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Essays on Momentum, Autoregressive Returns, and Conditional Volatility: Evidence From the Saudi Stock Market

Abdullah Alsubaie

Old Dominion University

ESSAYS ON MOMENTUM, AUTOREGRESSIVE RETURNS, AND CONDITIONAL VOLATILITY: EVIDENCE FROM THE SAUDI STOCK MARKET

by

Abdullah Alsubaie
B.A. July 1996, King Saud University
M.B.A. May 2001 Duquesne University
M.S. August 2001 Duquesne University

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Approved by:

Dr. Mohammad Najand (Director)

Dr. Vinod Agarwal (Member)

Dr. Licheng Sun (Member)

ABSTRACT

ESSAYS ON MOMENTUM, AUTOREGRESSIVE RETURNS, AND CONDITIONAL VOLATILITY: EVIDENCE FROM THE SAUDI STOCK MARKET

Abdullah Alsubaie
Old Dominion University
Director: Dr. Mohammad Najand

The objective of this dissertation is to examine different aspects of return behavior and provide an out of sample evidence from the Saudi stock market (SSM). It consists of three essays. The first essay is organized into two parts. In the first part, I investigate the relationship between momentum profitability and trading volume in the SSM. The objective of this part is to find out whether momentum strategies exist in the SSM and whether trading volume affects momentum profitability. In the second part, I investigate whether a 52-week high price momentum profitability exists in the SSM. The empirical results document the existence of price momentum strategy in the SSM. In addition, the momentum strategy is more profitable when it is conditioned on high volume stocks than when it is conditioned on low volume stocks. High volume winner portfolio drives the momentum profit in the SSM. However, the results on the 52 week-high price indicate a reversal in portfolio returns which contradicts the results of earlier study conducted in the U.S and Australian markets.

The second essay examines the relationship between abnormal changes in trading volume of both firms and portfolio levels, and the short-term price autoregressive behavior in the SSM. The objective is to investigate the informational role that trading volume plays in predicting the direction of short-term returns. I evaluate whether the

abnormal change in lagged, contemporaneous, and lead turnover affects serial correlation in returns. Consistent with the prediction of Campbell, Grossman, and Wang (1993) model, the result of this essay indicates that lagged abnormal change in trading volume lead to reversal in consecutive weekly returns. Contemporaneous and lead changes in volume provide mixing results.

The third essay tests the effect of trading volume on the persistence of the time varying conditional volatility in the SSM. I utilize GARCH models to test the persistence of return volatility without volume, with contemporaneous volume, with lagged volume, and with two other alternative proxies of volume. This approach is applied to the market index, five industry indices, and 15 individual companies. In addition, this essay investigates the volatility spillover between size-based portfolios in the SSM using a two-stage GARCH approach. The results indicate that the SSM exhibit strong volatility persistence; however, when I include contemporaneous volume, the persistence vanishes, indicating that the rate of information arrival measured by the volume series can be a significant source of the conditional heteroskedasticity in SSM. The results show that the spillover effect is larger and statistically significant from large to small firm portfolios.

I dedicate this work to my father, my mother, my wife, and my daughter for all their love, encouragement, and support.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION AND IMPORTANCE OF THE RESEARCH

The objective of this research is to examine different aspects of return behavior and provide evidence from the Saudi stock market (SSM). It tests the empirical relationships between trading volume and intermediate-horizon momentum strategies, as well as short-term return autoregressive behavior and the time-varying conditional volatility of the SSM returns. The history of the SSM dates back to 1954, when the first public company was traded. However, organized trading did not begin until the start of 1985, when the Saudi Arabian Monetary Agency was charged with the day-to-day regulation of the market. Ever since, the market has witnessed significant developments, the last of which were the introduction of the new "Capital Market Law" and the establishment of the Capital Market Authority in 2003.

Over the last 20 years, the SSM has witnessed strong development and growth. It has become the largest market in the region and one of the fastest growing markets in the world. According to the Arab Monetary Fund's annual report for the year ending December 2005, which provides statistics for all 15 Arab stock markets, the capitalization of the SSM represents 50% of total market capitalization of all these markets, and the value traded on the SSM represents 76.9% of the total stock value traded in all these markets. The report includes the markets of all Arab countries, namely, the Abu Dhabi Securities Market, the Amman Stock Exchange, the Bahrain Stock Exchange, the Beirut Stock Exchange, the Casablanca Stock Exchange, the Doha Stock Exchange, the Dubai Financial Market, the Egyptian Capital Market, the Kuwait Stock Exchange, the Muscat

Securities Market, the Palestine Securities Exchange, the Saudi Stock Market, and the Tunis Stock Exchange. Figure 1.1 shows the relative market capitalization of these markets.

[Insert figure 1.1 here]

Moreover, the SSM has become one of the leading emerging markets. According to statistics provided by the World Federation of Exchanges (WFE) for December 2005, the SSM ranked 16th in terms of a market domestic capitalization of $650.18 billion, well ahead of the Bombay Stock Exchange, India, Taiwan, Shanghai, Singapore, and many other historically world-leading stock exchanges. The market index gained over 40% in 2005, which followed six years of growth at an average annual rate of 38%. Market volumes have also increased significantly. On average, market volume was worth over $4 billion a day in 2005 (Saudi Stock Exchange Annual Report 2005). Figure 1.2 and 1.3 show the recent increase in trading volume and market index for the SSM.

[Insert Figure 1.2 here]

[Insert Figure 1.3 here]

Even though the SSM is the largest market in the region in terms of capitalization and trading volume, academic studies on the market are lacking. Very few studies have been conducted on the SSM, possibly because acquiring the necessary data is difficult. I was able to circumvent this difficulty, however, through collecting a comprehensive dataset for this market. It is my objective to explore and pave the road for future academic research in this specific market. A distinctive aspect of this dissertation is that it examines the return behavior in the SSM over three different time horizons. The first

essay examines monthly return behavior, the second examines weekly return behavior, and the third examines daily return behavior.

Several characteristics of the SSM that differentiate it from other developed and emerging markets make it an interesting topic of study. In addition to the relatively large size of the market in the region and its strong development and growth, the behavior, structure, and size of the SSM differ in many ways from other markets. The SSM is a very large market in term of capitalization and trading volume, but with a relatively small number of 85 publicly traded companies. Relative to other markets, the breadth of this market is small while the capitalization and trading volume are relatively large; this makes it interesting to examine the effects of these specific characteristics on investors and the according return behavior. Another aspect of the SSM that differentiates it from the structure of most developed markets is the lack of an options market, which some studies have found to affect the price and volatility of the underlying market (Cornard 1989; St. Pierre 1989). In addition, even though many government-owned companies have gone public, the government still owns the majority shares of their stocks, which may impact stock market return behavior. Also, until early 2006, the SSM was inaccessible to foreigner investors except indirectly through mutual funds. But the SSM is now accessible to all investors, which indicates the ongoing process of market liberalization. These distinctive attributes of the SSM, along with the lack of academic studies on its behavior, ignited my motivation to embark upon this research.

This research is divided into three essays. The first essay is titled "Trading Volume, Price Momentum, and the 52-week High Price Momentum Strategy in the Saudi Stock Market," and is organized into two parts. In the first part, I investigate the

relationship between momentum profitability and trading volume in the SSM. The objective of this part is to find out whether momentum strategies exist in the SSM and whether trading volume affects momentum profitability. In addition, I examine whether momentum profitability is driven by loser or winner portfolios, since the existing literature is contradictory on this issue (Lee and Swaminathan 2000; Glaser and Weber 2003). In the second part, I investigate whether a 52-week high price momentum profitability exists in the SSM. In addition, I compare this to the profitability of a pure momentum strategy and momentum based on trading volume. The essay further analyzes the source of momentum profitability in the SSM. Specifically, I investigate whether less diffusion of information in the SSM lead to stronger investor underreaction and consequently higher momentum profit.

The evidence on the relationship among trading volume, the 52-week high price, and momentum strategies is mostly based on studies conducted in developed markets (Jegadeesh and Titman 1993; Chan, Jegadeesh, and Lakonishok 1996; Rouwenhorst 1996). Fewer studies have investigated this relationship in the context of developing markets (Forner and Marhuenda 2003; Kang, Liu, and Ni 2002; Griffin and Martin 2003; Chan, Hameed, and Tong 2000). Despite the obvious importance of momentum studies for academics and practitioners, the SSM lacks these types of studies. This essay adds out-of-sample evidence from the SSM to the existing literature.

This study is intended to deepen our understanding of the regularities of the SSM market, which is characterized by different structures from other developing markets. In addition, it adds to our knowledge of the sources of momentum. One explanation for the existence of momentum profit is that it is driven by investor underreaction (Jegadeesh

and Titman 1993; Chan, Jegadeesh, and Lakonishok 1996). If this explanation is true, I expect a stronger momentum effect in less transparent markets such as the SSM. Because few analysts follow the SSM, information diffusion is not as strong as in other developed markets. Therefore, I expect higher underreaction and higher momentum profitability. In addition, I examine whether the momentum profitability in SSM is driven by the winner portfolio as in Glaser and Weber (2003), or by the loser portfolio as in Lee and Swaminathan (2000). Furthermore, I compare the profitability of these three momentum strategies, as well as the 52-week high price momentum, pure price momentum, and momentum driven by trading volume; I then contrast this comparative evidence with the existing evidence in the literature.

The empirical results of this essay document the existence of price momentum strategy in the SSM. Moreover, the momentum strategy is more profitable when conditioned on high volume stocks than when it conditioned on low volume stocks. High volume winner portfolio drives the momentum profit in the SSM. However, the 52 week-high price leads to reversal in portfolio returns which contradicts the results of earlier studies conducted in the U.S and Australian markets. . Buying stocks that are near to their 52-week high price and selling stock that are far from their 52 week-high price generate negative returns in the SSM.

The second essay is titled "Abnormal Trading Volume and Autoregressive Behavior in Weekly Stock Returns in the SSM." This essay examines the relationship between abnormal changes in trading volume of both firms and portfolio levels, and the short-term price autoregressive behavior in the SSM. The objective is to investigate the

informational role that trading volume plays in predicting the direction of short-term returns. I evaluate whether the abnormal change in lagged, contemporaneous, and lead turnover affects serial correlation in returns. Specifically, I examine if and when the change in volume produces momentum (positive correlation) or reversal (negative correlation) in consecutive weekly stock returns.

The outcome of this essay will determine whether the SSM is dominated by liquidity traders or by informed traders under an environment of asymmetric information. On one hand, according to Campbell, Grossman, and Wang (1993), if the market is dominated by liquidity traders, then price changes accompanied by high volume will tend to reverse, which will not hold given low volume. On the other hand, according to Wang (1994), if the market is characterized by asymmetric information and is dominated by informed investors, stock returns will follow the direction of the trading volume. The SSM has witnessed remarkable increases in trading volume in recent years and is an ideal market to test these predictions. The results of this essay are important for practical applications, because they shed light on the short-term predictability of stock returns.

I apply the filter-rules-based methodology and analysis used by Cooper (1999) and the market-adjusted turnover-shocks methodology applied by Connolly and Stivers (2003). These two methodologies are favored because they consider not only the effects of trading volume, but also the effects of abnormal changes in trading volume on stock return behavior. The empirical tests of this essay are applied to the aggregate SSM, large- and small-cap portfolios, and individual firms using both ordinary least squares (OLS) and generalized autoregressive conditional heteroskedasticity (GARCH).

This essay adds an out-of-sample testing to the findings of previous studies on developed markets, and deepens our understanding of the connection between return dynamics and turnover shocks

Consistent with the prediction of Campbell, Grossman, and Wang (1993) model, the result of this essay indicates that lagged abnormal change in trading volume lead to reversal in consecutive weekly returns. Contemporaneous and lead change in volume provides mixing result, but, in general, they lead to returns continuation.

The third essay is titled "Trading Volume, Time Varying Conditional Volatility, and Asymmetric Volatility Spillover in the Saudi Stock Market." Volatility and trading volume are two important variables in the financial economic literature, as they provide insight into the structure of financial markets and have important implications for event studies. Although volatility modeling is an essential task in investment, security valuation, and risk management, studies examining the relationship between volatility and other variables have yet to be conducted on the SSM. This essay consists of two parts. First, it tests the effect of trading volume on the persistence of the time varying conditional volatility in the SSM. I utilize GARCH models to test the persistence of return volatility without volume, with contemporaneous volume, with lagged volume, and with two other alternative proxies of volume. This approach is applied to the market index, its five sub-indices, and 15 individual companies. Trading volume is measured primarily by the number of shares traded during the day as well as other proxies.

The second part of this essay investigates the volatility spillover between size-based portfolios in the SSM. Using a two-stage GARCH (1, 1) approach, I test the

direction of the volatility spillover between large- and small-cap portfolios to determine whether or not it is asymmetric in the SSM.

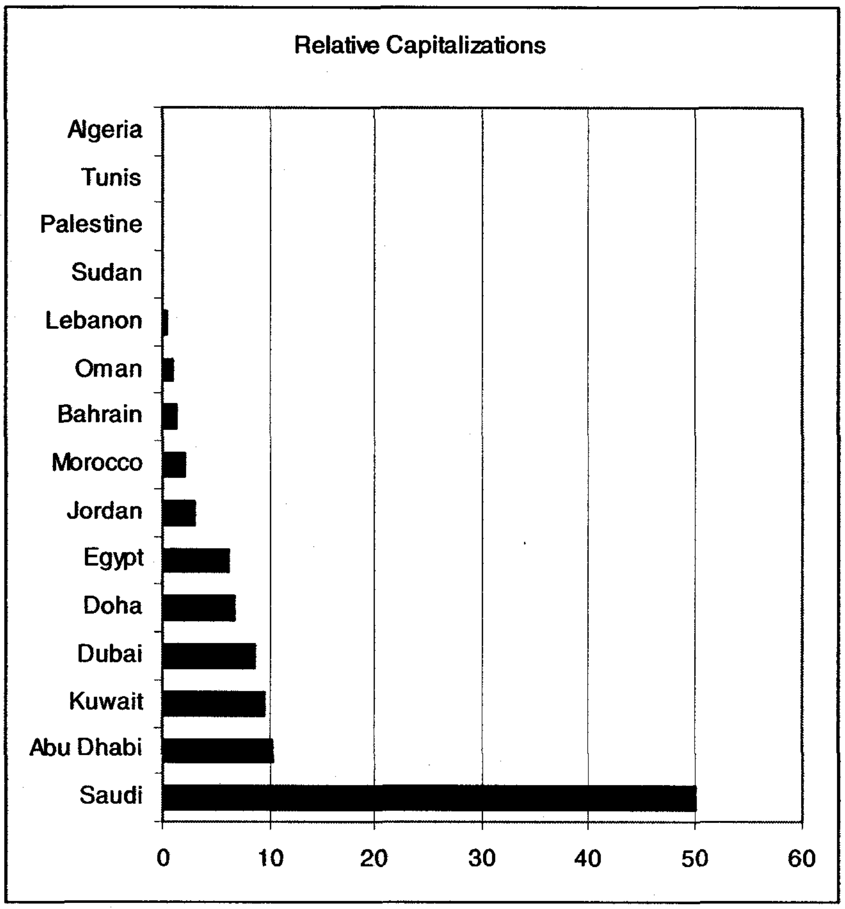
The empirical evidence for the effect of trading volume on volatility is not conclusive. Some studies have found that the GARCH effect disappears after including trading volume in the conditional variance (Lamoureux and Lastrapes 1990; Anderson 1996; Najand and Young 1991; Gallo and Pacini 2000; Foster 1995; Brailsford 1996), while others have found that the effect of trading volume on volatility persistence is weak (Sharma et al.1996; Darrat et al. 2003; Bohl and Henke 2003). Inconsistent results are also found in the literature on volatility spillover between different size portfolios. Volatility transmission is found to be asymmetric in some studies (Conard, Gultekin, and Kaul 1991; Reyes 2001) and symmetric in others (Pyuna et al. 2000). The two parts of this essay add an out-of-sample empirical test from a different market to the existing literature and deepen our understanding regarding information transmission, volatility estimation, and pricing in the SSM.

The results of this essay show that the indices and sample firms of the SSM exhibit strong volatility persistence; however, when I include contemporaneous volume for the firm level data, the persistence vanishes, indicating that the rate of information arrival measured by the volume series can be a significant source of the conditional heteroskedasticity in SSM. Lagged volume does not decrease the persistence of volatility in a significant way .These results support the mixture of distribution hypothesis (MDH) at the firm level, as contemporaneous volume largely reduces the persistence of volatility. The findings on volatility spillover indicate a clear and distinct asymmetry in volatility spillover in the Saudi market. The results show that the spillover effect is larger and

statistically significant from large to small companies. This finding indicates that the volatility of small companies can be predicted by observing the volatility of large companies. However, the volatility of large companies can not be predicted by observing the volatility of small companies.

Figure 1.1: Relative Stock Market Capitalization of All Arab Markets.

This figure shows the relative stock market capitalizations for 15 Arab stock markets.



Source: Arab Monetary Fund's annual report (2005)

Figure 1.2: Market Index Value
This figure shows the monthly market index value for period from Jnauary1993 to December 2005.

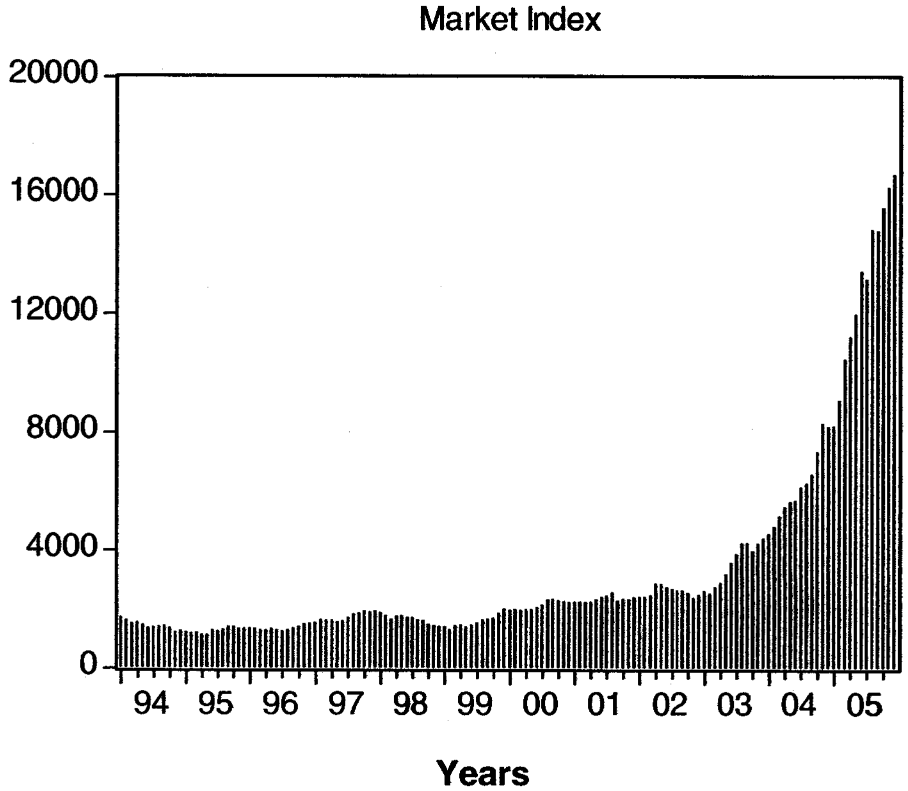
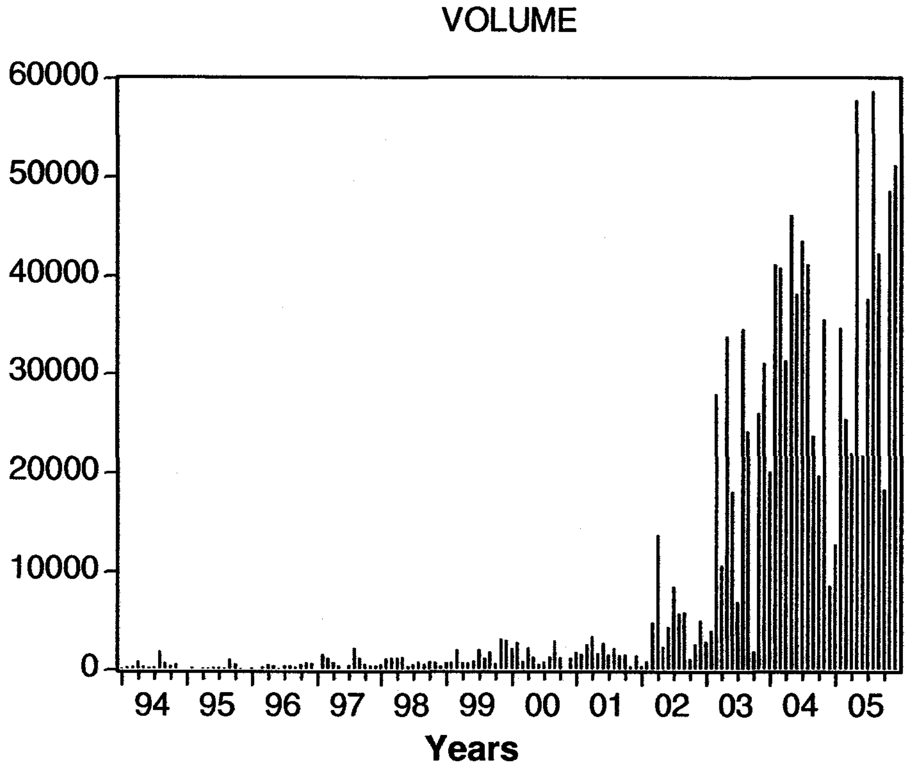


Figure 1.3: Market Trading Volume

This figure shows the monthly trading volume for the Saudi Stock Market from January 1994 to December 2005. (Trading volume numbers are in thousands)



CHAPTER II

TRADING VOLUME, PRICE MOMENTUM, AND THE 52-WEEK HIGH PRICE MOMENTUM STRATEGY IN THE SAUDI STOCK MARKET

INTRODUCTION

Ever since the seminal article of Jegadeesh and Titman (1993) documented the existence of momentum profit in the US stock market, a large literature has developed in this area of research. The authors document that buying stocks with the highest returns (winners) in the previous few months, selling stocks with the lowest returns (losers) in the previous few months, and then holding this zero-cost portfolio over intermediate horizons from 3 to 12 months yields abnormal returns. Jegadeesh and Titman (2001) reexamine momentum strategies for the US equity market and find they were persistent in the 1990s. Several other authors find "pure momentum" to be persistent in both developed countries (Chan, Jegadeesh, and Lakonishok 1996; Rouwenhorst 1996) and emerging markets (Forner and Marhuenda 2003; Kang, Liu, and Ni 2002). Griffin and Martin (2003) find that momentum profits exist in 40 countries, but that Asian and emerging markets have weaker momentum than developed markets. Chan, Hameed, and Tong (2000) find that a momentum strategy was profitable for 23 countries from 1980 to 1995.

Recent research in this area considers other factors that contribute to a stronger profitability of momentum strategies. The first part of this essay is motivated by the study of Lee and Swaminathan (2000), who introduce the role of trading volume on momentum profitability. They find that stocks with high past turnover exhibit stronger momentum than stocks with low past turnover in the US equity market, and that they even produce

higher profit than pure momentum. The first part of this essay investigates the relationship between momentum profitability and trading volume in the SSM to determine whether a momentum strategy exists in the SSM, and whether trading volume affects this profitability. Additionally, I examine whether momentum profitability is driven by loser or winner portfolios, since the existing literature is contradictory on this issue (Lee and Swaminathan 2000 in Glaser and Weber 2003).

The second part of the essay is motivated by the recent findings of George and Hwang (2004), who introduce a new momentum strategy related to one of the most readily available pieces of information to investors: the 52-week high price. They show that a strategy of purchasing stocks near their 52-week high is even more profitable than Jegadeesh and Titman's (1993) momentum strategy. In this part, I investigate whether this momentum profitability exists in the SSM. In addition, I compare the 52-week high price momentum profitability in the SSM to the profitability of both a pure momentum strategy and a momentum strategy that employs trading volume.

The evidence from the relationship between trading volume, the 52-week high, and momentum strategies is mostly based on studies conducted in developed markets. Few studies have investigated this relationship in the context of developing markets. This essay adds out-of-sample evidence from the SSM. Despite the obvious importance of momentum studies for academics and practitioners, the SSM lacks these types of studies.

This research will deepen our understanding of the regularities of the SSM market, which is characterized by a different structure and higher trading activity than other developing markets. In addition, it will add to our knowledge concerning the source of momentum. One explanation for the existence of momentum profit is that it is driven

by investor underreaction. If this explanation is valid, I expect a stronger momentum effect in less transparent markets like the SSM. Because few analysts follow the SSM, information diffusion is not as strong as in other developed markets. Therefore, we should expect higher investor underreaction and consequently higher momentum profitability.

Moreover, the literature lacks confirming evidence regarding these anomalies. In studies of price momentum and trading volume, profitability is found to be driven by the loser portfolio in the US equity market (Lee and Swaminathan 2000); however, the winner portfolio seems to drive profitability in the German market (Glaser and Weber 2003). In this essay, I examine this issue of profitability drivers in the SSM. Additionally, only two studies investigate the existence of the 52-week high momentum, one in the US market (George and Hwang 2004) and the other in the Australian market (Marshal and Cahan 2005).

The remainder of this essay includes a detailed literature review in the next section. The section that follows presents the methodology employed in this essay. Then, the data and the empirical results are discussed. The last section provides the conclusion.

LITERATURE REVIEW

The seminal article of Jegadeesh and Titman (1993) examines the momentum strategy in the US equity market from 1965 to 1989 and finds that buying the winning decile stocks, short selling the losing decile, and then holding this zero-cost portfolio for the next 3-12 months can earn significant abnormal profits. For example, the 6-month formation period produces returns of about 1% per month regardless of the holding period. Chan et al. (1996) confirm the significant profitability of intermediate-horizon price momentum strategies for the US equity market from 1977 to 1993. Jegadeesh and Titman (2001) reexamine whether momentum strategies were still profitable during the 1990s and find the evidence to be largely supportive. For example, the monthly mean return for a momentum portfolio based on a 6 x 6 strategy (formation x evaluation period) was 1.39 % from 1990 to 1998 and 1.23 % from 1965 to 1998.

Lee and Swaminathan (2000) introduce the effect of trading volume on the profitability of price momentum and document the power of the interaction between past returns and past trading volume in predicting future returns over an intermediate horizon. Using all firms listed on the NYSE and the AMEX from January 1965 through December 1995, they find that price momentum (winners-losers) is more pronounced for high volume firms than for low volume firms. For example, they find that for a 6 x 6 strategy, the price momentum return is 1.46% for the high volume firms and only 0.54 % for the low volume firms. The return difference between [(high winners-high losers) – (low winners-low losers)] is around 0.91% per month, or approximately 11% a year, and is statistically significant. On one hand, they find this 0.91% return to be mainly driven by the returns differential of loser portfolios (high volume loser-low volume loser). On the

other hand, the differential of the winner portfolio (high volume winner-low volume winner) is relatively small. In most cases, they find high volume winners to underperform low volume winners. This means that buying high volume winners does not enhance price momentum as much as selling high volume losers. This last result contradicts the findings of Glaser and Weber (2003).

Glaser and Weber (2003) investigate the relationship between trading volume and momentum for 441 large stocks listed on the Frankfurt Stock Exchange. Similar to Lee and Swaminathan (2000), they find that momentum profitability is stronger among high-turnover stocks. For example, in the 6 x 6 strategy, the price momentum (winner-loser) return is 1.16 % per month for high volume firms, and only 0.11 % per month for low volume firms. The return difference is around 01.05% per month and is statistically significant. However, contrary to Lee and Swaminathan (2000), they find that momentum profit is driven by high volume winners. For example, in the 6 x 6 strategy, the return is 1.05%, and is mainly driven by the return differential of the winner.

In other words, the price momentum with respect to trading volume is equal to ((high volume winner return) – (high volume loser return)), which can also be calculated as ((high minus low volume winner return) – (high minus low volume loser return)). In the case of Glaser and Weber (2003), momentum profit is = (0.78) – (-0.27) = 1.5%. For the same strategy in Lee and Swaminathan (2000), momentum profit is = (-012) – (-1.04) = .91%. Therefore, buying high volume winners enhances momentum profitability in Glaser and Weber (2003), while selling high losers enhances momentum profitability in Lee and Swaminathan (2000). Additionally, in Glaser and Weber (2003), high turnover

winners have higher returns than low turnover winners, while in Lee and Swaminathan (2000), high turnover winners have lower returns than low turnover winners.

Two studies analyze the effect of trading volume on momentum in a group of Asian countries. Chui, Titman, and Wei (2000) examine the momentum strategy in eight Asian countries for various time periods and find momentum profits to be higher in stocks with high turnover ratios in five of these countries. They also find that when a country-neutral momentum strategy (no specific country momentum) is employed, momentum profits are five times higher among high-turnover stocks than among low-turnover stocks. Hameed and Yunato (2001) examine the relationship between turnover and momentum profitability in six Asian countries from 1979 to 1994. They find a momentum profit for the high turnover portfolio in only two countries (Malaysia and South Korea); in the other four countries (Hong Kong, Singapore, South Taiwan, and Thailand), they find no systematic effect of turnover on price momentum.

Using a different methodology, Rouwenhorst (1999) finds that average turnover is positively related to momentum strategies in 16 out of 20 countries studied. In a similar study, Chan, Hameed, and Tong (2000) use a different proxy for volume (increase in volume for the previous period) to test the relation between trading volume and momentum strategies using several international stock market indices. They find that momentum is stronger following an increase in trading volume.

Motivated by the remarkable finding of George and Hwang (2004), I investigate the 52-week high price momentum in the SSM. George and Hwang (2004) add a new finding to the momentum literature by investigating the role of a readily available piece

of information—the 52-week price high—on momentum profitability. They examine all stocks in the Center for Research in Security Prices (CRSP) database from 1963 to 2001 and show that a strategy of purchasing stocks near their 52-week price high and selling stocks far from their 52-week price high largely explains the momentum profit and is even more profitable than Jegadeesh and Titman's (1993) momentum strategy. They find that the predictive power of the nearness of the price to the 52-week high is strong whether or not the stocks have experienced extreme past returns. They interpret this result to mean that traders use the 52-week high as a reference point against which they evaluate the potential impact of news. "When good news has pushed a stock's price near to a new 52-week price high, traders are reluctant to bid the price of the stock higher even if the information warrants it. The information eventually prevails and the price moves up, resulting in a continuation. Similarly, when bad news pushes a stock price far from its 52-week high, traders are initially unwilling to sell the stock at prices that are as low as the information implies. The information eventually prevails and the price falls" (George and Hwang 2004 p. 2146).

Marshall and Cahan (2005) apply the same test to the stocks listed on the Australian stock exchange from 1990 to 2003. Similar to George and Hwang (2004), they find that the 52-week high momentum strategy in the Australian market outperforms the price momentum of Jegadeesh and Titman (1993) and the industry momentum of Moskowitz and Grinblatt (1999). Specifically, they find that the 52-week price high strategy generates returns of 2.14% per month, as compared with 0.59% and 0.16% for the price and industry momentums, respectively.

The lack of a single theoretical explanation for the momentum anomaly has motivated numerous studies in this area of research. Several studies attempt to provide sound theoretical explanations for the source of the momentum strategy. Briefly, there are three strands of theoretical explanations. First, Jegadeesh and Titman (1993) and Chan, Jegadeesh, and Lakonishok (1996) argue that the underreaction of stock prices to information contained in past stock returns and past firm earnings gives rise to price momentum. Second, Barberis, Shleifer, and Vishny (1998), Daniel et al. (1998), and Hong and Stein (1999) develop models of investor behavior where they argue that price momentum is consistent with cognitive biases by which investors interpret imperfect information that leads to a time-series predictability of stock returns. Third, Conrad and Kaul (1998) argue that the profitability of momentum strategies is generated by cross-sectional variations in expected returns rather than by predictable time-series variations in security returns. They show that momentum strategies buy stocks with high average mean returns and sell stocks with low average mean returns. They demonstrate that these differences reflect cross-sectional variations in expected returns and risk.

Hong and Stein (1999) argue that stocks with low analyst coverage are prone to experiencing a slow diffusion of fundamental information. Based on this argument and the underreaction explanation of momentum (Chan et al. 1996), the SSM is a good candidate for testing this claim. The SSM, as a developing market, is less transparent than most developed markets and is followed by few analysts. Therefore, if these explanations are sound, I expect the SSM to experience stronger momentum than developed markets.

The SSM is characterized by a different structure and higher trading volume in recent years. It is of great importance to both academics and practitioners to investigate

these investment strategies in such a market. This essay investigates and compares the profitability of the 52-week high momentum with other momentum strategies and contrasts them with earlier empirical results. The current essay is the first study to investigate these investment strategies in the SSM and adds a new out-of-sample test to the existing literature. Moreover, I hope my results contribute to the ongoing debate on the source of momentum profitability.

