Hypothesis	Positive	Negative
Information Hypothesis	Positive	Positive or zero

Note: Abnormal returns of a security are defined as the actual *ex-post* returns minus the estimated or forecasted normal returns of that security.

Table 2.3: Descriptive Statistics of Daily Returns and Abnormal Returns for SAMBA during the Estimation Window

Variable	Mean	Standard Deviation	Skewness	Kurtosis
Returns	0.0020	0.0175	1.8874	11.2381
Abnormal returns	0.0015	0.0130	1.9799	15.6347

Table 2.4: Descriptive Statistics of Daily Returns and Abnormal Returns for Rival Banks during the Estimation Window

Variable	Mean	Standard Deviation	Skewness	Kurtosis
Returns	0.0011	0.0083	1.2633	5.2222
Abnormal returns	0.0000	0.0042	0.4929	5.1112

Table 2.5: Regression Estimates of the Market Model using Ordinary Least Squares (OLS) for the SAMBA and Rival Banks

	Merged Bank	Rival Banks			
Independent Variable	SAMBA	Alrajhi	Aljazira	Arab National	Saudi Fransi
Intercept	0.0012 (0.0013)	0.0012* (0.0006)	- 0.0004 (0.0014)	0.0012 (0.0016)	0.0014 (0.0010)
Rm	1.4309*** (0.1543)	1.1815*** (0.0748)	1.4748*** (0.1616)	1.3472*** (0.1861)	1.3640*** (0.1167)
T-statistics:					
Intercept	0.94	1.87	-0.29	0.76	1.36
Rm	9.27	15.78	9.12	7.24	11.69
Adj-R	0.4885	0.7359	0.4803	0.3662	0.6038
F-Statistic	86.00***	248.97***	83.26***	52.43***	136.61***

Note: This table represents the regression estimates of the market model when the event date is the actual merger date. The numbers in parentheses represent OLS standard errors.
*** Significance at the 1 percent level, two tailed test
** Significance at the 5 percent level, two tailed test
* Significance at the 10 percent level, two tailed test

Table 2.5: Regression Estimates of the Market Model using Ordinary Least Squares (OLS) for the SAMBA and Rival Banks (Continued)

	Merged Bank	Rival Banks		
Independent Variable	SAMBA	Riyad	Saudi Investment	Saudi British
Intercept	0.0012 (0.0013)	0.0010 (0.0009)	-0.0003 (0.0011)	0.0010 (0.0011)
Rm	1.4309*** (0.1543)	0.8577*** (0.1020)	0.9883*** (0.1289)	1.1176*** (0.1327)
T-statistics:				
Intercept	0.94	1.10	-0.30	0.88
Rm	9.27	8.41	7.66	8.42
Adj-R	0.4885	0.4393	0.3935	0.4398
F-Statistic	86.00***	70.73***	58.74***	70.88***

Note: This table represents the regression estimates of the market model when the event date is the actual merger date. The numbers in parentheses represent OLS standard errors.
*** Significance at the 1 percent level, two tailed test
** Significance at the 5 percent level, two tailed test
* Significance at the 10 percent level, two tailed test

Table 2.6: Abnormal & Cumulative Returns and their Test Statistics for SAMBA

Event Day	AR	T-Test	CAR	T-Test
-10	-0.0026	-0.2079	-0.0026	-0.2079
-9	-0.0034	-0.2697	-0.0060	-0.4775
-8	-0.0003	-0.0255	-0.0063	-0.5030
-7	-0.0016	-0.1255	-0.0079	-0.6285
-6	-0.0020	-0.1576	-0.0099	-0.7861
-5	0.0003	0.0261	-0.0095	-0.7600
-4	0.0009	0.0726	-0.0086	-0.6874
-3	0.0078	0.6214	-0.0008	-0.0659
-2	0.0089	0.7086	0.0081	0.6427
-1	0.0063	0.5006	0.0144	1.1433
0	0.0001	0.0089	0.0145	1.1523
1	0.0237	1.8855*	0.0382	3.0378***
2	-0.0051	-0.4091	0.0330	2.6287***
3	-0.0073	-0.5825	0.0257	2.0462**
4	0.0005	0.0430	0.0263	2.0892**
5	-0.0031	-0.2469	0.0232	1.8422*
6	-0.0068	-0.5363	0.0164	1.3059
7	0.0000	0.0016	0.0164	1.3075
8	0.0027	0.2136	0.0191	1.5211
9	-0.0011	-0.0908	0.0180	1.4303
10	-0.0013	-0.1054	0.0167	1.3249

*** Significance at the 1 percent level, two tailed test
** Significance at the 5 percent level, two tailed test
* Significance at the 10 percent level, two tailed test

Table 2.7: Abnormal & Cumulative Returns and their Test Statistics for Rival Banks

Event Day	AR*	BMP Test Statistic	CAR*	BMP Test Statistic
-10	-0.0078	-0.0962	-0.0078	-0.0962
-9	-0.1994	-1.3489	-0.2072	-1.1113
-8	-0.0646	-0.4648	-0.2718	-1.3675
-7	-0.0295	-0.3225	-0.3013	-2.2293**
-6	-0.0924	-0.6877	-0.3936	-2.2415**
-5	-0.3915	-1.6179	-0.7852	-2.7147***
-4	-0.2230	-2.4485**	-1.0081	-4.1529***
-3	-0.3217	-1.5443	-1.3299	-5.3709***
-2	-0.0721	-0.5526	-1.4020	-4.1836***
-1	-0.3258	-2.4134**	-1.7278	-5.2267***
0	0.0827	0.4126	-1.6451	-4.0057***
1	-0.6246	-3.1753***	-2.2697	-4.5532***
2	0.1663	0.9039	-2.1034	-3.6703***
3	-0.3106	-1.7741*	-2.4141	-3.3208***
4	0.0278	0.1421	-2.3863	-3.1132***
5	0.1106	0.8960	-2.2756	-2.7091***
6	0.3976	0.5257	-1.8780	-1.2879
7	-0.0638	-0.2244	-1.9418	-1.5435
8	-0.6888	-1.8427*	-2.6306	-2.7709***
9	-0.1839	-0.6783	-2.8146	-2.6367***
10	-0.0288	-0.1575	-2.8433	-2.4647**

*** Significance at the 1 percent level, two tailed test
** Significance at the 5 percent level, two tailed test
* Significance at the 10 percent level, two tailed test

Table 2.8: Regression Estimates of the Market Model using Ordinary Least Squares (OLS) for the SAMBA and Rival Banks

	Merged Bank	Rival Banks			
Independent Variable	SAMBA	Alrajhi	Aljazira	Arab National	Saudi Fransi
Intercept	-0.0003 (0.0012)	0.0001 (0.0012)	-0.0017 (0.0018)	-0.0011 (0.0015)	0.0006 (0.0015)
Rm	0.7180*** (0.1345)	1.1924*** (0.1441)	1.1748*** (0.2078)	1.1276*** (0.1653)	0.8292*** (0.1719)
T-statistics:					
Intercept	-0.28	0.12	-0.94	-0.72	0.43
Rm	5.34	8.27	5.65	6.82	4.82
Adj-R	0.2362	0.4311	0.2581	0.3385	0.2001
F-Statistic	28.52***	68.45***	31.96***	46.53***	23.27***

Note: This table represents the regression estimates of the market model when the event date is the announcement date. The numbers in parentheses represent OLS standard errors.
*** Significance at the 1 percent level, two tailed test
** Significance at the 5 percent level, two tailed test
* Significance at the 10 percent level, two tailed test

Table 2.8: Regression Estimates of the Market Model using Ordinary Least Squares (OLS) for the SAMBA and Rival Banks (Continued)

	Merged Bank	Rival Banks		
Independent Variable	SAMBA	Riyad	Saudi Investment	Saudi British
Intercept	-0.0003 (0.0012)	0.0001 (0.0012)	0.0014 (0.0015)	0.0013 (0.0017)
Rm	0.7180*** (0.1345)	1.0258*** (0.1417)	0.8291*** (0.1696)	0.9917*** (0.1990)
T-statistics:				
Intercept	-0.28	0.08	0.95	0.77
Rm	5.34	7.24	4.89	4.98
Adj-R	0.2362	0.3661	0.2046	0.2112
F-Statistic	28.52***	52.39***	23.90***	24.83***

Note: This table represents the regression estimates of the market model when the event date is the announcement date. The numbers in parentheses represent OLS standard errors.
*** Significance at the 1 percent level, two tailed test
** Significance at the 5 percent level, two tailed test
* Significance at the 10 percent level, two tailed test

Table 2.9: Abnormal and Cumulative Abnormal Returns and their Test Statistics for SAMBA using Announcement Date

Event Day	AR	T-Test	CAR	T-Test
-10	-0.0251	-2.3319**	-0.0251	-2.3319**
-9	0.0114	1.0526	-0.0137	-1.2793
-8	-0.0064	-0.6010	-0.0200	-1.8803*
-7	-0.0042	-0.3976	-0.0242	-2.2780**
-6	-0.0040	-0.3753	-0.0282	-2.6533***
-5	0.0166	1.5549	-0.0116	-1.0984
-4	-0.0123	-1.1402	-0.0239	-2.2386**
-3	0.0062	0.5827	-0.0177	-1.6558*
-2	-0.0054	-0.5125	-0.0232	-2.1683**
-1	0.0634	5.9601***	0.0402	3.7918***
0	-0.0025	-0.2342	0.0377	3.5576***
1	-0.0096	-0.9107	0.0281	2.6469***
2	-0.0234	-2.2090**	0.0046	0.4379
3	-0.0221	-2.0842**	-0.0175	-1.6463*
4	0.0081	0.7677	-0.0093	-0.8786
5	-0.0017	-0.1573	-0.0110	-1.0358
6	0.0096	0.9018	-0.0015	-0.1340
7	-0.0154	-1.4514	-0.0168	-1.5854
8	0.0082	0.7707	-0.0087	-0.8148
9	0.0056	0.5327	-0.0030	-0.2820
10	-0.0006	-0.0551	-0.0036	-0.3371

*** Significance at the 1 percent level, two tailed test
** Significance at the 5 percent level, two tailed test
* Significance at the 10 percent level, two tailed test

Table 2.10: Abnormal and Cumulative Abnormal Returns and their Test Statistics for Rival Banks using Announcement Date

Event Day	AR*	BMP Test Statistic	CAR*	BMP Test Statistic
-10	-1.3862	-5.1732***	-1.3862	-5.1732***
-9	0.6311	1.7142*	-0.7551	-1.7378*
-8	-0.6079	-2.5079**	-1.3629	-3.6396***
-7	0.2429	2.4495**	-1.1200	-2.7683***
-6	0.3430	1.3490	-0.7771	-1.8217*
-5	0.2755	0.9547	-0.5016	-1.0880
-4	0.3351	0.7347	-0.1665	-0.3558
-3	-0.2895	-1.7961*	-0.4560	-0.8065
-2	-0.4040	-1.8188*	-0.8600	-1.6347
-1	0.5061	2.1377**	-0.3539	-0.5982
0	-0.2331	-1.4576	-0.5870	-0.9539
1	0.4761	2.4776**	-0.1108	-0.1537
2	-1.0418	-6.0114***	-1.1526	-1.7547*
3	0.8707	1.8010*	-0.2819	-0.6600
4	-0.2316	-2.0083**	-0.5135	-1.2488
5	0.1358	0.7279	-0.3777	-0.8211
6	0.7244	3.6904***	0.3467	0.6545
7	-0.0761	-0.3109	0.2707	0.3685
8	-0.5197	-1.3154	-0.2490	-0.2431
9	-0.4490	-2.0079**	-0.6980	-0.7950
10	-0.8805	-1.5881	-1.5785	-1.5018

*** Significance at the 1 percent level, two tailed test
** Significance at the 5 percent level, two tailed test
* Significance at the 10 percent level, two tailed test

Figure 2.1: Announced Mergers & Acquisitions in Saudi Arabia during the period 1991-2011

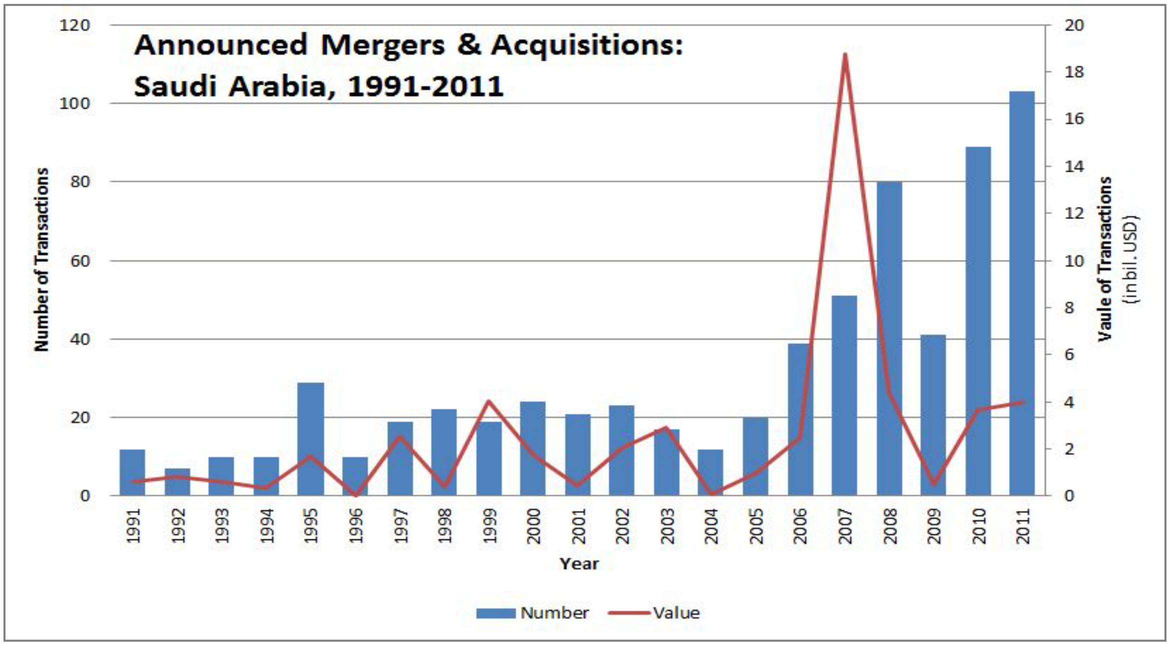

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Figure 2.2: Theoretical Event Study Time Line