METHODOLOGY

For pure momentum and momentum based on trading volume, I follow the methodology used by Jegadeesh and Titman (1993) and Lee and Swaminathan (2001). At the start of each calendar month, all stocks are sorted independently on the basis of past returns and past trading volume. Based on this sorting, stocks are then assigned to one of five portfolios based on the geometric average monthly return over the previous j months (j = 3, 6, 9, or 12), and to one of three portfolios based on the average trading turnover over the same time frame. R1 represents the portfolio with the lowest past return (loser) over the formation period, while R5 represents the portfolio with the highest past return. T1 represents the portfolio with the lowest turnover over the formation period, while T3 represents the portfolio with the highest turnover. The intersections resulting from the two independent sorting procedures result in 15 price momentum-volume portfolios for each j/k (formation/evaluation) period. In each month, winners are bought and losers are sold, and the resulting zero-cost portfolios are held for k months (k =3, 6, 9, or 12) producing returns with overlapping periods. The average buy-and-hold return is calculated for each k month.

For the 52-week high momentum strategy, I follow the methodology used by George and Hwang (2004). First I determine stocks that are near their 52-week high price. This is calculated for each stock at the end of each month using the following formula: Ratios of nearness to the 52-week high price:

$$= \frac{p_{i,t-1}}{high_{i,t-1}}$$ Where

$p_{i,t-1}$ = the closing price of the stock at the end of the month, and

$high_{i,t-1}$ = the highest price of the stock during the previous 12-month period (52-week high). The 52-week high period ends on the last day of the month.

The stocks are then ranked according to the previous ratio, starting from stocks with the highest ratio (closest to the 52-week high price) to those with the lowest ratio (furthest from the 52-week high price). The next step is to construct equally weighted portfolios where the top third of the ranked stocks represents the winner portfolio, and the bottom third represents the loser portfolio. I also use another sorting where the top fifth represents the winner portfolio and the bottom fifth represents the loser portfolio. Similar to Jegadeesh and Titman (1993), I calculate the evaluation period buy-and-hold returns. I compare this 52-week high strategy with the pure momentum strategy and a momentum strategy based on trading volume

DATA AND EMPIRICAL RESULTS

The data include all firms listed in the SSM from January 1993 through December 2005. To be included in the data, the firms must have one year of data prior to the portfolio formation data. The final sample starts with 41 firms at the first formation period and ends with 71 firms at the last formation period. For each stock, the following information is collected: daily closing prices, number of shares traded on a particular day, and number of shares outstanding at the end of that day. Trading volume is defined as the average daily turnover during the portfolio formation period, where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day. I then calculate the geometric average monthly return and average daily turnover for each stock during the *k* evaluation period (3, 6, 9, and 12 months) and calculate the buy-and-hold average monthly return for each *j* evaluation period (3, 6, 9, and 12 months).

The next section presents the results for three distinctive momentum strategies: the price momentum strategy, the volume and momentum strategy, and the 52-week price momentum strategy.

1) Results for the price momentum strategy

Table 2.1 presents the results for the price momentum strategy. At the beginning of each month, stocks are ranked and grouped into five portfolios based on their returns during the previous 3, 6, 9, and 12 month, which is called formation period *j*. I then evaluate the performance of these portfolios during the next 3 to 12 months, which is called evaluation period (*k*).The first column shows the *j* formation period for 3, 6, 9, and

12 months. The second column shows R1, R3, and R5, where R1 represents the loser portfolio with the lowest returns, R5 represents the winner portfolio with the highest returns, and R3 resents the middle portfolio. R5 – R1 represents the momentum strategy of the winner – loser portfolio. I concentrate on extreme winner R1 and extreme loser R1, and therefore show just one middle portfolio R3 for simplicity. The third column shows the geometric average monthly return during the formation period. The fifth column shows the average daily turnover during the formation period. *N* represents the average number of firms for each portfolio. The next columns represent the average monthly return during the evaluation period (*k*) for 3, 6, 9, and 12 months, respectively. All returns and turnover numbers are in percentages.

The descriptive statistics in Table 2.1 show that returns during the formation period increase with the increase in turnover for all portfolios in all formation periods. The highest (lowest) turnover is associated with the winner (loser) portfolio, which is consistent with previous studies. One distinctive observation from this table is the positive returns momentum strategy (R5 – R1) for all evaluation periods. R5 – R1 (winners – losers) is positive for all 16 strategies and statistically significant for 11 strategies. This table indicates a continuation in return during the intermediate horizon. The winner continues to perform better than the loser over the 3-to-12 month evaluation period. For example, in the *j*3/*k*3 strategy, the difference between the winner and loser portfolios is equal to 0.71% per month, or about 8.12% per year with *t*-statistics of 2.95. These results clearly indicate the existence of a price momentum strategy in the Saudi market, which is consistent with the results documented in the literature.

[Insert Table 2.1 here]

Table 2.2 shows the results for the price momentum strategy with a different sorting. I group stocks into three portfolios instead of the five shown in Table 2.1. The results of the three-portfolio sorting confirm the results of the five-portfolio sorting. The differences between R3 – R1 for all 16 strategies are positive and statistically significant. For example, in the j3/k3 strategy, the difference between the winner and loser portfolios (R3 – R1) is equal to 0.66% per month, or about 7.92% per year, with a *t*-statistic of 3.59.

[Insert Table 2.2 here]

To further examine the existence of a price momentum in the Saudi market, I split all data into two sub-periods. The first sub-period ranges from January 1993 to June 1999, and the second from July 1996 to December 2005. Table 2.3 reports the results for the first sub-period using the five portfolio ranking. The descriptive statistics show a positive relation between turnover and return during the formation period. However, the return of the formation period during the first period is lower than the return using the whole sample. The loser and middle portfolios have a negative return, which may indicate a down market during that period. The result is constant regarding the profitability of the momentum strategy. All 16 strategies are positive and statistically significant in most cases. The return for the momentum strategy in the first sub-period is stronger than that of the whole sample. For example, the return for j12k3 is equal to 0.92% per month, or about 11.04% per year, with a *t*-statistic of 3.09. This is consistent with Griffin et al. (2003), who find that momentum profit tends to be stronger during a down market.

[Insert Table 2.3 here]

Table 2.4 represents the results for the second sub-period. The return during the formation months (*j*) is higher than the return for the whole sample and first sub-sample, which may indicate a bull or up market during this period. The results of this table show a weaker momentum than the previous tables. Twelve of the 16 strategies have positive returns, while four strategies have a negative return. However, all of the four negative return strategies are statistically insignificant.

[Insert Table 2.4 here]

Overall, the results of this section document the existence of a pure momentum strategy in the SSM, which is consistent with the findings of Jegadeesh and Titman's (1990) seminal work on momentum strategy. Winner stock continues to outperform loser stocks over the following 3 to 12 months. The result doesn't indicate a higher momentum in the SSM than those found in developed market. The less diffusion of information in the SSM doesn't lead to higher than normal momentum profit.

2) Results for momentum portfolio based in price momentum and volume.

This section examines in depth the relationship between momentum strategy and volume. In addition to ranking stocks into five portfolios based on past returns as described in the previous section, I independently rank stocks into three portfolios based on past turnover during the formation period. T1 represents the portfolio with the lowest turnover over the formation period, while T3 represents the portfolio with the highest turnover. T2 represents the portfolio in the middle. The intersections resulting from the

two independent sortings of the five price-portfolio and three volume-portfolio (5 x 3 strategy) procedures results in 15 price momentum-volume portfolios. In each month, winners are bought and losers are sold, and the resulting zero-cost portfolio is held for k months (k = 3, 6, 9, or 12).

Table 2.5 shows the results of momentum strategy that is based on the intersection of five price momentum and three volume sorting (5x3). Its main finding is that momentum is stronger for high turnover stocks. The difference between the winner and loser portfolios (R5 – R1), when conditioned on high volume firms (T3), is always higher than the difference conditioned on low volume firms (T1). This indicates that buying high-volume winners and selling high-volume losers is more profitable than buying low-volume winners and selling low-volume winners. In all cases, high-volume winners minus high-volume losers are positive, while low-volume winners minus low-volume losers are negative. For example, in the *j9/k9* strategy, the high-volume winner portfolio return is 2.30% per month, while the high-volume loser portfolio is 1.46% per month. The difference equals 0.84% per month and is statistically significant at 5% level. On the other hand, for the same strategy, the *j9/k9* low-volume winner portfolio return is 1.31% per month, while the low-volume loser portfolio return is 2.12% per month. The difference is negative at 0.81% per month. The difference (R5 – R1) between the momentum strategy based on high-volume portfolio and the momentum of the low-volume portfolio in this case is 1.65% per month and is statistically significant at 1% level. This indicates that the high-volume-based momentum strategy is more profitable than the low-volume-based. T1-T3 column shows the difference between the high volume and the low volume for each portfolio. One key result from this table is that this

difference is negative for the loser portfolio (R1), and positive for the winner portfolio (R5). This can be translated to mean that for the loser portfolio, the low-volume stock has a higher return than the high-volume loser stock, while for the winner portfolio, the high-volume firms have a higher return than the low-volume firms. It can be concluded from this table that a momentum profit is driven by the return of a high-volume winner portfolio. For example, for the *j3/k3* portfolio, the difference(T3-T1) for the loser portfolio (R1) is equal to -0.05%, while it is positive of 0.94% for the winner portfolio (R5). The difference between winner and loser portfolio (R5-R1) is equal to around 1% per month.

The main result of Table 2.5 is that a high-volume-based momentum strategy is more profitable than a low-volume-based strategy, which is consistent with the findings of Lee and Swaminathan (2000) and Glaser and Weber (2003). When I examine the relation between volume and momentum in depth, my results are consistent with Glaser and Weber (2003) that momentum profit is driven by the high-volume winner portfolio (R5-R1 conditioned on TO3); at the same time, they contradict Lee and Swaminathan (2000), who find momentum to be driven by the low-volume loser portfolio.

[Insert Table 2.5 here]

The descriptive statistics for the five price/three volume portfolio strategies is shown in Table 2.6. R1 represents the loser portfolio, R3 the middle portfolio, and R5 the winner portfolio; T1 represents the lowest turnover portfolio, T3 the highest turnover portfolio, and T2 the portfolio in the middle. Return represents the geometric average

monthly return during the formation period, turnover represents the average daily turnover during the formation period, and *N* represents the average number of stocks in each portfolio. Return is measured in percentage. There is a positive relation between turnover and return for all *j* periods. The highest return is for the high-volume winner portfolio (R5/T3) with 8.16% per month in *j*3, while the lowest is for low-volume loser portfolio (R1/T3) with -5.23% per month in *j*3.

[Insert Table 2.6 here]

Table 2.7 shows the results of volume momentum using a different sorting. I rank stocks into three portfolios based on the returns during the formation period, and into three portfolios based on the turnover during the formation period. The interaction between these two sortings produces the volume momentum using a 3 price/3 volume portfolio sorting. Except for the momentum strategies in *j*3/*k*6, *j*3/*k*9, and *j*6/*k*6, out of 16 strategies, the return of the high-volume winner portfolios is greater than the return of the high-volume loser portfolios. The high-volume-based momentum (R3 – R1 conditioned on T3) is also higher than the low-volume-based-momentum (R3 – R1 conditioned on T1) in all cases except for the three strategies mentioned above. The 3 x 3 sorting still confirms the 5 x 3 strategy in Table 2.5. It also shows that when I loosen the sorting and use the less extreme one of volume, momentum becomes lower than in the strategy implementing the more extreme volume. The higher the volume sorting, the higher the momentum profit, as it shows in Table 2.4 and 2.5. The descriptive statistics for this 3 price/3 volume portfolio is shown in Table 2.8.

[Insert Table 2.7 here]

[Insert Table 2.8 here]

To further examine this issue, I use a third sorting method. I sort stocks into three portfolios according to past returns during the formation period, and into five portfolios according to the turnover during the formation period. The interaction of these two independent sortings produces 15 portfolios for each formation/evaluation (*j*/*k*) combination. The results of this sorting in Table 2.9 are consistent with and conform to the previous sorting. All momentum strategies (R3-R1) based on high trading volume are more profitable than the momentum based on low trading volume. The high-volume winner portfolio continues to perform better than the high-volume loser portfolio; it is also more profitable than the momentum based on low volume (low-volume winner minus low-volume loser.) .The descriptive statistics for this 3 price/5 volume portfolio is shown in Table 2.10.

[Insert Table 2.9 here]

[Insert Table 2.10 here]

In the following section, I examine the volume momentum strategy for two sub-sample periods. The sample is divided into two periods, the first from January 1993 to June 1999, and the second from July 1999 to December 2005. I use the 5 x 3 sorting strategy for the sub-sample tests. Table 2.11 shows the results of volume momentum for the first sub-period. The difference between the high-volume winner and the high-volume loser is not significant in all cases, and it is negative for four of the 16 strategies. In this period, the momentum based on low volume is more profitable than the strategy based on high volume. The low volume stocks perform better than the high volume stocks, which

can be seen from the negative return for most of the T3-T1 portfolios. This negative difference is more pronounced for the winner portfolio. This period is characterized by a downturn return, which may indicate that in a downturn, the high-volume portfolio performs worse than the low-volume portfolio.

[Insert Table 2.11 here]

Table 2.12 shows the results for the second sub-period. For *j*9 and *j*12, the high-volume firms perform better than the low-volume firms, just as in the whole sample, the high-volume winner performs better than the high-volume loser, which causes the momentum based on high trading volume (R5 – R3) to be positive. However, for *j*3 and *j*6, the momentum based on low trading volume is more profitable than that based on high trading volume. Therefore, the results of this table are mixed and not conclusive.

[Insert Table 2.12 here]

Overall, this section indicates that incorporating volume into a momentum strategy affects its profitability. Except for the first sub-period, the evidence indicates that momentum based on high trading volume is more profitable than momentum based than low trading volume. The results also indicate that momentum profit is driven mainly by the return of high-volume winner portfolios.

3) Results for the 52-week high price momentum strategy

For the 52-week high price momentum strategy, I follow the methodology used by George and Hwang (2004). First, I determine stocks that are near their 52-week high price. This is calculated for each stock at the end of each month using the following formula: Ratios of nearness to the 52-week high price

$$= \frac{p_{i,t-1}}{high_{i,t-1}}$$ Where

$p_{i,t-1}$ = the closing price of the stock at the end of the month.

$high_{i,t-1}$ = the highest price of the stock during the previous 12-month period (52-week high-price). The 52-week high price period ends on the last day of the month. Stocks are then ranked according to the previous ratio, going from stocks with the highest ratio (closest to the 52-week high price) to those with the lowest ratio (furthest from the 52-week high price).

Table 2.13 shows the results of the 52-week high strategy using three portfolio sorts. R1 represents the portfolio including stocks far from their 52-week high, which I label the loser portfolio, while R3 includes stocks near their 52-week high, which I label the winner portfolio. R2 is the middle portfolio. Except for the 3-month formation period, the results show that stocks far from their 52-week high price are more profitable than those near their 52-week high price. In other words, buying stocks near their 52-week high price and selling stocks far from their 52-week high price (R3 – R1) is negative and statistically significant for all evaluation periods. Buying the loser portfolio (R1) and

selling the winner portfolio (R3) would be more profitable. This result contradicts the results of George and Hwang (2004) and Marshall and Cahan (2005), who find that stocks near their 52-week high price perform better than stocks far from their 52-week high price during an evaluation period of 6 months.

[Insert Table 2.13 here]

To further examine this result, I sort stocks according to their nearness to their 52-week high price using five portfolios to see if a different sorting will affect the results. Table 2.14 shows the results of the five-portfolio sort, which confirm those of the three-portfolio sorts; the evaluation periods *k*6, *k*9 and *k*12 still have a negative return, with statistically significant results for *k*9 and *k*12.

[Insert Table 2.14 here]

I also investigate this issue by splitting my sample into two sub-periods, the first ranging from January 1993 to June 1999, and the second from July 1999 to December 2005. I use the three-portfolio sort for the sub-sample tests. Table 2.15 shows that the results for the first sub-period are opposite those of the whole sample. The difference between R3 and R1 is always positive and statistically significant. This result is consistent with George and Hwang (2004) and Marshall and Cahan (2005). As shown in the previous section, the first sub-period is characterized by a down market; therefore, we can infer that the 52-week price strategy works in our example in a down market.

[Insert Table 2.15 here]

Table 2.16 shows the results for the second sub-period, which are consistent with the results of the whole sample; the strategy of buying stocks near their 52-week high price and selling those far from it produces a negative return. The difference in the results for the first sub-period might be explained by the different behavior of investors during an up or down market.

[Insert Table 2.16 here]

Overall, and except for the first sub-period, the evidence from the whole sample with the five- and three-portfolio sorting and from the second sub-sample indicates that stocks far from their 52-week high price perform better than stocks near their 52-week high price for the 3-, 6-, 9-, and 12-months evaluation periods. These results contradict those of George and Hwang (2004) and Marshall and Cahan (2005).

CONCLUSIONS

These results document the existence of a pure momentum strategy in the SSM. Price momentum profitability in the SSM is very similar in magnitude and significance to these found in developed market. I also document that trading volume affects the profitability of a momentum strategy. Momentum with a high volume during the previous 3, 6, 9, and12 months continues to perform better in the following 3, 6, 9, and 12 months than do

stocks with a low trading volume. One explanation for the pure momentum profit is investor underreaction: stock prices rise when good news hits the market and will continue to rise after the market fully adjusts to public information. The opposite is true with bad news. The underreaction of investors lengthens this continuation of return. If this is true, I expect a market like the SSM, with less diffusion of information, to have a stronger investor underreaction and consequently momentum profit. However, the results indicate a momentum profit in the SSM that is very close to the level of profit documented in more transparent developed markets like the US, which have greater diffusion of information. The diffusion of information may not have the expected effect on investor underreaction

The results regarding volume based momentum strategy are best accounted for by the theoretical explanation of Daniel, Hirshleifer, and Subrahmanyam (1998), who argue that stocks that are more difficult to evaluate generate stronger overconfidence among investors. If stocks with a higher trading volume proxy for the disagreement among investors and for the difficulty of evaluation, then momentum caused by the self-biased overconfidence of investors should be more pronounced among high turnover stocks. My results are consistent with this prediction and show a stronger momentum among high turnover stocks. The 52-week high price result contradicts the empirical result of George and Hwang 2004 documented in the US market. My results indicate a reversal in stocks that have reached their 52-week high. George and Hwang (2004) argue that when a stock reaches it 52-week high price, investors are reluctant to bid the price higher even if the information warrants it. Thus, the information of good new prevails and stocks continue to drift. One possible explanation of the different result found SSM is that in a market

such as the SSM with less diffusion of information, stocks reaching their 52-week high price might not be attributable to good information. Stocks might reach their 52-week high price because investor speculation moves the price to their 52-week high; then, when more accurate news reaches the market, the stocks drop below their 52-week high price.

The sub-sample results indicate a different pattern of result during the first sub-period, which characterized by low returns. Future research in this area should investigate the effects of upturns and downturns in the SSM market regarding the profitability of momentum with trading volume, and with the 52-week high price.

Table 2.1: Returns of Price Momentum Portfolios Based on Five Portfolios.

This table presents the average equal-weighted monthly returns of price momentum for the SSM from January 1993 to December 2005. At the beginning of each month stocks are ranked and grouped into five equally-weighted portfolios based on their returns during the previous J months= 3, 6, 9 and 12 months. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to winner portfolio (R5). (R3) represents the middle portfolio. (R 5 – R1) represents the momentum strategy of winners minus losers. K represents the evaluation periods in months = 3, 6, 9 and 12 months. Monthly evaluation returns are computed using the average monthly buy and hold during the evaluation period. *Return* is the geometric average monthly return during the formation period. *Turnover* is the average daily turnover during the formation period .*N* represents the average number of firms for each portfolio. All return and turnover numbers are in percentages. The t-statistics are reported in parentheses.

					Monthly Returns			
J	Portfolio	*Returns*	*Turnover*	*N*	K=3	K=6	K=9	K=12
3	R1	-4.46	0.62	11.00	0.90	1.19	1.72	1.93
					(5.82)*	(8.28)*	(11.08)*	(13.11)*
	R3	0.25	0.81	11.00	1.37	1.74	1.94	2.28
					(8.69)*	(11.80)*	(14.77)*	(16.51)*
	R5	6.15	1.61	11.00	1.61	1.63	1.78	2.20
					(8.75)*	(11.27)*	(13.94)*	(16.53)*
	R5-R1				0.71	0.43	0.06	0.27
					(2.95)*	(2.12)**	(0.29)	(1.37)
6	R1	-3.19	0.44	11.00	1.01	1.48	1.73	2.12
					(6.49)*	(9.17)*	(10.92)*	(13.44)*
	R3	0.26	0.74	11.00	1.33	1.61	1.94	2.18
					(9.00)*	(11.81)*	(14.58)*	(16.45)*
	R5	4.49	1.54	11.00	1.64	1.64	1.90	2.32
					(8.89)*	(11.60)*	(14.85)*	(17.42)*
	R5-R1				0.63	0.15	0.17	0.21
					(2.62)*	(0.72)	(0.82)	(1.00)
9	R1	-2.62	0.35	11.00	1.00	1.28	1.62	2.00
					(6.30)*	(8.10)*	(10.87)*	(13.81)*
	R3	0.24	0.72	11.00	1.43	1.70	2.03	2.23
					(8.33)*	(12.37)*	(14.60)*	(16.41)*
	R5	3.72	1.49	11.00	1.58	1.69	2.01	2.51
					(8.68)*	(11.88)*	(15.06)	(17.35)
	R5-R1				0.57	0.41	0.39	0.51
					(2.38)*	(1.91)***	(1.94***)	(2.52)**
12	R1	-2.33	0.34	11.00	0.78	1.16	1.54	1.89
					(4.97)*	(8.27)*	(11.28)*	(14.20)*
	R3	0.24	0.59	11.00	1.49	1.76	2.00	2.31
					(9.16)*	(12.67)*	(14.87)*	(16.31)*
	R5	3.21	1.40	11.00	1.55	1.70	2.11	2.65
					(8.16)*	(11.61)*	(14.98)*	(16.79)*
	R5-R1				0.76	0.54	0.57	0.76
					(3.09)*	(2.67)*	(2.89)*	(3.66)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 2.2: Returns of Price Momentum Portfolios Based on Three Portfolios.

This table presents the average equal-weighted monthly returns of price momentum for the SSM from January 1993 to December 2005. At the beginning of each month stocks are ranked and grouped into three equal portfolio based on their return during the previous J months= 3, 6, 9 and 12 months. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to winner portfolio (R3). (R2) represents the middle portfolio. (R3 – R1) represents the momentum strategy of winners minus losers. K represents the evaluation periods in months = 3, 6, 9 and 12 months. Monthly evaluation returns are computed using the average monthly buy and hold during the evaluation period. *Return* is the geometric average monthly return during the formation period. *Turnover* is the average daily turnover during the formation period .*N* represents the average number of firms for each portfolio. All return and turnover numbers are in percentages. The t-statistics are reported in parentheses

					Monthly Returns			
J	**Portfolio**	***Return***	***Turnover***	***N***	**K=3**	**K=6**	**K=9**	**K=12**
3	**R1**	-3.32	0.64	18.00	0.90	1.29	1.75	1.97
					(7.62)*	(11.66)*	(15.16)*	(17.67)*
	R2	0.25	0.79	19.00	1.35	1.67	1.90	2.22
					(10.89)*	(15.19)*	(18.95)*	(21.29)*
	R3	4.64	1.40	18.00	1.56	1.61	1.79	2.28
					(11.21)*	(15.00)*	(18.47)*	(21.96)*
	R3-R1				0.66	0.32	0.03	0.31
					(3.59)*	(2.07)**	(0.23)	(2.03)**
6	**R1**	-2.23	0.49	18.00	0.96	1.44	1.71	2.07
					(7.95)*	(11.83)*	(14.92)*	(18.00)*
	R2	0.28	0.84	19.00	1.33	1.60	1.89	2.18
					(10.97)*	(15.19)*	(18.35)*	(21.16)*
	R3	3.61	1.56	18.00	1.71	1.65	1.95	2.41
					(11.77)*	(15.45)*	(19.52)*	(22.54)*
	R3-R1				0.75	0.21	0.25	0.33
					(3.96)*	(1.29)	(1.62)	(2.12)**
9	**R1**	-1.78	0.45	18.00	1.01	1.33	1.65	2.05
					(8.00)*	(11.05)*	(14.75)*	(18.55)*
	R2	0.40	0.82	18.00	1.39	1.73	2.03	2.28
					(10.61)*	(15.45)*	(18.55)*	(20.48)*
	R3	3.22	1.70	18.00	1.63	1.70	2.06	2.53
					(11.91)*	(15.91)*	(20.17)*	(23.23)*
	R3-R1				0.62	0.38	0.41	0.47
					(3.31)*	(2.34)**	(2.70)*	(3.06)*
12	**R1**	-1.46	0.44	18.00	0.97	1.31	1.69	1.99
					(7.36)*	(11.50)*	(15.46)*	(19.04)*
	R2	0.45	0.83	18.00	1.46	1.79	2.03	2.39
					(11.41)*	(15.95)*	(19.25)*	(21.79)*
	R3	2.89	1.75	18.00	1.71	1.88	2.24	2.68
					(12.17)*	(15.97)*	(19.61)*	(22.12)*
	R3-R1				0.74	0.57	0.56	0.69
					(3.82)*	(3.46)*	(3.52)*	(4.32)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 2.3: Returns of Price Momentum Portfolios from January 1993 to June 1999.
This table presents the average equal-weighted monthly returns of price momentum for the SSM from January 1993 to June 1999. At the beginning of each month stocks are ranked and grouped into five equal portfolio based on their return during the previous J months= 3, 6, 9 and 12 months. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to winner portfolio (R5). (R3) represents the middle portfolio. (R5 – R1) represents the momentum strategy of winners minus losers. K represents the evaluation periods in months = 3, 6, 9 and 12 months. Monthly evaluation returns are computed using the average monthly buy and hold during the evaluation period. *Return* is the geometric average monthly return during the formation period. *Turnover* is the average daily *turnover* during the formation period .N represents the average number of firms for each portfolio. All return and turnover numbers are in percentages. The t-statistics are reported in parentheses.

					Monthly Returns			
J	*Portfolio*	*Return*	*Turnover*	*N*	K=3	K=6	K=9	K=12
3	R1	-5.77	0.21	9	-0.82	-0.72	-0.74	-0.67
					(-4.67)*	(-5.77)*	(-7.07)*	(-7.95)*
	R3	-1.30	0.18	10	-0.74	-0.48	-0.41	-0.40
					(-4.25)*	(-3.91)*	(-3.95)*	(-4.55)*
	R5	3.38	0.23	9	-0.40	-0.25	-0.17	-0.16
					(-2.16)**	(-1.94)**	(-1.63)*	(-1.73)***
	R5-R1				0.42	0.48	0.57	0.51
					(1.66)***	(2.64)*	(3.87)*	(4.00)*
6	R1	-4.58	0.18	9	-0.90	-0.81	-0.74	-0.59
					(-4.95)*	(-6.38)*	(-6.85)*	(-6.79)*
	R3	-1.36	0.19	10	-0.54	-0.46	-0.40	-0.36
					(-3.46)*	(-3.94)*	(-4.20)*	(-4.32)*
	R5	2.13	0.23	9	-0.24	-0.18	-0.10	-0.07
					(-1.17)	(-1.35)*	(-0.93)	(-0.68)
	R5-R1				0.66	0.63	0.64	0.52
					(2.43)**	(3.45)*	(4.18)	(4.05)*
9	R1	-4.01	0.18	9	-1.10	-0.92	-0.75	-0.63
					(-6.02)*	(-7.07)*	(-6.77)	(-7.06)*
	R3	-1.28	0.20	10	-0.48	-0.45	-0.32	-0.31
					(-2.80)*	(-3.77)*	(-3.38)	(-3.75)*
	R5	1.64	0.25	9	-0.25	-0.09	-0.01	0.00
					(-1.29)	(-0.69)	(-0.09)	(0.01)
	R5-R1				0.86	0.83	0.74	0.63
					(3.22)*	(4.42)*	(4.68)	(4.72)*
12	R1	-3.63	0.19	9	-1.21	-0.96	-0.80	-0.65
					(-6.39)*	(-7.28)*	(-7.29)	(-7.24)*
	R3	-1.21	0.20	10	-0.64	-0.35	-0.29	-0.30
					(-3.71)*	(-2.76)*	(-2.90)	(-3.52)*
	R5	1.34	0.26	9	-0.29	-0.09	-0.01	-0.01
					(-1.46)	(-0.62)	(-0.10)	(-0.11)
	R5-R1				0.92	0.87	0.79	0.64
					(3.37)*	(4.57)*	(4.85)	(4.68)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 2.4: Returns of Price Momentum Portfolios from July 1999 to December 2005.

This table presents the average equal-weighted monthly returns of price momentum for the SSM from July 1999 to December 2005. At the beginning of each month stocks are ranked and grouped into five equally-weighted portfolios based on their returns during the previous J months= 3, 6, 9 and 12 months. . Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to winner portfolio (R5). (R3) resents the middle portfolio. (R5 – R1) represents the momentum strategy of winners minus losers. K represents evaluation periods in months = 3, 6, 9 and 12 months. Monthly evaluation returns are computed using the average monthly buy and hold during the evaluation period. *Return* is the geometric average monthly return during the formation period. *Turnover* is the average daily turnover during the formation period .*N* represents the average number of firms for each portfolio. All return and turnover numbers are in percentages. The t-statistics are reported in parentheses.

					Monthly Returns			
J	***Portfolio***	***Return***	***Turnover***	***N***	**K=3**	**K=6**	**K=9**	**K=12**
3	**R1**	-3.32	0.98	12	2.38	2.84	3.83	4.17
					(10.26)*	(12.36)	(15.22)	(17.57)*
	R3	1.60	1.36	13	3.21	3.66	3.99	4.62
					(13.62)*	(15.62)	(19.53)	(21.28)*
	R5	8.57	2.81	12	3.36	3.26	3.47	4.26
					(11.55)*	(14.11)	(17.09)	(20.27)*
	R5-R1				0.98	0.42	-0.36	0.09
					(2.62)*	(1.28)	(-1.11)	(0.29)
6	**R1**	-2.03	0.65	12	2.60	3.39	3.79	4.38
					(11.54)*	(13.11)	(14.91)	(17.26)*
	R3	1.62	1.21	13	2.89	3.36	3.90	4.31
					(12.96)*	(15.76)	(18.68)	(20.84)*
	R5	6.47	2.64	12	3.21	3.16	3.57	4.33
					(11.44)*	(14.28)	(18.02)	(20.90)*
	R5-R1				0.61	-0.23	-0.22	-0.05
					(1.70)**	(-0.69)	(-0.68)	(-0.14)
9	**R1**	-1.50	0.49	12	2.70	3.06	3.54	4.12
					(11.82)*	(12.33)	(15.23)	(18.37)*
	R3	1.48	1.14	13	2.98	3.44	3.94	4.29
					(11.16)*	(16.30)	(18.07)	(20.30)*
	R5	5.40	2.49	12	3.05	3.12	3.64	4.54
					(10.96)*	(14.22)	(17.70)	(20.19)*
	R5-R1				0.34	0.06	0.10	0.42
					(1.32)	(0.31)	(0.19)	(0.96)
12	**R1**	-1.30	0.45	12	2.35	2.82	3.37	3.87
					(10.52)*	(13.47)	(16.44)	(19.47)*
	R3	1.38	0.89	13	3.16	3.41	3.79	4.35
					(13.09)*	(16.22)	(18.45)	(19.87)*
	R5	4.68	2.28	12	2.98	3.10	3.77	4.72
					(10.27)*	(13.74)	(17.52)	(19.29)*
	R5-R1				0.63	0.28	0.39	0.85
					(1.73)***	(0.92)	(1.32)	(2.68)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 2.5: Returns of Portfolios Based on 5 Price Momentum and 3 Turnover Portfolios.

This table presents the average equal-weighted monthly returns of portfolios based on price momentum and turnover for the SSM from January 1993 to December 2005. At the beginning of each month stocks are ranked and grouped into five equally-weighted portfolios based on their returns during the previous J months= 3, 6, 9 and 12 months. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to loser portfolio (R1). (R3) represents the middle portfolio. (R5- R1) represents the momentum strategy of winners minus losers. Stocks are then independently sorted into three equal-weighted portfolios based on their average daily turnover during previous J months. Stocks with the lowest turnover are assigned to low volume portfolio (T1) and stocks with the highest turnover are assigned to high volume portfolio (T3). (T2) represents the middle portfolio. The intersections from the two independent sorting procedures result in 15 price momentum-volume portfolios for each J/K strategy. K represents evaluation periods in months = 3, 6, 9 and 12 months Monthly evaluations returns are computed using the average monthly buy and hold during the evaluation period. The monthly returns are reported in percentage.