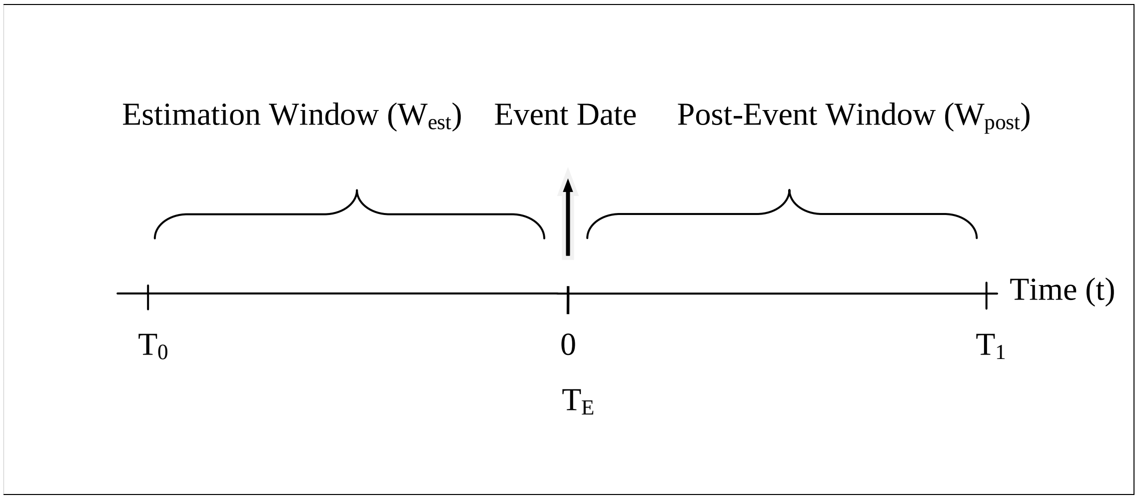


Figure 2.3: Empirical Event Study Time Line

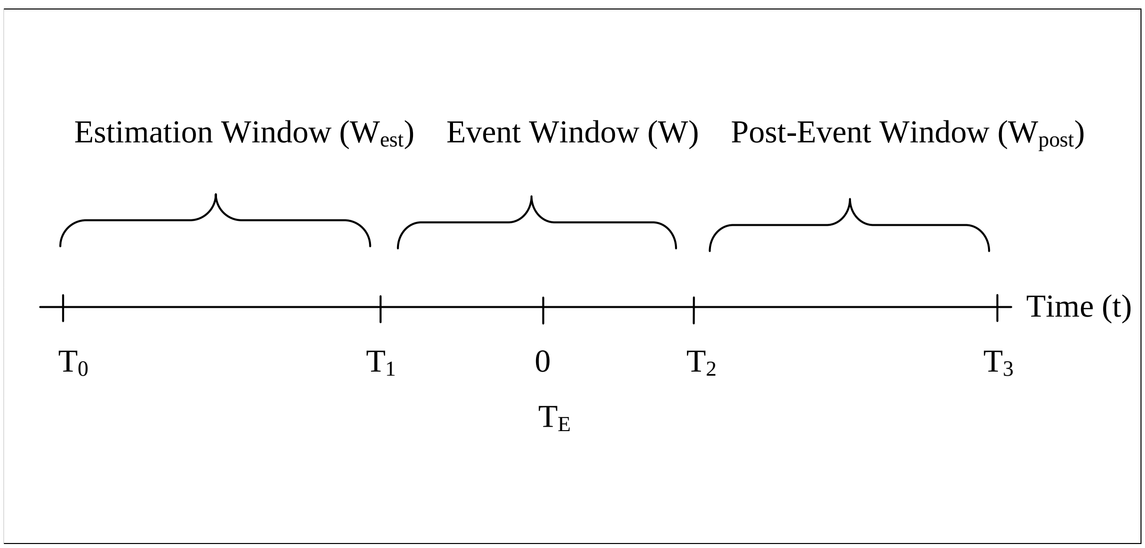
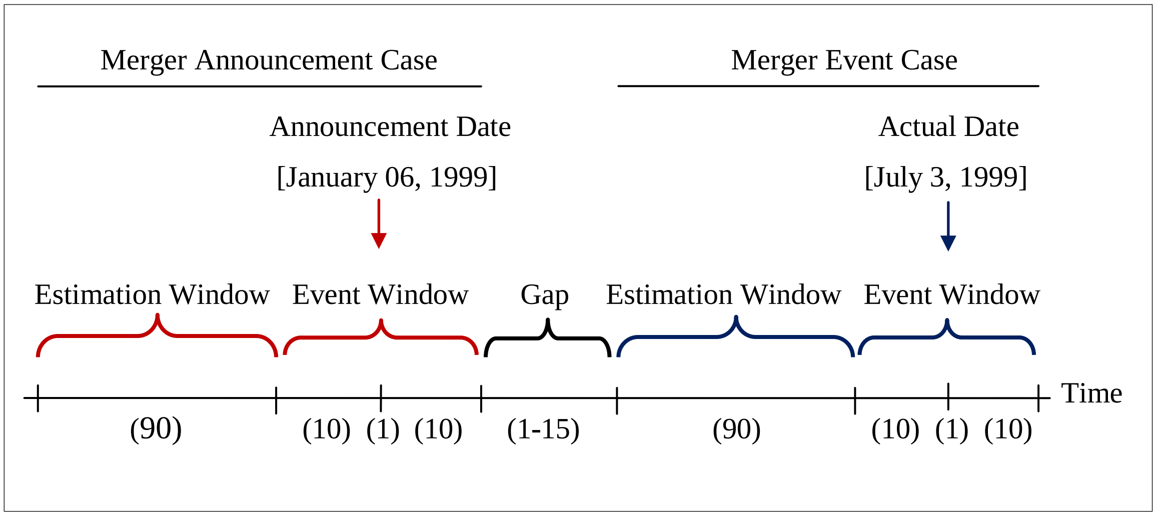


Figure 2.4: A Chronological order of All Windows



Note: The number in the parentheses represents the number of days. Gap represents the number of days between the two events. This number varies because the number of trading days is not the same for each firm.

Figure 2.5: Distribution of Returns and Abnormal Returns for SAMBA and Rival Banks

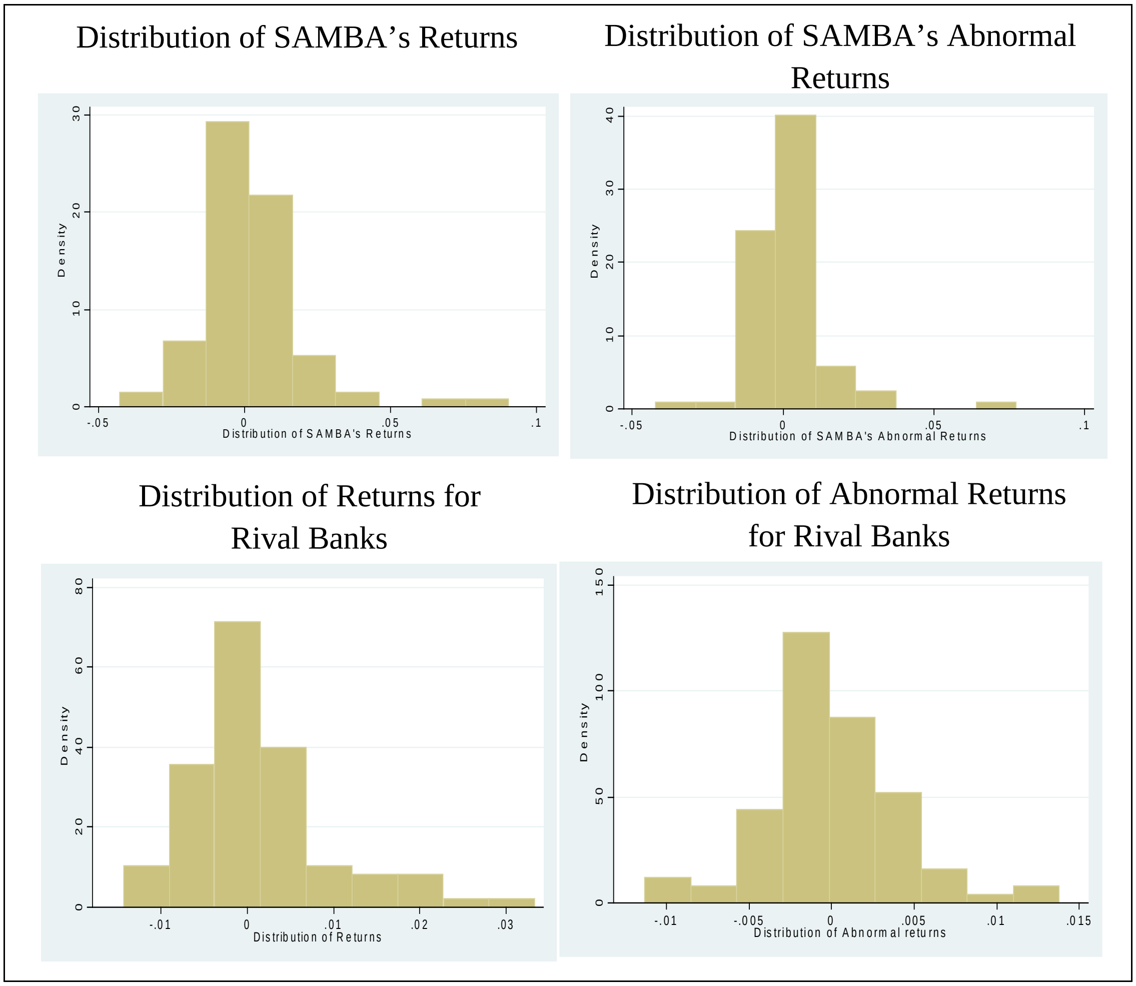


Figure 2.6: SAMBA's Abnormal Returns (AR) during the Event Window

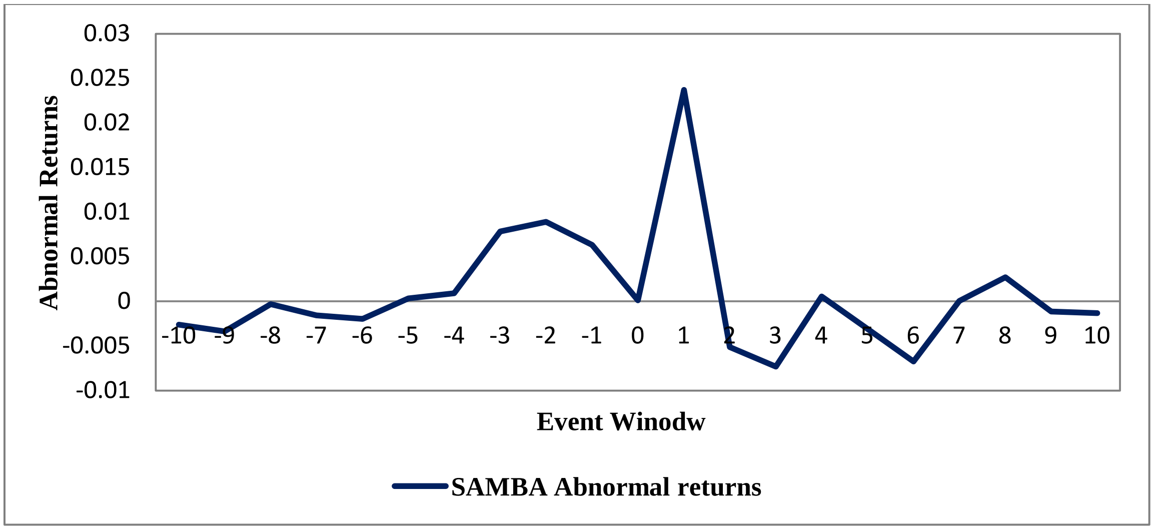


Figure 2.7: SAMBA's Cumulative Abnormal Returns (CAR) during the Event Window

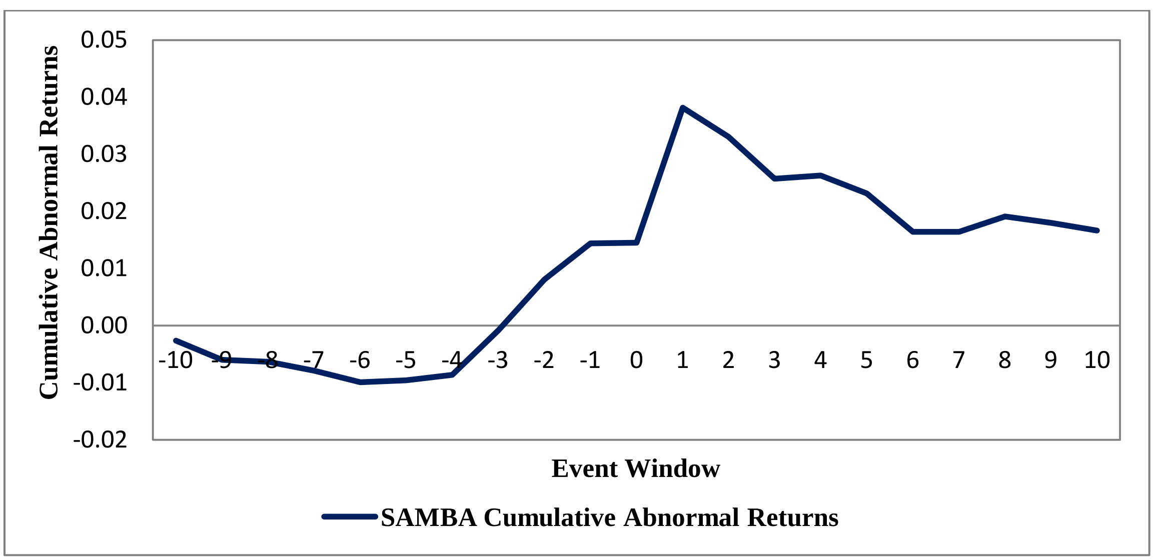


Figure 2.8: Average Standardized Abnormal Returns (AR^*) for Rival Banks

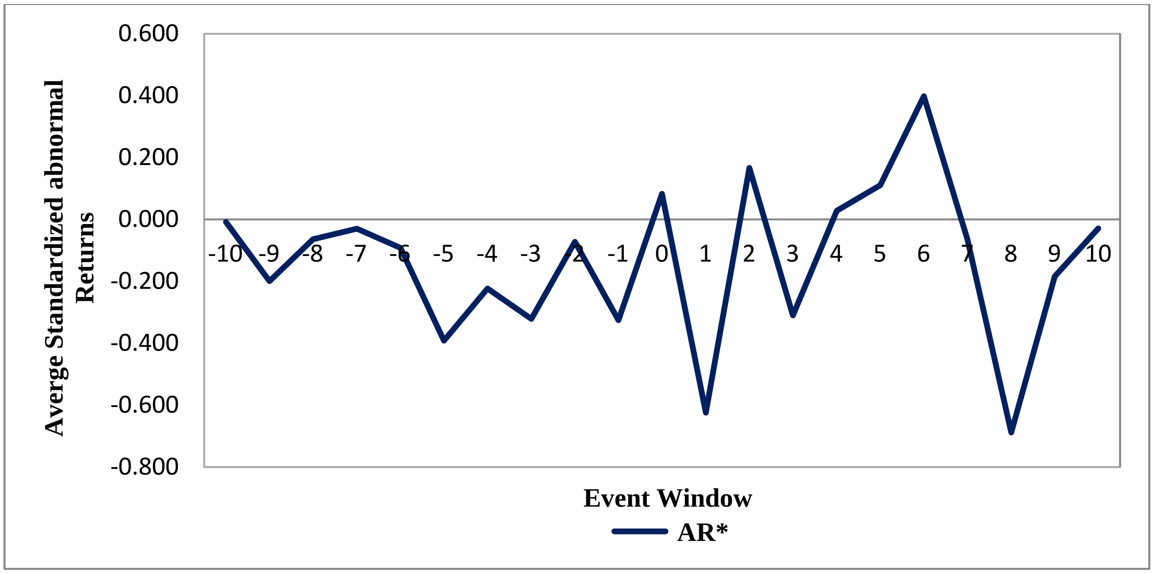


Figure 2.9: Average Standardized Cumulative Abnormal Returns (CAR^*) for Rival Banks

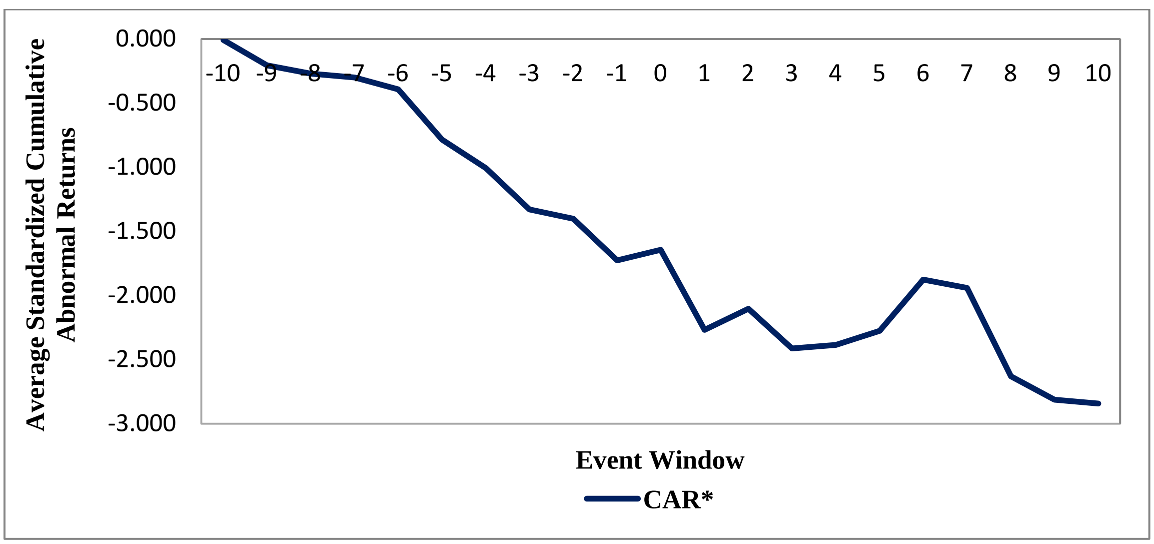


Figure 2.10: SAMBA's Abnormal Returns (AR)

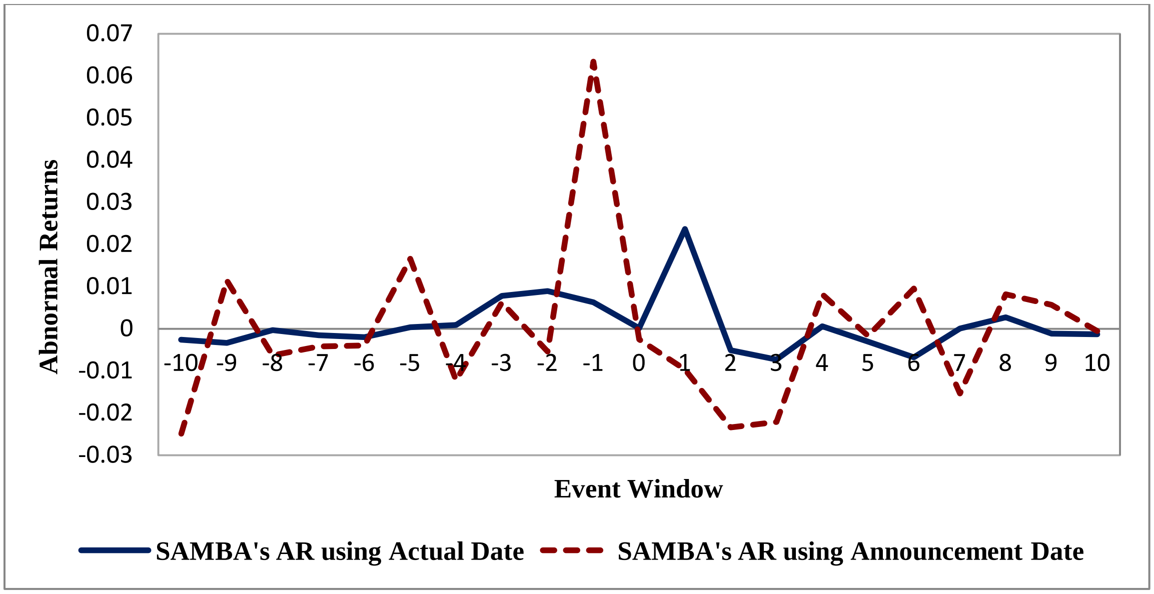


Figure 2.11: SAMBA's Cumulative Abnormal Returns (CAR)

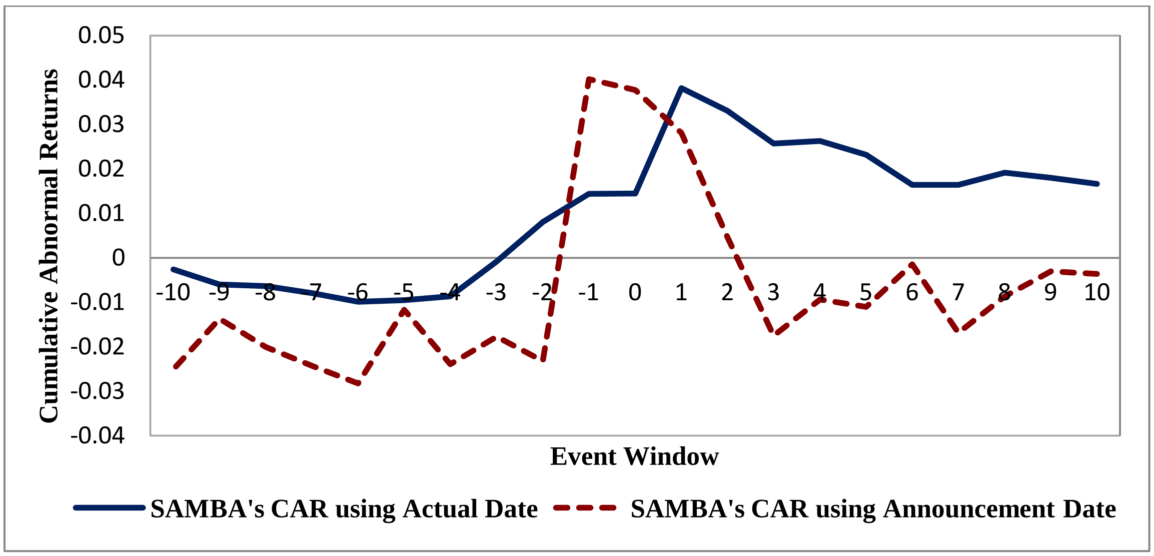


Figure 2.12: Average Standardized Abnormal Returns for Rival Banks (AR^{*})

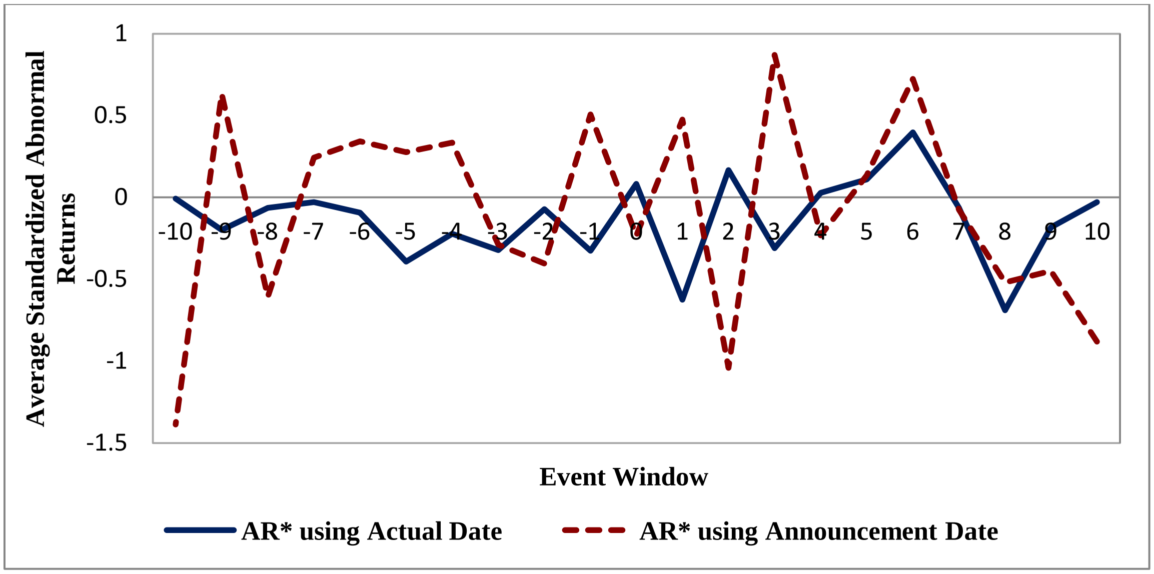
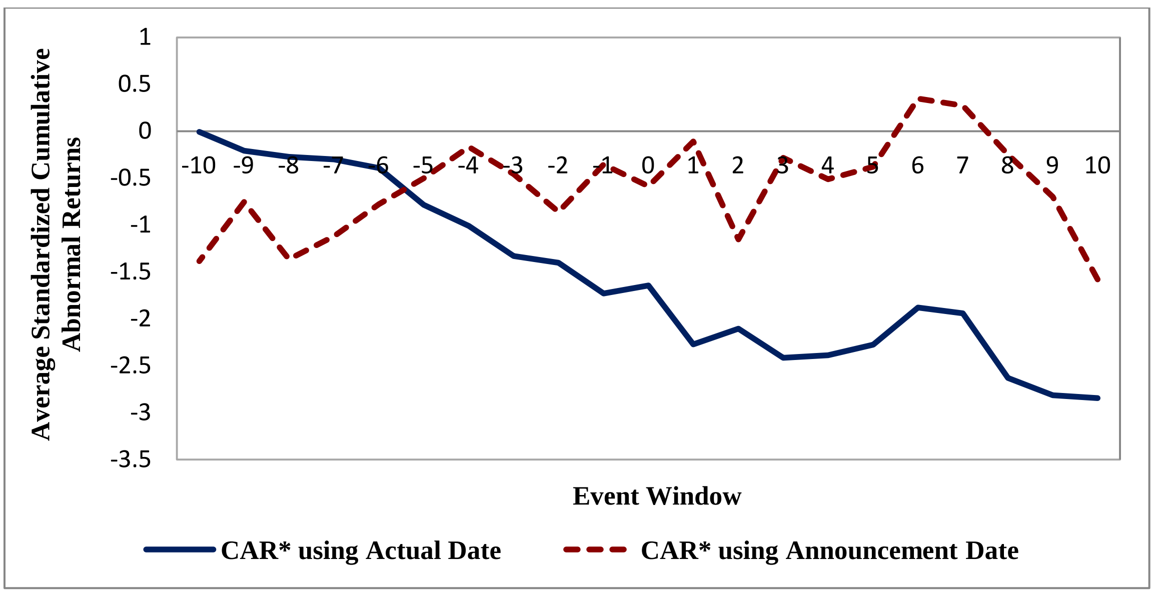


Figure 2.13: Average Standardized Cumulative Abnormal Returns for Rival Banks (CAR^{*})



Chapter 3

Measuring Security Price Misvaluation and Forecasting Stock Market Bubbles

3.1 Introduction

The recent global financial crisis has sparked a renewed discussion of the effects of asset price booms and busts on the economy, the driving forces behind asset price booms and busts, the methods of identifying such events, and finally the role of central banks and regulatory agencies in preventing such crises. All these issues are important not only from an academic prospective but also from a policy prospective as well. Therefore, the goal of this paper is to contribute to this discussion.

Even though the exact relationship between the stock market and financial intermediaries or macroeconomic aggregates (consumption, investment, net exports, or government spending) is not fully understood, the conventional wisdom holds that the stock market plays a vital role in the real economy (Raunig and Scharler, 2010). Crashes in asset markets, in general, and in stock markets, in particular, have often been associated with financial instability and declines in economic activity. This association exists because there are several channels from which the impact of a stock market crash can be transmitted through the economy. For example, a stock market crash can have an impact on macroeconomic aggregates via changes in family income or wealth, liquidity or credit, consumer and investor confidence about future economic conditions (Green, 1971, Mishkin, 1995, and Rauning and Scharler, 2010).

Stock market crashes are often found to be the end result in what appears to have been a “bubble”. The word “bubble” has been defined in the literature in various ways depending on the underline causes (see Gerdesmeier et al., 2013). This paper defines a bubble (bust) as a state where security market values persistently go above (below) fundamental values.[67] A security’s fundamental value is defined as the discounted present value of all future cash flows that investors expect to gain from holding the security. There are two points to mention regarding the definition of a bubble. First, by defining a bubble in terms of the deviation of security market values from their fundamentals, we are including all types of bubbles (rational or irrational) with any patterns (explosive or non-explosive) regardless of their underlying causes. Second, by restricting the definition to deviations that last for a period of time, we are excluding any short market misvaluation that may occur for various reasons.

The literature on bubbles and on the conditions under which they occur can be divided into two groups.[68] The first deals with bubbles that occur when agents are fully rational. These are called rational bubbles. This line of research shows that rational bubbles can exist when agents have asymmetric information (Allen et al., 1993), limited liability (Allen and Gorton, 1993; Allen and Gale, 2000), or relative wealth concerns (DeMarzo et al., 2008).

[67] The definition raises the empirical question of how large a deviation should be or how long should it take until it is classified as a bubble.

[68] For more information on bubbles, see Scherbina (2013).

The second view comes from behavioral finance, where at least one group of agents is assumed to have behavioral weakness.[69] In this view, bubbles (irrational bubbles) can exist, for example, when agents suffer from overconfidence and there are short-sale restrictions (Scheinkman and Wei Xiong, 2003), there is positive feedback trading (DeLong et at., 1990), or when behavioral agents get caught up in a herd behavior (Avery and Zemsky, 1998; Lux, 1995).[70]

Various techniques have been used to detect the existence of bubbles. All of those tests are based on the standard present value models of security prices. Those techniques include variance-bounds tests for equity prices (Shiller, 1981; LeRoy and Porter, 1981), West's two-step tests of bubbles (West, 1987; 1988), integration/cointegration based tests (Diba and Grossman, 1988; 1988), and Froot and Obstfeld test for bubbles (Froot and Obstfeld, 1991).[71] In a survey on econometric tests of asset price bubbles, Gurkaynak (2008) concludes that these tests do not provide a satisfactory degree of certainty in detecting asset price bubbles. He also claims that for almost each technique that 'finds' evidence of bubbles, there is another one that relaxes some assumptions on the fundamentals and fits the data equally well without allowing for a bubble.

The goal of this paper is to provide a new technique that can help identify bubbles, whether they follow an explosive trajectory or sustains for a considerable period of time. We use a composite-error model developed by Gokhale et al. (2014), which can detect whether returns on a security are systematically overvalued or undervalued. This model is

[69] Agents with behavioral weakness are those who suffer from cognitive or psychological weakness that causes them to make systematic errors.

[70] For more information on bubbles and their causes, see Camerer (1989) and Scherbina (2013).

[71] For further information on each of these tests, see Gurkaynak (2008).

different from the standard present value models of security prices found in the literature. Using this model, we introduce a new index called “Market Valuation Index”, which measures the daily total security market misvaluation. By analyzing the pattern of this index, we can then identify any persistent misvaluation in the stock market and therefore discover any existed bubble. The capability of this index to identify financial bubbles is tested on two historical crashes that occurred in the Saudi stock market during the years 2006 and 2008. In addition, we use various sensitivity analyses to test whether our index is sensitive to alternative specifications, namely the estimation period, the level of significance, and the weight used to calculate the average misvaluation of a security.

This study can be useful to central banks and stock market regulators since bubbles are of great concern. The usefulness of the market valuation index is that it can help eliminate financial bubbles in two ways. First, the introduction of the market valuation index to the public can raise the level of awareness in investors about the deviation of security market values from their fundamental values. As a result, this may help purge any market overvaluation or undervaluation, which in turn may prevent the formation of bubbles. Second, this index can also be used by central banks and market regulators to set a valuation targeting policy - a policy that can be put into effect once the index gets too high or too low.

The remainder of the paper is organized as follows. In section 3.2, we first present the model used in measuring security market misvaluation. Then, we introduce a security valuation index and market valuation index which measure misvaluation in security returns at the firm and market levels, respectively. Section 3.3 discusses the data while section 3.4 presents the empirical results. Section 3.5 summarizes the main results and outlines future research.

3.2 Methodology

3.2.1 The Composite-Error Model

Recently Gokhale et al. (2014) have introduced a new valuation model called the composite-error model. They introduce a formal procedure that estimates the deviation of returns from their fundamental values. It uses a composite-error term in which one component represents the traditional white noise while the other component represents the degree of overvaluation or undervaluation in returns.[72]

The composite-error model's theoretical basis comes from the notion that the efficient market hypothesis may not always hold true. The efficient market hypothesis (EMH) states that security prices fully and accurately reflect all available information (Fama, 1970).[73] This implies that economic agents are fully rational and that the market is frictionless. Models that support EMH assume that prices will immediately reflect all available information and that they will equal their fundamental economic values. However, due to various market frictions and/or due to investors' behavioral biases, security prices may not represent their fundamental values all the time and instead may be systematically misvalued. This systematic misvaluation will not be captured when using

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[72] The composite-error term was first introduced by Aigner, Lovell, and Schmidt (1977) and Meeusen and Van den Broeck (1977). They used the composite-error term to estimate inefficiency in production. For comprehensive reviews on the use of the composite-error term in production theory, see Kumbhakar and Lovell (2000) and Greene (2008).

[73] For reviews and discussions of the efficient market hypothesis, see Fama (1970, 1991), and Malkiel (2003, 2011).

models that are based on EMH. As a result and to take into account the systematic misvaluation in security prices, Gokhale et al. (2014) suggest that a model should include a dual-error structure.

The traditional market model is a single-error model that was originally developed by Markowitz (1959) and has been used extensively to analyze the stock market returns of securities.[74] The model assumes that there is no systematic misvaluation, as in EMH. The model is represented in the following linear form

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{3.1}$$

$$\varepsilon_{it} \sim N(0, \sigma^2)$$

where R_{it} and R_{mt} are period *t* returns on security *i* and on the market portfolio, respectively.[75] α_i, β_i, and σ^2 are the parameters of the market model that measure the mean returns, the sensitivity of security *i* to the market (a measure of risk), and the variance of the disturbance term, respectively. Finally, ε_{it} is a “pure” white noise error term with a zero mean and a finite variance σ^2. If EMH holds, then this model is consistently and accurately estimated by the Ordinary Least Squares (OLS) (i.e. security’s estimated returns will accurately represent their fundamental values).

If EMH does not hold, which as mentioned earlier might be due to various frictions in the market and/or due to behavioral biases caused by behavioral agents who suffer from cognitive or psychological bias, then the market model estimated returns will no longer

[74] To read more about the market model, see See Fama (1976, chapter 3 and 4).

[75] A stock return R_{it} for firm *i* at time *t* is calculated as $R_{it} = [P_{it} + D_{it} - P_{it-1}]/P_{it-1}$, where P_{it} and P_{it-1} are stock prices for firm *i* at the end of the day *t* and *t-1*, respectively. D_{it} is the dividend per share of a common stock of company *i* at time *t*.

represent their fundamental values.[76] This is true since the existence of frictions, and/or behavioral agents in the market may lead to systematic errors, which in turn may cause the market value of returns to deviate from their fundamentals. As a result, the error term in these models may no longer be a "pure" white noise. Therefore, the OLS estimator will not be accurate and will either overestimate or underestimate the true or fundamental value of returns.

The composite-error model modifies the market model to allow for systematic misvaluation. It replaces the single-error term in the market model with a dual-error term.[77] In this case, the error term in equation (3.1) will be become $\varepsilon_{it} = v_{it} + u_{it}$ and the composite-error model will take the form

$$R_{it} = \alpha_i + \beta_i R_{mt} + v_{it} + u_{it} \tag{3.2}$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$u_{it} \sim \begin{cases} N^{+}(0, \sigma_u^2) & \text{If measuring overvaluation} \\ N^{-}(0, \sigma_u^2) & \text{If measuring undervaluation} \end{cases}$$

where v_{it} is the pure white noise error term of security *i* at time *t*. It is assumed to have a symmetric normal distribution with zero mean and variance σ_v^2.[78] u_{it} is the systematic

[76] For more information on the types of frictions and constraints in the market that lead to inefficiency in the market, see Madhavan (2000), and Biais et al. (2005). For reviews on the type of behavioral issues an agent may suffer, which leads to inefficiency in the market, see Shiller (2003) and Barberis and Thaler (2003, 2005) and Coates (2012).

[77] The modification can also be applied to other models such as the multifactor models.

[78] The error term v_{it} is viewed as the stochastic part of the error term ε_{it}.

error term of security *i* at time *t* that represents the misvaluation in a security return.[79] $N^{+}(0, \sigma_u^2)$ and $N^{-}(0, \sigma_u^2)$ are a non-negative half normal and a non-positive half normal distributions with zero mean and variance σ_u^2, respectively.[80] When measuring overvaluation of security returns, u_{it} is assumed to follow the non-negative half normal distribution, $N^{+}(0, \sigma_u^2)$. This is called the overvaluation model. When measuring undervaluation of security returns, u_{it} is assumed to follow the non-positive half normal distribution, $N^{-}(0, \sigma_u^2)$. This is the undervaluation model. Both u_{it} and v_{it} are assumed to be independently and identically distributed, but are independently distributed from each other. If the return of security *i* at time *t* is overvalued, then $u_{it} > 0$. If the return of security *i* at time *t* is undervalued, then $u_{it} < 0$. If the return of security *i* at time *t* is neither overvalued nor undervalued (the market value of the return equals its fundamental value), then $u_{it} = 0$.