J	Port.	K3 T1	K3 T2	K3 T3	K3 T3-T1	K6 T1	K6 T2	K6 T3	K6 T3-T1	K9 T1	K9 T2	K9 T3	K9 T3-T1	K12 T1	K12 T2	K12 T3	K12 T3-T1
3	R1	1.08	0.61	1.03	-0.05	1.17	0.89	1.56	0.40	1.60	1.39	2.22	0.63	1.66	1.82	2.38	0.72
		(4.70)	(2.31)	(3.24)	(-0.14)	(4.76)	(4.26)	(5.28)	(1.05)	(5.91)	(6.29)	(7.07)	(1.52)	(6.90)	(8.38)	(7.63)	(1.84)
	R3	1.06	0.95	2.16	1.10	1.50	1.31	2.44	0.94	1.79	1.76	2.31	0.52	2.16	1.98	2.74	0.58
		(5.12)	(4.22)	(5.82)	(2.64)	(7.19)	(5.90)	(7.48)	(2.47)	(8.84)	(7.79)	(8.99)	(1.60)	(9.89)	(9.50)	(9.46)	(1.61)
	R5	0.84	2.08	1.79	0.94	0.99	2.29	1.57	0.57	1.12	2.21	1.90	0.78	1.22	2.55	2.61	1.39
		(3.12)	(6.20)	(5.58)	(2.10)	(5.11)	(7.42)	(6.91)	(1.80)	(6.09)	(8.70)	(9.12)	(2.64)	(7.12)	(9.59)	(11.65)	(4.53)
	R5-R1	-0.24	1.47	0.76	1.00	-0.17	1.39	0.00	0.18	-0.48	0.82	-0.33	0.15	-0.44	0.73	0.24	0.68
		(-0.68)	(3.50)	(1.64)	(3.38)	(-0.54)	(3.80)	(0.01)	(0.72)	(-1.40)	(2.43)	(-0.90)	(0.62)	(-1.43)	(2.14)	(0.63)	(2.77)
6	R1	1.39	0.50	1.17	-0.22	1.64	1.00	1.91	0.27	1.93	1.27	2.06	0.13	2.29	1.79	2.32	0.02
		(5.82)	(2.11)	(3.45)	(-0.53)	(6.15)	(4.45)	(5.26)	(0.61)	(6.82)	(5.89)	(6.21)	(0.29)	(8.67)	(7.67)	(6.97)	(0.06)
	R3	1.37	0.76	1.90	0.53	1.59	1.03	2.28	0.69	1.86	1.50	2.51	0.66	2.04	1.97	2.58	0.54
		(7.02)	(3.17)	(5.74)	(1.43)	(8.72)	(4.66)	(7.47)	(2.00)	(9.67)	(7.31)	(8.55)	(1.92)	(10.45)	(9.15)	(9.16)	(1.61)
	R5	1.16	2.07	1.63	0.47	1.16	2.14	1.58	0.42	1.07	2.31	2.12	1.05	1.40	2.60	2.71	1.31
		(3.74)	(6.21)	(5.42)	(1.03)	(4.81)	(7.82)	(7.23)	(1.24)	(5.65)	(9.32)	(10.22)	(3.48)	(6.41)	(10.24)	(12.76)	(4.09)
	R5-R1	-0.23	1.57	0.46	0.68	-0.48	1.15	-0.33	0.15	-0.87	1.04	0.06	0.93	-0.89	0.81	0.39	1.28
		(0.59)	(3.90)	(0.99)	(2.27)	(-1.29)	(3.27)	(-0.83)	(0.54)	(-2.39)	(3.17)	(0.17)	(3.61)	(-2.50)	(2.34)	(1.04)	(4.99)
9	R1	1.63	0.57	0.84	-0.79	1.76	0.95	1.16	-0.59	2.12	1.31	1.46	-0.66	2.50	1.72	1.76	-0.74
		(6.50)	(2.23)	(2.55)	(-1.93)	(6.46)	(4.13)	(3.48)	(-1.39)	(8.10)	(5.64)	(5.03)	(-1.71)	(10.44)	(7.59)	(6.02)	(-1.99)
	R3	1.19	0.99	2.16	0.98	1.40	1.47	2.27	0.87	1.73	1.80	2.59	0.86	2.02	2.07	2.62	0.60
		(5.99)	(4.02)	(5.14)	(2.16)	(8.14)	(6.89)	(7.16)	(2.47)	(8.97)	(8.88)	(8.19)	(2.38)	(9.80)	(9.84)	(9.13)	(1.71)
	R5	1.34	1.87	1.51	0.18	1.28	1.95	1.76	0.48	1.31	2.21	2.30	0.99	1.61	2.60	3.00	1.38
		(3.89)	(6.11)	(5.18)	(0.39)	(5.05)	(8.00)	(7.52)	(1.34)	(5.79)	(9.63)	(10.33)	(2.95)	(5.84)	(10.89)	(12.88)	(3.76)
	R5-R1	-0.29	1.31	0.67	0.96	-0.48	1.00	0.59	1.07	-0.81	0.90	0.84	1.65	-0.89	0.88	1.24	2.13
		(-0.69)	(3.31)	(1.50)	(3.15)	(-1.26)	(2.97)	(1.50)	(3.94)	(-2.27)	(2.74)	(2.33)	(6.57)	(-2.44)	(2.65)	(3.32)	(8.21)
12	R1	1.50	0.26	0.65	-0.85	1.56	0.66	1.35	-0.21	2.12	0.95	1.66	-0.46	2.64	1.32	1.78	-0.86
		(6.25)	(1.08)	(1.91)	(-2.08)	(8.81)	(2.93)	(4.19)	(-0.60)	(11.82)	(4.47)	(5.23)	(-1.31)	(13.83)	(6.31)	(6.10)	(-2.52)
	R3	1.21	1.43	1.89	0.68	1.57	1.67	2.08	0.51	1.81	1.95	2.27	0.47	2.10	2.42	2.45	0.34
		(5.69)	(5.62)	(5.00)	(1.62)	(7.85)	(7.74)	(6.75)	(1.43)	(8.90)	(9.44)	(7.83)	(1.35)	(9.72)	(10.95)	(8.10)	(0.95)
	R5	1.26	1.26	1.93	0.67	1.26	1.76	1.94	0.67	1.50	2.07	2.53	1.04	1.85	2.17	3.49	1.64
		(3.80)	(4.03)	(6.00)	(1.40)	(5.02)	(7.09)	(7.84)	(1.83)	(5.71)	(8.94)	(10.93)	(2.90)	(5.64)	(9.87)	(13.54)	(3.96)
	R5-R1	-0.25	1.00	1.28	1.53	-0.30	1.10	0.59	0.89	-0.63	1.12	0.87	1.50	-0.79	0.85	1.71	2.50
		(-0.62)	(2.56)	(2.65)	(4.83)	(-0.99)	(3.26)	(1.47)	(3.48)	(-2.02)	(3.54)	(2.28)	(6.00)	(-2.17)	(2.77)	(4.33)	(9.28)

Table 2.6: Descriptive Statistics for Portfolios Based on 5 Price Momentum and 3 Turnover Portfolios.
This table presents the descriptive statistics of portfolios that are created based on the intersection five price momentum portfolios and three volume portfolios for the SSM from January 1993 to December 2005. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to loser portfolio (R1). (R3) represents the middle portfolio. Stocks with the lowest turnover are assigned to low volume portfolio (T1) and stocks with the highest turnover are assigned to high volume portfolio (T3). (T2) represents the middle portfolio. J (K) represents the formation (evaluation) periods in month = 3, 6, 9 and 12 months. Return represents the geometric average monthly returns during the formation period. Turnover represents the average daily turnovers during the formation period. N represents the average number of stocks in each portfolio. Return and turnover are reported in percentage.

			T1			T2			T3	
J	*Portfolio*	*Return*	*Volume*	*N*	*Return*	*Volume*	*N*	*Return*	*Volume*	N
3	R1	-3.74	0.055	4	-4.50	0.382	4	-5.23	1.558	3
	R3	0.13	0.052	4	0.41	0.428	4	0.22	2.047	4
	R5	3.64	0.035	3	5.71	0.454	3	8.16	3.510	5
6	R1	-2.68	0.062	4	-3.30	0.305	4	-3.67	1.071	3
	R3	0.21	0.056	4	0.32	0.441	4	0.25	1.875	3
	R5	2.73	0.037	3	4.30	0.421	3	5.71	3.254	5
9	R1	-2.02	0.065	4	-2.87	0.261	4	-3.00	0.816	3
	R3	0.21	0.062	4	0.36	0.460	4	0.15	1.710	3
	R5	2.38	0.040	3	3.71	0.405	3	4.56	3.134	5
12	R1	-1.68	0.064	4	-2.66	0.230	4	-2.63	0.787	3
	R3	0.12	0.059	4	0.49	0.478	4	0.12	1.336	3
	R5	2.06	0.042	3	3.26	0.389	3	3.92	2.964	5

Table 2.7: Returns of Portfolios Based on 3 Price Momentum and 3 Turnover Portfolios.
This table presents the average equal-weighted monthly returns of portfolio based on price momentum and turnover for the SSM from January 1993 to December 2005. At the beginning of each month stocks are ranked and grouped into three equally-weighted portfolios based on their return during the previous J months= 3, 6, 9 and 12 months. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to loser portfolio (R1). (R3) represents the middle portfolio. (R5-R1) represents the momentum strategy of winners minus losers. Stocks are then independently sorted into three equally-weighted portfolios based on their average daily turnover during previous J months. Stocks are then independently sorted into three equal weighted portfolio based on average daily turnover during previous J months. Stocks with the lowest turnover are assigned to low volume portfolio (T1) and stocks with the highest turnover are assigned to high volume portfolio (T3). (T2) resents the middle portfolio. The intersections from the two independent sorting procedures result in 15 price momentum-volume portfolios for each J/K strategy. K represents evaluation periods in months = 3, 6, 9 and 12 months Monthly evaluations returns are computed using the average monthly buy and hold during the evaluation period. The monthly returns are reported in percentage.

		K3				K6				K9				K12			
J	Port.	T1	T2	T3	T3-T1	T1	T2	T3	T3-T1	T1	T2	T3	T3-T1	T1	T2	T3	T3-T1
3	R1	1.04	0.52	1.20	0.15	1.21	0.88	1.87	0.66	1.58	1.40	2.36	0.78	1.72	1.78	2.47	0.75
		(5.99)	(2.77)	(4.67)	(0.51)	(7.04)	(5.63)	(7.50)	(2.21)	(8.26)	(8.64)	(9.45)	(2.52)	(9.33)	(10.88)	(10.55)	(2.55)
	R2	1.19	1.06	1.82	0.63	1.55	1.35	2.14	0.59	1.71	1.78	2.23	0.52	2.05	2.09	2.53	0.48
		(7.06)	(5.72)	(6.50)	(1.95)	(9.71)	(8.14)	(8.90)	(2.08)	(11.57)	(10.58)	(10.95)	(2.09)	(13.07)	(12.53)	(11.72)	(1.82)
	R3	0.93	1.78	1.88	0.95	1.15	2.08	1.58	0.43	1.33	2.02	1.95	0.62	1.59	2.43	2.70	1.11
		(4.86)	(7.18)	(7.21)	(2.82)	(7.99)	(9.51)	(8.71)	(1.80)	(9.67)	(11.10)	(11.37)	(2.72)	(10.65)	(13.00)	(14.32)	(4.45)
	R3-R1	-0.12	1.26	0.68	0.80	-0.06	1.20	-0.28	-0.22	-0.25	0.62	-0.41	-0.16	-0.13	0.65	0.22	0.36
		(-0.45)	(4.10)	(1.84)	(3.43)	(-0.26)	(4.50)	(-0.94)	(-1.16)	(-1.04)	(2.56)	(-1.40)	(-0.84)	(-0.55)	(2.65)	(0.76)	(1.83)
6	R1	1.16	0.68	1.07	-0.09	1.34	1.18	1.87	0.53	1.70	1.50	1.98	0.28	2.09	1.92	2.25	0.16
		(6.69)	(3.69)	(3.96)	(-0.29)	(7.33)	(6.91)	(6.61)	(1.61)	(8.77)	(9.01)	(8.20)	(0.93)	(11.27)	(11.06)	(9.14)	(0.53)
	R2	1.20	1.01	1.82	0.62	1.41	1.31	2.12	0.71	1.70	1.64	2.37	0.67	1.86	2.11	2.60	0.74
		(7.09)	(5.25)	(6.83)	(2.01)	(10.04)	(7.50)	(9.22)	(2.68)	(11.60)	(9.93)	(10.67)	(2.58)	(12.83)	(12.57)	(11.80)	(2.88)
	R3	1.07	1.78	2.13	1.06	1.25	1.88	1.76	0.51	1.31	2.11	2.32	1.01	1.60	2.46	2.98	1.38
		(5.02)	(7.62)	(7.70)	(2.89)	(7.18)	(9.82)	(9.64)	(1.99)	(8.41)	(12.20)	(12.94)	(4.12)	(8.88)	(13.82)	(15.93)	(5.21)
	R3-R1	-0.09	1.10	1.06	1.15	-0.09	0.70	-0.11	-0.02	-0.39	0.61	0.34	0.73	-0.49	0.54	0.73	1.22
		(-0.33)	(3.72)	(2.68)	(4.74)	(-0.36)	(2.73)	(-0.33)	(-0.07)	(-1.54)	(2.55)	(1.16)	(3.76)	(-1.90)	(2.18)	(2.41)	(6.12)
9	R1	1.20	0.74	1.14	-0.06	1.49	1.08	1.45	-0.04	1.93	1.46	1.57	-0.36	2.31	1.96	1.88	-0.42
		(6.63)	(3.84)	(3.98)	(-0.19)	(8.01)	(6.12)	(5.43)	(-0.12)	(10.13)	(8.27)	(7.21)	(-1.23)	(13.15)	(11.17)	(8.26)	(-1.49)
	R2	1.35	0.97	1.92	0.56	1.66	1.31	2.26	0.60	1.95	1.68	2.52	0.57	2.20	2.05	2.65	0.45
		(7.60)	(5.09)	(6.11)	(1.62)	(10.35)	(8.10)	(8.77)	(2.03)	(11.62)	(10.88)	(10.19)	(1.97)	(12.41)	(12.65)	(10.93)	(1.53)
	R3	1.19	1.74	1.87	0.68	1.22	1.84	1.96	0.74	1.27	2.13	2.58	1.30	1.49	2.51	3.30	1.81
		(5.36)	(7.86)	(7.53)	(1.97)	(7.08)	(9.86)	(10.44)	(2.81)	(8.46)	(12.23)	(13.91)	(5.19)	(8.80)	(14.10)	(16.82)	(6.68)
	R3-R1	-0.01	1.00	0.73	0.74	-0.27	0.76	0.51	0.78	-0.66	0.67	1.00	1.66	-0.82	0.55	1.42	2.23
		(-0.05)	(3.42)	(1.92)	(3.07)	(-1.07)	(2.94)	(1.60)	(3.77)	(-2.67)	(2.68)	(3.51)	(8.67)	(-3.34)	(2.20)	(4.71)	(11.32)
12	R1	1.43	0.53	1.04	-0.38	1.69	0.89	1.44	-0.26	2.19	1.22	1.74	-0.46	2.62	1.62	1.78	-0.85
		(7.65)	(2.77)	(3.39)	(-1.08)	(9.85)	(5.13)	(5.76)	(-0.85)	(12.57)	(7.34)	(7.56)	(-1.60)	(16.18)	(10.06)	(8.04)	(-3.11)
	R2	1.23	1.37	1.81	0.59	1.60	1.71	2.10	0.51	1.81	1.98	2.33	0.52	2.20	2.40	2.59	0.39
		(6.83)	(6.78)	(6.48)	(1.81)	(9.48)	(9.76)	(8.79)	(1.76)	(11.59)	(12.37)	(10.18)	(1.90)	(13.00)	(14.23)	(11.25)	(1.39)
	R3	1.34	1.49	2.19	0.85	1.39	1.89	2.26	0.87	1.64	2.15	2.81	1.17	1.76	2.36	3.69	1.93
		(5.97)	(6.71)	(8.26)	(2.38)	(7.57)	(9.91)	(10.23)	(2.92)	(8.28)	(12.07)	(13.52)	(4.01)	(8.28)	(13.54)	(16.49)	(6.13)
	R3-R1	-0.09	0.96	1.15	1.23	-0.30	1.00	0.82	1.12	-0.56	0.94	1.07	1.63	-0.86	0.74	1.91	2.77
		(-0.30)	(3.30)	(2.83)	(4.90)	(-1.19)	(3.88)	(2.47)	(5.33)	(-2.11)	(3.85)	(3.45)	(7.97)	(-3.23)	(3.10)	(5.98)	(13.25)

Table 2.8: Descriptive Statistics Portfolios Based on 3 Price Momentum and 3 Turnover Portfolios.

This table presents the descriptive statistics of portfolios that are created based on the intersection three price momentum portfolios and three volume portfolios for the SSM from January 1993 to December 2005. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to loser portfolio (R1). (R3) represents the middle portfolio. Stocks with the lowest turnover are assigned to low volume portfolio (T1) and stocks with the highest turnover are assigned to high volume portfolio (T3). (T2) represents the middle portfolio. J (K) represents the formation (evaluation) periods in month = 3, 6, 9 and 12 months. Return represents the geometric average monthly returns during the formation period. Turnover represents the average daily turnover during the formation period. N represents the average number of stocks in each portfolio. Return and turnover are reported in percentage

			TI			T2			T3	
J	Portfolio	Return	Volume	N	Return	Volume	N	Return	Volume	N
3	R1	-2.73	0.055	6	-3.32	0.374	7	-3.98	1.601	5
	R2	0.18	0.050	6	0.34	0.418	6	0.22	1.966	6
	R3	2.80	0.041	6	4.26	0.422	6	6.43	3.313	7
6	R1	-1.91	0.062	6	-2.44	0.344	7	-2.84	1.133	5
	R2	0.13	0.054	7	0.31	0.416	6	0.27	1.986	6
	R3	2.06	0.041	5	3.33	0.450	6	4.55	3.181	7
9	R1	-1.47	0.063	6	-2.16	0.296	7	-2.29	0.955	5
	R2	0.19	0.062	7	0.35	0.440	6	0.15	1.746	6
	R3	1.65	0.041	5	2.99	0.438	6	3.74	3.071	7
12	R1	-1.20	0.066	6	-2.02	0.275	7	-2.07	0.837	5
	R2	0.09	0.060	7	0.46	0.454	6	0.13	1.458	6
	R3	1.49	0.043	5	2.47	0.393	6	3.37	3.067	7

Table 2.9: Returns of Portfolios Based on 3 Price Momentum and 5 Turnover Portfolios.

This table presents the average equal-weighted monthly returns of portfolios based on price momentum and turnover for the SSM from January 1993 to December 2005. At the beginning of each month stocks are ranked and grouped into three equally-weighted portfolios based on their return during the previous J months= 3, 6, 9 and 12 months. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to winner portfolio (R3). (R2) represents the middle portfolio. (R3-R1) represents the momentum strategy of winners minus losers. Stocks are then independently sorted into five equally-weighted portfolios based on average daily turnover during previous J months. Stocks are then independently sorted into three equal weighted portfolio based on their average daily turnover during previous J months. Stocks with the lowest turnover are assigned to low volume portfolio (T1) and stocks with the highest turnover are assigned to high volume portfolio (T3). (T2) represents the middle portfolio. The intersections from the two independent sorting procedures result in 15 price momentum-volume portfolios for each J/K strategy. K represents evaluation periods in months = 3, 6, 9 and 12 months Monthly evaluations returns are computed using the average monthly buy and hold during the evaluation period. The monthly returns are reported in percentage.

J	Port.	K3 T1	K3 T3	K3 T5	K3 T5-T1	K6 T1	K6 T3	K6 T5	K6 T5-T1	K9 T1	K9 T3	K9 T5	K9 T5-T1	K12 T1	K12 T3	K12 T5	K12 T5-T1
3	R1	1.16	0.64	1.24	0.07	1.38	0.90	1.71	0.32	1.83	1.28	2.26	0.43	1.91	1.71	2.41	0.50
		(5.06)	(2.54)	(3.50)	(0.18)	(5.58)	(4.30)	(5.41)	(0.82)	(6.57)	(6.15)	(6.92)	(1.02)	(7.60)	(8.00)	(7.70)	(1.26)
	R2	1.10	1.00	2.42	1.32	1.17	1.43	2.53	1.37	1.27	1.93	2.36	1.10	1.49	2.15	2.53	1.03
		(5.20)	(4.50)	(5.45)	(2.81)	(7.10)	(6.66)	(6.75)	(3.49)	(8.44)	(8.69)	(7.87)	(3.39)	(10.15)	(10.25)	(8.54)	(3.26)
	R3	0.73	1.92	1.87	1.14	0.99	2.09	1.71	0.72	1.23	2.13	2.15	0.92	1.57	2.65	3.02	1.45
		(3.11)	(5.69)	(5.35)	(2.51)	(6.07)	(7.47)	(6.86)	(2.22)	(7.99)	(9.16)	(9.27)	(3.04)	(8.17)	(11.04)	(11.71)	(4.21)
	R3-R1	-0.44	1.27	0.63	1.07	-0.39	1.19	0.00	0.40	-0.60	0.85	-0.11	0.49	-0.34	0.95	0.61	0.95
		(-1.33)	(3.07)	(1.24)	(3.48)	(-1.28)	(3.45)	(0.01)	(1.57)	(-1.81)	(2.72)	(-0.29)	(1.90)	(-1.04)	(2.97)	(1.52)	(3.65)
6	R1	1.51	0.58	0.68	-0.83	1.71	1.07	1.48	-0.23	2.13	1.43	1.42	-0.71	2.40	1.81	1.54	-0.87
		(6.29)	(2.30)	(1.85)	(-1.94)	(6.08)	(4.85)	(3.76)	(-0.49)	(7.06)	(6.66)	(4.67)	(-1.63)	(8.69)	(8.68)	(5.10)	(-2.12)
	R2	1.08	1.04	2.18	1.11	1.23	1.33	2.36	1.13	1.46	1.70	2.71	1.26	1.62	2.15	2.92	1.29
		(5.88)	(4.02)	(5.59)	(2.69)	(7.73)	(5.77)	(7.39)	(3.30)	(8.52)	(7.93)	(8.51)	(3.62)	(9.10)	(9.82)	(9.18)	(3.68)
	R3	0.60	1.78	2.46	1.85	0.85	1.75	1.97	1.12	1.05	1.98	2.51	1.45	1.32	2.24	3.27	1.95
		(2.50)	(6.26)	(6.24)	(3.62)	(4.89)	(7.25)	(7.85)	(3.34)	(6.15)	(8.74)	(10.47)	(4.53)	(6.27)	(9.85)	(12.76)	(5.52)
	R3-R1	-0.91	1.19	1.77	2.68	-0.86	0.68	0.49	1.35	-1.08	0.55	1.08	2.16	-1.08	0.43	1.74	2.82
		(-2.66)	(3.14)	(3.10)	(7.97)	(-2.53)	(2.07)	(1.11)	(4.82)	(-3.01)	(1.75)	(2.80)	(8.27)	(-3.07)	(1.40)	(4.33)	(10.61)
9	R1	1.57	1.02	1.22	-0.34	1.88	1.20	1.37	-0.51	2.33	1.49	1.21	-1.12	2.66	1.94	1.32	-1.34
		(6.19)	(3.78)	(3.05)	(-0.75)	(6.77)	(5.10)	(3.66)	(-1.12)	(8.23)	(6.63)	(4.20)	(-2.75)	(10.93)	(9.00)	(4.41)	(-3.52)
	R2	1.34	0.78	2.22	0.88	1.47	1.30	2.27	0.80	1.67	1.70	2.58	0.91	1.82	2.03	2.71	0.89
		(5.49)	(3.29)	(4.88)	(1.76)	(7.06)	(6.13)	(6.62)	(2.04)	(7.14)	(8.30)	(7.84)	(2.30)	(7.19)	(9.49)	(8.20)	(2.16)
	R3	0.75	1.61	2.06	1.31	0.89	1.85	2.26	1.37	1.01	2.13	2.85	1.84	1.18	2.27	3.70	2.52
		(3.37)	(6.28)	(6.13)	(2.98)	(5.29)	(7.29)	(8.76)	(4.09)	(6.99)	(8.68)	(11.31)	(5.73)	(8.58)	(9.80)	(14.07)	(7.58)
	R3-R1	-0.82	0.59	0.84	1.65	-1.00	0.64	0.89	1.89	-1.32	0.64	1.64	2.96	-1.48	0.33	2.38	3.86
		(-2.41)	(1.57)	(1.58)	(5.26)	(-3.02)	(1.85)	(2.01)	(6.88)	(-4.07)	(1.91)	(4.19)	(11.75)	(-5.18)	(1.05)	(5.83)	(15.55)
12	R1	1.65	0.88	0.82	-0.83	1.92	1.10	0.93	-0.99	2.37	1.32	1.14	-1.24	2.67	1.82	0.96	-1.72
		(6.80)	(3.36)	(1.78)	(-1.70)	(8.25)	(5.03)	(2.92)	(-2.56)	(9.86)	(6.26)	(4.07)	(-3.36)	(13.14)	(8.87)	(3.61)	(-5.23)
	R2	0.93	1.33	2.42	1.49	1.28	1.80	2.49	1.21	1.44	2.08	2.68	1.24	1.76	2.51	2.81	1.04
		(3.74)	(5.36)	(5.81)	(3.11)	(5.37)	(7.98)	(7.12)	(2.90)	(6.57)	(9.75)	(8.20)	(3.18)	(7.54)	(11.21)	(8.38)	(2.58)
	R3	1.18	1.53	2.31	1.14	1.35	2.04	2.59	1.24	1.56	2.31	3.19	1.63	1.74	2.41	4.17	2.43
		(4.68)	(5.37)	(6.60)	(2.45)	(6.43)	(7.73)	(8.72)	(-2.29)	(6.91)	(9.20)	(11.60)	(4.36)	(6.87)	(10.01)	(14.21)	(5.99)
	R3-R1	-0.47	0.65	1.50	1.97	-0.58	0.94	1.65	2.23	-0.82	1.00	2.05	2.87	-0.93	0.59	3.21	4.14
		(-1.35)	(1.69)	(2.60)	(5.91)	(-1.83)	(2.75)	(3.62)	(8.13)	(-2.47)	(3.06)	(4.94)	(10.95)	(-2.89)	(1.88)	(7.47)	(15.60)

Table 2.10: Descriptive Statistics Portfolios Based on 3 Price Momentum and 3 Turnover Portfolios

This table presents the descriptive statistics for portfolios based that are created based on intersection three price momentum portfolios and three volume portfolios for the SSM from January 1993 to December 2005.Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to winner portfolio (R3). (R2) represents the middle portfolio. Stocks with the lowest turnover are assigned to low volume portfolio (T1) and stocks with the highest turnover are assigned to high volume portfolio (T3). (T2) represents the middle portfolio. J (K) represents the formation (evaluation) periods in month = 3, 6, 9 and 12 months. Return represents the geometric average monthly returns during the formation period. Turnover represents the average daily turnover during the formation period. N represents the average number of stocks in each portfolio. Return and turnover are reported in percentage

			T1			T3			T5	
J	*Portfolio*	*Return*	*Volume*	*N*	*Return*	*Volume*	*N*	*Return*	*Volume*	N
3	R1	-2.93	0.030	4	-3.48	0.335	4	-4.04	2.014	3
	R2	0.14	0.026	4	0.36	0.420	4	-0.02	2.473	4
	R3	2.85	0.024	3	4.31	0.412	3	6.93	4.449	4
6	R1	-2.00	0.037	4	-2.54	0.330	4	-2.86	1.189	3
	R2	0.00	0.030	4	0.43	0.421	4	0.22	2.586	3
	R3	2.00	0.024	3	3.36	0.399	3	4.80	4.244	4
9	R1	-1.48	0.041	3	-2.11	0.308	4	-2.41	0.99	3
	R2	-2.41	0.992	4	0.06	0.031	4	0.22	2.197	3
	R3	1.56	0.024	3	2.80	0.386	3	3.94	4.083	4
12	R1	-1.20	0.042	3	-1.99	0.275	4	-2.07	0.911	3
	R2	-0.01	0.030	3	0.53	0.414	3	0.19	1.804	3
	R3	1.32	0.025	3	2.27	0.337	3	3.34	3.886	4

Table 2.11: Returns of Portfolios Based on Price Momentum and Turnover from January 1993 to June 1999.
This table presents the average equal-weighted monthly returns for portfolio based on price momentum and turnover for the SSM from January 1993 to June 1999. At the beginning of each month stocks are ranked and grouped into five equally-weighted portfolios based on their returns during the previous J months= 3, 6, 9 and 12 months. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to loser portfolio (R1). (R3) represents the middle portfolio. (R5 – R1) represents the momentum strategy of winners minus losers. Stocks are then independently sorted into three equal weighted portfolio based on their average daily turnover during previous J months. Stocks with the lowest turnover are assigned to low volume portfolio (T1) and stocks with the highest turnover are assigned to high volume portfolio (T3). (T2) resents the middle portfolio. The intersections from the two independent sorting procedures result in 15 price momentum-volume portfolios for each J/K strategy. K represents evaluation periods in months = 3, 6, 9 and 12 months Monthly evaluations returns are computed using the average monthly buy and hold during the evaluation period. The monthly returns are reported in percentage.

		K3				K6				K9				K12			
J	Port.	T1	T2	T3	T3-T1	T1	T2	T3	T3-T1	T1	T2	T3	T3-T1	T1	T2	T3	T3-T1
3	R1	-0.40	-1.17	-0.82	-0.42	-0.62	-0.78	-0.76	-0.14	-0.64	-0.80	-0.75	-0.12	-0.62	-0.59	-0.81	-0.19
		(-1.33)	(-4.44)	(-2.36)	(-0.91)	(-3.05)	(-3.48)	(-3.45)	(-0.46)	(-3.65)	(-4.19)	(-4.45)	(-0.48)	(-4.38)	(-4.01)	(-5.47)	(-0.95)
	R3	-0.60	-0.88	-0.76	-0.16	-0.31	-0.68	-0.45	-0.14	-0.10	-0.54	-0.60	-0.50	-0.06	-0.55	-0.61	-0.55
		(-2.22)	(-3.38)	(-2.09)	(-0.35)	(-1.51)	(-3.37)	(-2.02)	(-0.46)	(-0.50)	(-2.87)	(-3.86)	(-2.01)	(-0.35)	(-3.45)	(-4.42)	(-2.61)
	R5	-0.44	0.15	-0.83	-0.39	0.00	0.04	-0.76	-0.76	0.07	0.10	-0.64	-0.72	0.19	0.09	-0.75	-0.94
		(-1.66)	(0.45)	(-2.36)	(-0.89)	(0.02)	(0.17)	(-3.38)	(-2.59)	(0.42)	(0.51)	(-3.89)	(-2.98)	(1.17)	(0.48)	(-5.72)	(-4.45)
	R5-R1	-0.04	1.33	0.00	0.03	0.63	0.82	0.00	-0.62	0.71	0.91	0.11	-0.80	0.81	0.68	0.07	-0.75
		(-0.09)	(3.11)	(-0.01)	(0.10)	(2.24)	(2.42)	(0.01)	(-2.95)	(2.85)	(3.26)	(0.46)	(-3.51)	(3.66)	(2.87)	(0.34)	(-5.03)
6	R1	-0.77	-1.16	-0.70	0.07	-0.82	-0.97	-0.60	0.22	-0.77	-0.85	-0.59	0.17	-0.64	-0.52	-0.63	0.01
		(-2.18)	(-4.54)	(-1.97)	(0.13)	(-3.75)	(-4.77)	(-2.59)	(0.67)	(-4.13)	(-4.52)	(-3.28)	(0.67)	(-4.19)	(-3.59)	(-4.18)	(0.04)
	R3	-0.15	-0.92	-0.54	-0.39	-0.06	-0.86	-0.46	-0.39	0.02	-0.67	-0.53	-0.55	0.12	-0.60	-0.59	-0.71
		(-0.63)	(-3.61)	(-1.71)	(-0.98)	(-0.31)	(-4.66)	(-2.08)	(-1.30)	(0.13)	(-4.38)	(-3.61)	(-2.34)	(0.80)	(-4.43)	(-4.12)	(-3.43)
	R5	0.32	-0.19	-0.87	-1.19	0.27	0.10	-0.89	-1.16	0.21	0.27	-0.76	-0.97	0.29	0.30	-0.76	-1.05
		(0.96)	(-0.61)	(-2.22)	(-2.32)	(1.22)	(0.43)	(-3.92)	(-3.65)	(1.13)	(1.29)	(-4.83)	(-3.97)	(1.73)	(1.55)	(-6.09)	(-5.03)
	R5-R1	1.09	0.97	-0.17	-1.26	1.09	1.06	-0.29	-1.38	0.97	1.12	-0.17	-1.14	0.92	0.83	-0.13	-1.06
		(2.21)	(2.42)	(-0.31)	(-3.47)	(3.40)	(3.51)	(-0.89)	(-6.07)	(3.63)	(3.95)	(-0.70)	(-6.41)	(3.97)	(3.46)	(-0.69)	(-7.06)
9	R1	-0.79	-1.32	-1.05	-0.25	-1.01	-0.85	-0.95	0.06	-0.83	-0.73	-0.74	0.09	-0.62	-0.51	-0.79	-0.17
		(-2.41)	(-5.01)	(-2.86)	(-0.49)	(-4.02)	(-4.11)	(-4.24)	(0.18)	(-4.21)	(-3.81)	(-4.12)	(0.35)	(-4.12)	(-3.40)	(-5.27)	(-0.76)
	R3	0.21	-0.90	-0.78	-0.99	0.03	-0.50	-0.86	-0.89	0.19	-0.36	-0.80	-0.99	0.22	-0.46	-0.70	-0.92
		(0.85)	(-3.12)	(-2.32)	(-2.36)	(0.15)	(-2.52)	(-4.42)	(-3.09)	(1.06)	(-2.21)	(-5.41)	(-4.27)	(1.43)	(-3.36)	(-5.41)	(-4.57)
	R5	0.50	-0.32	-0.97	-1.47	0.55	0.02	-0.86	-1.42	0.48	0.21	-0.70	-1.18	0.41	0.18	-0.57	-0.98
		(1.44)	(-1.05)	(-2.96)	(-3.07)	(2.34)	(0.08)	(-4.22)	(-4.51)	(2.38)	(0.92)	(-4.42)	(-4.58)	(2.50)	(0.95)	(-3.49)	(-4.23)
	R5-R1	1.29	1.00	0.08	-1.21	1.56	0.87	0.08	-1.47	1.31	0.93	0.04	-1.27	1.03	0.69	0.22	-0.81
		(2.55)	(2.45)	(0.17)	(-3.47)	(4.37)	(2.69)	(0.28)	(-6.43)	(4.42)	(3.15)	(0.15)	(-6.85)	(4.35)	(2.89)	(0.98)	(-5.05)
12	R1	-0.86	-1.10	-1.60	-0.74	-1.05	-0.88	-1.02	0.03	-0.73	-0.80	-0.85	-0.12	-0.50	-0.60	-0.82	-0.31
		(-2.18)	(-3.89)	(-4.78)	(-1.42)	(-4.16)	(-4.09)	(-4.66)	(0.09)	(-3.96)	(-4.09)	(-5.28)	(-0.48)	(-3.35)	(-3.93)	(-5.61)	(-1.46)
	R3	-0.23	-0.84	-0.91	-0.68	0.08	-0.44	-0.73	-0.81	0.16	-0.36	-0.73	-0.89	0.23	-0.38	-0.80	-1.03
		(-0.79)	(-2.61)	(-3.21)	(-1.68)	(0.38)	(-1.82)	(-3.55)	(-2.78)	(0.89)	(-1.87)	(-4.96)	(-3.81)	(1.58)	(-2.42)	(-6.58)	(-5.36)
	R5	0.49	-0.40	-1.05	-1.55	0.60	0.10	-0.99	-1.59	0.52	0.21	-0.77	-1.30	0.37	0.29	-0.68	-1.05
		(1.44)	(-1.13)	(-3.28)	(-3.28)	(2.47)	(0.38)	(-4.85)	(-4.96)	(2.70)	(0.89)	(-4.05)	(-4.75)	(2.30)	(1.34)	(-4.43)	(-4.70)
	R5- R1	1.36	0.70	0.55	-0.81	1.65	0.97	0.03	-1.62	1.25	1.00	0.08	-1.18	0.87	0.89	0.14	-0.73
		(2.51)	(1.57)	(1.18)	(-2.33)	(4.45)	(2.88)	(0.10)	(-7.00)	(4.33)	(3.28)	(0.31)	(-6.28)	(3.65)	(3.45)	(0.67)	(-4.69)

Table 2.12: Returns of Portfolios Based on Price Momentum and Turnover from July 1999 to December 2005.