The model is estimated using a maximum likelihood estimator (MLE). Overvaluation and undervaluation of returns are estimated separately using the overvaluation model and undervaluation model respectively. In order to obtain the likelihood function of security *i* at a particular time *t*, the probability density function of the compound random variable ε_{it} must be derived.[81] The end result is

$$f(\varepsilon_{it}) = \frac{2}{\sqrt{2\pi(\sigma_u^2 + \sigma_v^2)}} \left[F\left(\frac{s.\, \varepsilon_{it} \left({}^{\sigma_u}/_{\sigma_v} \right)}{\sqrt{\sigma_u^2 + \sigma_v^2}} \right) \right] exp\left\{ -\frac{\varepsilon_{it}^2}{2(\sigma_u^2 + \sigma_v^2)} \right\} \tag{3.3}$$

[79] The error term u_{it} is viewed as the deterministic part of the error term ε_{it}.

[80] Other distributions can be used such as the truncated-normal, the exponential, and the gamma distributions.

[81] For more information on how to obtain equation (3.3), see appendix B.

where σ_v^2 is the variance of v_{it} , σ_u^2 is the variance of u_{it} , $F(.)$ is the cumulative standard normal distribution and the variable s is a sign indicator that takes the following form

$$S = \begin{cases} 1, & \text{for overvaluation model} \\ -1, & \text{for undervaluation model} \end{cases}$$

The log likelihood function is then given by

$$lnL_i(\alpha, \beta, \sigma_v, \sigma_u) = \frac{T}{2}\ln\left(\frac{2}{\pi}\right) - T\ln(\sigma) + \sum_{t=1}^{T} ln\left[F\left(\frac{s.\varepsilon_{it}\lambda}{\sigma}\right) - \frac{1}{2}\left(\frac{\varepsilon_{it}}{\sigma}\right)^2\right] \tag{3.4}$$

where T is the number of time periods, $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$, $\lambda = \frac{\sigma_u}{\sigma_v}$.[82] By maximizing this log likelihood function, estimates of $\alpha,\ \beta,\ \sigma_v,\ \sigma_u$, and their standard errors can be obtained. Following Jondrow et al. (1981), the estimates of u_{it} are obtained as follow:[83]

$$E_i(u_{it}|\varepsilon_{it}) = u_{it}^* + \sigma^*\left[\frac{f(-u_{it}^*/\sigma^*)}{F(u_{it}^*/\sigma^*)}\right] \tag{3.5}$$

where

$$u_{it}^* = -s\varepsilon_{it}\,\sigma_u^2/\sigma^2$$

$$\sigma^* = \sigma_u\sigma_v/\sigma$$

Since overvaluation and undervaluation of returns are estimated separately, testing their existence will also be done separately. Following Coelli (1995), the null hypothesis that σ_u= 0 is tested using a one-sided likelihood ratio test, which requires the estimation of

[82] For more information on how to obtain equation (3.4), see appendix B.
[83] See Jondrow et al (1981) for a complete derivation.

the selected model under both the null and alternative hypotheses. The likelihood ratio test statistic is calculated as:

$$LR = -2[log(L_0) - log(L_1)] \tag{3.6}$$

where log (L_0) is the log-likelihood value under the null hypothesis and log (L_1) is the log-likelihood value assuming the null is false.[84] This test is used since $\sigma_u \to 0$ means that the distribution collapses to a spike at zero, which means that $u_{it} \to 0$ as well. As a result, if we fail to reject the null hypothesis, then there is no over or under valuation bias. However, if the null hypothesis is rejected when testing for overvaluation (undervaluation), then u_{it} is positive (negative) and returns are overvalued (undervalued).

3.2.2 Security Valuation Index and Market Valuation Index

In this section, we introduce the Market Valuation Index (MVI), which measures the degree to which the market is overvalued, undervalued, or correctly valued. We first calculate a moving average of the Security Valuation Index (SVI), defined as an index that measures the degree to which a security is overvalued, undervalued, or correctly valued.[85,86] We then obtain MVI by summing the SVI over all securities where each of which is weighted by their market value.

To obtain a moving average of the SVI for security *i*, we need to create a series of averages of the security estimated biases, which is calculated as follows:

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[84] The likelihood ratio statistic has an asymptotic distribution equal to a mixture of chi-square distributions [$(^1/_2)\ \chi_0^2\ +\ (^1/_2)\ \chi_1^2$] (Coelli, 1995).

[85] Gokhale et al. (2013) are the first to introduce this index, which they call the fundamental value index.

[86] A moving average is a set of numbers where each number represents an average of a corresponding subset of an original set.

$$SVI_i^\tau = \sum_{t=\tau}^{t=T+\tau-1} w_t \, \hat{u}_{it} \tag{3.7}$$

where

$$w_t = \begin{cases} \frac{1}{T} & \text{if } \hat{u}_{it} \text{ are equally weighted} \\ (1-\alpha)\alpha^{t-1} & \text{if } \hat{u}_{it} \text{ are not equally weighted}^{87} \end{cases}$$

where $\hat{u}_{it}$ is the estimated systematic error of security *i* at time *t*. w_t is the weight given to the estimated systematic error at time *t*. α is a constant that represents the degree of which the weight decreases, and $0 < \alpha < 1$. The superscript τ represents the time period of the SVI moving average and $\tau = \{1,2,3,\dots,T^* - T\}$, where T^* is the last period in the data sample. τ is introduced to set the beginning and ending of the time interval and allow it to shift for each SVI in the moving average. For instance, if we are using a 100 day estimation period (*T=100*) and our data sample is consisted of 500 periods, then SVI_i^1 is the first-period SVI of security *i* and is calculated over the time interval [*1,100*]. SVI_i^2 is the second-period SVI of security *i* and is calculated over the time interval [*2,101*]. SVI_i^3 is the third-period SVI of security *i* and is calculated over the time interval [*3,102*], etc. By changing τ, Equation (3.7) will then produce the moving average of SVI for security *i* ($SVI_i^1, SVI_i^2, SVI_i^3, \dots, SVI_i^{400}$).

To have an equally weighted SVI_i^τ, we let w_t equals to $\frac{1}{T}$. In this case, the SVI_i^τ will become the simple average of the estimated errors. However, if we are interested in giving more weight to more recent errors, then $w_t$is set to equal $(1-\alpha)\alpha^{t-1}$. A low value

[87] In this case the weight will be either exponential, linear, or a single point (scalar) depending on the choice of α.

of α will discount older estimates of $\hat{u}_{it}$ more than recent estimates of $\hat{u}_{it}$. For example, if α equals .0000001, then a weight equals almost one will be given to the first (the most recent) $\hat{u}_{it}$ while a weight equals almost zero will be given to the remaining estimates of $\hat{u}_{it}$ for all t > 0 (see Figure 3.1). A very high value of α will slowly discount older estimates of $\hat{u}_{it}$. For example, if α equals .999, then a downward linear weight will be given to estimates of $\hat{u}_{it}$ (see Figure 3.2). An exponential weight is achieved, if α is chosen to equal .888 (see Figure 3.3).

Equation (3.7) provides us with the magnitude and direction of the bias in security returns. If $SVI_i^\tau > 0$, then returns of security *i* are overvalued. If $SVI_i^\tau < 0$, then returns of security *i* are undervalued. If $SVI_i^\tau = 0$, then returns of security *i* are neither overvalued nor undervalued, which suggests that they equal their fundamental values.

The MVI at a particular period τ is measured as the weighted average of all securities' SVIs of that period. Since as mentioned earlier the overvaluation and undervaluation of security returns are estimated separately and since a security can be either significantly overvalued, significantly undervalued, or neither, MVI is calculated as follows:

$$MVI^\tau = \left(\sum_{i=1}^{I} \omega_i \, SVI_i^\tau \, D_O \; - \; \sum_{i=1}^{I} \omega_i \, SVI_i^\tau \, D_U \right) \tag{3.8}$$

where ω_i is the market value weight of company *i* relative to the total market value.[88] The dummy variables are defined as follow:

[88] The market value weight of company *i* at time *t* is calculated as the number of outstanding shares at time t multiplied by their market prices at time *t* and divided by the market value index at time *t*.

$D_O = 1$ if SVI_i^τ is significantly overvalued

$D_O = 0$ otherwise

and

$D_U = 1$ if SVI_i^τ is significantly undervalued

$D_U = 0$ otherwise

This specification implies that when there is no significant overvaluation or undervaluation, SVI_i^τ equals zero (i.e. security *i* returns are correctly valued).

To obtain the time series of the MVI, simply calculate MVI^τ for each τ-period. Once the time series of the MVI is calculated, one can then track the overall market misvaluation and identify any existing bubble. By predicting an existing bubble, we might then be able to avoid a potential crash.

3.3 The Data

During the last decade, the Saudi stock market has experienced two crashes, where the market index lost more than 50 percent of its value (see Figure 3.4). On February 25, 2006, the Saudi stock market index, called the Tadawul All-Share Index (TASI), registered its highest close ever at 20,634.86 points. However, on the next day, February 26, 2006, the market witnessed the start of a historical crash that resulted in substantial losses to investor wealth and confidence in the stock market. Within a window of four months, the market index lost about 50 percent of its value. By the end of 2006, the index reached 7,933.29 dropping by 12,701.57 points (a 62 percent decrease). However, the index started to recover from 2007 through mid-2008. In June 2008, the index experienced another crash similar in magnitude to that in 2006. Within five months, the index dropped from 9,789.91 in June 23, to 4,264.52 in November 23, 2008, a 56 percent decrease.

The dataset used for this study consists of the daily stock returns, adjusted for dividends, the daily market capitalization, and the daily value weighted market index, TASI.[89] The dataset spans over five years, starting from February 28, 2004 and ending in February 25, 2009. The sample includes 67 companies, which represents about 96 percent of the total number of companies in the market as of February 28, 2004.[90] Data were unavailable for the remaining companies.[91] All related data were gathered from the Saudi Stock Exchange Company, called “Tadawul”.[92]

3.4 Methods and Empirical Results

In this section, we will investigate the existence of bubbles during the periods surrounding the two crashes. We are going to focus on the time series of the MVI, which allows us to track the magnitude and direction of market misvaluation during the periods of interest. If the two crashes were preceded by periods of general overvaluation, we would expect MVI to indicate a persistent positive misvaluation during the period before each market crash and a persistent zero or negative misvaluation during the period after each market crash.

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[89] Daily market capitalization is calculated as the number of shares multiplied by the daily security prices. The Saudi stock exchange updates the number of shares of each company on a quarterly basis.

[90] To be able to do a comparison before and after the crash, the number of companies as of February 28, 2004 was kept unchanged.

[91] The number of companies that were traded as of February 28, 2004 and are excluded from this study is only three. The reason for their exclusion is because these companies either stopped their operations at some point in time during the study period or have too many missing observations.

[92] The name of the company “TADAWUL” is the Arabic word for “Trading”. The official website of Tadawul is (www.tadawul.com.sa).

There are three measurement issues one should address when computing the MVI. The first issue is the choice of the length of the estimation period used to calculate the average of the estimates $\hat{u}_{it}$.[93] On the one hand, a short estimation period leads to a small sample. On the other hand, a long estimation period may include other unwanted events, which may give inaccurate estimates. To test the robustness of the results, this study will apply three different estimation periods (100 days, 200 days, and 250 days).

The second issue is the choice of the level of significance. This is important because the level of significance plays a role in computing the MVI as described in equation (3.8). The choice of the level of significance will dictate the number of securities that are overvalued, undervalued, or correctly valued. During a typical estimation period, a small level of significance will include a smaller number of misvalued securities. Since the appropriate level of significance is difficult to calculate in practice, we will choose various levels of significance (.1, .5, 1, and 5 percent) to check the sensitivity of the results.

The third and final issue is the choice of the weight scheme used in calculating the average of the estimates $\hat{u}_{it}$. The average can be calculated based on an equally weighted average or based on other weighting schemes. When using an equal weight, every security's misvaluation during the estimation period will be given the same weight. This weight scheme is easy to implement, but it will not produce accurate results when bubbles come on suddenly. Fortunately, there are other weighting schemes such as an exponential

[93] In the literature on event studies, it is widely agreed that the length of the estimation period can be chosen to be anywhere between 100-300 days (Peterson, 1989; Armitage, 1995).

weighting scheme that puts more weight on more recent estimates of security misvaluation. This paper calculates the average estimates of $\hat{u}_{it}$ using 1) An equal weight; 2) An exponential weight; 3) A linear weight, defined as downward linear weight that gives more weight to recent estimates; 4) A first observation weight that gives a full weight (w = 1) to the first (most recent) estimate and no weight (w = 0) to the rest of the estimates of misvaluation. These weights are obtained by using equation (3.7) with α= .888, α=.999, and α=.000, respectively (as described in Figures 3.1, 3.2, 3.3).

In the following, we are going to present the empirical results that are based on a 100 day estimation period, .1 percent significant level, and an exponential weight. We are going to start by analyzing the time series of MVI during the period surrounding each crash. Then, we are going analyze the time series of MVI over the whole period of study. After that, we will evaluate the sensitivity of the results when alternative specifications are used. Finally, we will look at the number of overvalued and undervalued securities during the period before and after each crash.

Looking at the 2006 market crash, Figure 3.5 shows that as the crash approaches, MVI rises, which implies greater average overvaluation. MVI appears to correctly predict the crash. In the post-market crash period, the MVI falls sharply right after the crash and stays close to zero for a period of time. This suggests that the values of securities after the crash are correctly valued.

When looking at the 2008 market crash, Figure 3.6 shows that during the pre-crash period, from April 2007 until the crash date, MVI is positive, signaling market overvaluation. But after the crash date, MVI falls and becomes again very close to zero and sometimes negative, representing market undervaluation. Therefore, this evidence suggests that the MVI is again able to capture the correct state of the stock market (overvalued, undervalued, or correctly valued) during the period before and after the crash.

Figure 3.7 depicts the time series of MVI over the whole period of study covering both crashes. When looking at Figure 3.7, we notice that there are persistent positive values of the MVI before each of the two crashes. This suggests the existence of bubbles (one before each crash). In addition, the sudden decrease in the MVI after each crash suggests the bursting of those bubbles.

Figure 3.7 also shows that during the year before the 2006 crash the pattern of the MVI shows a dramatic increase followed by a sharp fall, while during the year before the 2008 crash the MVI shows a less dramatic divergence between market and fundamental values followed by a sharp fall. This different pattern of the MVI during the year before each crash suggests that the two bubbles might have been of different types.

When analyzing the burst of these two bubbles, we find that factors that cause the burst of these two bubbles might have been different as well. Figure 8 shows the annual growth rate of the real Gross Domestic product (GDP) of Saudi Arabia and the world. The figure shows that there was an increase in real GDP growth rate of Saudi Arabia and the world in the years from 2004 through 2006. It shows that the economy of Saudi Arabia and the world were stable and growing during the period before the 2006 crash. This may suggest that the burst of the 2006 bubble was due to an internal shock, defined as a shock that originates from within the country. However, Figure 3.8 shows that in 2008 there was a large drop in world's real GDP growth rate, which was due to the worldwide financial crises. This large drop may have increased uncertainty and pessimism among the Saudi investors regarding the future economic prosperity of the country and the world and caused the bubble to burst. In this case, we may suggest that the burst of the 2008 bubble was due to an external shock, defined as a shock that originates from outside the country.[94]

A final observation about Figure 3.7 is that MVI is positive almost all the time except at the beginning of the 2009 year. One explanation for this persistent overvaluation is that the selected period may reflect persistent optimism among investors. Another possible explanation is the existence of restrictions on the short selling of stocks in the Saudi stock market.[95] In a recent survey, Scherbina (2013) states

> "… In contrast, short sellers, who search the market for overvalued assets in order to sell them short, are routinely vilified by governments, the popular press, and, not surprisingly, by the overvalued firms themselves. Trading against an overvaluation involves the additional costs and risks of maintaining a short position, such as the potentially unlimited loss, the risk that the borrowed asset will be called back prematurely, and a commonly charged fee that manifests itself as a low interest rate paid on the margin account; for this reason, a persistent overvaluation is more common than a persistent undervaluation."

Thus far, the above analysis is based on a 100 day estimation period, .1 percent significance level, and an exponential weight. To evaluate the sensitivity of the results, a number of alternative specifications is considered. We first consider alternative weights

[94] For more details on how bubbles are initiated and on why they burst, see Scherbina (2013).

[95] Short selling is the practice of borrowing and immediately selling a security at period one and agreeing to return it back to the lender along with any dividends paid at period two. In Saudi Arabia, short selling is not permitted.

when calculating the average of the estimated biases of a security. To get a sense of how similar the results are when different weights are used, Table 1 presents the correlation coefficients between MVI when different weights are used, giving a selected level of significance and estimation period. The first two columns of the table show the level of significance and estimation period used to calculate the MVI. The remaining columns represent the correlation coefficients of the MVI when an exponential weight is used and the MVI when equal, linear, and first observation weights are used, respectively.

When looking at the correlation coefficients between the results that are based on an exponential weight and those that are based on an equal weight, we find that it ranges from 99 percent to 93 percent depending on the selected estimation period and level of significance. Table 1 also shows a similar range in the correlation coefficients between the results that are based on an exponential weight and the results that are based on a linear weight. The lowest correlation coefficients in Table 3.1 are found to be between the results when an exponential weight is used and the results when a first observation weight is used and ranges from 89 percent to 77 percent. In general, Table 3.1 shows that the correlation coefficients are high between our initial results and those found when alternative weights are used. Therefore, this method is robust across different weights.

Figures 3.9 and 3.10 provide a visualization of how similar the results are when alternative weights are used. Figure 3.9 compares the results during the period surrounding the 2006 crash while Figure 3.10 compares the results during the period surrounding the 2008 crash. The two figures show that the results are similar when exponential, equal, linear, and first observation weights are used. However, only when the first observation weight is used does the MVI become more volatile. This is true because we are simply using only the first observation as an average, which represents the stock market volatility without smoothing. In conclusion, the evidence found in Figures 3.9 and 3.10 supports our earlier conclusion that our method is robust across alternative weights.

Next, we evaluate the sensitivity of the results when different levels of significance are used. Once more, our evaluation will be based on the correlation coefficients analysis. It is important to mention that in our analysis, we do not advocate the use of one level of significance over the other. To determine the proper significance level, one should calculate the loss function – costs of type I versus type II errors. Table 3.2 presents the correlation coefficients between the MVI when different levels of significance are used, giving a particular weight and estimation period. The first two columns of the table show the weight and estimation period used to calculate the MVI. The remaining columns represent the correlation coefficients between the results when .1 percent level of significance is used and those when .5, 1, and 5 percent levels are used, respectively.

When looking at the correlation coefficients between the results that are based on .1 percent significance level and those that are based on .5 percent significance level, we find that it ranges from 91 percent to 90 percent depending on the selected weight and estimation period. The relationship becomes weaker when we compare the results that are based on .1 percent and 1 percent significance levels. The lowest correlation coefficients are found when comparing the results that are based on .1 percent and 5 percent. The increase in the differences between the results when moving away from the .1 percent significance level is due to the fact that the number of overvalued or undervalued securities is becoming larger, which may change the pattern of the MVI. In general, Table 3.2 shows medium to high levels of correlation between the results when different significance levels are used.

Figures 3.11 and 3.12 depict the results when different significance levels are used. Figure 3.11 presents the results over the period from February 24, 2005 until February 24, 2007 covering the first crash. Figure 3.12 presents the results over the period from February 25, 2007 until February 25, 2009 covering the second crash. The two figures show that the smaller the level of significance, the lower the value of MVI. This is because when a small level of significance is chosen, a smaller number of securities will be considered overvalued or undervalued (i.e. those securities with high level of overvaluation or undervaluation). This will then lower the value of MVI. On the other hand, with a large level of significance many securities will be considered either overvalued or undervalued and since overvaluation is more common than undervaluation during this time period, this will raise the level of MVI. In conclusion, the evidence found in Figure 3.11, Figure 3.12, and Table 3.2 suggests that the pattern of the results is generally not affected by the choice of significance levels.

Finally, we evaluate the sensitivity of the results when different estimation periods are used. The correlation coefficients between the results when different estimation periods are used are provided in Table 3.3. The first two columns of the table show the selected weight and significance levels. The remaining columns represent the correlation coefficients between the results when a 100 day estimation period is used and those when 200 and 250 day estimation periods are used, respectively.

Looking at Table 3.3, we find that the correlation coefficients between the results when using a 100 day estimation period and those when using a 200 day estimation period are not high. The correlation is even weaker when comparing our initial results with the results that are based on a 250 day estimation period. In general, the results seem to differ when using different estimation periods.

Figures 3.13 and 3.14 show the results when 100, 200, and 250 day estimation periods are used and represent the period surrounding the 2006 and 2008 crashes, respectively. In general, it is found that the longer the estimation period, the flatter the MVI line. This is expected since the MVI is nothing but a weighted moving average of the value of all securities, which becomes smoother and flatter as the estimation period gets longer.

Another indicator that not only supports the previous results but also adds additional information to them is the number of overvalued and undervalued securities. In Tables 3.4 and 3.5, we show the number of overvalued and undervalued securities during the periods before and after each crash. The two tables provide the number of overvalued securities when different specifications are used. The number of overvalued (undervalued) securities is calculated based on the average of the daily number of overvalued (undervalued) securities over an eight month period.[96]

Table 3.4 shows that the number of overvalued securities was higher during the pre-crash period. This number decreased during the post-crash period. These results are

[96] We chose to calculate the number of overvalued and undervalued securities over an eight months period to be able to compare between the pre-period results and the post-period results and between the results of 2006 and 2008 crashes.

not affected by the choice of the estimation period and/or the level of significance. When looking at Table 3.5, we notice that there is no clear pattern in the number of undervalued securities during the period before and after the 2006 crash. However, when looking at the period surrounding the 2008 crash, we notice an increase in the number of undervalued securities from the pre-crash to the post-crash periods.

Figures 3.15, 3.16, and 3.17 plot the time series of the number of overvalued securities using different levels of significance and 100, 200, and 250 day estimation periods, respectively. By looking at these figures, one can notice that the number of overvalued securities during the period before each of the two crashes is higher compared to the period after the crash. This pattern is consistent with what one would expect to occur during these periods. In a similar fashion, the paper also plots the time series of the number of undervalued securities in Figures 3.18, 3.19, and 3.20. The figures show a clear increase in the number of undervalued securities only during the period following the second crash.

The fact that there is a clear decrease in the number of overvalued securities and no obvious pattern in the number of undervalued securities from before to after the 2006 crash periods can be interpreted as an indication that the burst of the first bubble reflects the correction of the level of optimism, which was prevalent among investors' expectations. In addition, the clear decrease in the number of overvalued securities and the increase in the number of undervalued securities from before to after the 2008 crash periods can be interpreted as an indication that the burst of the second bubble reflects an increase in the level of pessimism among investors' expectations. This pessimism was due to the uncertainty about the future economic prosperity that was caused by a macroeconomic shock, which was due to the 2008 worldwide financial crisis.

Thus far, the results show that the MVI is able to identify a bubble. They are consistent with what one would expect during the period before and after a bubble (i.e. a persistent positive misvaluation during the period before a market crash and a persistent zero or negative misvaluation during the period after a market crash). The results are of importance because they can show a way to avoid financial bubbles. One way this can be done is by making the daily MVI available to the public.[97] This will raise the level of awareness among investors about market misvaluation. Increased awareness can be then incorporated into investors decisions and eliminate any misvaluation, which in turn may prevent bubbles from initiating. For example, assume that the index is available to public investors and assume that the index starts to show some overvaluation. Then investors will realize that, on average, securities are overvalued. This may motivate some investors to arbitrage from this overvaluation and/or motivate others to go back to fundamentals when buying a security, which in both cases will bring prices down until the market is correctly valued.

Another way in which knowledge of MVI can be useful is that it can lead to a targeting policy, defined earlier as a policy that can be put into effect once the index gets too high or too low. In order to use such a policy, central banks or market regulators should first assign a benchmark MVI, based on all historical crashes. For example, by

[97] The methods and timing of introducing the index to the public are important since the introduction of such an index may itself trigger a market crash.

looking at Figure 3.7, a benchmark for MVI might be set at .5 percent.[98] Once the benchmark is chosen, central banks or market regulators can then select the appropriate policy to deal with cases where MVI exceeds the selected benchmark. For example, central banks might sell short all identified overvalued securities. This will then bring the prices of those securities down and help correct market misvaluation.

Another policy that might be used by regulators is to inform the public when a sector is believed to be overvalued. Market regulators may prefer to gradually introduce such information to sectors instead of informing the public that the whole market is overvalued if they fear that such information might itself trigger a market crash.

3.5 Conclusion

Stock market bubbles are of great concern to any economy since they can lead to a dramatic stock market crash. As a result, much research has focused on understanding and identifying the existence of bubbles. However, the majority of previous studies use the traditional present value models to identify such bubbles. In general, those models cannot identify all types of bubbles, nor can they provide a satisfactory degree of certainty in detecting them.

The purpose of this paper is to introduce a new method that can help detect and forecast the existence of a bubble. This is done by introducing an index that can identify any persistent overvaluation in the overall stock market. The index is based on a recently

[98] This benchmark may not be accurate since it is based only on two historical market crashes.

developed valuation model that measures the deviation between market and fundamental returns of a security.

Using this index, we investigate the existence of bubbles during periods surrounding two stock market crashes that occurred in the Saudi stock market. The results show that the constructed index is able to identify two bubbles with a satisfactory degree of certainty. The results are found to be consistent with our initial expectation that there is a persistent positive misvaluation during the period before a market crash and a persistent zero or negative misvaluation during the period after a market crash.

We also do various sensitivity analyses to test whether our method is sensitive to alternative specifications. In general, the results show that our method does not change when different weights, levels of significance, and estimation periods are used.

The results are important because they provide new insights on how to identify bubbles. They can also open the door for new polices that may become effective in reducing the likelihood of potential stock market crashes. For this reason, this paper will be extended in the future to include a longer period that covers as many stock market crashes as possible. Finally, the method in this paper will also be applied to other stock markets such as the US stock markets to investigate its consistency in identifying bubbles.

Table 3.1: Correlation Coefficients of the Market Valuation Indices of Different Weights

Level of Significance	Estimation Period	Correlation Coefficients		
		$MVI_{(Exponential)}$ and $MVI_{(Equal)}$	$MVI_{(Exponential)}$ and $MVI_{(Linear)}$	$MVI_{(Exponential)}$ and $MVI_{(First\ observation)}$
.1% Level of Significance	100	0.99	0.99	0.89
	200	0.97	0.97	0.86
	250	0.96	0.96	0.85
.5% Level of Significance	100	0.99	0.99	0.89
	200	0.96	0.96	0.84
	250	0.95	0.95	0.83
1% Level of Significance	100	0.98	0.98	0.87
	200	0.96	0.96	0.83
	250	0.94	0.94	0.81
5% Level of Significance	100	0.97	0.98	0.83
	200	0.95	0.95	0.81
	250	0.93	0.93	0.77

Note: Columns 1 and 2 represent the level of significance and estimation period used to calculate the market valuation index. Columns 3, 4, and 5 represent the correlation coefficients of the market valuation index with exponential weight and the market valuation index with equal, linear, and first observation weights, respectively.

Table 3.2: Correlation Coefficients of the Market Valuation Indices of Different Levels of Significance

Weight	Estimation Period	Correlation Coefficients		
		$MVI_{(.1\%)}$ and $MVI_{(.5\%)}$	$MVI_{(.1\%)}$ and $MVI_{(1\%)}$	$MVI_{(.1\%)}$ and $MVI_{(5\%)}$
Exponential Weight	100	0.91	0.88	0.78
	200	0.91	0.83	0.64
	250	0.88	0.82	0.59
Equal Weight	100	0.89	0.86	0.75
	200	0.89	0.80	0.57
	250	0.84	0.76	0.50
Linear Weight	100	0.89	0.86	0.75
	200	0.89	0.80	0.58
	250	0.84	0.76	0.50
First Weight	100	0.90	0.87	0.75
	200	0.91	0.85	0.70
	250	0.90	0.85	0.69

Note: Columns 1 and 2 represent the weight and estimation period used to calculate the security valuation index. Columns 3, 4, and 5 represent the correlation coefficients of the market valuation index when .1 percent level of significance is used and the market valuation index when .5, 1, and 5 percent levels of significance are respectively used.

Table 3.3: Correlation Coefficients of the Market Valuation Indices of Different Estimation Periods

Weight	Level of Significance	Correlation Coefficients	
		$MVI_{(100)}$ and $MVI_{(200)}$	$MVI_{(100)}$ and $MVI_{(250)}$
Exponential Weight	.1%	0.75	0.66
	.5%	0.68	0.49
	1%	0.64	0.48
	5%	0.72	0.61
Equal Weight	.1%	0.69	0.59
	.5%	0.60	0.37
	1%	0.56	0.36
	5%	0.63	0.46
Linear Weight	.1%	0.69	0.59
	.5%	0.60	0.37
	1%	0.56	0.36
	5%	0.63	0.46
First Weight	.1%	0.73	0.65
	.5%	0.70	0.56
	1%	0.69	0.58
	5%	0.77	0.70

Note: Columns 1 represents the weight used to calculate security valuation index. Column 2 represents the level of significance used to calculate the market valuation index. Columns 3 and 4 represent the correlation coefficients of the market valuation index when a 100 day estimation period is used and the market valuation index when a 200 and 250 day estimation periods are used, respectively.

Table 3.4: Number of Overvalued Securities using Different Specification

Time Period	Estimation Period	.1% Level of Significance	.5% Level of Significance	1% Level of Significance	5% Level of Significance
Before the Crash of 2006	100	29.15	38.06	42.13	52.18
	200	48.62	56.42	58.39	62.16
	250	55.77	59.48	60.59	64.15
After the Crash of 2006	100	9.83	16.29	20.66	31.66
	200	23.32	31.07	34.99	44.36
	250	30.07	38.16	40.62	50.35
Before the Crash of 2008	100	14.65	21.42	26.29	40.43
	200	22.61	31.30	35.94	48.75
	250	26.04	34.87	39.14	52.11
After the Crash of 2008	100	7.01	12.76	16.56	28.40
	200	19.53	27.63	32.38	42.87
	250	24.43	31.35	35.76	47.66

Note: The period before the crash of 2006 is from June 25, 2005 to February 25, 2006 and the period after the crash of 2006 is from February 26, 2006 to October 10, 2006. The period before the crash of 2008 is from October 22, 2007 to June 22, 2008 and the period after the crash of 2008 is from June 23, 2008 to February 23, 2009. The calculated numbers represent the average of the daily number of overvalued securities over an eight months period.

Table 3.5: Number of Undervalued Securities using Different Specification

Time Period	Estimation Period	.1% Level of Significance	.5% Level of Significance	1% Level of Significance	5% Level of Significance
Before the Crash of 2006	100	0.51	0.55	0.62	0.89
	200	0.18	0.55	0.55	0.55
	250	0.05	0.42	0.42	0.42
After the Crash of 2006	100	0.00	0.02	0.07	0.41
	200	0.38	0.42	0.54	0.69
	250	0.23	0.45	0.75	0.91
Before the Crash of 2008	100	0.01	0.09	0.22	0.72
	200	0.00	0.00	0.00	0.56
	250	0.00	0.00	0.00	0.12
After the Crash of 2008	100	1.92	3.56	4.37	7.70
	200	1.28	2.22	2.87	5.28
	250	0.13	1.19	1.74	4.48

Note: The period before the crash of 2006 is from June 25, 2005 to February 25, 2006 and the period after the crash of 2006 is from February 26, 2006 to October 10, 2006. The period before the crash of 2008 is from October 22, 2007 to June 22, 2008 and the period after the crash of 2008 is from June 23, 2008 to February 23, 2009. The calculated numbers represent the average of the daily number of overvalued securities over an eight months period.

Figure 3.1: A First Observation Weight ($\alpha = .000$)

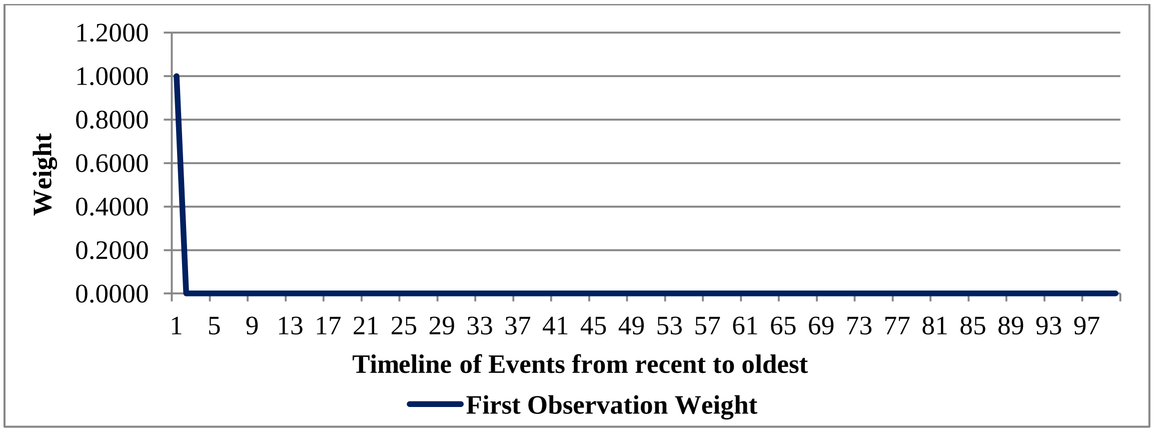


Figure 3.2: A Linear Weight ($\alpha =$ .999)