This table presents the average equal-weighted monthly returns for portfolio based on price momentum and turnover for the SSM from July1999 to December 2005. At the beginning of each month stocks are ranked and grouped into five equally-weighted portfolios based on their returns during the previous J months= 3, 6, 9 and 12 months. Stocks with the lowest returns are assigned to loser portfolio (R1) and stocks with the highest returns are assigned to loser portfolio (R1). (R3) represents the middle portfolio. (R5-R1) represents the momentum strategy of winners minus losers. Stocks are then independently sorted into three equal weighted portfolio based on their average daily turnover during previous J months. Stocks with the lowest turnover are assigned to low volume portfolio (T1) and stocks with the highest turnover are assigned to high volume portfolio (T3). (T2) represents the middle portfolio. The intersections from the two independent sorting procedures would result in 15 price momentum-volume portfolios for each J/K strategy. K represents evaluation periods in months = 3, 6, 9 and 12 months Monthly evaluations returns are computed using the average monthly buy and hold during the evaluation period. The monthly returns are reported in percentage.

J	Port.	K3 T1	K3 T2	K3 T3	K3 T3-T1	K6 T1	K6 T2	K6 T3	K6 T3-T1	K9 T1	K9 T2	K9 T3	K9 T3-T1	K12 T1	K12 T2	K12 T3	K12 T3-T1
3	R1	2.07	2.32	2.90	0.83	2.36	2.50	3.91	1.55	3.09	3.51	5.23	2.14	3.18	4.14	5.59	2.41
		(6.58)	(5.50)	(5.78)	(1.47)	(6.38)	(7.75)	(7.72)	(2.53)	(7.43)	(10.10)	(9.68)	(3.19)	(8.70)	(11.92)	(10.61)	(3.88)
	R3	2.43	2.42	5.08	2.65	2.99	2.91	5.34	2.35	3.33	3.61	5.21	1.88	3.98	4.02	6.09	2.11
		(8.54)	(7.49)	(8.53)	(4.24)	(9.46)	(8.64)	(9.59)	(3.83)	(10.95)	(10.56)	(12.55)	(3.72)	(11.63)	(13.18)	(12.75)	(3.67)
	R5	2.75	3.63	3.45	0.70	2.47	4.10	3.04	0.58	2.68	3.92	3.52	0.84	2.75	4.54	4.75	2.00
		(5.37)	(7.01)	(7.60)	(0.91)	(6.77)	(8.37)	(9.49)	(1.07)	(7.77)	(9.77)	(11.87)	(1.67)	(8.74)	(10.91)	(15.21)	(3.89)
	R5-R1	0.68	1.32	0.55	-0.13	0.11	1.60	-0.86	-0.97	-0.41	0.41	-1.71	-1.30	-0.43	0.40	-0.84	-0.41
		(1.20)	(1.98)	(0.78)	(-0.28)	(0.19)	(2.74)	(-1.51)	(-2.47)	(-0.66)	(0.78)	(-3.02)	(-3.22)	(-0.79)	(0.74)	(-1.47)	(-1.06)
6	R1	2.53	2.17	3.30	0.77	2.94	2.96	4.76	1.82	3.36	3.39	5.07	1.71	3.84	4.10	5.66	1.82
		(8.56)	(5.76)	(5.83)	(1.33)	(7.91)	(8.19)	(7.07)	(2.57)	(8.38)	(9.90)	(8.30)	(2.43)	(10.40)	(10.37)	(9.34)	(2.71)
	R3	2.48	2.23	4.18	1.70	2.80	2.69	4.84	2.04	3.20	3.41	5.36	2.16	3.44	4.22	5.53	2.09
		(9.10)	(6.05)	(7.90)	(3.05)	(10.89)	(7.61)	(9.63)	(3.85)	(11.37)	(10.69)	(11.00)	(4.05)	(11.62)	(12.73)	(12.23)	(4.02)
	R5	2.45	4.01	3.04	0.58	2.53	3.90	2.97	0.43	2.39	4.05	3.74	1.35	3.12	4.57	4.66	1.54
		(4.20)	(7.63)	(7.59)	(0.79)	(5.18)	(8.83)	(10.06)	(0.77)	(6.59)	(10.43)	(13.25)	(2.66)	(6.75)	(11.44)	(16.56)	(2.87)
	R5-R1	-0.08	1.84	-0.27	-0.19	-0.40	0.94	-1.79	-1.39	-0.97	0.66	-1.33	-0.36	-0.73	0.46	-1.00	-0.27
		(-0.13)	(2.89)	(-0.38)	(-0.43)	(-0.63)	(1.66)	(-2.84)	(-3.28)	(-1.53)	(1.29)	(-2.26)	(-0.88)	(-1.16)	(0.82)	(-1.72)	(-0.68)
9	R1	2.75	2.50	2.91	0.16	3.04	2.79	3.47	0.43	3.49	3.39	3.85	0.36	3.95	4.01	4.54	0.59
		(8.75)	(6.16)	(5.56)	(0.27)	(8.46)	(7.31)	(5.65)	(0.65)	(10.06)	(8.77)	(7.39)	(0.60)	(12.63)	(10.39)	(8.74)	(1.04)
	R3	1.93	2.41	4.90	2.97	2.44	2.96	5.18	2.73	2.91	3.42	5.76	2.85	3.41	3.98	5.71	2.30
		(6.80)	(6.85)	(6.92)	(4.14)	(10.28)	(9.39)	(9.97)	(5.06)	(9.90)	(11.42)	(11.06)	(4.96)	(10.54)	(12.83)	(12.37)	(4.18)
	R5	2.65	3.52	2.90	0.25	2.42	3.39	3.22	0.80	2.62	3.72	3.98	1.35	3.51	4.42	4.99	1.48
		(3.88)	(7.69)	(7.22)	(0.32)	(4.63)	(9.51)	(9.95)	(1.30)	(5.56)	(11.08)	(13.02)	(2.35)	(5.53)	(12.53)	(16.12)	(2.32)
	R5-R1	-0.10	1.02	-0.01	0.09	-0.62	0.60	-0.25	0.37	-0.87	0.33	0.12	0.99	-0.45	0.41	0.44	0.89
		(-0.15)	(1.68)	(-0.01)	(0.20)	(-0.98)	(1.15)	(-0.40)	(0.88)	(-1.44)	(0.64)	(0.21)	(2.55)	(-0.71)	(0.78)	(0.77)	(2.23)
12	R1	2.52	1.70	2.88	0.36	2.68	2.29	3.69	1.01	3.35	2.80	4.14	0.79	3.99	3.36	4.35	0.36
		(9.00)	(4.43)	(5.26)	(0.64)	(13.51)	(5.99)	(6.64)	(1.98)	(16.00)	(7.97)	(7.42)	(1.53)	(17.66)	(9.36)	(8.69)	(0.73)
	R3	2.34	2.99	4.42	2.08	2.74	3.11	4.62	1.88	3.09	3.53	4.99	1.89	3.57	4.33	5.38	1.81
		(8.09)	(8.84)	(7.03)	(3.23)	(9.04)	(10.59)	(9.20)	(3.35)	(9.84)	(12.31)	(10.58)	(3.46)	(10.31)	(14.08)	(10.94)	(3.10)
	R5	2.40	2.43	3.55	1.15	2.26	2.94	3.53	1.27	2.96	3.38	4.33	1.37	4.06	3.50	5.75	1.69
		(3.77)	(5.29)	(8.00)	(1.42)	(4.48)	(8.06)	(10.40)	(2.02)	(5.20)	(10.11)	(14.15)	(2.27)	(5.42)	(11.06)	(17.05)	(2.37)
	R5-R1	-0.12	0.73	0.67	0.79	-0.42	0.65	-0.16	0.26	-0.39	0.58	0.19	0.58	0.07	0.15	1.40	1.33
		(-0.20)	(1.22)	(0.92)	(1.66)	(-0.93)	(1.23)	(-0.26)	(0.67)	(-0.78)	(1.20)	(0.32)	(1.50)	(0.12)	(0.31)	(2.38)	(3.15)

Table 2.13: Returns of Momentum Portfolios Based on 52 Week-High Price Based on 3 Portfolios.

This table presents the average equal-weighted monthly returns of portfolios that are created based on 52 week-high price for all the firms in the SSM during the period from January 1993 to December 2005. At the beginning of each month stocks are sorted into three equally-weighted portfolios according to the ratio of the current price to its 52 week high. Stocks with the lowest ratio (furthest from the 52-week high price) are assigned to the loser portfolio (R1). Stocks with the highest ratio (closest to the 52-week high price) are assigned to the winner portfolio (R3). (R3-R1) represents the 52 week-high price momentum strategy of winner –loser portfolio. K represents monthly evaluation periods (J = 3, 6, 9 and 12 months). Monthly evaluation returns are computed using the average monthly buy and hold during the evaluation period. The t-statistics are reported in parentheses. The monthly returns are reported in percentage.

		Monthly Returns			
J	**Portfolio**	**K=3**	**K=6**	**K=9**	**K=12**
52 Week-High Price	**R1**	1.37	1.65	2.16	2.62
		(8.95)*	(12.37)*	(16.22)*	(18.92)*
	R2	1.36	1.73	2.04	2.42
		(10.44)*	(15.28)*	(19.13)*	(22.26)*
	R3	1.42	1.62	1.75	2.00
		(12.49)*	(17.23)*	(21.06)*	(24.57)*
	R3-R1	0.050	-0.031	-0.407	-0.624
		(0.26)	(-0.19)	(-2.61)*	(-3.90)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 2.14: Returns of Momentum Portfolios Based on 52 Week-High Price Based on 5 Portfolios.

This table presents the average equal-weighted monthly returns of portfolios that are created based on 52 week-high price for all the firms in the SSM during the period from January 1993 to December 2005. At the beginning of each month stocks are ranked to five equally-weighted portfolios according to the ratio of the current price to its 52 week high. Stocks with the lowest ratio (furthest from the 52-week high price) are assigned to the loser portfolio (R1). Stocks with the highest ratio (closest to the 52-week high price) are assigned to the winner portfolio (R5). (R5-R1) represents the 52 week momentum strategy of winner –loser portfolio. K represents monthly evaluation period = 3, 6, 9 and 12 months. Monthly evaluation return is computed using the average monthly buy and hold during the evaluation period. The t-statistics are reported in parentheses. The monthly returns are reported in percentage.

		Monthly Returns			
J	**Portfolio**	**K=3**	**K=6**	**K=9**	**K=12**
52 Week-High Price	**R1**	1.30	1.61	2.16	2.63
		(6.79)*	(9.10)*	(11.92)*	(13.95)*
	R2	1.36	1.71	2.11	2.56
		(7.11)*	(10.34)*	(13.86)*	(16.31)*
	R3	1.36	1.71	2.05	2.44
		(8.21)*	(11.77)*	(14.42)*	(16.70)*
	R4	1.58	1.83	1.90	2.12
		(10.05)*	(14.44)*	(16.91)*	(19.43)*
	R5	1.30	1.48	1.69	2.00
		(8.89)*	(12.58)*	(16.15)*	(18.81)*
	R5-R1	0.0008	-0.126	-0.464	-0.635
		(0.00)	(-0.59)	(-2.23)**	(-2.94)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 2.15: Returns of Momentum Portfolios Based on 52 Week-High Price from January 1993 to June 1999.

This table presents the average equal-weighted monthly returns from portfolios that are created based on 52 week-high price for all the firms in the SSM during the period January 1993 to June 1999. At the beginning of each month stocks are ranked to three equally-weighted portfolios according to the ratio of the current price to its 52 week high. Stocks with the lowest ratio (furthest from the 52-week high price) are assigned to the loser portfolio (R1). Stocks with the highest ratio (closest to the 52-week high price) are assigned to the winner portfolio (R5). (R3-R1) represents the 52 week momentum strategy of winner –loser portfolio. K represents monthly evaluation period = 3, 6, 9 and 12 months. Monthly evaluation return is computed using the average monthly buy and hold during the evaluation period. The t-statistics are reported in parentheses. The monthly returns are reported in percentage.

			Monthly Returns		
J	**Portfolio**	**K=3**	**K=6**	**K=9**	**K=12**
52 Week-High Price	**R1**	-1.00	-0.84	-0.69	-0.61
		(-6.89)*	(-8.70)*	(-8.97)*	(-9.10)*
	R2	-0.79	-0.46	-0.40	-0.37
		(-6.04)*	(-4.96)*	(-4.99)*	(-5.27)*
	R3	-0.25	-0.04	0.10	0.14
		(-1.78)**	(-0.36)	(1.17)	(1.90)***
	R3-R1	0.753	0.800	0.787	0.749
		(3.77)*	(5.77)*	(6.89)*	(7.58)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 2.16: Returns of Momentum Portfolios Based on 52 Week-High Price from July 1999 to December 2005.

This table presents the average equally-weighted monthly returns of portfolio that are created based on 52 week-high price for all the firms in the SSM during the period July 1999 to December 2005. At the beginning of each month stocks are ranked to three equally-weighted portfolios according to the ratio of the current price to its 52 week high. Stocks with the lowest ratio (furthest from the 52-week high price) are assigned to the loser portfolio (R1). Stocks with the highest ratio (closest to the 52-week high price) are assigned to the winner portfolio (R3). (R5-R1) represents the 52 week momentum strategy of winner –loser portfolio. K represents monthly evaluation period = 3, 6, 9 and 12 months. Monthly evaluation return is computed using the average monthly buy and hold during the evaluation period. The t-statistics are reported in parentheses. The monthly returns are reported in percentage.

		Monthly Returns			
J	**Portfolio**	**K=3**	**K=6**	**K=9**	**K=12**
52-Week High Price	**R1**	3.25	3.62	4.41	5.18
		(13.69)*	(17.11)*	(20.94)*	(23.77)*
	R2	3.04	3.45	3.96	4.62
		(15.51)*	(19.75)*	(24.50)*	(28.17)*
	R3	2.75	2.95	3.07	3.48
		(16.76)*	(21.15)*	(25.14)*	(29.06)*
	R3-R1	-0.50	-0.68	-1.34	-1.70
		(-1.72)***	(-2.68)*	(-5.53)*	(-6.87)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

CHPATER III

ABNORMAL TRADING VOLUME AND AUTOREGRESSIVE BEHAVIOR IN WEEKLY STOCK RETURNS IN THE SAUDI STOCK MARKET

INTRODUCTION

The short-run predictability of asset returns has attracted many researchers and practitioners since it deals with the market efficiency debate. Past studies have found that past prices contain useful information with which to predict future individual stock returns (negative autocorrelation) (Lehmann 1990; Conard, Kaul, and Nimalendran 1991) and future portfolio returns (positive autocorrelation) (Lo and MacKinlay 1989).

Later developments in the literature have added trading volume as an important factor that determines stock autocorrelation at the market and individual stocks level (Blume, Easley, and O'Hara 1994; Wang 1994; Llorente, Michaely, Saar, and Wang 2002). Several authors have investigated this relationship in developed markets. Their results indicate the strong role of volume in predicting future returns direction in either individual stocks returns or portfolio returns. (Connolly and Stivers 2003; Cooper 1999; Stickel and Verrecchia 1994; Campbell, Grossman, and Wang 1993). However, the literature lacks confirming evidence from developing markets.

This essay examines the relationship between the abnormal change in trading volume of both stocks and portfolios and short-term price autoregressive behavior in the Saudi stock market (SSM). Its objective is to investigate the informational role that trading volume plays in predicting the direction of short-term returns. I evaluate whether the abnormal change in lagged, contemporaneous, and lead turnovers affects serial correlation in returns. Specifically, I examine if and when the change in volume produces

momentum (positive correlation) or reversal (negative autocorrelation) in consecutive weekly stock returns.

The outcome of this essay will determine whether the SSM is dominated by liquidity traders or by informed traders in an environment of asymmetric information. On one hand, according to Campbell, Grossman, and Wang (1993), if the market is dominated by liquidity traders, then price changes accompanied by high volume tend to reverse, which will not hold given a low trading volume. On the other hand, according to Wang (1994), if the market is characterized by asymmetric information and is dominated by informed investors, stock returns follow the direction of trading volume. The SSM has witnessed remarkable increases in trading volume in recent years and is an ideal market for testing these predictions. The results of this essay have important practical applications because they shed light on the short-term predictability of stock returns.

I apply the filter-rules-based methodology and analysis used by Cooper (1999) and the market-adjusted turnover shocks using the ordinary least squares (OLS) and the generalized autoregressive conditional heteroskedasticity (GARCH) methodology applied by Connolly and Stivers (2003). These are applied to the aggregate SSM, large and small-cap portfolios, and individual firms. These two methodologies are favored because they consider not just the effects of trading volume, but the effects of abnormal changes in trading volume on stock return behavior as well.

This essay adds an out-of-sample testing to the findings of previous studies on developed markets and deepens our understanding of the connection between return dynamics and turnover shocks.

The remainder of this essay includes a detailed literature review in the next section. The section that follows presents the methodology employed in this essay. Then, the data and the empirical results are discussed. The last section provides the conclusion.

LITERATURE REVIEW

Several theoretical models attempt to explain the relationship between trading volume and stock returns. Specifically, the following four studies discuss possible explanations for this relationship. Blume, Easley, and O'Hara (1994) investigate and develop a model that links trading volume to stock price behavior. In their model, the aggregate supply is fixed, and traders receive signals of different quality about assets' fundamental values. In their analysis, trading volume indicates the quality or precision of information in past price movements. The main implication of their model is that investors who focus on past trading volume can obtain additional profits and perform better than those who use only price measures.

Campbell, Grossman, and Wang (1993) present a model in which risk-averse market makers accommodate the selling pressure of liquidity or non-informational traders. They argue that stock prices decline because of either public information that causes them to decline or selling pressure from uninformed liquidity traders. They argue that if the decline is due to public information, there is no reason to expect any further change in price. However, if liquidity traders sell, prices must drop in order to induce market makers to assume the other side of the trade. They argue that "price changes accompanied by high volume will tend to be reversed; this will be less true of price changes in days with low volume" (Campbell, Grossman, and Wang, 1993, p. 906).

Wang (1994) argues that change in trading volume causes a change in the autoregressive behavior of stock returns because volume conveys important information about how assets are priced in the economy. He further argues that heterogeneity among investors gives rise to different volume behavior and return-volume dynamics. In Wang's model, there are two types of investors: informed and uninformed. Informed investors trade for one of two reasons: either because they have better information about the stock traded or to rebalance their portfolio to take advantage of another investment opportunity outside the market. The dynamic relationship between volume and returns varies depending upon the informed investors' motive for trading. A reversal in consecutive returns is likely if the trading by informed traders is driven by changes of investment opportunities outside the stock market. Due to risk aversion, and because the uninformed investors do not know whether trading is information based, prices move with turnover in the former period. Thus, the subsequent price movement in the latter period tends to exhibit some reversal from the former period's price movement. However, momentum is likely if the informed investors trade due to better private information. The partial incorporation of information in the former period tends to generate a positive autocorrelation between the former and latter period returns (Connolly and Stivers 2003).

In the model of Llorente, Michaely, Saar, and Wang (2002), trading occurs for two reasons: speculation and hedging. They explain that "when subsets of investors sell a stock for hedging reasons, the stock's price must decrease to attract other investors to buy. Since the expectation of future stock payoff remains the same, the decrease in the price causes a low return in the current period and a high expected return for the next period. However, when a subset of investors sells a stock for speculative reasons, its price

decreases, reflecting the negative private information about its future payoff. Since this information is usually only partially impounded into the price, the low return in the current period will be followed by a low return in the next period when the negative private information is further reflected in the price" (Llorente et al. 2002, p. 105). The main implication of the model is that in periods of high volume, stocks with speculative trading motives tend to exhibit a positive return autocorrelation, while stocks with hedging trading motives tend to exhibit negative returns

Recent empirical studies show how the change in relative volume affects the serial correlation of stock returns. Connolly and Stivers (2003) examine the relationship between weekly returns and the weekly volume of large- and small-firm portfolios, equity index futures, and individual firm returns in the US, Japanese, and UK stock markets. Their results show a significant momentum (reversal) in consecutive weekly returns when the latter week has an unexpectedly high (low) turnover.

In other words, they find a strong positive (negative) autocorrelation between weekly returns when there is a high (low) turnover shock in the second consecutive week. For example, they find that the first-order autoregressive coefficient of returns for a large-firm US portfolio over their sample in week t and $t-1$ is .41 when abnormal turnover in week t is at its 95th percentile, while it is -0.309 when abnormal turnover in week t is at its 5th percentile. On average, they find the autoregressive coefficient to increase by around 0.80 as the turnover shock moves from its 5th to its 95th percentile.

Cooper (1999) investigates the weekly returns and weekly volume for the top 300 largest market capitalization NYSE and AMEX individual securities from July 2, 1962, to December 31, 1993. He uses the weekly percentage of change in turnover as a measure

of change in trading volume. The results indicate that high-growth-in-volume stocks tend to show weaker reversals and even positive autocorrelation, while low-growth-in-volume securities exhibit greater reversals.

Stickel and Verrecchia (1994) test the relationship between the change in prices and volume around quarterly earning announcements for firms listed on the NASDAQ National Market System from 1982 to 1990. They document that large stock price changes on days with a weak trading volume tend to reverse the next day. However, a large increase in price with strong volume support tends to be followed by another price increase the next day.

The evidence in the literature is not conclusive regarding the relationship between weekly returns and return autocorrelation. Conrad, Hameed, and Niden (1994) examine the relationship between trading volume and the weekly return autocorrelation for stocks listed on NASDAQ from 1983 to 1990. They find that low-volume small capitalization stocks exhibit positive autocorrelation, while high-volume stocks exhibit negative correlation. Moreover, Campbell, Grossman, and Wang (1993) study the relationship between the daily correlation of the index return and the trading volume for stocks listed on the New York Stock Exchange and American Stock Exchange from 1962 to 1987. They find that the first daily autocorrelation of stock returns is lower on high-volume days than on low-volume days.

One of the few studies that examines this issue in emerging markets is by Gebka (2005), who examines the relationship between the level of trading volume and stock return behavior on the Warsaw Stock Exchange from 1996 to 2000. The results indicate

that high volume stocks experience strong price reversal, while low volume stocks experience weak price reversal and even continuation.

There is a paucity of empirical research on emerging markets in this literature. Most of the empirical studies are based on US data and other developed markets. In addition to examining the SSM and understanding its return behavior, this essay adds an out-of-sample test to the literature.

METHODOLOGY

To find out how the abnormal change is related to the serial correlation of stock returns, I use two different methodologies: the market adjusted relative turnover methodology of Connolly and Stivers (2003), and the filter-based rule methodology of Cooper (1999).

I follow these two methodologies, since they explicitly take into consideration not only the effect of trading volume, but also the effect of abnormal changes in trading volume on stock return behavior. I examine the results of each methodology and analyze whether or not they are consistent.

1) Market adjusted relative turnover

Connolly and Stivers (2003) construct a market-adjusted relative turnover (MRTO) series to discover the abnormal change in volume. They define MRTO as the "unexpected variation in turnover after controlling for the autoregressive properties of turnover and for variation associated with the sign and magnitude of both the week t and $t-1$ portfolio return" (p.1529). The MRTO is the residual μ_t obtained from estimating the following time series regression model:

$$TO_t = \gamma_o + \sum_{k=1}^{3} \gamma_k TO_{t-k} + \gamma_4 |R_t| + \gamma_5 D_t^- |R_t| + \gamma_6 |R_{t-1}| + \lambda_7 D_{t-1}^- |R_{t-1}| + \mu_t \quad (1)$$

where TO_t is the natural log of the turnover for all Saudi firm portfolios. Turnover is the number of shares traded divided by the shares outstanding. $|R_t|$ is the excess return of the portfolio, D_t^- =1 if $R_{L,t}$ is negative and is 0 otherwise, and γ is the estimated coefficient. The excess return is equal to the cumulative weekly return less the 3-month Saudi T-bill rate. I choose (AR3) on the lagged term for the log of turnover because the log turnover is significant up to three lags. Also, the same analysis is conducted using a large- and small-firm portfolio.

Regression (1) is used to construct the lagged turnover shock $MRTO_{t-1}$, which is the $week_{t-1}$ MRTO from estimating regression (1).

The lead turnover shock $MRTO_{L,t+1}$ is constructed using the following regression model :

$$TO_{t+1} = \gamma_o + \sum_{k=1}^{3} \gamma_k TO_{t-k} + \gamma_4 |R_{t+1}| + \gamma_5 D_t^- |R_{t+1}| + \gamma_6 |R_{t-1}| + \lambda_7 D_{t-1}^- |R_{t-1}| + \mu_t \quad (2)$$

Following Connolly and Stivers (2003), I construct the lead $MRTO_{t+1}$ where TO_{t+1} is the natural log of the turnover for all Saudi firm portfolios. Turnover is the numbers of shares traded divided by the shares outstanding. $|R_t|$ is the excess return of the portfolio, D_t^- =1 if R_t is negative and 0 otherwise, and γ is the estimated coefficient. I use next week return and absolute return instead of contemporaneous week return in model 1 because if variables from period t are included in construction of $MRTO_{t+1}$, it will be orthogonal to $MRTO_t$. In addition, there will be no information from period *t*, which provides a clean temporal separation from week t.

The following main model tests whether the autoregressive behavior of my portfolio return differs with $MRTO_j$:

$$R_t = \beta_o + (\beta_1 + \beta_2 MRTO_j)R_{t-1} + \varepsilon_t \qquad (3)$$

where R_t is the excess weekly return of the large-firm portfolio in week *t*; $MRTO_t$ is the MRTO of all firm portfolio in week *j* (j = t, t-1, or t +1). In this model, I investigate the contemporaneous, lagged, and lead shock effect of turnover on the return of week *t*. β's are the estimated coefficients, and β_2 is the main coefficient.

To test the effect of different changes in the MRTO on the implied first order autocorrelation AR (1) measured by β_2, I use an alternative specification presented by Connolly and Stivers (2001) that includes dummy variables that measure the change in the MRTO. The following model presents this specification:

$$R_t = \beta_0 + (\beta_1 + \beta_2 D^{LOW}_{MRTO,j} + \beta_3 D^{HIGH}_{MRTO,j})R_{t-1} + \varepsilon_t \qquad (4)$$

where $D^{LOW}_{MRTO,j}$ is a dummy variable that equals 1 when the MRTO of period *j* is equal to or less than its 10th percentile value and 0 otherwise. $D^{HIGH}_{MRTO,j}$ is another dummy variable that equals 1 when the MRTO of period j is equal to or higher than its 90th percentile value and 0 otherwise. Other terms are specified in model 1.

In addition to the relationship between abnormal volume and return at the portfolio level, I examine this relationship at the firm level. Following Connolly and Stivers (2004), I examine 1) the question of whether a firm's turnover shock affects the firm's return autocorrelation, and 2) the relationship between the turnover shock of the all firm portfolio and the cross-serial relationship between the firm's return and the lagged return of the all firm portfolio. I estimate the following equation for 10 individual firms.

Similar to estimating the MRTO for the portfolio level (equation 1), the firm-adjusted relative turnover (FRTO) is the residual from estimation of the following equation:

$$TO_{i,t} = \gamma_o + \sum_{j=1}^{3} \gamma_j TO_{i,t-j} + \gamma_4 |R_{i,t}| + \gamma_6 D_t^- |R_{i,t}| + \gamma_6 |R_{i,t-1}| + \lambda_7 D_{t-1}^- |R_{i,t-1}| + \mu_t \qquad (5)$$

where i represents the firm level values. All other terms are defined in equation (1).To test the effect of change in FRTO and MRTO on the implied first order autoregressive (AR1) of weekly reruns for the individual firms we employ the following model:

$$R_{i,t} = \beta_0 + (\beta_1 + \beta_2 D_{FRTO,j}^{LOW} + \beta_3 D_{FRTO,j}^{HIGH}) R_{i,t-1} + (\beta_4 + \beta_5 D_{MRTO,j}^{LOW} + \beta_6 D_{MRTO,j}^{HIGH}) R_{M,t-1} + \varepsilon_t \quad (6)$$

where $R_{i,t}$ is the excess weekly return of firm i in week t, $D_{FRTO,j}^{LOW}$ is a dummy variable that equals 1 when the FRTO of firm i in week t is in it 10th percentile value and 0 otherwise. $D_{FRTO,j}^{HIGH}$ is a dummy variable that equals 1 when the FRTO of firm i is in its 90th percentile value. All other terms are defined in equation (2).

The all firm portfolio MRTO is estimated using OLS in previous specification. In addition, and following Connolly and Stivers (2001, 2003), I estimate a nonlinear GARCH (1, 1) model at the portfolio level to see if the results are consistent when using a different econometric method.

$$R_t = \beta_o + (\beta_1 + \beta_2 MRTO_j) R_{t-1} + \varepsilon_t \qquad (7)$$

$$V_t = \delta_0 + \delta_1 \varepsilon_{t-1}^2 + \delta_2 D_{t-1 \varepsilon_{t-1}^2}^- + \delta_3 V_{t-1} + \delta_4 MROT_{t-1} \qquad (8)$$

where $V_{L,t}$ is the conditional variance, D_{t-1}^- is a dummy variable that equals 1 if the lagged return residual ε_{t-1} is negative and 0 otherwise. All other terms are defined in

$$\begin{cases} loser_{k*A} if\ R_{r,t-1} < -K^{*}A \\ Winer_{k*A} if\ R_{i,t-1} \geq K^{*A} \end{cases}$$

equation (2). Also, I estimate the model with dummy variables that measure the effect of change in MRTO on the consecutive weekly returns as follows:

$$R_t = \beta_0 + (\beta_1 + \beta_2 D^{LOW}_{MRTO\ ,j} + \beta_3 D^{HIGH}_{MRTO\ ,j}) R_{t-1} + \varepsilon_t \qquad (9)$$

$_{2}D^{LOW}_{MRTO\ ,j}$

All terms are specified in 2, while the variance equation is specified in 6.

2) Volume and Price Filter-based rules

The other methodology I use is the filter-based methodology, where I test the relation between the consequence weekly return, which is conditioned on the past week return and change in volume. Cooper (1999) investigates the relationship between the lagged weekly volume and subsequent weekly return by developing a filter-based methodology. He forms portfolios by screening the magnitude of the lagged return and the change of the lagged weekly volume. I adapt some parts that are applicable to this essay.

I use a price filter to create two strategies: a "loser-price" strategy and a "winner-price" strategy. I also use a volume filter to create two volume portfolios: a "low-volume" portfolio and a "high-volume" portfolio. The interaction of these portfolios creates four strategies: "loser-price, low-volume" "loser-price, high-volume" "winner-price, low-volume" and "winner-price, high-volume."

The following is the rule that defines the price loser and winner for week $t-1$:

$$return\ state = \begin{cases} For\ k = 0,1,\ldots,4: \begin{cases} loser_{k*A} if\ -k^{*}A > R_{r,t-1} \geq -(k+1)^{*}A \\ Winer_{k*A} ifk^{*}A \leq R_{i,t-1} < (k+1)^{*}A \end{cases} \\ \\ For\ k = 5: \qquad \begin{cases} loser_{k*A} if\ R_{r,t-1} < -K^{*}A \\ Winer_{k*A} if\ R_{i,t-1} \geq K^{*A} \end{cases} \end{cases}$$

where $R_{i,t}$ is the return for security i in week t, k is the filter counter that ranges from 0 to 5, and A is the lagged return parameter equal to 2%. I construct several portfolios that fit the above constraints of K*A. In other words, in week *t*, I select those stocks that have positive returns in week *t*-1 to form the winner portfolio if they fit the following lagged return in percentage:

$\geq 0\, and < 2, \geq 2\, and < 4, \geq 4and < 6, \geq 6\, and < 8, \geq 8\, and < 10, \geq 10$

Also, I select those stocks that have negative returns in week *t*-1 to form the loser portfolio if they fit the above lagged return but with a negative sign.

To examine whether trading volume can explain reversal, Cooper (1999) uses the "growth in volume," which is a stock weekly percentage change in volume, adjusted for the number of outstanding shares of the stock as follows:

$$\%\Delta_{vi,t} = \left[\frac{V_{i,t}}{S_{i,t}} - \frac{V_{i,t-1}}{Si-1,t}\right] \Big/ \left[\frac{V_{i,t-1}}{S_{i,t-1}}\right]$$

where Si,t is the number of outstanding shares for stock i in week t. $V_{i,t}$ is the weekly volume for stock i in week t.

Cooper (1999) uses the following rule to define the growth in volume $\%\Delta_{vi,t}$ in week $t-1$ to determine whether the stock has high or low volume growth:

$$Growth\ in\ volume\ state = \begin{cases} For\, k = 0,1,\ldots,4: \begin{cases} Low_{k*B}\ if - k^*B > \%\Delta_{vi,t-1} \geq -(k+1)^*B \\ High_{k^*c}\ if k^*C \leq \%\Delta_{vi,t-1} < (k+1)^*C \end{cases} \\ \\ For\, k = 5: \qquad \begin{cases} Low_{k*B}\ if\ \%\Delta_{vi,t-1} < -K^*B \\ High_{k*c}\ if\ \%\Delta_{vi,t-1} \geq K^*C \end{cases} \end{cases}$$

where k is the filter counter that ranges from 0 to 5, B is the parameter for low growth in volume and equal to 15%, and C is the parameter for high growth in volume and is equal

to 50%.In other words, based on the percentage change in turnover in week $t-1$, I form portfolios of high turnover with stocks that fit the following positive percentage change in volume according to K*C:

$\geq 0\, and < 50, \geq 50\, and < 100, \geq 100\, and < 150, \geq 150\, and < 200, \geq 200$

For the low turnover, I form a portfolio with stocks that fit the following negative percentage change in volume according to K*B:

$< 0 \geq -15, < -15 \geq -30, < -30 \geq -45, < -45 \geq -60, < -60 \geq -75, < -75$

For each of the four strategies—price only and price plus volume—I form portfolios in week t that meet the appropriate lagged filter level constraints. For example, consider the winner-price, high-volume strategy. If the minimum level of the price filter is set at 4% (K = 2 and A = 2%) and the minimum level of high growth-in-volume filter is set at 100% (K = 2 and C = 50%), this forms an equally-weighted portfolio for stocks that have a price increase greater than or equal to 4% and less than 6%, and whose growth in volume is greater than or equal to 100% and less than 150% (Cooper, 1999).

All equally weighted portfolios of the four strategies with different levels of lagged price returns and changes in volume are held for a period of one week and then liquidated. The mean returns for these portfolios are then calculated, which shows whether there is a reversal or continuation in price with high or low lagged changes in volume.

DATA AND EMPIRICAL RESULTS

I collect daily data for return, turnover, and market capitalization for all Saudi firms from January 1, 1993, to December 31, 2005. I form an equally average weighted portfolio return for all firms from Monday to Monday, which sums to 675 weeks. Studies conducted in the US market usually select Wednesday for portfolio formation, however I choose Monday for my portfolio formation day because it is the third day of weekly trading in the SSM. I also create two portfolios of large and small firms based on market capitalization every week. In Table 3.1, panels A, B, C, D, and E show the descriptive statistics for the mean weekly returns and turnover for the whole sample period, the first sub-sample period from 1/1/1993 to 6/281999, the second from 7/05/1999 to 12/25/2005, and for the large-firm and small-firm portfolios. The statistics indicate that the mean weekly returns and turnover are highest in the second period. Also, small firms have a higher return and turnover than large firms.

[Insert Table 3.1 here]

Table 3.2 presents the results for $MRTO_t$ (model 1) for the whole sample period and for the two sub-sample periods in panels A, B, and C, respectively. The MRTO is the residual from estimating model. The results show that for all three periods, the log turnover is positive and significant for the first and third lag. The log turnover is also positively related to the absolute returns for the contemporaneous and lag return, and negatively related to the negative returns for the contemporaneous and one-week lag return.

[Insert Table 3.2 here]

Table 3.3 presents the estimate coefficients for the lead turnover shock $MRTO_{t+1}$ as specified by model 2. As with $MRTO_t$, the same results hold for the lead turnover shock $MRTO_{t+1}$. It is positively related to absolute returns and negatively related to negative returns for the one-week lead and one-week lag return.

[Insert Table 3.3 here]

The results for the main model as specified in equation 3 are shown in Table 3.4. Panel A reports the results for the whole period, panel B for the first sub-sample, and panel C for the second sub-sample. The coefficient of interest is the β_2 which is a measure for the relation between $week_t$ return and the interaction of the $week_{t-1}$ return and $MRTO_j$. This coefficient (β_2) is basically the implied first order autoregressive AR(1) for weekly returns. I test for one lag, contemporaneous and the one-week lead effect of $MRTO_j$ on the consecutive weekly returns. The results show that β_2 is negative and significant for all three periods when conditioned on the lag MRTO, while it is positive for the contemporaneous shock but not statistically significant for two of the periods. The coefficient β_2 is positive and significant for two of the periods and negative for the first sub-period when conditioned on the lead MRTO. The results indicate that the relation between the return of $week_t$ and $week_{t-1}$ decreases in the lagged MRTO.

[Insert Table 3.4 here]

To investigate the effect of the increase and decrease in $MRTO_j$ on the relation between $week_t$ and $week_{t-1}$ returns, I estimate the model with a different percentile of $MRTO_j$. I include a dummy variable that equals 1 if the $MRTO_j$ is in its 90th percentile

and 0 otherwise. I also create a dummy variable that equals 1 if the $MRTO_j$ is in its 10th percentile and 0 otherwise, so that I can measure the increase (decrease) in the relation between $week_t$ and $week_{t-1}$return when the MRTO moves from its 10th to its 90th percentile value. Table 3.5 shows that the relation between week t and week t-1 negatively decreases with the increase of the lagged MRTO. In all three periods, the difference between the implied first order autoregressive AR (1) at the 10th percentile and AR (1) at the 90th percentile is negative. The difference when the lagged MRTO moves from the 10th to the 90th percentiles is equal to -0.196, -0.23, and -0.019 for the whole period, the first sub-period, and the second sub-period, respectively. It is evident that the increase in turnover shock for the one-week lag leads to a reversal in the consequences weekly return. The increase of the MRTO for the contemporaneous week and lead week MRTO leads to different results for different periods and, in most cases, is not significant. However, the overall direction is that contemporaneous and lead MRTO leads to a positive relation between week t and week t-1 returns.

[Insert Table 3.5 here]

Table 3.6 reports the results for the large- and small-firm portfolios as specified in model 3. Every week I sort the sample based on market capitalization to the largest 50% of all firms and the smallest 50% of all firms. The lagged MRTO is consistent with the overall sample, and leads to a significant negative relationship between $week_t$ and $week_{t-1}$ for the large- and small-firm portfolios. But the contemporaneous and lead MRTOs lead to a positive relationship between $week_t$ and $week_{t-1}$ for both portfolios.

[Insert Table 3.6 here]

Table 3.7 shows the results of the main model conditioned on different percentiles of $MRTO_j$ as specified in model 4. The largest difference in magnitude between the implied first order autoregressive when the MRTO changes from its lowest to highest percentile is when it is conditioned on the lagged MRTO. The relation is negative and decreases by -0.60 and -0.238 for the large and small firms, respectively, when the lagged MRTO moves from its 10th to 90th percentiles. The AR (1) increases for the small-firm portfolio and decreases for the large-firm portfolio when conditioned on the contemporaneous MRTO. The implied AR (1) increases with the increase in the lead MRTO, but with less magnitude and significance than the decrease in the lagged MRTO.

[Insert Table 3.7 here]

For a robustness test for the main result, I use another methodology to test whether the main result is consistent through different methodological specifications. I use GARCH methodology to test the effect of contemporaneous, lead, and lagged MRTO on the relation between $week_t$ and $week_{t-1}$.

Table 3.8 shows the results of estimating the GARCH model as specified in models 7 and 8. The interaction of the lagged MRTO with the lagged weekly returns leads to a negative relationship with the consequence weekly returns, while leading to a positive relationship for the contemporaneous and lead MRTO. These relationships hold for all three periods.

[Insert Table 3.8 here]

This relation is clearer when I test for the percentile change in the MRTO in Table 3.9 as specified in model 9. The increase in lagged MRTO leads to a decreasing negative relation between weeks t and t-1, decreasing by -0.329, -0.532, and -0.308 for the whole sample, first sub-period, and second sub-period, respectively. The relation is positive, but with less magnitude with the increase of lead MRTO than with lagged MRTO. It is positive for one period and negative for two periods for the contemporaneous MRTO.

[Insert Table 3.9 here]

Overall, results at the portfolio level indicate that the relation between week_t and week_{t-1} returns is negative, and decreases with the increase in lagged MRTO for the whole sample, first sub-period, second sub-period, and large- and small-firm portfolios, and with different methodological specifications (OLS and GARCH). With some exceptions, the overall result for contemporaneous and lead MRTO is positive and increasing with the change in MRTO, but with less significance than lagged MRTO, and with inconsistent results for the different sub-sample periods.

The next section tests my main model using firm level data. Tables 3.10, 3.11, and 3.12 report the results of contemporaneous, lagged, and lead MRTO for 10 individual companies. For contemporaneous MRTO, the difference between the MRTO at its 10th and 90th percentiles is positive for seven firms and negative for three, while for lead MRTO it is negative for six and positive for four. The most consistent result is the relation between firm return at week t and t-1 when conditioned on the change on lagged MRTO. When lagged MRTO increases from the 10th to the 90th percentiles, it leads to a decreasing negative relation between the consecutive weekly return. In most cases the

relations are positive at the 10th and negative at the 90th percentiles. The differences range from -0.11 to -0.43.

[Insert Table 3.10 here]

[Insert Table 3.11 here]

[Insert Table 3.12 here]

The next part of this essay examines the relations between week *t* and week *t*-1 returns based on lagged weekly changes in price and volume. I follow the methodology of Cooper (1999) as described in the methodology section using a specific filter level for return and volume every week a stock is included in one of the four portfolios: loser-price, high-volume; loser-price, low-volume; winner-price, high volume; and winner-price, low-volume.

Table 3.13 shows the mean return for the loser-price, high-volume strategy. It indicates s a reversal in weekly returns. The loser price becomes the winner when conditioned on a high volume change. For example, the mean return is -0.648 % when conditioned on a lagged return that is < 0 and >= -.02, and a lagged volume change that is > 0 and <= 50%. For the same strategy, the returns increase to 1.779 % when the lagged volume increases to >= 250 %. This is evident for all cases of the loser-price, high-volume portfolio. The higher-volume filter leads to a higher reversal. When the results of the loser-price, high-volume strategy are compared with the loser-price, low-volume strategy presented in Table 3.14, it can be seen that there is no reversal in the loser-price, low-volume portfolio. There is a continuation of negative returns with the decrease in volume in this case.

[Insert Table 3.13 here]

[Insert Table 3.14 here]

However, this relation does not hold in the winner-price, high-volume and winner-price, low-volume portfolios. Tables 3.15 and 3.16 indicate that high volume leads to continuation in weekly return while low volume leads to reversal in weekly return.. The main conclusion of this part is that high-volume stock is more profitable than low-volume stock. When last week returns are negative, high-volume stock leads to reversal, while when last week returns are positive, high-volume stock leads to continuation. The opposite is true for low-volume stock: when past week returns are negative, a low change in volume leads to a continuation of negative returns, while when past week returns are positive, a low change in volume leads to a reversal in returns.

[Insert Table 3.15 here]

[Insert Table 3.16 here]

CONCLUSIONS

These results indicate a reversal in weekly stock returns when conditioned on the change in lagged volume. They are consistent for the whole sample, the two sub-sample periods, and the large- and small-firm portfolios, as well as at the firm level and with OLS and GARCH econometrics methods. The results are consistent with Campbell, Grossman, and Wang (1993), who present a model in which risk-averse market makers accommodate the selling pressure of liquidity or non-informational traders. If liquidity traders sell, prices must drop to induce market makers to assume the other side of the trade; consequently, prices tend to reverse the following week. This will be less true of price changes on days with low volume. I also find that reversal is more pronounced with the loser portfolio as specified by filter-based methodology. This result is also consistent with Campbell et al.'s (1993) model, where the pressure of liquidity trader is higher when stocks are dropping in price. The overall result of this essay is also consistent with the empirical finding of Conrad, Hameed, and Niden (1994) and Gebka (2005) where they report price reversal for stock with high trading volume.

The contemporaneous and the lead turnover shocks produce different results in different sample periods. However, in most cases, contemporaneous and lead changes in volume lead to a positive serial correlation between consequent weekly prices.

Table 3.1: Summary Statistic for Weekly Portfolio Returns and Turnovers.
This table presents the summery statistics for weekly portfolio returns and turnovers. Weekly portfolio return is the cumulative average daily returns. Weekly portfolio turnover is the cumulative average daily turnovers. Daily turnover is measured as the number of shares traded during the day divided by the number of shares outstanding at the end of the day. Panel A reports the statistics for the whole period from January 4, 1993 to December 26, 2005. Penal B reports the statistics for the first sub-sample from January 4, 1993 to June 28, 1999. Panel C reports the result for the second sub-sample from July 5, 1999 to December 26, 2005. Panel D and E present the statistics for large and small firm portfolios respectively from January 4, 1993 to December 26, 2005.The statistics: mean, median maximum, minimum and standard deviation are in percentage.

	Panel A		Panel B		Penal C		Penal D		Panel E	
	Whole sample		First Period		Second period		Large firms		Small Firms	
	Returns	Turnover	Returns	Turnover	Returns	Turnover	Returns	Turnover	Returns	Turnover
Mean	0.253	6.878	-0.242	0.984	0.746	12.754	2.546	0.288	11.285	0.216
Median	0.331	1.305	-0.126	0.626	0.699	5.033	0.809	0.272	1.783	0.086
Maximum	10.959	57.661	6.351	8.552	10.959	57.661	20.450	8.405	104.434	15.524
Minimum	-16.250	0.031	-7.603	0.031	-16.250	0.234	0.019	-10.174	0.043	-22.327
Std. Dev.	2.436	12.208	1.880	1.056	2.803	15.086	3.945	2.165	20.982	3.060
Skewness	-0.560	2.320	-0.415	3.047	-0.901	1.296	2.158	-0.477	2.429	-0.321
Kurtosis	8.470	7.684	4.471	15.649	9.054	3.615	7.085	5.852	8.348	10.198
Jarque-Bera	876.697	1222.703	40.074	2768.063	562.007	99.927	993.145	254.389	1465.984	1466.495
Observations	675	675	337	337	338	338	675	675	674	674

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.2: Estimating Market Adjusted Relative Turnover ($MRTO_t$).

This table presents the estimation of Market Adjusted Relative Turnover (MRTO). $MRTO_t$ is the residual μ_t obtained from estimating the following time series regression model (1).

$$TO_t = \gamma_o + \sum_{k=1}^{3} \gamma_k TO_{t-k} + \gamma_4 |R_t| + \gamma_5 D_t^- |R_t| + \gamma_6 |R_{t-1}| + \lambda_7 D_{t-1}^- |R_{t-1}| + \mu_t \quad (1)$$

Where TO_t is the natural log of the weekly turnovers for all SSM firms portfolio. Weekly turnover is the cumulative daily turnovers. Turnover is number of shares traded divided by the shares outstanding. $|R_t|$ Is the excess weekly return of the portfolio. D_t^- is a dummy variable that is equal to 1 if R_t is negative and is zero otherwise, γ's are the estimated coefficients. The excess return is equal to the average cumulative weekly return less the three-month Saudi T-bill rate. The last row shows the residual standard deviation.

	Panel A	**Panel B**	**Panel C**
Coefficient	**1/1993-12/2005**	**1/1993-6/1999**	**7/1999-12/2005**
γ_0	-0.513	-0.953	-0.461
	(-7.20)*	(-5.47)*	(-5.26)*
γ_1	0.716	0.636	0.747
	(18.98)*	(11.77)*	(13.90)*
γ_2	-0.020	0.033	-0.076
	(-0.45)	(0.53)	(-1.19)
γ_3	0.202	0.165	0.217
	(5.83)*	(3.28)*	(4.49)*
γ_4	16.392	25.110	13.916
	(10.83)*	(7.23)*	(8.36)*
γ_5	-15.729	-21.798	-14.087
	(-9.92)8	(-6.68)*	(-7.66)*
γ_6	0.479	4.396	-0.111
	(0.29)	(1.18)	(-0.06)
γ_7	-3.317	-7.032	-2.119
	(-1.95)***	(-2.02)**	(-1.07)
R^2	0.859	0.705	0.900
$\sigma(u_t)$	0.589	0.466	0.452

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.3: Estimating Lead Market Adjusted Relative Turnover (MRTO$_{t+1}$)
This table presents the estimation of lead Market Adjusted Relative Turnover (MRTO). MRTO$_{t+1}$ is the residual μ_t obtained from estimating the following time series regression model (1).

$$TO_{t+1} = \gamma_o + \sum_{k=1}^{3} \gamma_k TO_{t-3} + \gamma_4 |R_{t+1}| + \gamma_5 D_t^- |R_{t+1}| + \gamma_6 |R_{t-1}| + \lambda_7 D_{t-1}^- |R_{t-1}| + \mu_t \quad (2)$$

Where TO$_{t+1}$ is the natural log of weekly turnover for all SSM firms portfolio. Weekly turnover is the cumulative daily turnovers Turnover is the numbers of shares traded divided by the shares outstanding. |R$_t$| Is the excess return of the portfolio. D_t^- is a dummy variable that is equal to 1 if R$_t$ is negative and is zero otherwise, γ's are the estimated coefficients. The excess return is equal to the average cumulative weekly return less the three-month Saudi T-bill rate. The last row shows the residual standard deviation.

	Panel A	**Panel B**	**Panel C**
Coefficient	**1/1993-12/2005**	**1/1993-6/1999**	**7/1999-12/2005**
γ_0	-0.653	-1.355	-0.626
	(-7.21)*	(-6.43)*	(-5.42)*
γ_1	0.507	0.447	0.498
	(10.67)*	(6.86)*	(7.14)*
γ_2	0.136	0.134	0.111
	(2.40)*	(1.77)***	(1.34)
γ_3	0.216	0.158	0.229
	(4.95)*	(2.58)*	(3.65)*
γ_4	19.349	28.294	16.387
	(10.31)*	(6.67)*	(7.67)*
γ_5	-20.186	-26.377	-17.722
	(-10.26)*	(-6.68)*	(-7.51)*
γ_6	0.501	-0.236	0.961
	(0.24)	(-0.05)	(0.41)
γ_7	-4.739	-6.645	-3.326
	(-2.22)**	(-1.59)	(-1.29)
R^2	0.859	0.564	0.832
$\sigma(u_t)$	0.589	0.563	0.586

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.4: The Relationship between Consecutive Weekly Returns and $MRTO_j$
This table presents the result of the model that tests the relationship between consecutive weekly returns and market-adjusted relative turnover (MRTO) specified by the following model:

$$R_t = \beta_o + (\beta_1 + \beta_2 MRTO_j)R_{t-1} + \varepsilon_t \qquad (3)$$

Where R_t is the excess weekly return of the large firm portfolio in week t; $MRTO_t$ is the market-adjusted relative turnover of the large-firm portfolio in week j (j=t, t-1, or t +1). In this model, I investigate the contemporaneous, lagged, and lead shock effect of turnover on the relation between the return of $week_t$ and $weekt_{-1}$ and $.\beta's$ are the estimated coefficients and β_2 is the main coefficient. Panel A, B and C present the result for the whole sample, the first sup-period and the second sup-period respectively.

	Panel A			Panel B			Panel C		
	1/1993 to 12/2005			1/1993 to 6/1999			7/1999 to 12/ 2005		
	Cont.	Lag	Lead	Cont.	Lag	Lead	Cont.	Lag	Lead
Coefficients	(j =t)	(j =t-1)	(j = t +1)	(j =t)	(j = t-1)	(j =t +1)	(j =t)	(j = t-1)	(j =t +1)
β_0	-0.0009	-0.0010	-0.0009	-0.0059	-0.0058	-0.0058	0.0037	0.0037	0.0037
	(-0.99)	(-1.04)	(-1.00)	(-5.44)*	(-5.42)*	(-5.39)*	(2.40)**	(2.37)**	(2.44)**
β_1	0.232	0.216	0.227	0.161	0.169	0.166	0.198	0.181	0.194
	(6.16)*	(5.72)*	(6.03)*	(2.99)*	(3.14)*	(3.07)*	(3.67)*	(3.31)*	(3.64)*
β_2	0.076	-0.252	0.111	0.278	-0.279	-0.145	0.085	-0.220	0.245
	(0.84)	(-3.24)*	(1.85)***	(2.22)**	(-2.51)**	(-1.41)	(0.62)	(-1.73)**	(2.83)*
R^2 %	5.48	6.84	5.86	4.12	4.47	3.23	4.02	4.91	6.2

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.5: The Relationship Between Consecutive Weekly Returns and Abnormal Change in $MRTO_j$.

To test the effect of changes in $MRTO_j$, the following model specification includes dummy variables that measure the effect of change in MRTO.

$$R_t = \beta_0 + (\beta_1 + \beta_2 D^{LOW}_{MRTO,j} + \beta_3 D^{HIGH}_{MRTO,j}) R_{t-1} + \varepsilon_t \qquad (4)$$

R_t is the excess weekly return of the large firm portfolio in week t; $MRTO_t$ is the market-adjusted relative turnover of the large-firm portfolio in week j (j=t, t-1, or t +1). $D^{LOW}_{MRTO,j}$ is a dummy variable that is equal to 1 when MRTO of period j is equal or less than its 10th percentile value and zero otherwise. $D^{HIGH}_{MRTO,j}$ is another dummy variable that is equal to 1 when MRTO of period j is equal or higher than its 90th percentile value and zero otherwise. Panel A, B and C present the result for the whole sample, the first sup-period and the second sup-period respectively.

	Panel A			Panel B			Panel C		
	1/1993 to 12/2005			1/1993 to 6/1999			7/1999 to 12/ 2005		
Coefficients	**Cont.**	**Lag**	**Lead**	**Cont.**	**Lag**	**Lead**	**Cont.**	**Lag**	**Lead**
	(j =t)	**(j =t-1)**	**(j = t +1)**	**(j =t)**	**(j = t-1)**	**(j =t +1)**	**(j =t)**	**(j = t-1)**	**(j =t +1)**
β_0	-0.0010	-0.0010	-0.0010	-0.0059	-0.0058	-0.0060	0.0036	0.0036	0.0036
	(-1.03)	(-1.03)	(-1.07)	(-5.38)*	(-5.27)*	(-5.49)	(2.30)**	(2.31)**	(2.32)**
β_1	0.216	0.235	0.204	0.162	0.190	0.137	0.196	0.187	0.202
	(5.19)*	(5.53)*	(4.76)*	(2.78)*	(3.15)*	(2.35)	(3.37)*	(3.22)*	(3.30)*
AR(1)- 10th MRTO	-0.093	-0.175	0.077	0.248	-0.070	-0.148	-0.121	-0.295	0.273
	(-0.63)	(-1.38)	(0.73)	(1.05)	(-0.29)	(0.93)	(-0.55)	(-1.42)	(1.95)***
AR(1)- 90th MRTO	0.121	-0.371	0.276	0.243	-0.305	0.200	-0.063	-0.314	0.271
	(0.70)	(-2.67)*	(2.69)*	(1.04)	(-1.83)***	(-0.72)	(-0.23)	(-1.23)	(1.63)
Increase or decrease	0.214	-0.196	0.199	-0.005	-0.234	0.348	0.058	-0.019	-0.002
R^2 %	5.49	6.77	6.56	3.3	3.66	2.99	4.16	5.15	6.19

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.6: The Relationship between Consecutive Weekly Returns and $MRTO_j$ for Small and Large Firm Portfolios

This table presents the result of model tests the relationship between consecutive weekly return and market-adjusted relative turnover (MRTO) for large firm portfolio in panel A and small firm portfolio in panel B specified by the following model:

$$R_t = \beta_o + (\beta_1 + \beta_2 MRTO_j)R_{t-1} + \varepsilon_t \qquad (3)$$

Where R_t is the excess weekly return of the large (small) firms portfolio in week t; $MRTO_t$ is the market-adjusted relative turnover of the large-firm portfolio in week j (j=t, t-1, or t +1). In this model, I investigate the contemporaneous, lagged, and lead shock effect of turnover on the relation between the return of $week_t$ and $weekt_{-1}$ and. β's are the estimated coefficients and β_2 is the main coefficient.

	Panel A Large Firms			Panel B Small Firms		
Coefficients	**Cont.**	**Lag**	**Lead**	**Cont.**	**Lag**	**Lead**
	(j =t)	(j = t-1)	(j = t +1)	(j =t)	(j = t-1)	(j = t +1)
β_0	-0.0007	-0.0007	-0.0007	-0.0013	-0.0013	-0.0013
	(-0.76)	(-0.76)	(-0.75)	(-1.07)	(-1.11)	(-1.08)
β_1	0.137	0.138	0.135	0.195	0.182	0.188
	(3.58)*	(3.61)*	(3.53)*	(5.16)*	(4.76)*	(4.95)*
β_2	0.124	-0.140	0.041	0.148	-0.199	0.154
	(1.68)***	(-1.65)***	(0.60)	(1.83)***	(-2.89)*	(2.81)*
R^2 %	2.29	2.27	1.93	4.4	5.12	5.05

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.7: The Relationship between Consecutive Weekly Returns and Abnormal Change in $MRTO_j$ of Large and Small Firm Portfolios.

To test the effect of changes in $MRTO_j$, for large firms portfolio in panel A and small firms portfolio in Panel B, the following specification includes dummy variables that measure the effect of change in MRTO.

$$R_t = \beta_0 + (\beta_1 + \beta_2 D^{LOW}_{MRTO,j} + \beta_3 D^{HIGH}_{MRTO,j}) R_{t-1} + \varepsilon_t \qquad (4)$$

Where $D^{LOW}_{MRTO,j}$ is a dummy variable that is equal to 1 when MRTO of period j is equal or less than its 10th percentile value and zero otherwise. $D^{HIGH}_{MRTO,j}$ is another dummy variable that is equal to 1 when MRTO of period j is equal or higher than its 90th percentile value and zero otherwise. R_t is the excess weekly return of the large (small) firm portfolio in week t; $MRTO_t$ is the market-adjusted relative turnover of the large (small) firm portfolios in week j (j=t, t-1, or t+1).

	Penal A Large Firms			Penal B Small Firms		
Coefficients	**Cont. (j =t)**	**Lag (j = t-1)**	**Lead (j = t +1)**	**Cont. (j =t)**	**Lag (j = t-1)**	**Lead (j = t +1)**
β_0	-0.0006	-0.0008	-0.0007	-0.0013	-0.0012	-0.0013
	(-0.69)	(-0.82)	(-0.73)	(-1.06)	(-1.01)	(-1.08)
β_1	0.126	0.194	0.121	0.201	0.207	0.182
	(2.97)*	(4.47)*	(2.81)	(4.86)*	(4.97)*	(4.29)*
AR(1)- 10th MRTO	0.143	0.210	-0.081	0.126	-0.103	0.205
	(1.37)	(1.29)	(-0.68)	(0.81)	(-0.98)	(2.12)**
AR(1)- 90th MRTO	0.404	-0.398	0.073	0.111	-0.341	0.271
	(2.43)*	(-2.79)*	(0.60)	(0.72)	(-2.42)*	(2.91)*
Increase or decrease	0.261	-0.608	0.154	-0.016	-0.238	0.066
R^2 %	3.13	1.98	3.14	4.12	4.98	6.01

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.8: The Relationship between Consecutive Weekly Returns and $MRTO_j$: GARCH Methodology.

This table presents the result of GARCH model that tests the relationship between consecutive weekly returns and market-adjusted relative turnover (MRTO) as give by the following model specification.

$$R_t = \beta_o + (\beta_1 + \beta_2 MRTO_j)R_{t-1} + \varepsilon_t \qquad (7)$$

$$V_t = \delta_0 + \delta_1 \varepsilon_{t-1}^2 + \delta_2 D_{t-1\varepsilon_{t-1}^2}^- + \delta_3 V_{t-1} + \delta_4 MROT_{t-1} \qquad (8)$$

R_t is the excess weekly return of all firm portfolio in week t; $MRTO_t$ is the market-adjusted relative turnover of the all SSM firms portfolio in week j (j=t, t-1, or t +1). D_{t-1}^- is a dummy variable that is equal to one if the lagged return residual ε_{t-1} is negative and zero otherwise. $V_{L,t}$ is the conditional variance. Panel A, B and C present the result for the whole sample, the first sup-period and the Second sup-period respectively.

	Panel A			**Panel B**			**Panel C**		
	1/1993 to 12/2005			**1/1993 to 6/1999**			**7/1999 to 12/ 2005**		
Coefficients	**Cont.**	**Lag**	**Lead**	**Cont.**	**Lag**	**Lead**	**Cont.**	**Lag**	**Lead**
	(j =t)	**(j = t-1)**	**(j = t +1)**	**(j =t)**	**(j = t-1)**	**(j = t +1)**	**(j =t)**	**(j = t-1)**	**(j = t +1)**
β_0	-0.00282	-0.00277	-0.00327	-0.00497	-0.00443	-0.00503	0.00092	0.00049	-0.00069
	(-3.84)*	(-3.83)*	(-4.65)*	(-6.11)*	(-3.98)*	(-4.51)	(0.76)	(0.38)	(-0.61)
β_1	0.216	0.217	0.208	0.245	0.242	0.254	0.180	0.160	0.129
	(5.82)*	(5.89)*	(5.99)*	(4.25)*	(4.04)*	(4.14)	(1.91)***	(2.80)	(2.51)**
β_2	0.252	-0.184	0.098	0.287	-0.227	0.074	0.267	-0.030	0.180
	(3.06)*	(-2.25)**	(1.88)**	(2.68)*	(-1.80)***	(0.86)	(1.33)	(-0.26)	(2.09)**
Variance Eq. 8									
δ_1	0.00006	0.00005	0.00005	0.00007	0.00006	0.00009	0.00017	0.00008	0.00007
	(5.17)*	(4.71)*	(5.36)*	(2.32)**	(2.97)*	(3.93)	(2.49)**	(3.55)	(4.50)*
δ_2	0.225	0.225	0.238	0.216	0.203	0.250	0.306	0.251	0.265
	(6.39)*	(5.24)*	(6.31)*	(3.00)*	(2.76)*	(3.16)	(2.51)**	(3.93)	(5.09)*
δ_3	0.671	0.708	0.682	0.576	0.606	0.516	0.490	0.665	0.658
	(14.67)*	(15.29)*	(16.19)*	(4.79)*	(5.37)*	(5.20)	(3.33)*	(10.26)	(12.57)*
δ_4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(7.41)*	(3.08)*	(7.42)*	(4.96)*	(-0.32)	(3.11)	(4.18)*	(2.99)	(6.97)*
R^2 %	4.33	6.19	4.93	3.19	4.40	1.36	1.75	2.70	2.46

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.9: The Relationship between Consecutive Weekly Returns and Abnormal Change in MRTO$_j$.