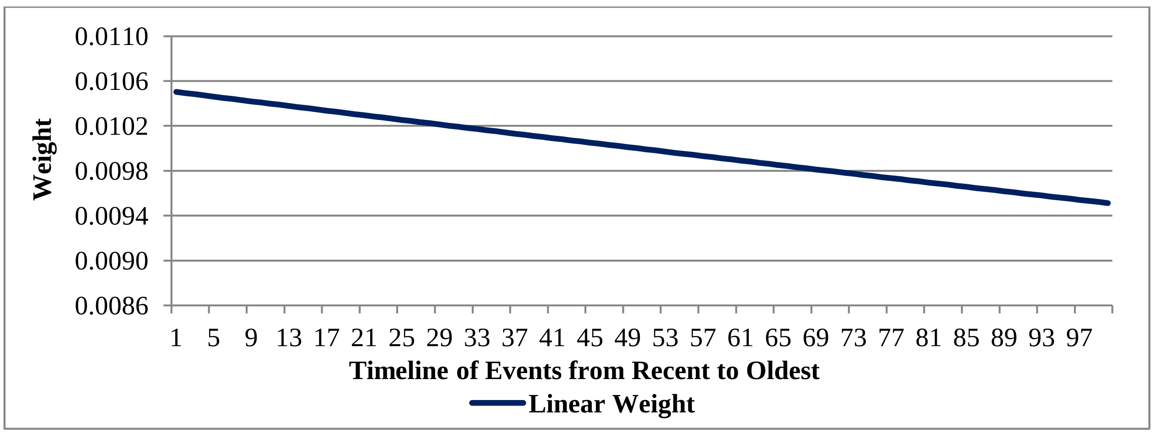


Figure 3.3: An Exponential Weight ($\alpha = .888$)

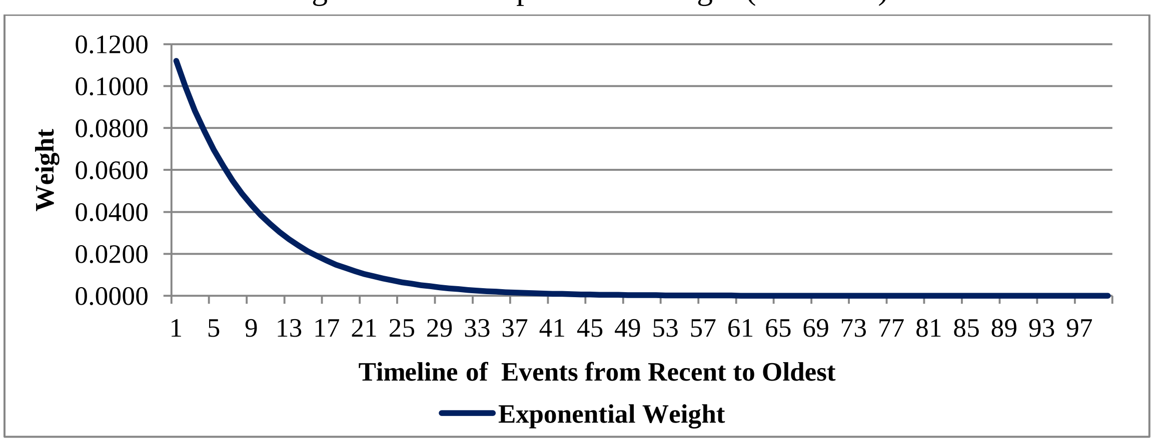
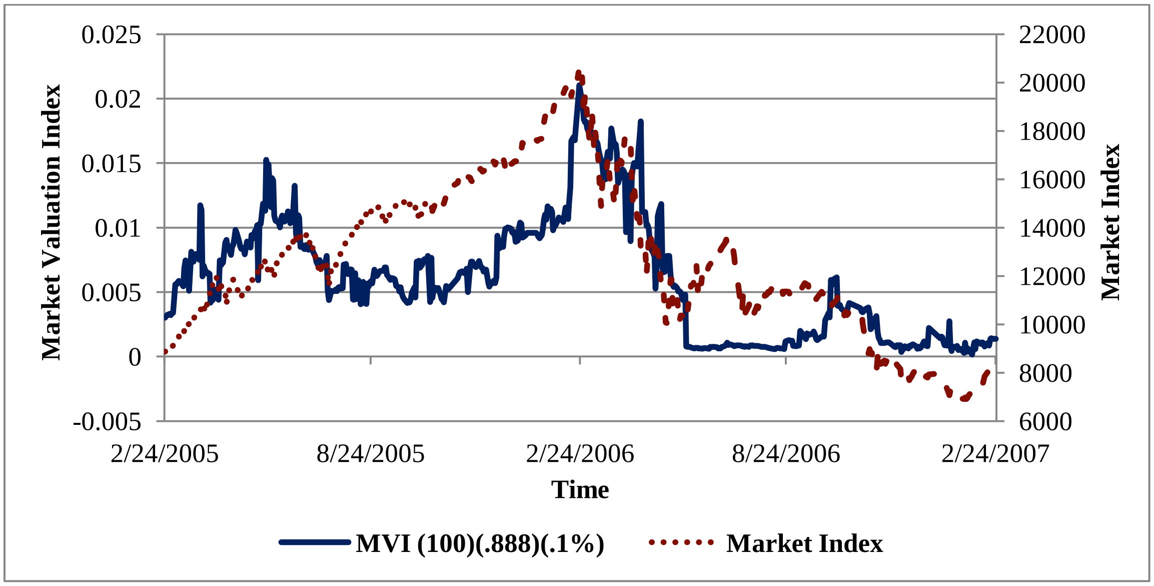


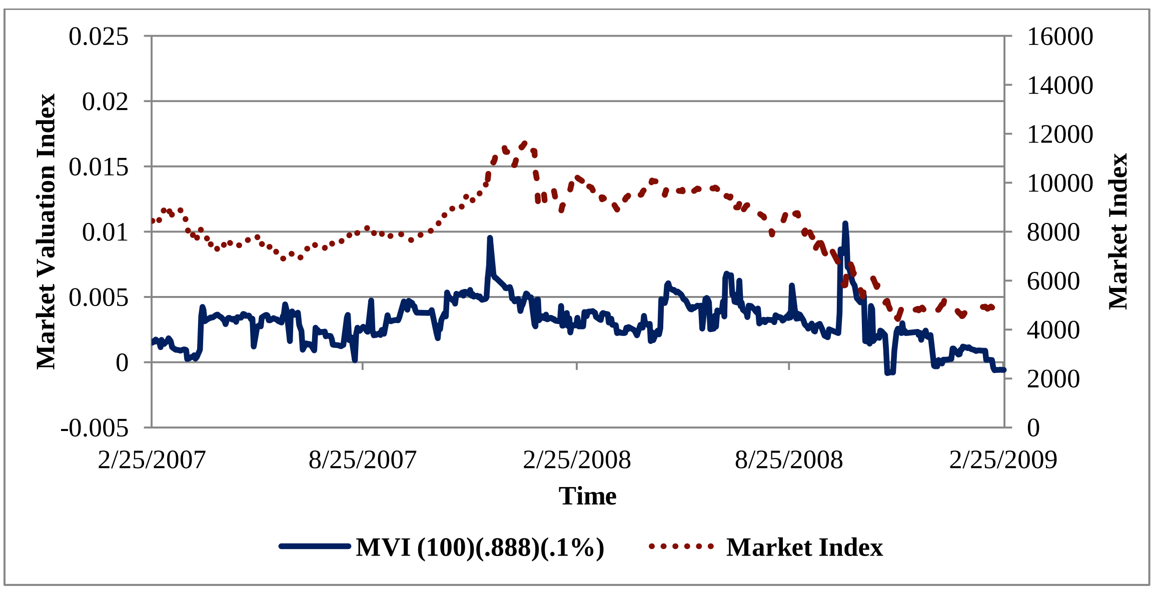
Figure 3.4: The Saudi Stock Market Index during the Period 2004-2009

Figure 3.5: Market Index and Market Valuation Index (2005-2007)



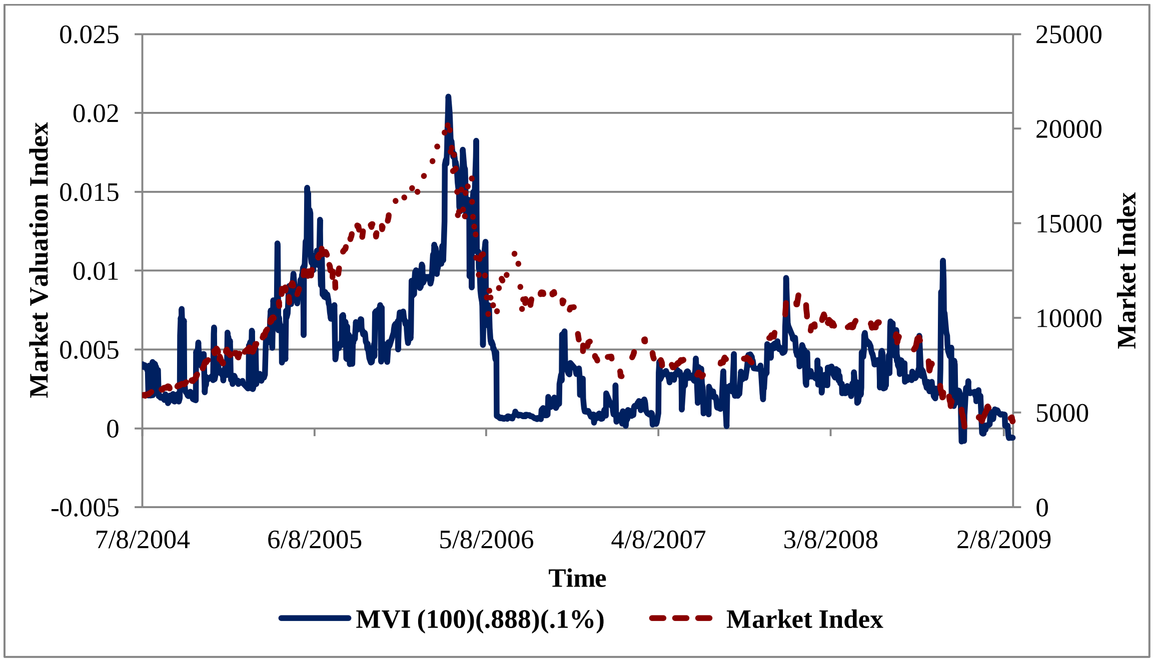
Note: The MVI is based on a 100 days estimation period, an exponential weight (α =.888), and .1 percent level of significance.

Figure 3.6: Market Index and Market Valuation Index (2007-2009)



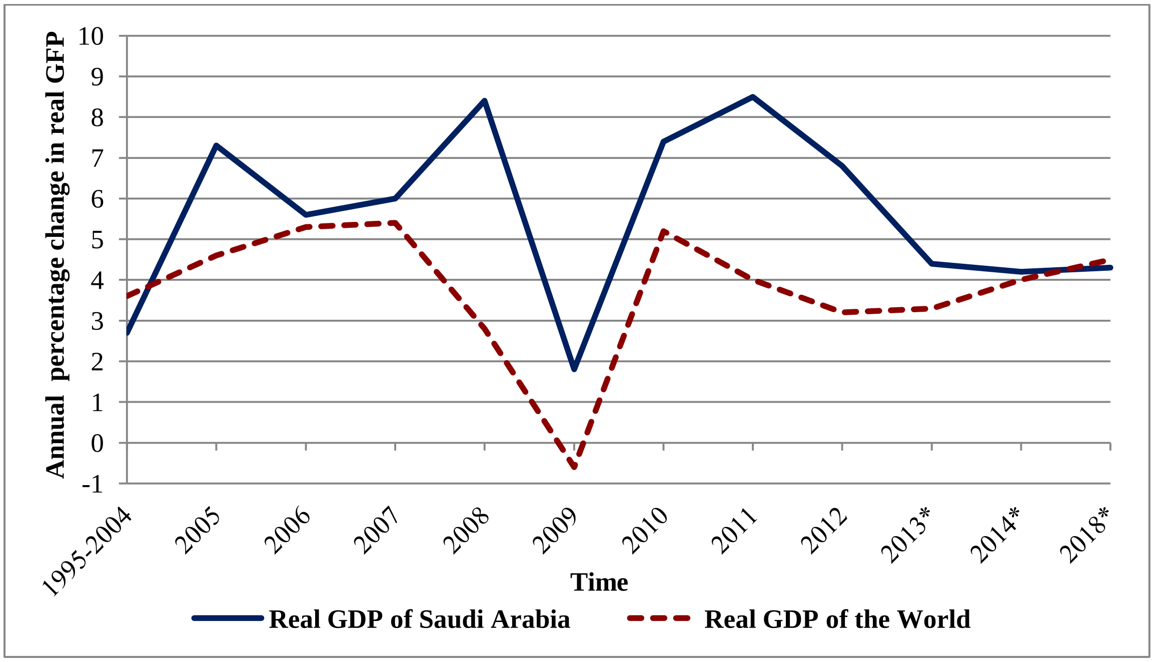
Note: The MVI is based on a 100 days estimation period, an exponential weight (α =.888), and .1 percent level of significance.

Figure 3.7: Market Index and Market Valuation Index (2004-2009)



Note: The MVI is based on a 100 estimation period, exponential weight (α =.888), and .1 percent level of significance.

Figure 3.8: Saudi Arabia and the World Annual Growth Rates (Based on Real GDP)



Source: The International Monetary Fund World Economic Outlook, April 2013.

Figure 3.9: Market Valuation Index based on a 100 Day Estimation Period, .1 Percent Significance Level, and Different Weighting Schemes (2005-2007)

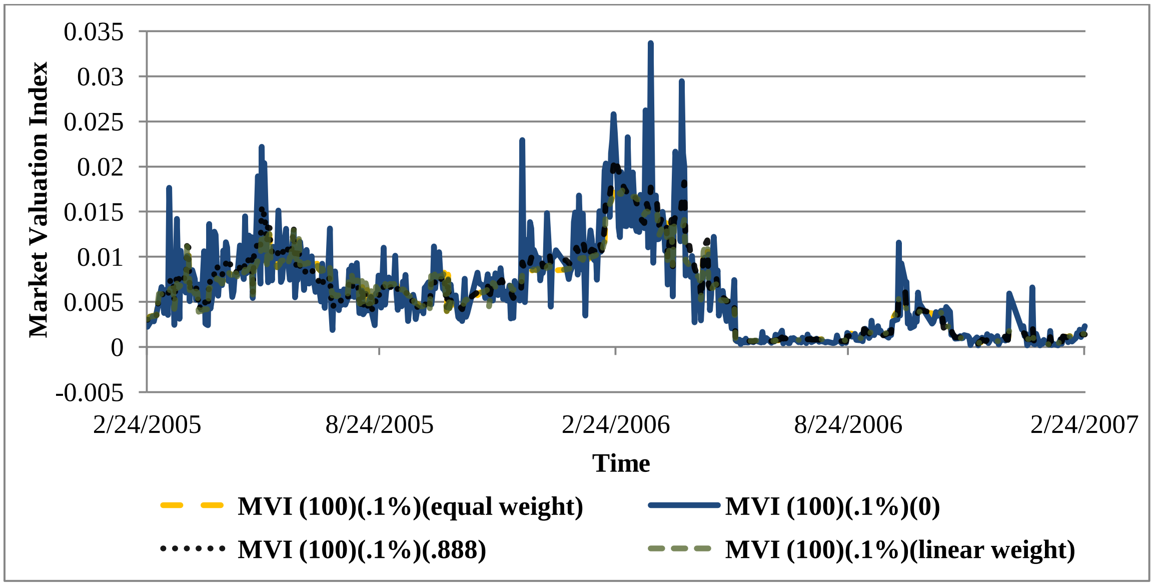


Figure 3.10: Market Valuation Index based on a 100 Day Estimation Period, .1 Percent Significance Level, and Different Weighting Schemes (2007-2009)

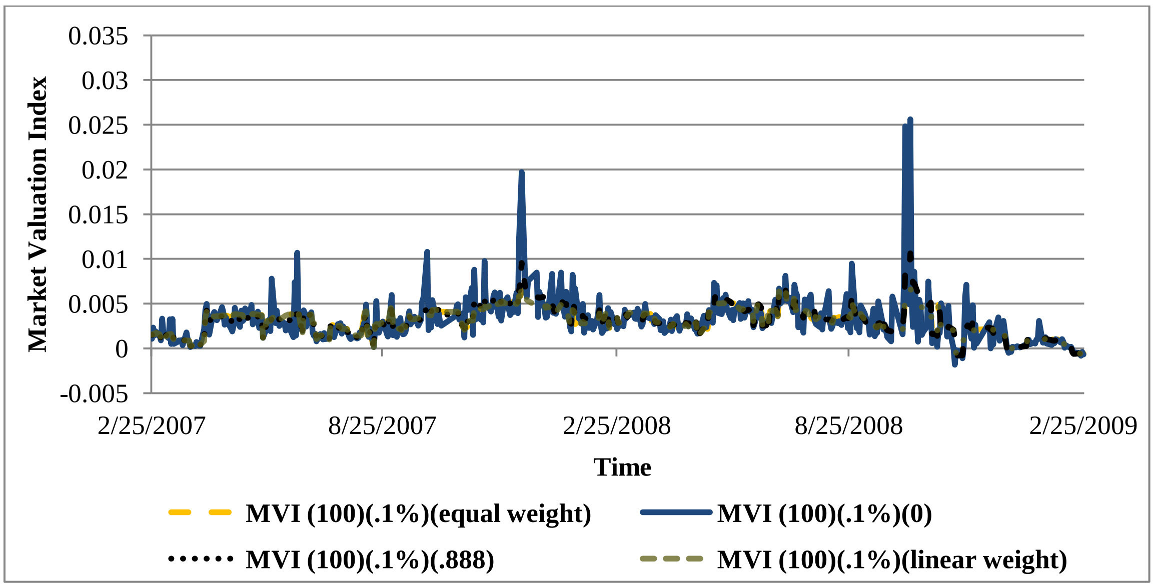


Figure 3.11: Market Valuation Index Based on a 100 Estimation Period, an Exponential Weight, and Different Levels of Significance for the Year (2005-2007)