This table presents the result of the effect of changes in MRTO$_j$ using GARCH model as specified below.

$$R_t = \beta_0 + (\beta_1 + \beta_2 D^{LOW}_{MRTO,j} + \beta_3 D^{HIGH}_{MRTO,j}) R_{t-1} + \varepsilon_t \qquad (9)$$

$$V_t = \delta_0 + \delta_1 \varepsilon^2_{tt-1} + \delta_2 D^-_{t-1\varepsilon^2_{t-1}} + \delta_3 V_{t-1} + \delta_4 MROT_{t-1} \qquad (8)$$

R_t is the excess weekly return of all firm portfolio in week t; MRTO$_t$ is the market-adjusted relative turnover of the large-firm portfolio in week j (j=t, t-1, or t +1). $D^{LOW}_{MRTO,j}$ is a dummy variable that is equal to 1 when MRTO of period j is equal or less than its 10th percentile value and zero otherwise. $D^{HIGH}_{MRTO,j}$ is another dummy variable that is equal to 1 when MRTO of period j is equal or higher than its 90th percentile value and zero otherwise.

	Panel A			Panel B			Panel C		
	1/1993 to 12/2005			1/1993 to 6/1999			7/1999 to 12/ 2005		
Coefficients	**Cont.**	**Lag**	**Lead**	**Cont.**	**Lag**	**Lead**	**Cont.**	**Lag**	**Lead**
	(j =t)	(j = t-1)	(j =t +1)	(j =t)	(j = t-1)	(j = t +1)	(j =t)	(j = t-1)	(j = t +1)
β_0	-0.00279	-0.00279	-0.00328	-0.00480	-0.00442	-0.00511	0.00051	0.00067	-0.00069
	(-3.81)*	(-3.25)*	(-4.51)*	(-4.24)*	(-3.99)*	(-4.54)*	(0.40)	(0.51)	(-0.58)
β_1	0.217	0.241	0.194	0.220	0.285	0.221	0.167	0.183	0.118
	(5.35)*	(4.26)*	(4.82)*	(3.30)*	(4.43)*	(3.43)*	(2.66)*	(2.96)*	(1.88)**
AR(1)- 10th MRTO	0.270	0.048	0.071	0.267	0.131	-0.005	0.283	0.146	0.142
	(2.45)**	(0.15)	(0.86)	(1.58)	(0.54)	(-0.05)	(2.06)**	(1.02)	(0.92)
AR(1)- 90th MRTO	0.262	-0.282	0.168	0.571	-0.401	0.367	0.056	-0.162	0.225
	(1.52)	(-1.96)**	(1.44)	(2.23)**	(-1.53)	(1.15)	(0.18)	(-0.63)	(1.36)
Increase or decrease	-0.009	-0.329	0.096	0.304	-0.532	0.372	-0.227	-0.308	0.083
Variance Eq. 8									
δ_1	0.00006	0.00005	0.00005	0.00007	0.00005	0.00009	0.00008	0.00008	0.00007
	(5.27)*	(2.38)**	(5.32)*	(3.25)**	(2.47)**	(3.84)*	(3.65)*	(3.50)*	(4.44)*
δ_2	0.226	0.217	0.235	0.223	0.175	0.247	0.256	0.248	0.266
	(6.44)*	(3.68)*	(6.44)*	(2.93)*	(2.59)*	(3.12)*	(4.76)*	(3.83)*	(5.22)*
δ_3	0.675	0.709	0.685	0.574	0.663	0.507	0.655	0.658	0.661
	(15.12)*	(13.00)*	(16.45)*	(4.98)*	(5.75)*	(4.86)*	(10.58)*	(9.63)*	(12.74)*
δ_4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(7.58)*	(1.02)	(7.15)*	(1.85)***	(-0.38)	(3.36)*	(4.92)*	(2.82)*	(7.14)*
R^2 %	3.822	5.636	5.471	3.027	4.139	2.698	1.000	1.876	2.782

Significance levels: * = 1%, ** = 2%, *** = 1

Table 3.10: The Relationship Between Consecutive Firms Weekly Returns and Abnormal Change in Contemporaneous MRTO$_j$.

To test the effect of changes in FRTO$_j$, we use an alternative specification than include dummy variables that measure that change in MRTO. The following model presents this specification.

$$R_{i,t} = \beta_0 + (\beta_1 + \beta_2 D^{LOW}_{FRTO,j} + \beta_3 D^{HIGH}_{FRTO,j}) R_{i,t-1} + (\beta_4 + \beta_5 D^{LOW}_{MRTO,j} + \beta_6 D^{HIGH}_{MRTO,j}) R_{M,t-1} + \varepsilon_t \quad (6)$$

Where $R_{i,t}$ is the excess weekly return of firm i in week t, $D^{LOW}_{FRTO,j}$ is a dummy variable that is equal to 1 when the firm-adjusted relative turnover (FRTO) of firm i in week t is in it 10[th] percentile value and 0 otherwise. $D^{HIGH}_{FRTO,j}$ is a dummy variable that is equal to 1 when FRTO of firm i is in its 90[th] percentile value. R_t is the excess weekly return of the large firm portfolio in week t; MRTO$_t$ is the market-adjusted relative turnover of all SSM firms portfolio in week j (j=t, t-1, or t +1). $D^{LOW}_{MRTO,j}$ is a dummy variable that is equal to 1 when MRTO of period j is equal or less than its 10[th] percentile value and zero otherwise. $D^{HIGH}_{MRTO,j}$ is another dummy variable that is equal to 1 when MRTO of period j is equal or higher than its 90[th] percentile value and zero otherwise.

Significance levels: * = 1%, ** = 2%, *** = 10%.

	B_0	B_1	B_2	B_3	B_4	B_5	B_6	B_3 - B_2	B_6-β_5
1010	-0.0013	0.0290	0.1981	0.0719	0.1155	-0.6245	0.4633	-0.1262	1.0878
	(-1.11)	(0.58)	(2.32)**	(0.61)	(1.92)***	(-3.26)*	(2.16)***		
2050	-0.0017	-0.0025	0.1500	-0.0971	0.2321	-0.1910	0.2220	-0.2470	0.4130
	(-1.15)	(-0.05)	(1.70)***	(-0.97)	(3.11)*	(-0.80)	(0.81)		
1040	0.0000	-0.0562	0.1238	0.0608	0.2118	0.0293	0.0848	-0.0629	0.0555
	(0.02)	(-1.11)	(3.00)*	(1.22)	(2.85)*	(0.12)	(0.29)		
2080	-0.0002	-0.1876	-0.2737	0.1685	0.2404	0.1936	0.0315	0.4423	-0.1621
	(-0.09)	(-3.76)*	(-4.27)*	(2.44)**	(2.80)*	(0.70)	(0.10)		
3010	-0.0013	-0.0141	0.0082	0.0918	0.2402	-0.7120	-0.2124	0.0836	0.4996
	(-0.93)	(-0.29)	(0.14)	(1.10)	(3.52)*	(-3.35)*	(-0.87)		
4080	0.0019	-0.0635	-0.0742	-0.1937	0.3876	0.5785	0.5838	-0.1195	0.0053
	(1.04)	(-1.21)	(-1.72)**	(-2.61)*	(3.99)*	(1.94)**	(1.71)***		
6040	-0.0013	-0.0761	-0.0948	0.1033	0.4301	0.2109	-0.9168	0.1981	-1.1277
	(-0.72)	(-1.65)***	(-1.48)	(1.55)	(4.96)*	(0.74)	(-2.84)*		
2130	-0.0008	-0.1837	-0.4444	0.0197	0.4519	0.5551	0.3668	0.4641	-0.1883
	(-0.39)	(-3.09)*	(-4.45)*	(0.17)	(3.61)*	(1.75)***	(0.88)		
2110	-0.0022	-0.0857	-0.2156	-0.0641	0.2116	0.5238	0.2139	0.1514	-0.3100
	(-0.99)	(-1.65)***	(-3.71)*	(-0.88)	(1.76)***	(1.31)	(0.52)		
4050	0.0005	-0.0444	-0.3283	0.2329	0.3632	-0.2572	-0.3235	0.5611	-0.0663
	(0.21)	(-0.86)	(-4.80)*	(3.13)*	(3.23)*	(-0.75)	(-0.78)		

Table 3.11: The Relationship Between Consecutive Firms Weekly Returns and Abnormal Change in Lagged MRTO$_j$.
To test the effect of changes in FRTO$_j$, we use an alternative specification than include dummy variables that measure that change in MRTO. The following model presents this specification.

$$R_{i,t} = \beta_0 + (\beta_1 + \beta_2 D^{LOW}_{FRTO,j} + \beta_3 D^{HIGH}_{FRTO,j})R_{i,t-1} + (\beta_4 + \beta_5 D^{LOW}_{MRTO,j} + \beta_6 D^{HIGH}_{MRTO,j})R_{M,t-1} + \varepsilon_t \quad (6)$$

Where $R_{i,t}$ is the excess weekly return of firm i in week t, $D^{LOW}_{FRTO,j}$ is a dummy variable that is equal to 1 when the firm-adjusted relative turnover (FRTO) of firm i in week t is in it 10th percentile value and 0 otherwise. $D^{HIGH}_{FRTO,j}$ is a dummy variable that is equal to 1 when FRTO of firm i is in its 90th percentile value. R_t is the excess weekly return of the large firm portfolio in week t; MRTO$_t$ is the market-adjusted relative turnover of all SSM firm portfolio in week j (j=t, t-1, or t +1). $D^{LOW}_{MRTO,j}$ is a dummy variable that is equal to 1 when MRTO of period j is equal or less than its 10th percentile value and zero otherwise. $D^{HIGH}_{MRTO,j}$ is another dummy variable that is equal to 1 when MRTO of period j is equal or higher than its 90th percentile value and zero otherwise. Significance levels: * = 1%, ** = 2%, *** = 10%.

	B$_0$	B$_1$	B$_2$	B$_3$	B$_4$	B$_5$	B$_6$	B$_3$ - B$_2$	B$_6$-β$_5$
1010	-0.0010	0.0500	0.0483	-0.3348	0.2349	0.0944	-0.1662	-0.3831	-0.2606
	(-0.87)	(1.00)	(0.53)	(-2.60)*	(3.78)*	(0.56)	(-0.90)		
2050	-0.0012	0.0408	0.1246	-0.1300	0.3531	0.6019	-0.7089	-0.2547	-1.3108
	(-0.84)	(0.80)	(2.10)**	(-1.60)	(4.76)*	(2.97)*	(-3.25)*		
1040	0.0000	-0.0060	0.1130	-0.0974	0.1857	-0.1435	-0.1020	-0.2104	0.0416
	(0.01)	(-0.12)	(2.59)*	(-1.92)***	(2.42)**	(-0.68)	(-0.44)		
2080	0.0000	0.0290	0.2112	-0.0665	0.1513	0.1077	-0.1147	-0.2776	-0.2224
	(-0.01)	(0.57)	(4.99)*	(-0.83)	(1.76)***	(0.46)	(-0.45)		
3010	-0.0010	0.0751	0.2058	-0.0132	0.2086	-0.6011	-0.3592	-0.2190	0.2418
	(-0.76)	(1.47)	(4.58)*	(-0.15)	(3.04)*	(-3.36)*	(-1.85)**		
4080	0.0020	0.0256	0.2829	-0.1506	0.3337	-0.2871	-0.6775	-0.4335	-0.3904
	(1.09)	(0.49)	(4.37)*	(-1.85)***	(3.33)*	(-1.10)	(-2.45)**		
6040	-0.0017	0.0083	-0.0055	-0.2533	0.3048	-0.5712	-0.0968	-0.2478	0.4744
	(-0.97)	(0.17)	(-0.14)	(-4.35)*	(3.48)*	(-2.41)**	(-0.37)		
2130	0.0000	0.0095	0.3866	-0.0295	0.3114	-0.8911	-0.7763	-0.4161	0.1148
	(0.00)	(0.15)	(6.40)*	(-0.33)	(2.45)**	(-3.17)*	(-2.48)**		
2110	-0.0015	0.0014	0.0860	-0.0694	0.2357	0.1055	-0.4938	-0.1554	-0.5993
	(-0.66)	(0.02)	(1.78)***	(-1.38)	(1.96)**	(0.27)	(-1.50)		
4050	0.0005	0.0444	-0.0349	-0.1538	0.2565	-1.7302	-0.4132	-0.1189	1.3170
	(0.25)	(0.74)	(-1.08)	(-1.76)***	(2.18)**	(-5.93)*	(-1.26)		

Table 3.12: The Relationship Between Consecutive Firms Weekly Returns and Abnormal Change in Lead MRTO$_j$.

To test the effect of changes in FRTO$_j$, we use an alternative specification than include dummy variables that measure that change in MRTO. The following model presents this specification.

$R_{i,t} = \beta_0 + (\beta_1 + \beta_2 D^{LOW}_{FRTO,j} + \beta_3 D^{HIGH}_{FRTO,j})R_{i,t-1} + (\beta_4 + \beta_5 D^{LOW}_{MRTO,j} + \beta_6 D^{HIGH}_{MRTO,j})R_{M,t-1} + \varepsilon_t$ (6) Where $R_{i,t}$ is the excess weekly return of firm i in week t, $D^{LOW}_{FRTO,j}$ is a dummy variable that is equal to 1 when the firm-adjusted relative turnover (FRTO) of firm i in week t is in it 10th percentile value and 0 otherwise. $D^{HIGH}_{FRTO,j}$ is a dummy variable that is equal to 1 when FRTO of firm i is in its 90th percentile value. R_t is the excess weekly return of the large firm portfolio in week t; MRTO$_t$ is the market-adjusted relative turnover of all SSM firm portfolio in week j (j=t, t-1, or t +1). $D^{LOW}_{MRTO,j}$ is a dummy variable that is equal to 1 when MRTO of period j is equal or less than its 10th percentile value and zero otherwise. $D^{HIGH}_{MRTO,j}$ is another dummy variable that is equal to 1 when MRTO of period j is equal or higher than its 90th percentile value and zero otherwise. Significance levels: * = 1%, ** = 2%, *** = 10%.

	B$_0$	B$_1$	B$_2$	B$_3$	B$_4$	B$_5$	B$_6$	B$_3$ - B$_2$	B$_6$-β$_5$
1010	-0.0011	-0.0398	0.0148	0.4482	0.1837	-0.0662	0.1058	0.4334	0.1720
	(-0.92)	(-0.80)	(0.15)	(4.33)*	(2.95)*	(-0.50)	(0.82)		
2050	-0.0015	-0.0073	0.0745	-0.1014	0.2624	0.0240	0.0850	-0.1759	0.0610
	(-1.03)	(-0.15)	(1.26)	(-1.05)	(3.46)*	(0.14)	(0.52)		
1040	0.0002	-0.0909	-0.0144	-0.0105	0.2343	0.1546	0.0783	0.0039	-0.0763
	(0.10)	(-1.90)***	(-0.30)	(-0.23)	(3.02)*	(0.86)	(0.45)		
2080	-0.0002	-0.1276	0.1035	0.4455	0.2020	-0.0092	-0.0935	0.3420	-0.0843
	(-0.12)	(-2.83)*	(1.23)	(4.62)*	(2.32)**	(-0.05)	(-0.49)		
3010	-0.0010	-0.0050	-0.0965	-0.0832	0.3390	0.3127	-0.0855	0.0133	-0.3982
	(-0.75)	(-0.10)	(-1.15)	(-1.08)	(4.75)*	(2.04)**	(-0.58)		
4080	0.0015	-0.0065	0.0805	-0.1588	0.3099	0.2897	0.4745	-0.2393	0.1848
	(0.80)	(-0.12)	(1.74)***	(-2.45)**	(3.07)*	(1.35)	(2.30)**		
6040	-0.0020	-0.0323	0.0912	-0.1273	0.3374	0.2556	0.5664	-0.2185	0.3108
	(-1.17)	(-0.70)	(1.61)	(-1.75)***	(3.83)*	(1.26)	(2.93)*		
2130	-0.0011	-0.1447	-0.0410	-0.1697	0.3180	-0.2206	0.9374	-0.1287	1.1579
	(-0.55)	(-2.49)**	(-0.54)	(-1.82)***	(2.52)**	(-0.95)	(4.19)*		
2110	-0.0024	-0.0338	0.1648	-0.0973	0.1706	-0.3919	0.5679	-0.2622	0.9597
	(-1.08)	(-0.68)	(2.22)**	(-1.51)	(1.44)	(-1.39)	(1.55)		
4050	0.0004	-0.1462	-0.2673	0.2680	0.5382	0.3396	-0.0925	0.5353	-0.4321
	(0.18)	(-2.52)**	(-4.79)*	(5.08)*	(4.59)*	(1.41)	(-0.35)		

Table 3.13: Returns to Loser-Price, High-Volume portfolios

This table presents the average weekly returns to the loser-price, high volume portfolio. For a stock to be included in the loser-price, high-volume portfolio, its lagged weekly return and change in volume must be within a given filter for lagged return and change in volume as indicated in the table. The sample includes all firms traded in the SSM from 1/4/1993 to 12/26/2005 period. *N* is the number of the weeks the portfolio traded at the perspective price and volume filter level out of a possible 674 weeks. The t-statistics are reported in parentheses. Weekly returns are reported in percentages.

		Lagged weekly return filter (%)					
Lagged weekly growth in volume filter (%)		**<0 and ≥ -2**	**<-2 and ≥-4**	**<-4 and ≥-6**	**<-6 and ≥ 8**	**< -8 and ≥-10**	**< -10**
No volume filter	*Mean*	-0.323	-0.487	-0.190	-0.048	0.946	1.627
	T-statistics	(9.35)*	(-7.80*)	(-1.65)***	(-0.24)	(3.54)*	(4.67)*
	N	671	639	519	349	213	255
>0 and <=50	*Mean*	-0.648	-1.128	-0.726	0.187	0.883	2.894
	T-statistics	(-9.33)*	(-7.44)*	(-2.72)*	(0.42)	(1.19)	(3.86)*
	N	585	375	202	109	44	60
>= 50 and < 100	*Mean*	0.081	-0.025	-0.131	1.161	2.040	5.158
	T-statistics	(0.72)	(-0.11)	(-0.38)	(1.31)	(1.62)	(5.85)*
	N	512	270	134	53	34	42
>= 100 and < 150	*Mean*	0.097	0.883	1.882	1.129	4.127	4.255
	T-statistics	(0.56)	(2.44)**	(3.38)*	(0.97)	(3.22)*	(3.03)*
	N	411	190	98	42	20	31
>= 150 and <200	*Mean*	0.704	1.826	0.084	1.645	4.147	5.955
	T-statistics	(3.24)*	(3.65)*	(0.11)	(0.86)	(1.91)***	(3.28)*
	N	317	134	55	21	11	14
>= 200 and < 250	*Mean*	0.674	1.834	2.242	1.234	3.064	3.040
	T-statistics	(2.62)*	(3.70)*	(1.87)***	(0.65)	(1.76)***	(1.19)
	N	223	101	34	15	9	11
>= 250	*Mean*	1.779	1.892	1.954	1.654	3.990	7.009
	T-statistics	(12.45)*	(6.02)*	(3.15)*	(1.71)***	(3.60)*	(4.40)*
	N	476	253	122	59	38	45

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.14: Returns to Loser-Price, Low-Volume portfolios

This table presents the average weekly returns to the loser-price, Low-volume portfolio. For a stock to be included in the loser-price, low-volume strategy, its lagged weekly return and change in volume must be within a given filter for lagged return and change in volume as indicated in the table. The sample includes all firms traded in the SSM from 1/4/1993 to 12/26/2005 period. *N* is the number of the weeks the portfolio traded at the perspective price and volume filter level out of a possible 674 weeks. The t-statistics are reported in parentheses. Weekly returns are reported in percentages.

		Lagged weekly return filter (%)					
Lagged weekly growth in volume filter (%)		**<0 and ≥ -2**	**<-2 and ≥-4**	**<-4 and ≥-6**	**<-6 and ≥ 8**	**< -8 and ≥10**	**< -10**
No volume filter	*Mean*	-0.323	-0.487	-0.190	-0.048	0.946	1.627
	T-statistics	(-9.35)*	(-7.80)*	(-1.65)*	(-0.24)	(3.54)*	(4.67)*
	N	671	639	519	349	213	255
<0 and >= -15	*Mean*	-0.910	-1.097	-0.898	0.044	-0.395	-0.396
	T-statistics	(-9.58)*	(-5.95)*	(-2.62)*	(0.09)	(-0.55)	(-0.36)
	N	430	258	122	54	28	35
<-15 and >= -30	*Mean*	-0.844	-0.935	-0.426	-0.422	0.398	0.983
	T-statistics	(-10.47)*	(-6.03)*	(-1.30)	(-0.60)	(0.46)	(0.76)
	N	462	280	126	63	28	31
<-30 and >= - 45	*Mean*	-1.032	-1.151	-0.832	-1.710	0.052	-3.139
	T-statistics	(-13.99)*	(-8.11)*	(-2.90)*	(-2.35)**	(0.10)	(-2.61)*
	N	491	293	152	68	36	40
< -45 and >= -60	*Mean*	-1.179	-1.339	-0.678	-1.138	0.393	-1.048
	T-statistics	(-13.95)*	(-10.17)*	(-2.41)*	(-2.33)**	(0.58)	(-1.27)
	N	469	315	140	72	37	52
<-60 and >= -75	*Mean*	-1.173	-0.991	-0.640	-0.581	-1.252	-0.400
	T-statistics	(-13.02)*	(-5.55)*	(-2.13)*	(-1.21)	(-2.34)*	(-0.31)
	N	425	270	123	85	39	52
< - 75	*Mean*	-1.140	-0.946	-0.950	-0.519	-0.702	-1.081
	T-statistics	(-11.36)*	(-7.19)*	(-3.41)*	(-1.37)	(-1.61)	(-1.67)***
	N	346	259	119	65	45	60

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.15: Returns to Winner-Price, High-Volume portfolios

This table presents the average weekly returns to the winner-price, high-volume portfolio. For a stock to be included in winner-price, high-volume strategy, its lagged weekly return and change in volume must be within a given filter for lagged return and change in volume as indicated in the table. The sample includes all firms traded in the SSM from 1/4/1993 to 12/26/2005 period. *N* is the number of the weeks the portfolio traded at the perspective price and volume filter level out of a possible 674 weeks. The t-statistics are reported in parentheses. Weekly returns are reported in percentages.

		Lagged weekly return filter (%)					
Lagged weekly growth in volume filter (%)		**≥ 0 and < 2**	**≥2 and <4**	**≥4 and < 6**	**≥6 and<8**	**≥8 and <10**	**≥10**
No volume filter	*Mean*	0.207	0.464	0.546	0.525	0.602	0.875
	T-statistics	(4.55)*	(5.08)*	(3.93)*	(2.25)**	(1.67)***	(2.82)*
	N	660	596	466	353	271	302
>0 and <=50	*Mean*	0.076	0.937	1.719	1.888	2.267	4.144
	T-statistics	(0.85)	(4.84)*	(5.67)*	(3.75)*	(2.92)*	(6.15)*
	N	505	316	185	110	89	110
>= 50 and < 100	*Mean*	0.940	1.839	3.641	4.396	7.960	5.678
	T-statistics	(7.77)*	(4.92)*	(5.47)*	(6.36)*	(5.00)*	(4.27)*
	N	403	206	115	82	35	51
>= 100 and < 150	*Mean*	1.368	2.267	2.997	3.191	6.896	10.204
	T-statistics	(7.16)*	(6.18)*	(4.73)*	(1.47)	(2.68)*	(4.52)*
	N	311	164	62	40	28	28
>= 150 and <200	*Mean*	2.041	3.006	2.992	3.064	2.485	5.689
	T-statistics	(7.42)*	(6.43)*	(2.69)*	(1.21)	(0.72)	(1.52)
	N	229	99	43	15	9	15
>= 200 and < 250	*Mean*	2.655	3.166	5.049	4.614	10.075	3.953
	T-statistics	(7.60)*	(4.49)*	(4.60)*	(1.56)	(3.87)*	(1.73)***
	N	159	68	26	21	5	6
>= 250	*Mean*	2.506	4.039	3.291	4.411	3.623	9.329
	T-statistics	(13.65)*	(9.49)*	(4.84)*	(3.71)*	(1.48)	(2.75)*
	N	362	192	91	44	26	29

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 3.16: Returns to Winner-Price, Low-Volume portfolios

This table presents the average weekly returns to the winner-price, low-volume portfolio. For a stock to be included in winner-price, low-volume strategy, its lagged weekly return and change in volume must be within a given filter for lagged return and change in volume as indicated in the table. The sample includes all firms traded in the SSM from 1/4/1993 to 12/26/2005 period. *N* is the number of the weeks the portfolio traded at the perspective price and volume filter level out of a possible 674 weeks. The t-statistics are reported in parentheses. Weekly returns are reported in percentages.

		Lagged weekly return filter (%)					
Lagged weekly growth in volume filter (%)		**≥0 and < 2**	**≥2 and <4**	**≥4 and < 6**	**≥6 and<8**	**≥8 and <10**	**≥10**
No volume filter	*Mean*	0.207	0.464	0.546	0.525	0.602	0.875
	T-statistics	(4.55)*	(5.08)*	(3.93)*	(2.25)**	(1.67)***	(2.82)*
	N	660	596	466	353	271	302
<0 and >= -15	*Mean*	-0.590	-0.033	0.210	-0.030	1.298	2.525
	T-statistics	(-3.17)*	(-0.12)	(0.53)	(-0.05)	(1.04)	(3.13)*
	N	344	183	107	67	33	68
<-15 and >= -30	*Mean*	-0.648	-0.770	-0.148	1.233	-0.708	1.588
	T-statistics	(-6.12)*	(-2.61)*	(-0.32)	(1.99)**	(-0.92)	(2.09)**
	N	368	222	120	74	47	78
<-30 and >= - 45	*Mean*	-1.060	-1.198	-1.369	-0.921	-1.107	1.627
	T-statistics	(-9.09)*	(-4.77)*	(-4.97)*	(-2.28)**	(-1.55)	(2.18)**
	N	380	211	139	100	54	90
< -45 and >= -60	*Mean*	-1.266	-1.300	-1.214	-2.058	-2.308	-3.869
	T-statistics	(-12.13)*	(-7.76)*	(-4.74)*	(-3.99)*	(-3.09)*	(-4.61)*
	N	383	226	125	89	65	84
<-60 and >= -75	*Mean*	-1.165	-1.698	-1.442	-2.793	-3.115	-4.089
	T-statistics	(-11.92)*	(-7.87)*	(-4.80)*	(-5.68)*	(-2.96)*	(-7.03)*
	N	328	213	132	80	52	103
< - 75	*Mean*	-1.176	-1.459	-1.966	-3.231	-2.682	-5.779
	T-statistics	(-11.55)*	(-9.78)*	(-5.54)*	(-4.95)*	(-5.01)*	(-7.95)*
	N	278	181	112	61	52	68

Significance levels: * = 1%, ** = 2%, *** = 10%.

CHAPTER IV

TRADING VOLUME, TIME VARYING CONDITIONAL VOLATILITY, AND ASYMMETRIC VOLATILITY SPILLOVER IN THE SAUDI STOCK MARKET

INTRODUCTION

The importance of volatility studies is well explained by Karpoff's (1987) review of the literature on the relationship between volatility and trading volume. Karpoff summarizes the importance of this research in the following points. First, the theory of the stock returns volatility-volume relationship provides insight into the structure of financial markets. It predicts that this relationship depends upon the rate of information flow to the market, information dissemination, market size, and the existence of short sale constraints. Second, the stock returns volatility-volume relationship has important implications for event studies that use a combination of price and volume data. And third, the relationship has important implications for the empirical distribution of speculative assets. In particular, the findings of the stock returns volatility-volume tests generally support the mixture of distributions hypothesis, which helps explain the observed kurtosis in empirical stock return distributions.

Despite the obvious importance of volatility studies, the Saudi stock market (SSM) lacks research that would contribute significantly to academic research and to investor knowledge.

To fill this gap, I test the effect of trading volume on the persistence of the time varying conditional volatility of returns in the SSM with the intention of offering support to either the mixture of distributions hypothesis (MDH) or the sequential information arrival hypothesis (SIAH). I use the generalized autoregressive conditional

heteroskedasticity (GARCH) (1, 1) methodology to test the persistence of return volatility without volume, with contemporaneous volume, and with lagged volume. Trading volume is measured as the number of traded shares during the day. In addition to volume, I use two different proxies for information arrival, intra-day volatility (IDV), and overnight indicators (ONI), which are introduced by Gallo and Pacini (2000). The empirical tests are applied on the SSM index, five industry indices, and a sample of 15 individual firms.

This essay also tests the direction of the volatility spillover between large- and small-cap portfolios. The objective is to determine whether the volatility spillover direction between large and small firms is asymmetric in the SSM. I use a two-stage GARCH (1, 1) approach to test for spillover direction.

The contribution of this essay can be summarized in the following points. First is the lack of any previous study that tests the conditional volatility in the SSM despite its relative importance in the region and high growth. According to the Arab Monetary Fund's annual report for the year ended December 2005, which provides statistics for all 15 Arab stock markets, the capitalization of the SSM represents 50% of the total market capitalization of these markets, while the value traded of the SSM represents 76.9% of the total stock value traded in all these markets. The report includes the markets of all Arab countries, namely, the Abu Dhabi Securities Market, the Amman Stock Exchange, the Bahrain Stock Exchange, the Beirut Stock Exchange, the Casablanca Stock Exchange, the Doha Stock Exchange, the Dubai Financial Market, the Egyptian Capital Market, the Kuwait Stock Exchange, the Muscat Securities Market, the Palestine Securities Exchange, the Saudi Stock Market, and the Tunis Stock Exchange.

Moreover, the SSM has become one of the leading emerging markets. According to statistics provided by the World Federation of Exchanges (WFE) for December 2005, the SSM was ranked 16th in terms of a market domestic capitalization of $650.18 billion, well ahead of Bombay Stock Exchange, India, Taiwan, Shanghai, Singapore, and many other historically world-leading stock exchanges. The market index has gained over 40% for 2005, which follows six years of growth at an average annual rate of 38%. Market volumes have also increased significantly. On average, market volume was worth over $4 billion a day in 2005 (Saudi Stock Exchange Report 2005).

Second, several characteristics of the SSM that differentiate it from other developed and emerging markets make it interesting to study. In addition to the relatively large size of the market in the region and its strong development and growth, the behavior, structure, and size of the SSM differ in many ways from other markets. The SSM is a very large market in term of capitalization and trading volume, with a relatively small number of 85 publicly traded companies. Relative to other markets, the breadth of this market is small while the capitalization and trading volume are relatively large; this makes it interesting to examine the effects of these specific characteristics on investors and accordingly on return behavior. Another aspect of the Saudi market that differentiates it from the structure of most developed markets is the lack of an options market, which in some studies has been found to affect the price and volatility of the underlying market (Cornard 1989; St. Pierre 1989). In addition, even though many government-owned companies have gone public, the government still owns the majority shares of their stocks, which may impact stock market return behavior.

Third, there are some inconsistent results in the literature on market volatility and trading volume, especially in emerging markets. For example, some studies find that the persistence of the GARCH effect disappears after including volume in the conditional variance (Lamoureux and Lastrapes 1990), while others find that the GARCH effect does not completely disappear (Sharma et al. 1996; Kamath and Chusanachoti 2000). In-between these two opposing views, some researchers find different results depending on the theory they use. For example, Darrat et al. (2003) does not find support for the MDH, but does find support for the SIAH for DJIA stocks. A point of caution is warranted, as there are several shortcomings in either the data or the methodology used by researchers in emerging market studies. It is my intention to overcome these shortcomings in the current study.

This essay adds an out-of-sample empirical test from a different market to the conditional and asymmetric volatility literature, and extends our knowledge of the information transmission, volatility estimation, and pricing behavior in the SSM.

The remainder of this essay includes a detailed literature review in the next section. The section that follows presents the methodology employed in this essay. Then, the data and the empirical results are discussed. The last section provides the conclusion.