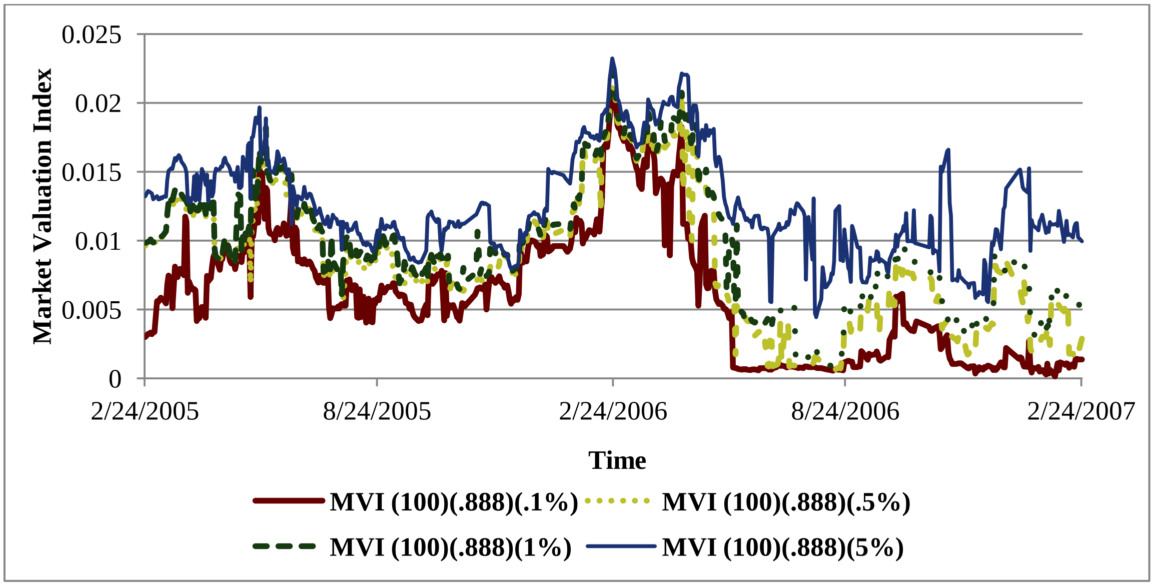


Figure 3.12: Market Valuation Index Based on a 100 Estimation Period, an Exponential Weight, and Different Levels of Significance for the Year (2007-2009)

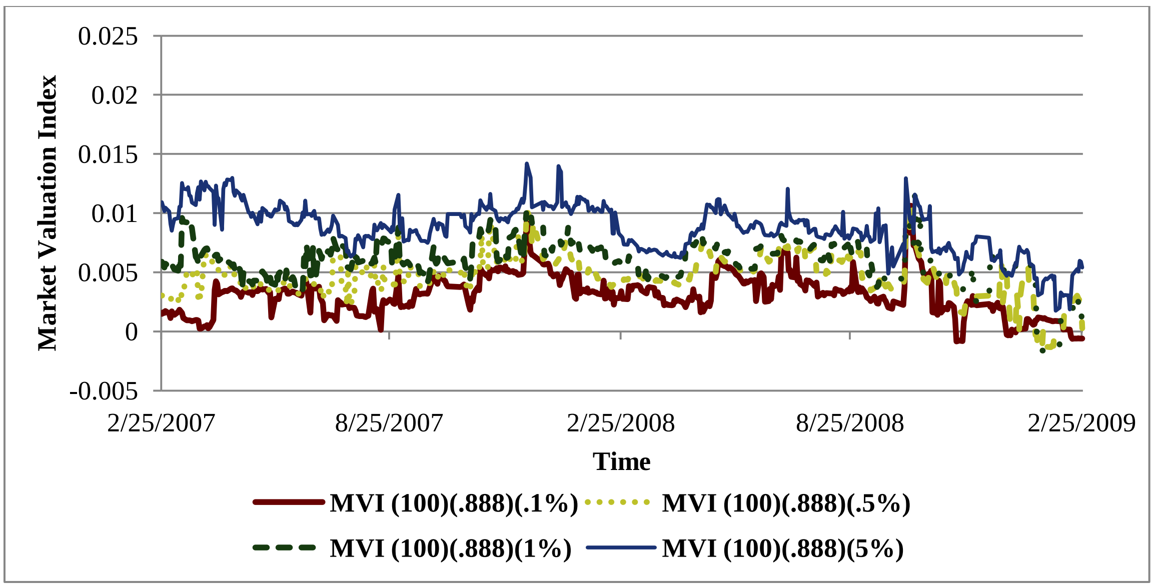


Figure 3.13: Market Valuation Index Based on an Exponential Weight, .1 Percent Level of Significance, and Different Estimation Periods for the Year (2005-2007)

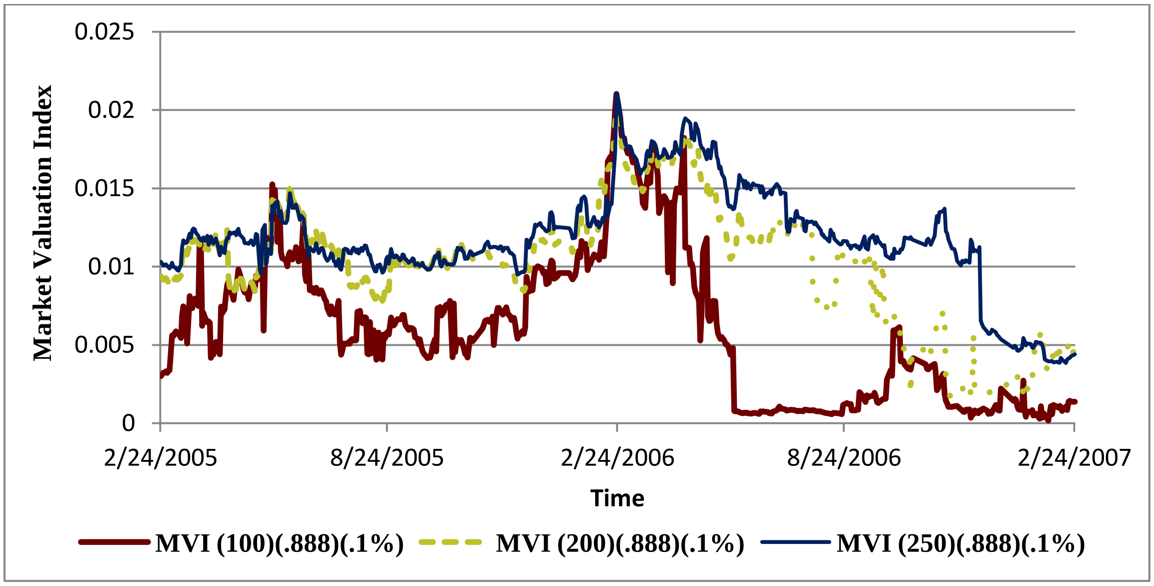


Figure 3.14: Market Valuation Index Based on an Exponential Weight, .1 Percent Level of Significance, and Different Estimation Periods for the Year (2007-2009)

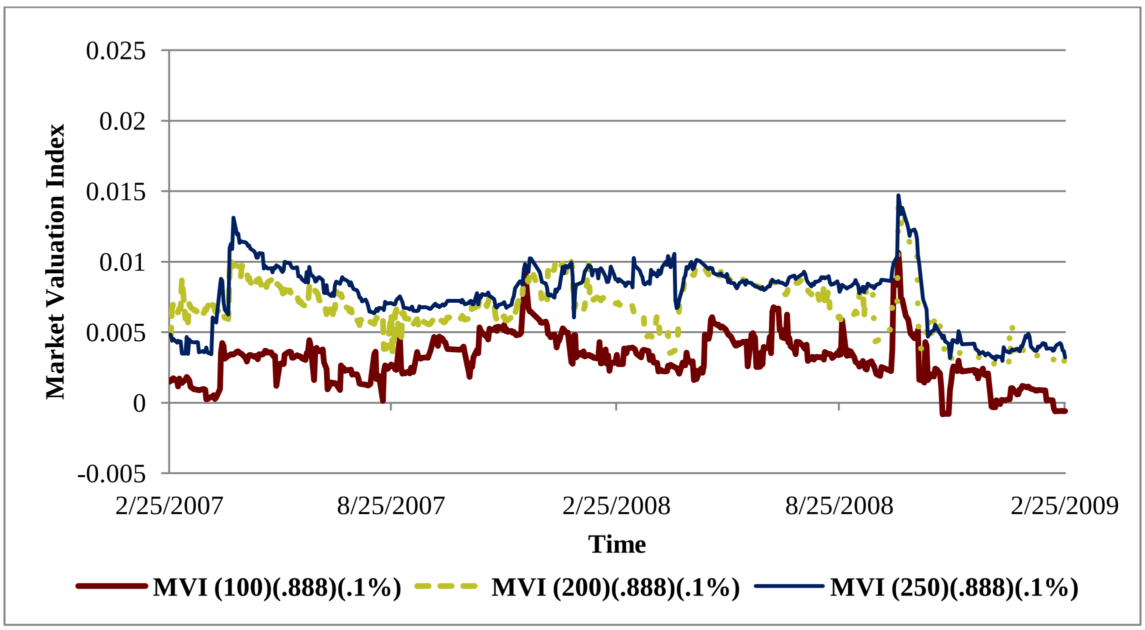


Figure 3.15: Number of Overvalued Securities using 100 Day Estimation Period and Different Levels of Significance

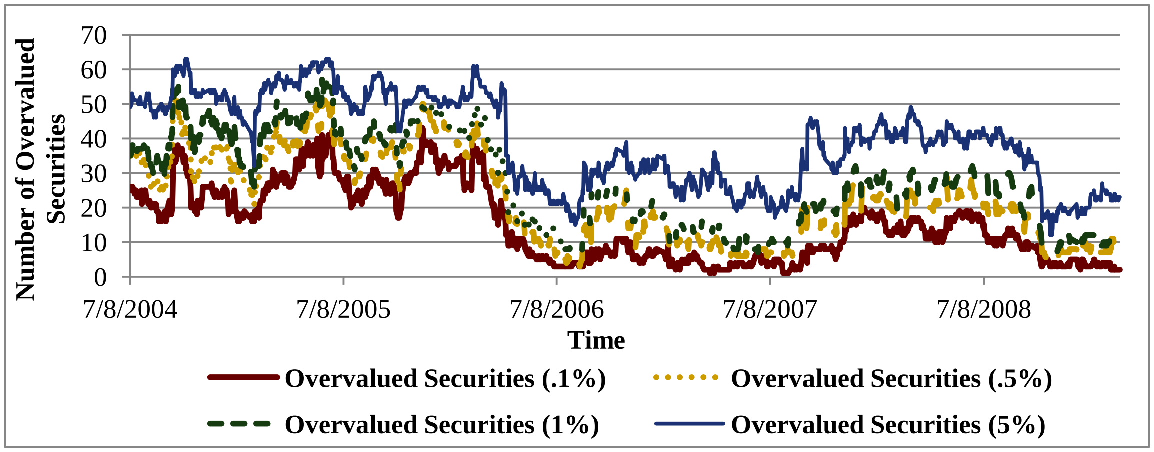


Figure 3.16: Number of Overvalued Securities using 200 Day Estimation Period and Different Levels of Significance

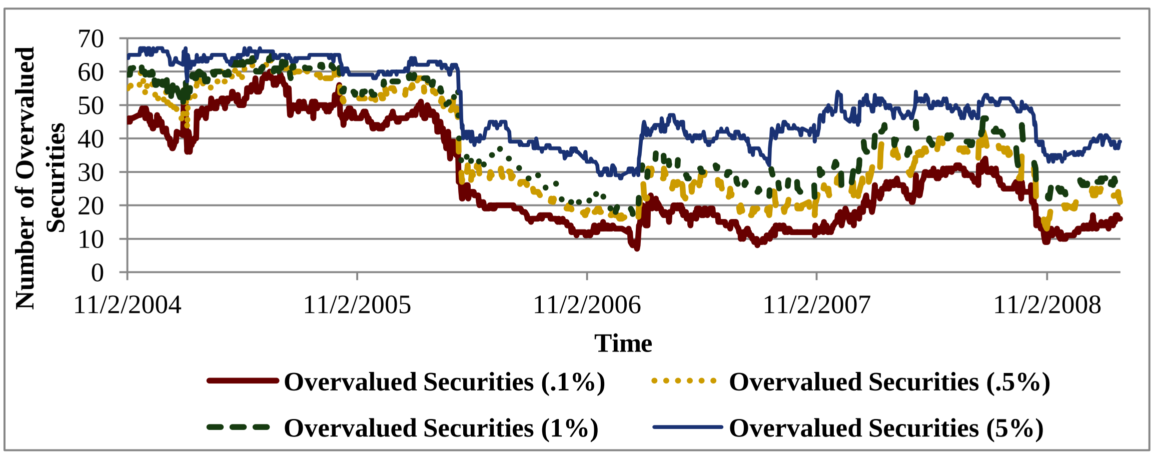


Figure 3.17: Number of Overvalued Securities using 250 Day Estimation Period and Different Levels of Significance

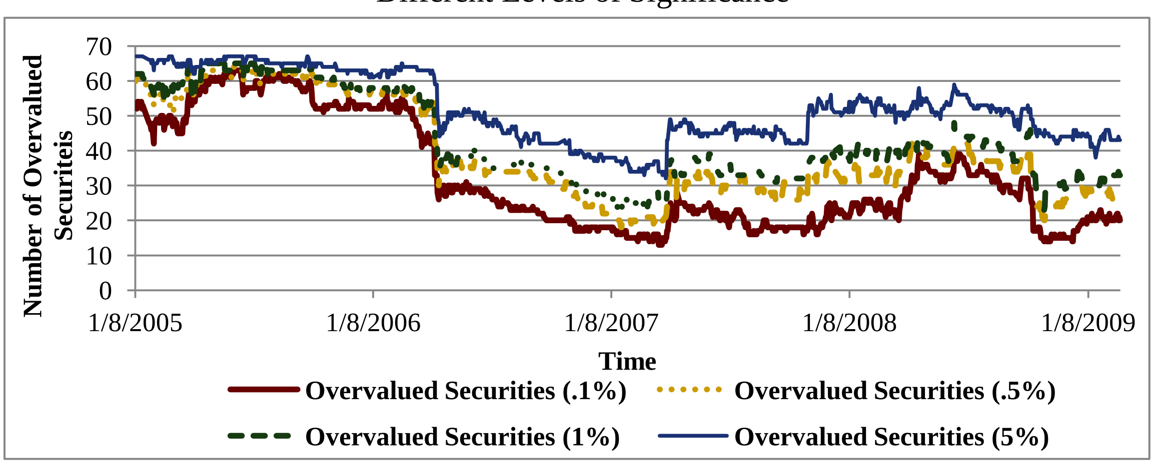


Figure 3.18: Number of Undervalued Securities in 100 Day Estimation Period and Different Levels of Significance

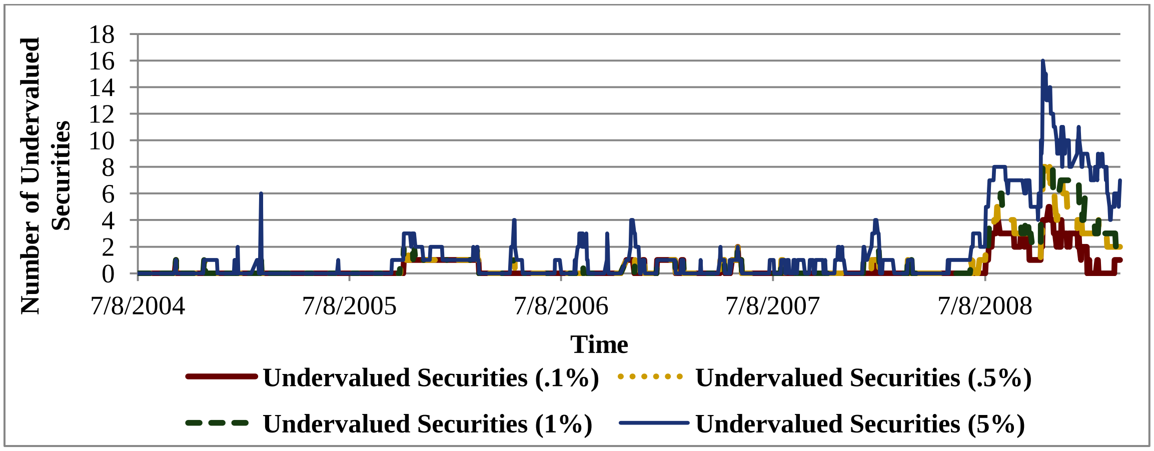


Figure 3.19: Number of Undervalued Securities in 200 Day Estimation Period and Different Levels of Significance