LITERATURE REVIEW

The main theoretical foundation of studies on the relationship between trading volume and volatility is related to either the SIAH or the MDH. The seminal study of Copeland (1976) assumes that traders receive new information in sequential random style; accordingly, he developed the SIAH. Starting at equilibrium, all traders possess the same set of information; traders then start to change their trading positions according to new news arriving in the market. This information signal is observed by each trader at a time and is not received by all traders simultaneously. The response of each individual trader to the information signal represents one of a series of incomplete equilibria. The final market equilibrium is established when all traders have received the information signal and have the same information set. The main implication of the SIAH is that the sequential reaction to information suggests that asset price volatility is potentially forecastable with knowledge of trading volume.

However, the MDH offers a different explanation by linking price change, volume, and rate of information flow (Clark 1973; Epps and Epps 1976; Harris 1987). The MDH implies a positive relationship between trading volume and price variability, and this relationship is a function of a mixing variable defined as the rate of information flow. The variance of daily prices is considered to be a random variable representing the sum of individual price changes within the day, while trading volume is positively related to the number of within-day price changes. It follows that the outcome of trading will be the contemporaneous changes of both prices and volume. This implies a common joint distribution between price and volume. The MDH predicts that prices and volume have a joint response to information due to this common distribution. In the MDH, the shift to a

new equilibrium is immediate, and the partial equilibrium of the sequential information model never occurs (Foster 1995).

Clark (1973) introduced the theoretical analysis of the stock price movement and trading volume by suggesting the MDH, which explores the role of trading volume as a proxy for a stochastic process of information arrival. This idea was extended and refined by later authors such as Copeland (1976), Epps and Epps (1976), and Harris (1987). Anderson (1996), at a later stage, introduced the modified mixture model. From that point on, an increasing number of studies have dealt with trading volume and stock market volatility. These studies can be divided into two types: developed markets and emerging markets.

Focusing on developed markets, Lamoureux and Lastrapes (1990) use the daily returns and volumes of 20 actively traded stocks in the US market from 1980 to 1984 to test the relation between conditional variance and trading volume. They use the MDH to derive a GARCH effect. They argue that daily trading volume can be used as a proxy for information arrival, and find that the volatility persistence disappears when they enter daily trading volume series in the conditional variance equation.

Anderson (1996) modifies the MDH with the Poisson distribution instead of assuming normal distributions of volume. He argues that stock returns and trading volumes are contemporaneously dependent on an underlying mixing variable representing the non-uniform intensity of information flow over time. He tests the modified MDH for five major individual common stocks on the NYSE over the period 1973-1991. The results support the prediction of both the standard and the modified MDH. However, he also finds that the new specification performs better than the

standard formulation. Najand and Yung (1991) use daily prices and volumes of Treasury-bond futures markets from 1984 to 1989 and find that the current volatility can be explained by past volatility, which tends to persist over time. However, in contrast to Lamoureux and Lastrapes (1990), they find that the GARCH effect persists even after volume is included in the conditional variance of their model.

Gallo and Pacini (2000) use the data of 10 actively trade US stocks from 1985 to 1995 and find that the estimated persistence decreases when trading volume is inserted into the conditional variance equation. In addition to the trading volume, they use the overnight indicator (ONI), which represents the surprise intervening between the closing of one day and the opening of the next day, and find it to account for most of the persistence in ARCH. Also, as a substitute for lagged volume, they use the intra-day volatility (IDV) as an indicator of previous-day volatility expressed as the difference between the highest and lowest price divided by the closing price; this is also found to have a significant effect on reducing the persistence of volatility.

Foster (1995) tests the prediction of the MDH for the oil futures market from 1990 to 1994 and finds that volume and volatility are largely contemporaneously related and are both driven by the same factor, which is assumed to be information.

At the same time, some studies find little, if any, effect of trading volume on the persistence of market volatility. Sharma et al. (1996) investigate the relationship between trading volume and GARCH for the NYSE index from 1986 to 1989. They find that trading volume does not completely explain the GARCH effect for the market index, and conclude that while trading volume might be a good proxy for the information arrival about individual firms, it is not true for the market as a whole.

Darrat et al. (2003) test the relationship between trading volume and return volatility for all DJIA stocks using 5 minutes interval data from April 1, 1998, through June 30, 1998. Using the exponential generalized autoregressive method, they find that contemporaneous correlations between trading volume and volatility are positive and statistically significant in only three of the 30 DJIA stocks. The other 27 DJIA stocks exhibit no significant positive correlation between trading volumes and return volatility. However, they also find that trading volume and return volatility follow a clear lead-lag pattern in a large number of the DJIA stocks. They conclude that their results do not support the MDH, but do support the SIAH.

Although several studies investigate volatility in emerging markets, few investigate the relationship between trading volume and volatility. Brailsford (1996) investigates the effect of trading volume as a proxy for information arrival on the persistence of volatility in the Australian stock market using the GARCH process from 1989 to 1993. He finds that including contemporaneous trading volume in the conditional variance equation significantly reduces volatility persistence in Australian stock returns. However, he also limits his study to five individual firms with no replication on either the industry or the market level.

Pyuna et al. (2000) investigate the Korean Stock Exchange from 1990 to 1994 and find that adding the current trading volume into the conditional variance equation significantly reduces the volatility persistence. Their results are consistent with the prediction of the MDH. However, their study is limited to the firm level and also uses the weekly data of 15 individual firms, which may affect the generalizability of their results. Bohl and Henke (2003) investigate the relation between trading volume and daily returns

for 20 individual Polish stocks from 1999 to 2000. They find weak support for the persistence of a GARCH decrease for some individual stocks when they insert volume into the conditional variance equation.

This essay also investigates the asymmetric conditional spillover between size-based portfolios in the SSM. Some of the empirical studies in this literature are as follows. Conard, Gultekin, and Kaul (1991) investigate the volatility spillover between different portfolios (large- and small-cap) of weekly returns for the US equity market from 1962 to 1988 using univariate and multivariate GARCH models. Their results show an asymmetry effect in both price and volatility. They find that the mean return and volatility shocks experienced by large stocks can explain the mean return and volatility of small stocks. However, they do not find that small stocks have a similar opposite effect on large stocks.

Reyes (2001) uses a bivariate EGARCH to test for the volatility spillover effect from large stocks on small stock monthly returns for the large and small Japanese firm indices from 1970 to 1996. His results are consistent with Conard et al. (1991), who find that the volatility of large firms affects small firms, but not vice versa.

Pyuna et al. (2000) investigate this relationship in the Korean market from 1990 to 1994. However, they find that, just as the volatility of smaller firms can be predicted by shocks to larger firms, so too can the volatility of larger firms be predicted by shocks to smaller firms. This relationship, however, is more pronounced going from large to small firms. This result contradicts previous studies that find asymmetry in the predictability of volatility.

The study of volatility spillovers is of great importance as it explains the process by which information is transmitted from large to small firms. As Rose (1998) explains, the variance of price change is directly related to the rate information flow. I aim to test this prediction to explain the flow of information in the SSM and whether or not the volatility spillover between different-size portfolios is asymmetric.

METHODOLOGY

This study uses the GARCH model proposed by Bollerslev (1986). The GARCH model is an extension of the autoregressive conditional heteroskedasticity (ARCH) model (Engle 1982) that allows conditional variance to change over time as a function of past error. This section follows Sahrma et al.'s (1996) presentation of GARCH modeling and its empirical application for studying volatility and trading volume.

The ARCH regression model is obtained by assuming that the mean of the random variable Y_t is given as $X'\beta$, a linear combination of lagged endogenous and exogenous variables included in the information set Φ_{t-1} with a vector of unknown parameters, β (Sharma et al. 1996).

$$Y_t = X_t \beta + \varepsilon_t \qquad (1)$$

$$\varepsilon_t \big| \Phi_{t-1} \approx N(0, h_t) \qquad (2)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{ti}^2 \qquad (3)$$

where p is the order of ARCH process and αs is the parameter to be estimated.

Bollerslev (1986) extends the ARCH process to GARCH, which allows for a more flexible lag structure. The GARCH (p,q) model is given by

$$Y_t = X_t\beta + \varepsilon_t \qquad (4)$$
$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t) \qquad (5)$$
$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (6)$$

$$\begin{aligned} &where \quad p \geq 0 \; q \geq 0 \\ &\alpha_0 \geq 0 \; \alpha i \geq 0 \quad i = 1,\ldots, p \\ &\beta_j \geq 0 \quad j = 1,\ldots., q \end{aligned}$$

For q = 0 the process reduces to the ARCH (p) process. To examine the effect of volume on stock returns volatility, the following GARCH (1, 1) model is employed:

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t \qquad (7)$$
$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t) \qquad (8)$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_t \qquad (9)$$

where r_t is the daily SSM market return measure, V_t is the daily volume, and $\beta_{,1}, \beta_2, \alpha_0, \alpha_1, \alpha_2, \& \ \alpha_3$ are the parameters to be estimated. The coefficient α_1 gauges the impact of past squared unexpected returns on the current conditional variance of the returns, whereas the coefficient α_2 gauges the impact of past conditional variance on the current conditional variance. The sum $(\alpha_{1,} + \alpha_2)$ is a measure of the persistence of a shock to the variance. The degree of persistence is determined by the magnitude of the sum $(\alpha_{1,} + \alpha_2)$. The effect of a shock on volatility is said to be persistent over future time as this sum approaches 1. I would expect the inclusion of trading volume as a proxy for information arrival in the conditional variance to reduce this sum. The stock return (*R*) is

calculated as the continuously – compound return using the closing price in the following formula:

$$R_t = [\ln(P_t) - \ln(P_{t-1})] \qquad (10)$$

where $\ln(P_t)$ denotes the natural logarithm of the closing price at time *t*. I use the number of shares traded to measure the trading volume. Another proxy for information arrival at t could be the trading volume at day $t-1$. So I also test for one lagged volume as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_{t-1} \qquad (11)$$

Gallo and Pacini (2000) suggest an IDV for the previous day as a substitute proxy for lagged volume. They use an indicator of previous day volatility expressed as the difference between the highest and the lowest price divided by the closing price. The IDV is calculated as follows:

$$IDV_t = \frac{P_t^H - P_t^L}{P_t^C} \qquad (12)$$

where P_t denotes respectively the highest (H), the lowest (L), and the closing (C) price on day *t*. The IDV is entered into the conditional variance as in the following equation:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 IDV_{t-1} \quad (13)$$

The other indicator that Gallo and Pacini (2000) suggest is the ONI. They argue that, instead of measuring returns as the difference between closing prices, the difference between the opening price of any given day and the closing price of the previous day represents an interesting indicator of the number of trades during the day. This proxy may act as a variable on the basis of which the decision of whether or not to engage in a trade during the day can be made. They argue that the ONI represents a good candidate to

capture the persistence of the conditional heteroskedasticity. It is calculated as

$$ONI_t = \left| \log \frac{open_t}{close_{t-1}} \right| \quad (14)$$

Therefore, the conditional variance is estimated including the ONI as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 ONI_{t-1} \qquad (15)$$

The second part of this essay examines the volatility spillover between large and small firms in the SSM. The following is a brief description of the proposed data and methodology for this part. At the beginning of each year, I rank all firms according to their market capitalization (number of shares outstanding multiplied by market price). I then construct two different-sized portfolios: a large-cap portfolio consisting of the 10 largest firms, and a small-cap portfolio consisting of the 10 smallest firms. The next step involves calculating the weekly return for each portfolio. To measure the spillover effect, I follow the methodology of Hamao, Masulis, and Ng (1990) by using a two-stage GARCH (1, 1) approach. In the first stage, I estimate a univariate GARCH (1, 1) model for each portfolio return separately, as in equations 16 and 17:

$$R_{it} = \beta_0 + \beta_1 R_{i,t-1} + \varepsilon_{it} \qquad (16)$$

$$Where \ \ \varepsilon_{it} \middle| \Omega i, t-1 \sim N(0, h_{i,t})$$

$$h_{it} = a_i + b_i \varepsilon_{i,t-1}{}^2 + c_i h_{i,t-1} \qquad where\, i, j = 1,2, \ \ i \neq j \qquad (17)$$

where $R_{i,t}$ is the weekly return of the size-based portfolios and the other variables are the same as explained in the previous section. In the second stage, I introduce the lagged squared standard errors for portfolio j as an exogenous variable in the conditional variance equation of portfolio i and estimate the following equations:

$$R_{it} = \beta_0 + \beta_1 R_{i,t-1} + \varepsilon_{it} \quad (18)$$

$$Where \varepsilon_{it} \big| \Omega i, t-1 \sim N(0, h_{i,t})$$

$$h_{it} = a_i + b_i \varepsilon_{i,t-1}{}^2 + c_i h_{i,t-1} + k_{ij} \varepsilon_{j,t-1} where i, j = 1,2 \forall i \neq j \quad (19)$$

The coefficient of interest is K_{ij}, which measures the impact of past return shocks portfolio *j* on the conditional volatility of portfolio *i*. Likewise, the coefficient K_{ij} of a similar specification can be used to measure the effect of past volatility of security *i* on the conditional variance of *j*.

DATA AND EMPIRICAL RESULTS

1) Descriptive statistics

Empirical tests are applied to daily stock return and volume data over three levels: 1) the market level as measured by the market index Tadawul All Shares Index (TASI);2) the industry level as measured by five industry indices, which are the Tadawul Banking Shares Index (TBSI), Tadawul Cement Shares Index (TBSI), Tadawul Agricultural Shares Index, Tadawul Industrial Shares Index (TISI), and Tadawul Service Shares Index (TSSI); and 3) the firm level as measured by the data of 15 individual companies listed in Appendix 1. Data used include the daily price and volume from January 1993 to December 2005. Return is measured as the continuous compound return as in equation 10.The daily trading volume is measured as the number of shares traded.

To assess the distributional properties of the daily compounded return and trading volume, various descriptive statistics are reported in Tables 1 and 2 for the market index and the five industry-level indices, and Tables 3 and 4 for the 15 individual companies.

Table 4.1 shows that the mean daily stock return is positive for the market index and the five industry indices, which range from 0.084% for the TISI to 0.048% for the

TSSI. Those data show a fat-tailed pattern in all indices. The excess kurtosis is highly positive for all indices and greater than 3, ranging from 20.06 for the TSSI to 10.7 for the TBSI. Return skewness is highest for the TISI at 0.651 and lowest for the TASI at -0.038. Applying the Jarque-Bera test for normality, I find strong support for the hypothesis that the return time series does not come from normal distribution. In addition to the above statistics implying the presence of the ARCH effect in the data, I apply the formal ARCH test to justify using the GARCH model. The *F*-statistics and Engle's LM test in Table 1 are highly significant at the 1% level for all indices and indicate the presence of the ARCH data.

[Insert Table 4.1here]

Table 4.2 shows the descriptive statistics for trading volume for the market index and its sub-indices. The highest mean of trading volume of industry indices is the TSSI, while the lowest is the TCSI. I find that trading volumes for all indices are characterized by positive skewness and kurtosis. Also, the Jarque-Bera test rejects the normality of trading volume for all indices.

[Insert Table 4.2 here]

Table 4.3 shows the descriptive statistics for daily stock returns for 15 individual companies. The mean daily stock returns are positive for all companies and range from 0.020% to 0.142%. The fat-tailed pattern is shown in the data. The excess kurtosis is highly positive and ranges from 5.723 to 14.954. Return skewness is highest at 1.136 and

lowest at -0.286. Applying the Jarque-Bera test for normality, I find strong support for the hypothesis that the return time series does not come from normal distribution. In addition to the above statistics implying the presence of the ARCH effect in the data, I apply the formal ARCH test to justify using the GARCH model. The *F*-statistics and Engle's LM test in Table 4.3 are highly significant at the 1% level for all firms and indicate the present of ARCH in the data.

[Insert Table 4.3 here]

Table 4.4 shows the descriptive statistics for trading volume for the market index and industry indices. I find that trading volume for all indices is characterized by positive skewness and kurtosis. Also, the Jarque-Bera test rejects the normality of trading volume for all indices.

[Insert Table 4.4 here]

To correctly specify the empirical models and avoid spurious correlation in the results, I test the stationary for the return and volume series. To test the return and volume for a unit root, I use the augmented Dickey-Fuller (ADF) test, which is given by

$$\Delta x_t = a_0 + a x_{t-1} + \sum_{t=1}^{n} \delta_i \Delta x_{t-i}$$

Table 4.5 shows the results for the ADF statistics for the market index and the five industry indices at the levels and one difference. The results show is that all return data are stationary at the levels for all indices. For the volume variable, only one index (TASI) is not stationary at the level, so I apply the first difference to achieve stationary.

[Insert Table 4.5 here]

Table 4.6 shows the results for the ADF statistics for the 15 individual companies. All returns data for all firms are stationary at level. For the volume variable, I apply the first difference to achieve stationary whenever the variable is not stationary.

[Insert Table 4.6 here]

2) Empirical results

Table 4.7 shows the results of the GARCH (1, 1) model for the market index and five industry indices. The second and third columns represent the parameters of the ARCH and GARCH terms respectively. The fourth column shows the sum of the ARCH and GARCH parameters, which measures the persistence of the conditional variance series. All ARCH and GARCH terms are statistically significant at the 1% level. The sum of these terms indicates a high persistence in the conditional variance in all indices. This is very close to 1 and ranges from 0.986 for the TGSI to 0.925 for the TCSI.

[Insert Table 4.7 here]

Table 4.8 shows the same test for the 15 firms. The sum of ARCH and GARCH is close to 1 and shows high persistence in the conditional variance for all firms. The sum of these two terms ranges from 0.834 to 0.984, with 11 firms showing persistence greater than 0.90. All GARCH and ARCH terms are statistically significant at the 1% level.

[Insert Table 4.8 here]

Tables 4.9 and 4.10 present the model of persistence of stock returns when I enter the contemporaneous trading volume into the conditional variance equation for the market indices and individual firms, respectively. The sum of the ARCH and GARCH

terms decrease for some market indices but not for all. The sum of ARCH terms and GARCH is still around 0.98 for both the TGSI and TISI. Also, the volume parameter is significant for four indices but not significant for the TSSI and TISI. Examining the individual companies shows that the sum largely decreases for all firms, ranging from 0.47 to 0.88. Additionally, the volume parameters are statistically significant for 12 of the 15 firms. It is evident that the sum of ARCH and GARCH with trading volume is less than the sum with no trading volume, meaning that the degree of persistence is reduced as trading volume enters into the variance equation. This result is consistent with the finding reported Lamoureux and Lastrapes (1990) for 20 actively traded stocks in the US market. These results imply that the persistence of the conditional heteroskedasticity is mostly absorbed by volume effect largely in individual companies and less in market indices. In other words, the rate of information arrival measured by the volume series can be a significant source of the conditional heteroskedasticity in stock returns in the Saudi market.

[Insert Table 4.9 here]

[Insert Table 4.10 here]

Tables 4.11 and 4.12 show the results of the model with one lagged volume for both the market indices and the 15 firms. I find that the results of lagged volume do not reduce persistence as contemporaneous volume does. The sum of ARCH and GARCH for the five indices increases more than that of contemporaneous volume and almost approaches the level of persistence without volume. For all 15 firms, the sum of ARCH and GARCH with lagged volume is greater than that with contemporaneous volume and

approaches the level achieved with no volume. Moreover, none of the lagged volume parameters for all firms and for five of the six indexes is significant. This result is of great interest, since it does not support the SIAH, which implies that lagged volume should be significant in reducing the persistence of volatility. My results contradict the results reported by Darrat et al. (2003) where they find lagged volume to decrease the persistence of variance.

[Insert Table 4.11 here]

[Insert Table 4.12 here]

As a substitute to lagged volume, I follow Gallo and Pacini (2000) where they suggest an alternative indicator for previous-day volatility. They suggest an IDV proxy expressed as the difference between the highest and the lowest price divided by the closing price as an alternative proxy for lagged volume. Table 4.13 shows the results for IDV applied at the firm level. The variable IDV is significant for 4 firms, and it reduces the persistence of volatility in all individual firms. It almost approaches the level of decrease in persistence achieved using contemporaneous volume.

[Insert Table 4.13 here]

I also test for another variable that acts as an alternative proxy for volume and flow of information. The ONI suggested by Gallo and Pacini measures the surprise intervening between the closing of one day and the opening of the following day, as specified in equation 14. Table 4.14 shows the results of estimating model 14, which includes ONI as an exogenous variable in the conditional variance. The variable ONI substantially decreases the persistence of volatility. All volume coefficients are

statistically significant. The results of including the variables IDV and ONI indicate that they are a good proxy for information and act as well as contemporaneous volume in explaining conditional volatility.

[Insert Table 4.14 here]

The next step checks for sub-period analysis at the market level. I split the sample into two sub-periods and test for volatility without volume, volatility with volume, and volatility with lagged volume, as specified in equations 9 and 11. Because the Saudi economy is heavily dependent on oil pricing, I choose one sub-period with low oil prices from January 1993 to December 1999, and another sub-period with relatively high oil prices from January 2000 to December 2005. Figure 4.1 presents the average oil prices from January 1993 to December 2005.

[Insert Figure 4.1 here]

Tables 4.15, 4.16, and 4.17 replicate the results I obtained from using the whole sample by dividing the sample into two periods: the first sub-period in panel A and the second sub-period in panel B. The first period is characterized by low oil prices and the second by high oil prices. The results indicate that volatility is more persistent for the whole market and most of the industry indices during the second period. They imply that an increase in oil prices leads to greater market volatility in the SSM. The main results of the two sub-samples are consistent with the whole sample. Contemporaneous volume decreases the persistence of volatility more than lagged volume does. However, the decrease in magnitude is still smaller than what is found at the firm level.

[Insert Table 4.15 here]

[Insert Table 4.16 here]

[Insert Table 4.17 here]

These results indicate that equilibrium in the SSM is immediate, as implied by the MDH. Contemporaneous volume does reduce persistence significantly. The MDH predicts that prices and volume have a joint response to information due to a common distribution. My results do not support the implications of the SIAH. The sequential reaction to information suggests that asset price volatility is potentially forecastable with knowledge of trading volume. As the results indicate, lagged volume is not significant in explaining volatility and does not reduce the persistence of volatility

To test the variance spillover effect between different-sized portfolios, I construct two portfolios, large-cap and small-cap. At the end of each year, all stocks listed are sorted according to market capitalization (price times the number of shares outstanding). I then construct two portfolios: the largest 10 companies and the smallest 10 companies. The weekly stock return is then calculated as the continuous compound weekly return. Weekly portfolio returns are calculated as an equally weighted average of weekly returns of the component stock as $R_t = \frac{1}{n}\sum_{k=1}^{n} r_{k,t}$

where k = 1, 2,..., n component stocks in the portfolio. Tables 15 and 16 present the estimate for equations 16 and 17 for the large- and small-firm portfolios. I use the lagged standardized residual of large- and small-firm portfolios as a volatility surprise that enters into the volatility spillover estimated in models 18 and 19.

[Insert Table 4.18 here]

[Insert Table 4.19 here]

Table 16 shows the results of the GARCH (1, 1) model. The finding on volatility spillover indicates a clear and distinct asymmetry in volatility spillover in the Saudi market. The results show that the spillover effect is larger and statistically significant from large to small companies. The estimated effect of lagged squared residual from large firms on the conditional variance of small firms is almost 18 times greater than the effect of lagged squared residual of small firms on the conditional variance of large firms. Also, the volatility estimate is significant from large to small while it is not significant in the other direction. Large and small firms' own volatility is significant for both small and large firms. This result indicates that the volatility of small companies can be predicted by observing the volatility of large companies. It also indicates that the volatility of small and large companies can be predicted by their own lagged volatility.

CONCLUSION

This paper tests the persistence of return volatility in the Saudi stock market (SSM) both with and without volume, with lagged volume, and with intra-day volatility (IDV) and overnight indicators (ONI). I apply the test to the market indices, five industry indices, and 15 individual companies. The results show that the indices and sample firms of the SSM exhibit strong volatility persistence; however, when I include contemporaneous volume, the persistence vanishes at the firm level, indicating that the rate of information arrival measured by the volume series can be a significant source of the conditional heteroskedasticity at the firm level in SSM. Lagged volume does not decrease the persistence of volatility. These results do not support the implications of the

SIAH. The sequential reaction to information suggests that asset price volatility is potentially forecastable with knowledge of trading volume. As the results indicate, lagged volume is not significant in explaining volatility and does not reduce the persistence of volatility. Sub-period analysis implies that the second period, which is characterized by high oil prices, leads to a higher persistence of volatility. Overall these results support the mixture of distribution hypothesis (MDH) at the firm level, as contemporaneous volume largely reduces the persistence of volatility. The results of including the variables IDV and ONI indicate that they are a good proxy for information and act as well as contemporaneous volume in explaining conditional volatility.

The findings on volatility spillover indicate a clear and distinct asymmetry in volatility spillover in the Saudi market. The results show that the spillover effect is larger and statistically significant from large to small companies. This finding indicates that the volatility of small companies can be predicted by observing the volatility of large companies. It also indicates that the volatility of both small and large companies can be predicted by their own lagged volatility.

Table 4.1: Summary Statistics and ARCH LM Test for Daily Returns of the Market and Industry Indices.

This table presents the summary statistics of the daily returns for the market index and five industries indices from January 1, 1994 to December 31, 2005. Return is measured as a continuously compound daily returns. Lagrange multiplier (LM) test for (ARCH) in the residuals is computed from an auxiliary test regression. To test the null hypothesis that there is no ARCH up to order in the residuals, we run the following regression

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s e_{t-s}^2 \right) + v_t$$

Where e is the residual. This is a regression of the squared residuals on a constant and lagged squared residuals up to order q. We test for up to 5 lagged residual. The F-statistic is an omitted variable test for the joint significance of all lagged squared residuals. Engle's LM test statistic is computed as the number of observations times the R^2 from the test regression. The statistics: mean, maximum, minimum and standard deviation are in percentages.

	TASI	TBSI	TCSI	TGSI	TISI	TSSI
Mean	0.064	0.061	0.049	0.072	0.084	0.048
Maximum	8.105	5.992	8.327	9.460	9.155	10.629
Minimum	-6.746	-6.298	-6.419	-10.391	-8.711	-10.138
Std. Dev.	0.882	0.884	0.983	1.481	1.253	1.230
Skewness	-0.038	0.477	0.428	0.424	0.561	-0.272
Kurtosis	13.274	10.705	12.524	15.658	12.872	20.069
Jarque-Bera	15460*	8828*	13381*	23492*	14458*	42704*
ARCH Tests						
F-statistics	133.47*	62.61*	109.40*	289.06*	81.01*	203.52*
LM test Statistics	561.53*	287.86*	473.91*	1023.88*	363.70	789.84*
Observations	3515	3515	3512	3503	3515	3514

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.2: Summary Statistics and for Daily Trading Volume of the Market and Industry Indices.

This table presents the summary statistics of the daily Volume for the market index and five industries indices from January 1 1994 to December 31 2005. Daily volume is measures as the number of shares traded during the day.

	Trading Volume					
	TASI	TBSI	TCSI	TGSI	TISI	TSSI
Mean	8673021	303167.9	249202.4	788497.8	2493959	3304128
Maximum	82873411	3357782	5148450	21015978	31182657	41115229
Minimum	2547	22	101	10	50	520
Std. Dev.	14997952	328475.7	431567.6	2065518	4830425	6043617
Skewness	2.189	2.951	4.497	3.775	2.566	2.475
Kurtosis	7.239	18.047	31.441	19.454	9.540	9.187
Jarque-Bera	5439.05*	38258.36*	130207.30*	47832.66*	10121.860	9194.05*
Observations	3515	3515	3512	3503	3515	3514

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.3: Summary Statistics and ARCH LM Test for Daily Returns of Individual Firms.

This table presents the summary statistics of the daily returns for 15 individual firms data from January 1 1993 to December 31 2005. Return is measured as a continuously compound daily return. Lagrange multiplier (LM) test for (ARCH) in the residuals is computed from an auxiliary test regression. To test the null hypothesis that there is no ARCH up to order in the residuals, we run the following regression

$$e_t^2 = \beta_0 + \left(\sum_{s=1}^{q} \beta_s e_{t-s}^2 \right) + v_t$$

where e is the residual. This is a regression of the squared residuals on a constant and lagged squared residuals up to order q. We test for up to 5 lagged residual. The F-statistic is an omitted variable test for the joint significance of all lagged squared residuals. Engle's LM test statistic is computed as the number of observations times the R^2 from the test regression.

	Return Statistics														
Firm Ticker	**1060**	**2010**	**2050**	**2060**	**2160**	**3010**	**3020**	**3030**	**3040**	**4050**	**4090**	**4110**	**4170**	**6030**	**6060**
Mean	0.069	0.082	0.079	0.081	0.124	0.054	0.069	0.036	0.056	0.049	0.025	0.020	0.142	0.038	0.056
Std. Dev.	1.304	1.444	1.422	2.061	2.277	1.615	1.382	1.344	1.493	2.298	1.998	2.282	2.988	2.488	2.824
Skewness	0.269	0.841	1.136	0.776	0.347	0.276	-0.209	-0.286	-0.053	0.207	0.366	0.225	0.140	0.167	0.180
Kurtosis	10.975	12.095	12.958	8.138	8.190	10.978	14.954	13.238	14.863	7.343	9.278	8.447	6.085	7.510	5.723
Jarque-Bera	9853*	13298*	16185	4526*	2668	8860*	20311*	16339*	19902*	2889*	6219*	4649*	612*	2778*	980*
ARCH Tests															
F-statistics	19.20*	50.92*	69.70*	107.25*	133.16*	82.59*	73.10*	43.67*	59.69*	177.07	193.62*	197.42*	68.66*	166.41*	156.71*
LM test Statistics	93.7*	238.7*	319.1*	470.0*	518.8*	367.8*	330.5*	206.5*	274.7*	712.9*	769.6*	781.52	281.1*	663.5*	626.9*
Observations	3701	3731	3723	3771	2335	3325	3407	3730	3394	3642	3736	3735	1532	3259	3118

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.4: Summary Statistics and for Daily Trading Volume of Individual Firms.
This table presents the summary statistics of the daily Volume 15 individual firms from January 1 1993 to December 31 2005. Daily volume is measures as the number of shares traded during the day.

	1060	2010	2050	2060	2160	3010	3020	3030	3040	4050	4090	4110	4170	6030	6060
Mean	7004.8	261950.5	33769.5	161458	57860.6	28120.6	14904.5	53089.1	9561.8	157488.6	181618.7	131340.8	122151.6	210292	57005.2
Maximum	158026	6468914	1184981	4568856	2659705	970919	361344	1317704	249910	7975362	7307945	4080905	2284820	8074688	2024929
Minimum	10	223	13	10	10	10	10	10	10	20	23	13	20	10	10
Std. Dev.	9866	506675	80839	357010	178938	57364	27347	102636	17504	414258	482015	332036	237328	600094	165355
Skewness	4.67	4.19	5.68	4.93	6.35	6.62	5.50	4.58	5.57	6.50	6.01	5.30	3.62	4.88	5.06
Kurtosis	41.76	28.67	50.28	36.80	57.65	71.06	46.59	31.05	51.14	70.31	55.47	39.59	20.55	36.16	36.23
Jarque-Bera	245173*	113384*	366822*	194818*	306341*	666251*	287042*	135333*	345335*	713463*	451233*	225957*	23008*	162300*	156835*
Observations	3702	3732	3724	3772	2336	3326	3408	3731	3395	3643	3737	3736	1533	3260	3119

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.5: Table 5 Unit Root Test for Return and Trading Volume Data of the Market Index and Industry Indices

This table presents the result of unit root test for the return and volume data of the market and industries indices data from January 1 1993 to December 31 2005 using the augmented Dickey-Fuller (ADF) test which is given by

	Return	Volume	
Index	ADF at Level(0)	ADF At Level(0)	ADF at 1st Difference
TASI	-55.48*	-1.52	-16.43*
TBSI	-22.31*	-6.76*	-21.93*
TCSI	-54.9*	-3.37*	-22.67*
TGSI	-20.9*	-2.66***	-23.7*
TISI	-56.47*	-2.1	-16.15*
TSSI	-57.23*	-2.67***	-18.62*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.6: Unit Root Test for Return and Trading Volume Data of Individual Firms.

This table presents the result of unit root test for the return and volume data of 15 individual firms' data from January 1 1993 to December 31 2005 using the augmented Dickey-Fuller (ADF) test which is given by

$$\Delta x_t = a_0 + a x_{t-1} + \sum_{t=1}^{n} \delta_i \Delta x_{t-i}$$

	Return	Volume	
Firm	ADF at Level(0)	ADF At Level(0)	ADF at 1st Difference
1060	-65.32*	-14.11*	-23.81*
2010	-59.64*	-4.82*	-18.15*
2050	-63.38*	-5.24*	-19.31*
2060	-63.99*	-5.83*	-24.19*
2160	-49.48*	-2.24	-12.64*
3010	-62.21*	1.58	-11.38*
3020	-62.49*	-8.06*	-22.54*
3030	-65.57*	-7.79*	-28.29*
3040	-64.22*	-5.95*	-18.06*
4050	-28.7*	-4.18*	-18.55*
4090	-67.82*	-7.34*	-18.1*
4010	-61.09*	-6.11*	-26.16*
4170	-37.49*	-8.75*	-18.44*
6030	-60.08*	-4.46*	-19.62*
6060	-63.64*	-7.33*	-28.6*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.7: Maximum likelihood Estimation of GARCH (1, 1) without Volume for the Market and Industry Indices.