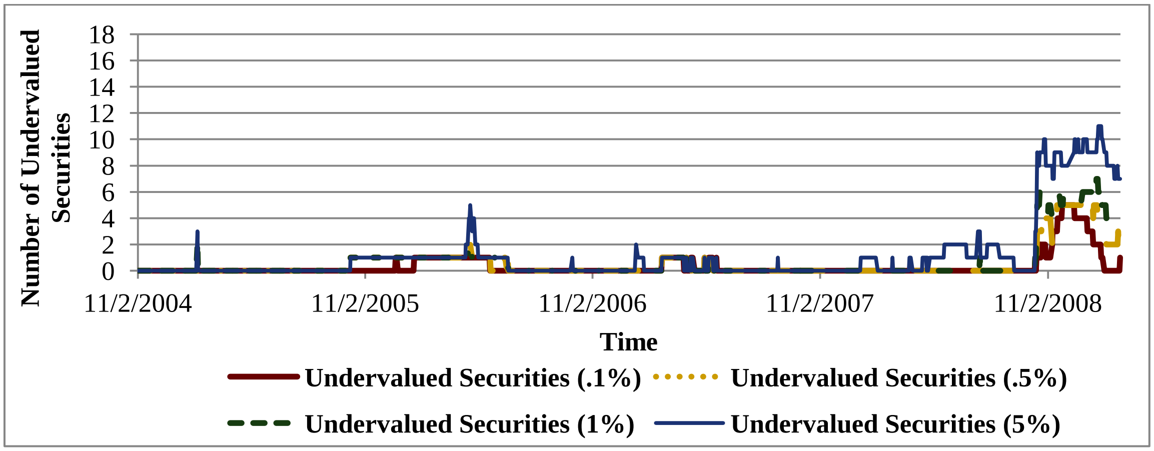
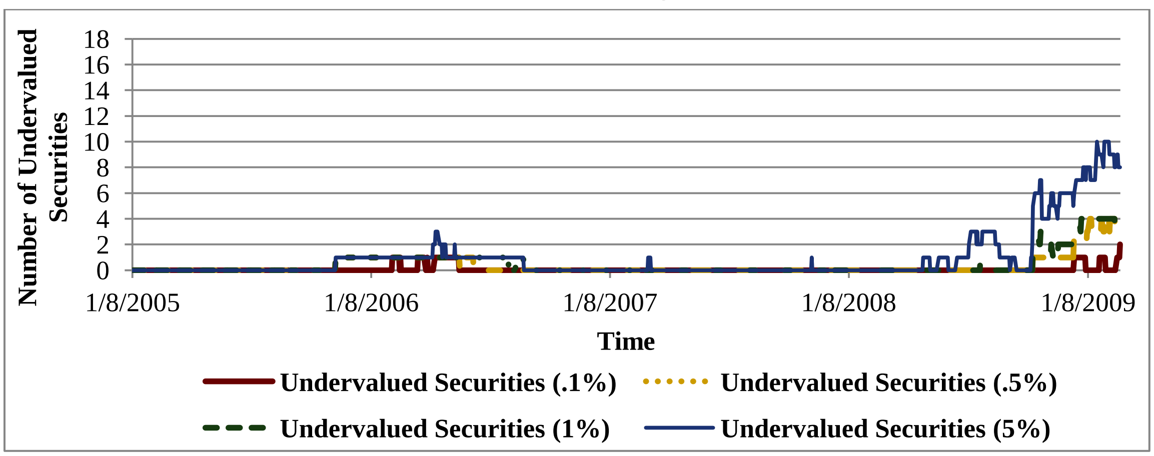


Figure 3.20: Number of Undervalued Securities in 250 Day Estimation Period and Different Levels of Significance



Chapter 4

Conclusion

In this dissertation, we focused on the analysis of the behavior of security returns around certain events that occurred in the Saudi stock market. Chapter 2 empirically investigated the economic impact of a single horizontal merger of two major banks in Saudi Arabia. The economic impact of the merger on the industry was determined based on investors' beliefs regarding the motivation behind the merger. Using the event study methodology, we were able to measure the reaction of investors to the merger news during the period surrounding the merger. We were able to identify the motivation behind the merger by testing the market power hypothesis, the efficiency hypothesis, and the information hypothesis. In chapter 3, we developed an index that measures the overall market misvaluation. We tested the ability of this index in identifying the overall market misvaluation on two historical crashes that occurred in the Saudi stock market during the years 2006 and 2008. We analyzed the pattern of the market misvaluation during the period before and after each crash to identify the existence of a bubble. Finally, we checked the sensitivity of our results to alternative specifications.

The main result of chapter 2 was that investors believed that the merger would increase economic efficiency rather than market power. We believe this was the case since our results were consistent with the productivity hypothesis when the effective date was chosen as the event date. When the announcement date was chose as the event date, we found that our results were consistent with the information hypothesis. In both cases, the results found support for the economic efficiency hypothesis but not the market power hypothesis.

In chapter 3, we concluded that the constructed index is believed to identify bubbles with a satisfactory degree of certainty. Our main result was that the index was able to detect the existence of two bubbles, one before each crash, in the Saudi stock market. The results were found to be consistent with our initial expectation that there is a persistent positive misvaluation during the period before a market crash and a persistent zero or negative misvaluation during the period after a market crash. In general, when alternative specifications were used to calculate the average estimated values of misvaluation, we found that the results did not change.

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Chapter 2

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Chapter 3

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Appendices

Appendix A

In this appendix, we derive the linear relationship found in the market model.

Let R_i and R_m be two random variables. If the distribution of R_i and R_m is bivariate normal, then their joint probability density function is

$$f(R_i, R_m) = \frac{1}{2\pi\sigma(R_i)\sigma(R_m)\sqrt{1-\rho^2}} exp\left\{-\frac{1}{2(1-\rho^2)}\left[\frac{\left(R_i - E(R_i)\right)^2}{\sigma^2(R_i)} - \frac{2\rho\left(R_i - E(R_i)\right)}{\sigma\ (R_i)}\frac{\left(R_m - E(R_m)\right)}{\sigma(R_m)} + \frac{\left(R_m - E(R_m)\right)^2}{\sigma(R_m)^2}\right]\right\} \qquad (A.1)$$

and their respective marginal density functions are :

$$f(R_i) = \int_{-\infty}^{\infty} f(R_i, R_m) dR_m = \frac{1}{\sqrt{2\pi}\sigma(R_i)} exp\left\{-\frac{(R_i - E(R_i))^2}{2\sigma^2(R_i)}\right\} \qquad (A.2)$$

$$f(R_m) = \int_{-\infty}^{\infty} f(R_i, R_m) dR_i = \frac{1}{\sqrt{2\pi}\sigma(R_m)} exp\left\{-\frac{(R_m - E(R_m))^2}{2\sigma^2(R_m)}\right\} \qquad (A.3)$$

This marginal density function shows that R_i is a normal random variable with mean $E(R_i)$ and standard deviation $\sigma(R_i)$. Similarly, R_m is a normal random variable with mean $E(R_m)$ and standard deviation $\sigma(R_m)$.

The conditional distribution of R_i given R_m is

$$f(R_i|R_m) = \frac{f(R_i, R_m)}{f(R_m)} \qquad (A.4)$$

$$= \frac{1}{\sqrt{2\pi}\sigma(R_i)\sqrt{1-\rho^2}} \exp\left\{-\frac{1}{2(1-\rho^2)}\left[\frac{\frac{\left(R_i - E(R_i)\right)^2}{\sigma^2(R_i)} - \left(\frac{2\rho\left(R_i - E(R_i)\right)}{\sigma\ (R_i)}\ \frac{\left(R_m - E(R_m)\right)}{\sigma(R_m)}\right)}{exp\left\{-\frac{\left(R_m - E(R_m)\right)^2}{2\sigma^2(R_m)}\right\}}\right.\right.$$

$$\left.\left. + \frac{\frac{\left(R_m - E(R_m)\right)^2}{\sigma(R_m)^2}}{exp\left\{-\frac{\left(R_m - E(R_m)\right)^2}{2\sigma^2(R_m)}\right\}}\right]\right\} \qquad (A.5)$$

By using the properties of the exponential function, the expression above can be written as

$$= \frac{1}{\sqrt{2\pi}\sigma(R_i)\sqrt{1-\rho^2}} exp\left\{-\frac{1}{2(1-\rho^2)}\left[\frac{\left(R_i - E(R_i)\right)^2}{\sigma^2(R_i)} - \frac{2\rho\left(R_i - E(R_i)\right)}{\sigma\ (R_i)}\ \frac{\left(R_m - E(R_m)\right)}{\sigma(R_m)}\right.\right.$$

$$\left.\left. + \frac{\left(R_m - E(R_m)\right)^2}{\sigma(R_m)^2} - \ (1-\rho^2)\frac{\left(R_m - E(R_m)\right)^2}{\sigma^2(R_m)}\right]\right\} \qquad (A.6)$$

Now we expand the bracket in the last term inside the exponential function to get

$$= \frac{1}{\sqrt{2\pi}\sigma(R_i)\sqrt{1-\rho^2}} exp\left\{-\frac{1}{2(1-\rho^2)}\left[\frac{\left(R_i - E(R_i)\right)^2}{\sigma^2(R_i)} - \frac{2\rho\left(R_i - E(R_i)\right)}{\sigma\ (R_i)}\ \frac{\left(R_m - E(R_m)\right)}{\sigma(R_m)}\right.\right.$$

$$\left.\left. + \frac{\left(R_m - E(R_m)\right)^2}{\sigma(R_m)^2} - \frac{\left(R_m - E(R_m)\right)^2}{\sigma^2(R_m)} + \ \rho^2\frac{\left(R_m - E(R_m)\right)^2}{\sigma^2(R_m)}\right]\right\} \qquad (A.7)$$

which equals

$$= \frac{1}{\sqrt{2\pi}\sigma(R_i)\sqrt{1-\rho^2}} exp\left\{-\frac{1}{2(1-\rho^2)}\left[\frac{\left(R_i - E(R_i)\right)^2}{\sigma^2(R_i)} - 2\rho\frac{\left(R_i - E(R_i)\right)}{\sigma\ (R_i)}\ \frac{\left(R_m - E(R_m)\right)}{\sigma(R_m)}\right.\right.$$

$$\left.\left. + \ \rho^2\frac{\left(R_m - E(R_m)\right)^2}{\sigma^2(R_m)}\right]\right\} \qquad (A.8)$$

Since the terms in the bracket inside the exponential function are nothing but the formula of the square of a sum of two terms, the expression can be restated as

$$= \frac{1}{\sqrt{2\pi}\sigma(R_i)\sqrt{1-\rho^2}} exp\left\{-\frac{1}{2(1-\rho^2)}\left[\frac{\left(R_i - E(R_i)\right)}{\sigma(R_i)} - \rho \frac{\left(R_m - E(R_m)\right)}{\sigma(R_m)}\right]^2\right\} \qquad (A.9)$$

which further can be rearranged to become the following density function of a normal distribution

$$= \frac{1}{\sqrt{2\pi}\sigma(R_i)\sqrt{1-\rho^2}} exp\left\{-\frac{1}{2(1-\rho^2)\,\sigma^2(R_i)}\left[R_i - \left(E(R_i) - \rho \frac{\sigma(R_i)}{\sigma(R_m)}\left(R_m - E(R_m)\right)\right)\right]^2\right\} \qquad (A.10)$$

From the above expression it follows that the conditional distribution of R_i given R_m, $f(R_i|R_m)$, is normal with conditional mean $E(R_i) - \rho \frac{\sigma(R_i)}{\sigma(R_m)}\left(R_m - E(R_m)\right)$ and conditional variance $(1-\rho^2)\sigma^2(R_i)$.

Since the correlation between R_i and R_m can be expressed as ,

$$\rho = \frac{cov(R_i, R_m)}{\sigma(R_i)\sigma(R_m)} \qquad (A.11)$$

the conditional mean can be restated as:

$$E(R_i|R_m) = E(R_i) - \frac{cov(R_i, R_m)}{\sigma^2(R_m)}\left(R_m - E(R_m)\right) \qquad (A.12)$$

$$E(R_i|R_m) = E(R_i) - \beta\left(R_m - E(R_m)\right) \qquad (A.13)$$

$$E(R_i|R_m) = E(R_i) - \beta\, E(R_m) + \beta R_m \qquad (A.14)$$

$$E(R_i|R_m) = \alpha + \beta R_m \qquad (A.15)$$

where

$$\beta = \frac{cov(R_i, R_m)}{\sigma^2(R_m)} \quad \text{and} \quad \alpha = E(R_i) - \beta\, E(R_m)$$

Appendix B

This appendix shows how to obtain the probability density function of the compound random variable ε_{it} for overvaluation and undervaluation models. First, rewrite equation (2) as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + v_{it} + s.u_{it} \qquad (B.1)$$

where $\varepsilon_{it} = v_{it} + s.u_{it}$ and the variable s is a sign indicator that takes the following form

$$S = \begin{cases} 1, & \text{representing overvaluation model} \\ -1, & \text{representing undervaluation model} \end{cases}$$

Since v_{it} is assumed to have a symmetric normal distribution and u_{it} is assumed to have a half-normal distribution, their density function is respectively given by

$$f(v_{it}) = \frac{1}{\sqrt{2\pi}\sigma_v} \exp\left\{-\frac{v_{it}^2}{2\sigma_v^2}\right\} \qquad (B.2)$$

$$f(u_{it}) = \frac{2}{\sqrt{2\pi}\sigma_u} \exp\left\{-\frac{u_{it}^2}{2\sigma_u^2}\right\} \qquad (B.3)$$

Now, since v_{it} and u_{it} are independent from each other, their joint density function is the product of their individual density functions

$$f(u_{it}, v_{it}) = \frac{2}{2\pi\sigma_u\,\sigma_v} \exp\left\{-\frac{u_{it}^2}{2\sigma_u^2} - \frac{v_{it}^2}{2\sigma_v^2}\right\} \qquad (B.4)$$

Because $v = \varepsilon - s.u$, the joint density function of u and ε can be restated as

$$f(u_{it}, \varepsilon_{it}) = \frac{2}{2\pi\sigma_v\,\sigma_u} \exp\left\{-\frac{u_{it}^2}{2\sigma_u^2} - \frac{(\varepsilon_{it} - s.u_{it})^2}{2\sigma_v^2}\right\} \qquad (B.5)$$

The marginal density function $f(\varepsilon_{it})$ is then obtained by integrating u out of $f(u, \varepsilon)$

$$f(\varepsilon_{it}) = \int_0^\infty f(u_{it}, \varepsilon_{it}) du \qquad (B.6)$$

The end result is

$$f(\varepsilon_{it}) = \frac{2}{\sqrt{2\pi(\sigma_u^2 + \sigma_v^2)}} \left[F\left(\frac{s.\varepsilon_{it}\left({}^{\sigma_u}/_{\sigma_v}\right)}{\sqrt{\sigma_u^2 + \sigma_v^2}} \right) \right] exp\left\{ -\frac{\varepsilon_{it}^2}{2(\sigma_u^2 + \sigma_v^2)} \right\} \qquad (B.7)$$

Appendix C

This appendix presents how to obtain the log likelihood function as in equation (4). The likelihood function of $f(\varepsilon_{it})$ for security *i* and *T* size sample is:

$$L_i = \left(\frac{2}{\sqrt{2\pi(\sigma_u^2+\sigma_v^2)}}\right)^T \prod_{t=1}^{T}\left[F\left(\frac{s.\varepsilon_{it}\left({}^{\sigma_u}/_{\sigma_v}\right)}{\sqrt{\sigma_u^2+\sigma_v^2}}\right)\right] exp\left\{-\frac{\sum_{t=1}^{T}\varepsilon_{it}^2}{2(\sigma_u^2+\sigma_v^2)}\right\} \qquad (C.1)$$

The log likelihood is

$$lnL_i = T\ln(2) - T\ ln\left(\sqrt{2\pi(\sigma_u^2+\sigma_v^2)}\right)$$

$$+\sum_{t=1}^{T} ln\left[F\left(\frac{s.\varepsilon_{it}\left({}^{\sigma_u}/_{\sigma_v}\right)}{\sqrt{\sigma_u^2+\sigma_v^2}}\right)\right] - \frac{\sum_{t=1}^{T}\varepsilon_{it}^2}{2(\sigma_u^2+\sigma_v^2)} \qquad (C.2)$$

$$lnL_i = T\ln(2) - T\ ln\sqrt{2\pi} - T\ ln\left(\sqrt{(\sigma_u^2+\sigma_v^2)}\right)$$

$$+\sum_{t=1}^{T} ln\left[F\left(\frac{s.\varepsilon_{it}\left({}^{\sigma_u}/_{\sigma_v}\right)}{\sqrt{\sigma_u^2+\sigma_v^2}}\right)\right] - \frac{\sum_{t=1}^{T}\varepsilon_{it}^2}{2(\sigma_u^2+\sigma_v^2)} \qquad (C.3)$$

$$lnL_i = T\ln\left(\frac{\sqrt{2}}{\sqrt{\pi}}\right) - T\ln\left(\sqrt{(\sigma_u^2+\sigma_v^2)}\right)$$

$$+\sum_{t=1}^{T} ln\left[F\left(\frac{s.\varepsilon_{it}\left({}^{\sigma_u}/_{\sigma_v}\right)}{\sqrt{\sigma_u^2+\sigma_v^2}}\right)\right] - \frac{\sum_{t=1}^{T}\varepsilon_{it}^2}{2(\sigma_u^2+\sigma_v^2)} \qquad (C.4)$$

$$lnL_i = \frac{T}{2}\ln\left(\frac{2}{\pi}\right) - T\ln(\sigma) + \sum_{t=1}^{T} ln\left[F\left(\frac{s.\varepsilon_{it}(\lambda)}{\sigma}\right) - \frac{1}{2}\left(\frac{\varepsilon_{it}}{\sigma}\right)^2\right] \qquad (C.5)$$

where $\sigma = \sqrt{\sigma_u^2+\sigma_v^2}$ and $\lambda = \frac{\sigma_u}{\sigma_v}$ and $F(.)$ is the cumulative standard normal distribution.