This table presents the results of GARCH (1, 1) model for the market index and five industry indices from January 1 1993 to December 31 2005 using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$$

Market Index	α_1	α_2	$\alpha_{1+}\alpha_2$
TASI	0.278	0.701	0.979
	(8.13)*	(25.08)*	
Industry indices			
TBSI	0.293	0.646	0.939
	(6.99)*	(16.39)*	
TCSI	0.261	0.664	0.925
	(6.97)*	(16.50)*	
TGSI	0.114	0.872	0.986
	(6.36)*	(55.90)*	
TISI	0.227	0.758	0.986
	(5.20)*	(26.04)*	
TSSI	0.192	0.786	0.977
	(6.42)*	(19.04)*	

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.8: Maximum likelihood Estimation of GARCH (1, 1) without Volume for Individual Firms.

This table presents the results of GARCH (1, 1) model for 15 individual firms from January 1 1993 to December 31 2005 using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$
$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$$

Company	α_1	α_2	$\alpha_{1+}\alpha_2$
1060	0.229	0.700	0.929
	(5.93)*	(15.66)*	
2010	0.342	0.643	0.984
	(8.17)*	(19.14)*	
2050	0.234	0.723	0.957
	(5.46)*	(15.08)*	
2060	0.201	0.741	0.942
	(7.91)*	(25.91)*	
2160	0.229	0.656	0.886
	(5.32)*	(12.31)*	
3010	0.119	0.847	0.966
	(4.08)*	(23.03)*	
3020	0.289	0.595	0.884
	(4.69)*	(8.17)*	
3030	0.339	0.572	0.911
	(6.25)*	(9.75)*	
3040	0.285	0.626	0.911
	(6.18)*	(13.68)*	
4050	0.160	0.779	0.939
	(6.42)*	(22.23)*	
4090	0.180	0.749	0.929
	(6.71)*	(22.14)*	
4110	0.176	0.753	0.929
	(7.77)*	(26.11)*	
4170	0.237	0.624	0.860
	(5.54)*	(11.27)*	
6030	0.250	0.645	0.895
	(7.81)*	(16.44)*	
6060	0.186	0.648	0.834
	(7.63)*	(15.33)*	

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.9: Maximum likelihood Estimation of GARCH (1, 1) with Contemporaneous Volume for the Market and Industry Indices.

This table presents the results of GARCH (1, 1) model with contemporaneous volume for the market index and five industry indices from January 1 1993 to December 31 2005 using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series. The fifth column represents the contemporaneous volume coefficient

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_t$$

Market Index	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3
TASI	0.248	0.652	0.900	2.58E-12
	(2.70)*	(4.40)*		(3.04)*
Industry indices				
TBSI	0.402	0.097	0.499	1.08E-10
	(7.12)*	(2.14)**		(4.61)*
TCSI	0.353	0.370	0.723	6.88E-11
	(7.13)*	(5.87)*		(2.50)**
TGSI	0.040	0.958	0.998	6.76E-11
	(5.34)*	(133.08)*		(3.39)*
TISI	0.223	0.760	0.983	4.85E-12
	(5.21)*	(25.99)*		(0.75)
TSSI	0.177	0.613	0.790	4.54E-12
	(3.49)*	(13.19)*		(1.15)

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.10: Maximum likelihood Estimation of GARCH (1, 1) with Contemporaneous Volume for Individual Firms.

This table presents the results of GARCH (1, 1) model with contemporaneous volume for the Individual firms from January 1 1993 to December 31 2005 using a GARCH (1, 1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series. The fifth column represents the contemporaneous volume coefficient

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_t$$

Company	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3
1060	0.293	0.431	0.724	3.85E-09
	(6.19)*	(5.78)*		(1.46)
2010	0.431	0.206	0.638	2.77E-10
	(7.03)*	(2.68)*		(2.42)**
2050	0.355	0.235	0.591	1.56E-09
	(5.33)*	(2.53)**		(2.26)**
2060	0.349	0.153	0.502	8.52E-10
	(8.89)	(2.40)**		(3.30)*
2160	0.336	0.399	0.735	1.17E-09
	(6.22)*	(5.19)*		(1.94)***
3010	0.334	0.349	0.682	8.40E-10
	(6.66)*	(4.71)*		(1.33)
3020	0.330	0.394	0.724	2.01E-09
	(5.37)*	(5.27)*		(1.45)
3030	0.474	0.395	0.869	4.85E-10
	(5.44)*	(5.21)*		(2.19)**
3040	0.368	0.451	0.818	3.30E-09
	(5.79)*	(7.37)*		(1.81)***
4050	0.170	0.716	0.886	1.12E-10
	(6.48)*	(15.94)*		(1.79)***
4090	0.284	0.194	0.478	6.58E-10
	(8.59)*	(3.14)*		(3.06)*
4110	0.369	0.157	0.526	1.24E-09
	(9.25)*	(2.50)**		(3.19)*
4170	0.391	0.096	0.488	2.17E-09
	(6.60)*	(1.59)		(3.05)*
6030	0.324	0.394	0.718	3.36E-10
	(7.61)*	(6.41)*		(2.29)**
6060	0.227	0.444	0.671	9.44E-10
	(8.52)*	(6.96)*		(1.99)**

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.11: Maximum likelihood Estimation of GARCH (1, 1) with Lagged Volume for the Market Index and Industry Indices.

This table presents the results of GARCH (1, 1) model with lagged volume for the market index and five industry indices from January 1 1993 to December 31 2005 using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series. The fifth column represents the lagged volume coefficient

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 Vt_{t-1}$$

Market Index	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3
TASI	0.241	0.640	0.881	-2.74E-12
	(10.07)*	(62.28)*		(-6.23)*
Industry indices				
TBSI	0.285	0.620	0.905	9.84E-12
	(6.58)*	(14.32)*		(1.03)
TCSI	0.267	0.606	0.873	1.82E-11
	(6.78)*	(13.49)*		(0.96)
TGSI	0.114	0.873	0.986	-3.75E-13
	(6.37)*	(56.33)*		(-0.02)
TISI	0.193	0.783	0.976	-4.17E-12
	(5.81)*	(35.24)*		(-0.95)
TSSI	0.198	0.778	0.975	-2.03E-12
	(6.28)*	(17.95)*		(-1.22)

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.12: Maximum likelihood Estimation of GARCH (1, 1) with Lagged Volume for Individual Firms.

This table presents the results of GARCH (1, 1) model with contemporaneous volume for the Individual firms from January 1 1993 to December 31 2005 using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series. The fifth column represents Lagged volume coefficient

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 Vt_{t-1}$$

Company	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3
1060	0.229	0.694	0.923	4.17E-10
	(6.15)*	(14.67)*		(0.45)
2010	0.321	0.594	0.915	4.92E-11
	(7.22)*	(14.02)*		(1.57)
2050	0.224	0.697	0.920	2.21E-10
	(5.19)*	(11.96)*		(1.08)
2060	0.198	0.721	0.919	5.49E-11
	(8.13)*	(22.81)*		(0.94)
2160	0.229	0.643	0.872	7.19E-11
	(5.38)*	(11.74)*		(0.71)
3010	0.114	0.851	0.965	4.02E-11
	(4.03)*	(23.05)*		(0.20)
3020	0.276	0.578	0.854	8.53E-10
	(4.94)*	(7.56)*		(0.85)
3030	0.328	0.562	0.891	8.09E-11
	(5.79)*	(8.79)*		(0.61)
3040	0.302	0.577	0.879	1.57E-09
	(6.56)*	(12.01)*		(0.94)
4050	0.149	0.782	0.932	2.63E-11
	(6.42)*	(21.89)*		(0.71)
4090	0.178	0.710	0.888	6.41E-11
	(6.82)*	(18.79)*		(1.40)
4110	0.173	0.731	0.904	9.48E-11
	(7.34)*	(22.53)*		(1.08)
4170	0.218	0.606	0.824	3.72E-10
	(5.31)*	(9.95)*		(1.13)
6030	0.242	0.613	0.855	1.04E-10
	(7.61)*	(14.43)*		(1.35)
6060	0.182	0.627	0.809	2.50E-10
	(7.71)*	(14.21)*		(0.97)

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.13: Maximum likelihood Estimation of GARCH (1, 1) with lagged Intra-day volatility (IDV) for Individual Firms.

This table presents the results of GARCH (1, 1) model with contemporaneous volume for the Individual firms from January 1 1993 to December 31 2005 using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series. The fifth column represents IDV coefficient

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 IDV_{t-1}$$

Where IDV is given by the following formula $IDV_t = \dfrac{P_t^H - P_t^L}{P_t^C}$ (12) Where P_t denotes respectively the highest (H), the lowest (L) and the closing (C) price on day t.

Company	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3
1060	0.154	0.564	0.718	0.0033
	(3.68)*	(7.36)*		(3.37)*
2010	0.166	0.452	0.618	0.0054
	(3.14)*	(4.16)*		(3.23)*
2050	0.146	0.515	0.660	0.0040
	(3.31)*	(6.09)*		(4.17)*
2060	0.185	0.679	0.864	0.0016
	(5.72)*	(17.95)*		(1.72)***
2160	0.225	0.544	0.769	0.0028
	(4.97)*	(8.39)*		(2.32)**
3010	0.115	0.847	0.962	0.0001
	(4.25)*	(21.84)*		(0.24)
3020	0.211	0.399	0.610	0.0047
	(4.04)*	(5.11)*		(3.36)*
3030	0.200	0.554	0.753	0.0029
	(5.61)*	(7.47)*		(3.31)*
3040	0.239	0.594	0.833	0.0019
	(5.14)*	(10.93)*		(1.96)**
4050	0.142	0.765	0.908	0.0009
	(6.24)*	(20.28)*		(1.93)***
4090	0.152	0.707	0.859	0.0015
	(5.39)*	(18.09)*		(1.73)***
4110	0.166	0.596	0.762	0.0031
	(5.65)*	(11.98)*		(3.12)*
4170	0.199	0.598	0.797	0.0025
	(5.04)*	(8.36)*		(1.54)
6030	0.212	0.589	0.800	0.0027
	(6.92)*	(12.52)*		(2.73)*
6060	0.181	0.614	0.795	0.0011
	(7.51)*	(13.11)*		(1.27)

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.14: Maximum likelihood Estimation of GARCH (1, 1) with lagged Over Night Indicator (ONI) for Individual Firms.

This table presents the results of GARCH (1, 1) model with contemporaneous volume for the Individual firms from January 1 1993 to December 31 2005 using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series. The fifth column represents IDV coefficient

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 ONI_{t-1}$$

ONI is give by the following equation using the open and close prices: $ONI_t = \left| \log \frac{open_t}{close_{t-1}} \right|$

Company	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3
1060	0.196	0.567	0.764	0.0140
	(4.50)*	(7.20)*		(4.04)*
2010	0.360	0.528	0.888	0.0140
	(9.09)*	(16.53)*		(5.42)*
2050	0.245	0.414	0.659	0.0265
	(6.64)*	(7.35)*		(5.66)*
2060	0.210	0.623	0.833	0.0195
	(6.11)*	(14.18)*		(4.88)*
2160	0.191	0.466	0.657	0.0314
	(3.79)*	(6.59)*		(3.95)*
3010	0.282	0.396	0.678	0.0238
	(5.29)*	(6.57)*		(7.36)*
3020	0.216	0.489	0.705	0.0238
	(4.87)*	(5.48)*		(4.99)*
3030	0.273	0.480	0.753	0.0178
	(7.14)*	(8.82)*		(5.47)*
3040	0.245	0.371	0.616	0.0213
	(6.19)*	(6.34)*		(4.06)*
3050	0.210	0.507	0.717	0.0223
	(6.51)*	(7.78)*		(5.28)*
4090	0.157	0.724	0.881	0.0115
	(5.67)*	(17.14)*		(4.27)*
4110	0.200	0.625	0.825	0.0211
	(6.56)*	(13.43)*		(5.32)*
4170	0.209	0.459	0.668	0.0522
	(4.38)*	(6.27)*		(5.04)*
6030	0.294	0.366	0.661	0.0383
	(6.62)*	(5.44)*		(6.43)*
6060	0.196	0.281	0.477	0.0465
	(5.69)*	(4.31)*		(8.84)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Figure 4.1: Average Yearly Oil Price.
This figure shows the average yearly price of oil from 1992 to 2005.

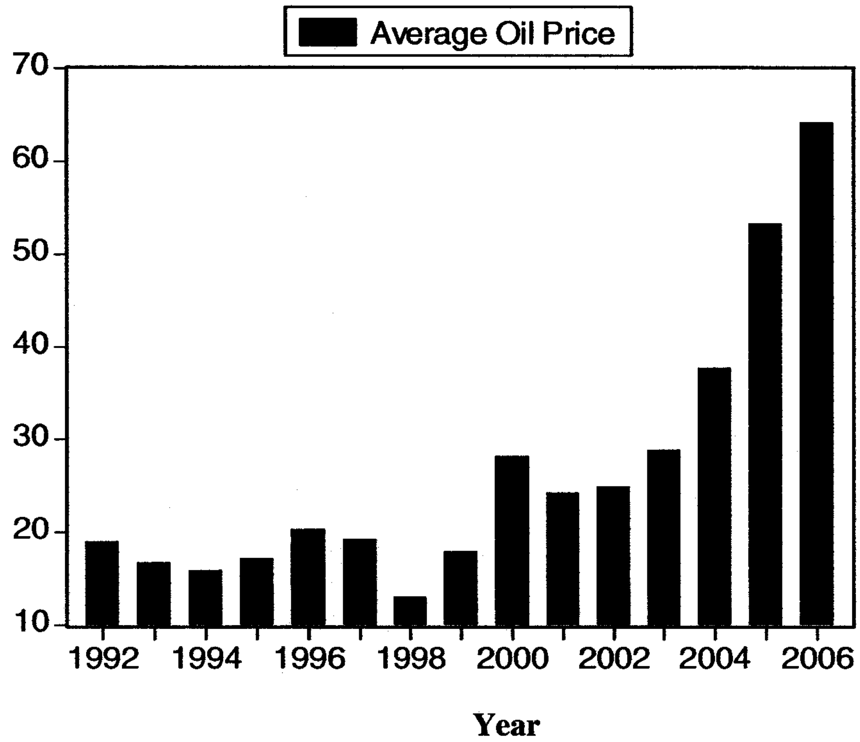


Table 4.15: Sub-Sample analysis for Maximum likelihood Estimation of GARCH (1, 1) without Volume for the Market and Industry Indices.

This table presents the results of GARCH (1, 1) model for the market index and five industry indices from January 1 1993 to December 31 1999 in panel A and from January 1 2000 to December 2005 in panel B using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$
$$\varepsilon_t|\Phi_{t-1} \approx N(0, h_t)$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}$$

	Panel A 1/1/ 1993 to 12/31 1999			**Penal B 1/1/2000 to 12/31/1005**		
Market Index	α_1	α_2	$\alpha_{1+}\alpha_2$	α_1	α_2	$\alpha_{1+}\alpha_2$
TASI	0.265	0.627	0.892	0.287	0.738	1.025
	(4.90)*	(9.89)*		(6.54)*	(26.14)*	
Industry indices						
TBSI	0.322	0.586	0.909	0.2553	0.7099	0.965
	(4.73)*	(9.21)*		(5.64)*	(19.23)*	
TCSI	0.271	0.620	0.891	0.254	0.680	0.935
	(4.33)*	(9.27)*		(5.61)*	(13.94)*	
TGSI	0.212	0.221	0.433	0.204	0.779	0.983
	(3.11)*	(1.62)		(6.38)*	(28.78)*	
TISI	0.231	0.681	0.912	0.258	0.761	1.019
	(3.45)*	(9.71)*		(6.16)*	(25.89)*	
TSSI	0.241	0.657	0.897	0.175	0.827	1.002
	(4.56)*	(5.47)*		(5.77)*	(26.16)*	

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.16: Sub-Sample analysis for Maximum likelihood Estimation of the GARCH (1, 1) with Contemporaneous Volume for the Market and Industry Indices. This table presents the results of GARCH (1, 1) model for the market index and five industry indices from January 1 1993 to December 31 1999 in panel A and from January 1 2000 to December 2005 in panel B using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$
$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_t$$

	Panel A First period					Panel B Second Period		
Market Index	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3
TASI	0.202	0.629	0.832	2.71E-11	0.250	0.646	0.896	3.37E-12
	(2.38)**	(19.93)*		(0.46)	(5.84)*	(13.71)*		(1.16)
Industry indices								
TBSI	0.438	0.211	0.649	8.64E-11	0.178	-0.063	0.115	1.81E-10
	(5.46)*	(3.31)*		(2.53)**	(6.89)*	-(20.94)*		(9.05)*
TCSI	0.389	0.349	0.738	1.33E-10	0.313	0.299	0.612	9.84E-11
	(4.56)*	(3.45)*		(1.53)	(5.90)*	(3.29)*		(2.46)**
TGSI	0.269258	0.266157	0.535	5.75E-10	0.101	0.891	0.992	2.78E-11
	(5.34)*	(7.36)*		(2.05)**	(6.38)*	(70.10)*		(0.75)
TISI	0.119	0.763	0.882	2.47E-10	0.346	0.629	0.974	7.43E-12
	(4.80)*	(54.64)*		(5.10)*	(7.71)*	(24.59)*		(1.65)***
TSSI	0.130	0.696	0.826	3.49E-11	0.179	0.613	0.793	4.96E-12
	(2.94)*	(14.00)*		(3.96)*	(2.70)*	(6.69)*		(2.25)**

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.17: Sub-sample analysis for Maximum likelihood Estimation of the GARCH (1, 1) with lagged Volume for the Market and Industry Indices .

This table presents the results of GARCH (1, 1) model for the market index and five industry indices from January 1 1993 to December 31 1999 in panel A and from January 1 2000 to December 2005 in panel B using a GARCH(1,1) model specified blew. The second and the third column represent the parameters of the ARCH and GARCH terms respectively. The forth column shows the sum of the ARCH and GARCH parameters which measures the persistence of the conditional variance series

$$r_t = \beta_1 + \beta_2 r_{t-1} + \varepsilon_t$$

$$\varepsilon_t | \Phi_{t-1} \approx N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 V_{t-1}$$

	Panel A First period				Panel B Second Period			
Market Index	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3	α_1	α_2	$\alpha_{1+}\alpha_2$	α_3
TASI	0.270	0.626	0.896	-2.13E-12	0.403	0.618	1.021	-7.28E-13
	(4.86)*	(9.58)*		(-0.29)	(7.72)*	(23.57)*		(-3.10)*
Industry indices								
TBSI	0.326	0.537	0.863	1.57E-11	0.237	0.704	0.941	6.92E-12
	(4.59)*	(8.22)*		(0.86)	(5.45)*	(18.01)*		(0.56)
TCSI	0.282	0.636	0.919	-2.56E-11	0.246	0.611	0.858	2.59E-11
	(4.57)*	(10.59)*		(-0.89)	(6.07)*	(10.69)*		(1.03)
TGSI	0.209	0.224*	0.433	1.87E-11	0.205	0.779	0.983	-1.67E-12
	(3.18)*	(1.45)		(0.08)	(6.29)*	(27.65)*		(-0.08)
TISI	0.236	0.677	0.913	-1.03E-11	0.267	0.753	1.021	-3.32E-12
	(3.60)*	(9.41)*		(-0.15)	(6.90)*	(33.12)*		(-1.27)
TSSI	0.221	0.673	0.894	1.46E-11	0.168	0.839	1.006	-2.51E-12
	(4.62)*	(5.92)*		(0.65)	(6.38)*	(40.87)*		(-1.35)

Significance levels: * = 1%, ** = 2%, *** = 10%.

134

Table 4.18: Volatility Spillover Between Sized Based Portfolios: First Stage.
This table present the estimate of a univariate GACH model for weekly return of Large and Small firm portfolio in the SSM from first week of January 1993 to the last week of December 2005. the following model is estimated for each portfolio.

$$R_{it} = \beta_0 + \beta_1 R_{i,t-1} + \varepsilon_{it}$$

$$\textit{Where} \quad \varepsilon_{it} | \Omega \; i,t-1 \sim N(0, h_{i,t})$$

$$h_{it} = a_i + b_i \varepsilon_{i,t-1}^{\;2} + c_i h_{i,t-1}$$

$$\textit{where} \quad i, j = 1,2 \,, \; i \neq j$$

Coefficients	Panel A **Large Firms**	Panel B **Small Firms**
Mean Eq.		
B_0	0.0017	-0.0003
	(2.15)**	-(0.29)
B_1	0.1882	0.1454
	(4.77)*	(3.12)*
Variance Eq.		
a	0.0001	0.0002
	(3.06)*	(5.13)*
b	0.1526	0.2988
	(4.08)*	(5.89)*
c	0.7264	0.5341
	(11.37)*	(8.19)*

Significance levels: * = 1%, ** = 2%, *** = 10%.

Table 4.19: Volatility Spillover between sized based Portfolios: Second Stage.
This table present the estimate of a univariate GACH model for weekly return of Large and Small firm portfolio in the SSM from first week of January 1993 to the last week of December 2005. the following model is estimated for each portfolio

$$R_{it} = \beta_0 + \beta_1 R_{i,t-1} + \varepsilon_{it}$$

$$Where \varepsilon_{it} \big| \Omega i, t-1 \sim N(0, h_{i,t})$$

$$h_{it} = a_i + b_i \varepsilon_{i,t-1}{}^2 + c_i h_{i,t-1} + k_{ij} \varepsilon_{j,t-1}$$

$$where i, j = 1,2 \, \forall i \neq j$$

The coefficient of interest is K_{ij} which measures the impact of past return shocks portfolio j on the conditional volatility of portfolio i. Likewise, the coefficient K_{ij} of a similar specification can be used to measure the effect of past volatility of security i on the conditional variance of j.

Coefficients	Panel A Large Firms	Panel B Small Firms
B_0	0.0017	-0.0004
	(2.08)**	-(0.32)
B_1	4.7390	0.1480
	(4.77)*	(3.20)*
a	0.0001	0.0002
	(3.70)*	(5.13)*
b	0.2462	0.2462
	(3.87)*	(6.24)*
c	0.7107	0.6080
	(10.71)*	(10.12)*
k	**0.00630**	**0.11696**
	(1.01)	**(2.89)***

Significance levels: * = 1%, ** = 2%, *** = 10%.

REFERENCES

Andersen, T. G., 1996, Return volatility and trading volume: an information flow interpretation of stochastic volatility, Journal of Finance 51, 169-204.

Arab Monetary Fund Reports at: http://www.amf.org.ae (2005 annual report).

Barberis, N., A. Shleifer, and R. Vishny, 1998, A model of investor sentiment, Journal of Financial Economics 49, 307-343.

Blume, L., D. Easley, and M. O'Hara, 1994, Market statistics and technical analysis: The role of volume, Journal of Finance 49, 153-181.

Bohl, M. T. and H. Henke, 2003, Trading volume and stock market volatility: The Polish case, International Review of Financial Analysis 12, 513-525.

Bollerslev, T., 1986, Generalized autoregressive conditional heteroskedasticity, Journal of Econometrics 31, 307-327.

Brailsford, T. J., 1996, The empirical relationship between trading volume, returns, and volatility, Accounting and Finance 35, 89-111.

Campbell, J. Y., S. J. Grossman, and J. Wang, 1993, Trading volume and serial correlation in stock returns, Quarterly Journal of Economics, 108, 905-939.

Campbell, J. Y., S. J. Grossman, and J. Wang, 1993, Trading volume and serial correlation in stock returns, Quarterly Journal of Economics, 108, 905–939.

Chan, K., A. Hameed, and W. Tong, 2000, Profitability of momentum strategies in the international equity markets, Journal of Financial and Quantitative Analysis 35, 153-172.

Chan, L. K. C., N. Jegadeesh, and J. Lakonishok, 1996, Momentum strategies, Journal of Finance 51, 1681-1713.
Chui, A. C. W., S. Titman, and K. C. Wei, 2000, Momentum, legal systems and ownership structure: An analysis of Asian stock markets, Working paper.

Clark, P., 1973, A subordinated stochastic process model with finite variances for speculative prices, Econometrica 41, 135-155.

Connolly, R. and C. Stivers, 2003, Momentum and reversals in equity-index returns during periods of abnormal turnover and return dispersion, Journal of Finance 58, 1521-1555.

Connolly, R. and C. Stivers, 2001 Momentum and reversal in market-level equity returns and firm-level market activity' working paper, SSRN.

Conrad, J., A. Hameed, and C. Niden, 1994, Volume and autocovariances in short-horizon individual security returns, Journal of Finance 49, 1305-1329.

Conrad, J., and G. Kaul, 1998, An anatomy of trading strategies, Review of Financial Studies 11, 489-519.

Conrad, J., G. Kaul, and M. Nimalendran, 1991, Components of short-horizon individual security returns. Journal of Financial Economics 29, 365-384.

Conrad, J., M. N. Gultekin, and G. Kaul, 1991, Asymmetric predictability of conditional variances, Review of Financial Studies 4, 597-662.

Cooper, M., 1999, Filter rules based on price and volume in individual security overreaction, Review of Financial Studies 12, 901-935.

Copeland, T., 1976, A model of asset trading under the assumption of sequential information arrival, Journal of Finance 31, 1149-1168.

Cornard, J., 1989, The price effect of option introduction, Journal of Finance 44, 487-498.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor psychology and security market under- and overreactions, Journal of Finance 53, 1893-1885.

Darrat, A. F, S. Rahman, and M. Zhong, 2003, Intraday trading volume and return volatility of the DJIA stocks: A note, Journal of Banking and Finance 27 (10): 2035 2043.

Engle, R. F., 1982, Autoregressive conditional heteroskedasticity with estimates of the Variance of United Kingdom inflation, Econometrica 50, 987-1007.

Epps, W. and M. Epps, 1976, The stochastic dependence of security price changes and transaction volumes: Implications for the mixture of distributions hypothesis, Econometrica 4, 305-321.

Forner, C. and J. Marhuenda, 2003, Contrarian and momentum strategies in the Spanish stock market, European Financial Management, 19, 67-88.

Foster, A. J., 1995, Volume-volatility relationships for crude oil futures markets, Journal of Futures Market 15, 929-951.

Gallo, G. M. and B. Pacini, 2000, The effects of trading activity on market volatility, European Journal of Finance 6, 163-75.
Gebka, B., 2005, Dynamic volume-return relationship: Evidence from an emerging market, Applied Financial Economics, 15, 1019-1029.

George, T. and C. Y. Hwang, 2004, The 52-week high and momentum investing, Journal of Finance 59, 2145-2176.

Glaser, M. and M. Weber, 2003, Momentum and turnover: Evidence from the German stock market, Schmalenbach Business Review 55, 108-135.

Griffin, J. M., S. Ji, and J. S. Martin, 2003, Momentum investing and business cycle risk: Evidence from pole to pole, Journal of Finance 58, 2515-2547.

Hamao, Y., R. W. Masulis and V. Ng' 1990, "Correlation in price change and volatility across international stock markets," Review of Financial Studies, 3, 281-307.

Hameed, A. and K. Yunato, 2002, Momentum strategies: Evidence from the Pacific basin stock markets, Journal of Financial Research 45, 383-398.

Harris, L., 1987, Transaction data tests of the mixture of distribution hypothesis, Journal of Financial and Quantitative Analysis, 22, 127-141.

Hong, H. and J. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, Journal of Finance 54, 2143-2184.

Jegadeesh, N. and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, Journal of Finance 1, 65–91.

Jegadeesh, N. and S. Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, Journal of Finance 2, 699-720.

Kamath, R. and J. Chusanachot, 2000, The dependence of market return volatility on trading volume in Korea and Thailand, Global Business and Finance Review 5, 61-71.

Kang, J., H. M. Liu, and X. S. Ni, 2002, Contrarian and momentum strategies in the China stock market: 1993–2000, Pacific-Basin Finance Journal 10, 243-265.

Karpoff, J. M., 1987, The relation between price changes and trading volume: A survey, Journal of Financial and Quantitative Analysis 22, 109-126.

Lamoureux, C. G. and W. D. Lastrapes, 1990, Heteroskedasticity in stock return data: Volume versus GARCH effects, Journal of Finance 45, 221-229.

Lee, C. M. C. and B. Swaminathan, 2000, Price momentum and trading volume, Journal of Finance 55, 2017–2069.

Lehmann, B., 1990, Fads, martingales, and market efficiency, Quarterly Journal of Economics, 105, 1-28.

Llorente, G., R. Michaely, G. Saar, and J. Wang, 2002, Dynamic volume-return relation of individual stocks, Review of Financial Studies 15, 1005-1047.

Lo, A. and MacKinlay, C., 1989, Stock market prices do not follow random walks: Evidence from a simple specification test, Review of Financial Studies, 1, 41–66.

Marshall, B. R. and R. M. Cahan, 2005. Is the 52-week high momentum strategy profitable outside the US? Applied Financial Economics, 15, 1259-1267. Rouwenhorst, K. G., 1998, International momentum strategies, Journal of Finance 53, 267-284.

Moskowitz, T. and M. Grinblatt, 1999, Do industries explain momentum? Journal of Finance 54, 1249-1290.

Najand, M. and K. Yung, 1991, A GARCH examination of the relationship between volume and price variability in futures markets, Journal of Futures Markets 11, 613-621.

Pyuna, C. S., S. Y. Lee, and K. Nam, 2000, Volatility and information flows in emerging equity market: A case of the Korean Stock Exchange, International Review of Financial Analysis 9, 405-420.

Reyes, M. G., 2001, Asymmetric volatility spillover in the Tokyo Stock Exchange, Journal of Economics and Finance 25, 206-213.

Ross, S. A., 1989, Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy, Journal of Finance 44, 1-17.

Rouwenhorst, K. G., 1998, International momentum strategies, Journal of Finance 53, 267-284.

Saudi Stock Exchange Reports at: http://www.tadawul.com.sa (2005 annual report).

Sharma, J. L., M. Mougous, and R. Kamath, 1996, Heteroscedasticity in stock market indicator return data: Volume versus GARCH effects, Applied Financial Economics 6, 337-342.

St. Pierre, E. F., 1998, The impact of option introduction on the conditional return distribution of underlying securities, Financial Review 33, 105.

Stickel, S. and R. Verrecchia, 1994, Evidence that volume sustains price changes, Financial Analysts Journal 50, 57-67.

Wang, J., 1994, A model of competitive stock trading volume, Journal of Political Economy, 102, 127-168.

World Federation of Stock Exchange statistics at: http://www.fibv.com (2005 statistics).

Appendix 1: Sample of Firms Used in Essay Three.

Ticker	Firm
1060	Saudi British Bank
2010	Saudi Basic Industries Corp.
2050	SAVOLA Group
2060	National Industrialization Co.
2160	Saudi Arabian Amiantit Co.
3010	Arabian Cement Co.LTd
3020	Yamamah Saudi Cement Co. Ltd
3030	Saudi Cement Company
3040	The Qassim Cement Co
4050	Saudi Automotive Services Co
4090	Taibah Investment & Real Estate Co
4110	Saudi Land Transport Co
4170	Tourism Enterprise Co
6030	Hail Agriculture Development Co
6060	Ashargiyah Agriculture Development Co.

VITA

Abdullah N. Alsubaie
Subaie2003@yahoo.com

Education

2003 to 2007 **Old Dominion University** **Norfolk, VA**
PhD in Business Administration -Finance

1999 – 2001 **Duquesne University** **Pittsburgh, PA**
Masters of Business Adminstration -Finance

1999 – 2001 **Duquesne University** **Pittsburgh, PA**
Masters of Science in Information System Management

1992 – 1996 **King Saud University** **Riyadh, Saudi Arabia**
B.S. in Business Administration –Finance

Certifications and Memberships

2001 – Present **Member of Institute of Management Accountants** **Montvale, NJ**
Certified in Financial Management, CFM (2003)
Certified in management Accountant, CMA (2006)

2007- Present **Member of Beta Gamma Sigma** (Business Honor Society)

Professional Experience

2005-2007 **Old Dominion University** **Norfolk, VA**
Adjunct Instructor

- Taught introductory finance and accounting courses.

2001 – 2003 **Institute of Public Administration** **Riyadh, Saudi Arabia**
Faculty Member

- Taught business and finance course.
- Supervised several student practical training programs

1996 – 1998 **Institute of Public Administration** **Riyadh, Saudi Arabia**
Trainer Assistant

- Administrative and managerial tasks of the Department

Seminars

- The Causes and Consequences of Recent Financial Market Bubbles, August 2005 Indiana University Bloomington, IN
- Graduate Teaching Assistant Seminar, August 2005 Old Dominion University, Norfolk, VA
- Developing Trainers' skills. Institute of Public Administration August, 2001,Riyadh, Saudi Arabia)

Languages and Skills

- Fluent in English and Arabic Languages
- Familiar with SQL language, database concepts and structures.
- Economic modeling using E-views and SAS software