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Two Essays on Lead-Lag Patterns Between Trading Volume and Stock Return in China Stock Markets

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TWO ESSAYS ON LEAD-LAG PATTERNS BETWEEN TRADING VOLUME AND STOCK RETURN IN CHINA STOCK MARKETS

by

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ABSTRACT

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This dissertation systematically investigate the lead-lag relations between the trading volume and stock return patterns in China A share and B share markets through two streams of behavioral postulations. In the first part, we summarize all the potential lead-lag patterns between trading volume and stock returns and link them to the corresponding behavioral explanations. In particular, Lee and Swaminathan's (2000) Momentum Life Cycle theory best explains the strong negative relations between lagged trading volume and subsequent return in China A share market. The strong positive relations between lagged market return and subsequent trading volume found in both China's B share markets best fit the expectations of Statman, Thorley, and Vorkink's (2006) overconfidence bias hypothesis, in which market investors are overly confident about the precision of their private information and such biased self-attribution causes the degree of confidence to increase when realized market returns are high, even when those returns are simultaneously enjoyed by the entire market.

The second part of this dissertation further investigate the relations between trading volume and profitability of contrarian/momentum strategies under the empirical

framework of Lee and Swaminathan's (2000) Momentum Life Cycle; Daniel, Hirshleifer, and Subrahmanyam's (1998) overconfidence bias on glamour stocks; and Hong and Stein's (1999) public information diffusion effect. The results reconfirm that Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis provides the best explanation not only on the strong negative lead-lag patterns between lagged trading volume and subsequent returns, but also on the profitability of momentum/contrarian strategies for winner/loser stocks with different levels of trading volumes in China A share market. In particular, late stage momentum performers, including high (low) volume winners (losers), will experience contrarian profits, whereas early stage momentum performers, including low (high) volume winners (losers), will experience momentum profits.

Co-Directors of Advisory Committee: Dr. Kenneth Yung
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Chapter 1

Introduction

The lead-lag relations between trading volume and stock return patterns have always been very interesting to both financial academics and investment practitioners. Many behavioral models or hypotheses have been developed trying to explain the potential lead-lag patterns between trading volume and stock return. There are mainly two ways to understand the economics of the relation and investigate it with existing behavioral models or explanations. One stream of behavioral literature tries to explain the lead-lag patterns based directly on whether there exist relations between lagged trading volume and subsequent return or between lagged stocks return and subsequent trading volume, as well as on whether such relations are negatively or positively related. Examples of such approaches include Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis; Statman, Thorley, and Vorkink's (2006) overconfidence bias hypothesis; Shefrin and Statman's (1985) disposition effects; Pietro Veronesi's (2000) market tendency to overreact to bad news and underreact to good news effect; and Thaler and Johnson's (1990) try-to-break-even effect. Another stream of literature attempts to understand and explain the relation between trading volume and stock return from the aspect of profitability of momentum or contrarian strategies; examples of this approach include Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis; Daniel, Hirshleifer and Subrahmanyam's (1998) overconfidence bias on glamour stocks; and Hong and Stein's (1999) information diffusion effect.

In this study, we investigate the lead-lag relations between trading volume and stock returns in China's A share and B share markets and examine whether behavioral postulations offer any implicit explanations on the existing lead-lag patterns in each particular stock market in China. The choice of China's stock market for this study is motivated by the following considerations. First, China's stock market is usually independent of its US counterpart (Lee and Rui 2000), and findings of similar asset price behavior from independent samples help to relieve the concern of data snooping biases. Second, although China's stock market has experienced rapid growth over the past decade, little is known about its stock price behavior. Particularly, to our best knowledge, no study has ever been done before to investigate the lead-lag relations between trading volume and stock returns in the China stock markets. Last, with China's entry into the WTO and its fully opening its financial market for foreign investors, its stock market increasingly attracts foreign investors' attention due to China's fast economic development and enormous growth opportunities. Understanding the lead-lag relations between trading volume and stock return patterns and choosing profitable trading strategies are, thus, of great interest to global institutional investors.

The purpose of the first part of the thesis is to investigate the lead-lag relations between trading volume and stock returns in China A share and B share markets and to try to explain such patterns under the first stream of literature in behavioral finance theories. After finding the statistically significant relations between trading volume and stock return patterns in the A share market, the second part of this study further investigates such patterns from the aspect of profitability of momentum or contrarian strategies, which belong to the second stream of literature of behavioral theories.

The organization of the dissertation is as follows. Chapter 2 investigates the dynamic relations between trading volume and stock returns by using the Vector Autoregressive method and attempts to explain the lead-lag patterns among the first stream of behavioral literature. In particular, the focus of this section is to explain the direct lead-lag relations between trading volume and stock return, as well as the sign of such relations. Chapter 3 explores the implications of the second stream behavioral literature on the relations between trading volume and stock returns by focusing on the aspect of profitable momentum or contrarian trading strategies. Chapter 4 summarizes the findings of both studies and discusses the conclusions.

Chapter 2

The Lead-Lag Patterns between Trading Volume and Stock Returns in China's Stock Markets

2.1 Introduction

The relation between trading volume and stock return in American markets is well documented in previous literature. There are mainly three categories of relation patterns between trading volume and stock returns: contemporaneous volume and return, current volume and subsequent return, and current return to subsequent volume. The relation between contemporaneous trading volume and stock returns has been documented in considerable empirical research, including Karpoff (1987); Stoll and Whaley (1987); Bessembinder and Seguin (1993); Bessembinder, Chan, and Seguin (1996); Chordia, Roll, and Subrahmanyam (2000); and Lo and Wang (2000). In addition, some empirical research relates current volume to lagged returns. Gallant, Rossi, and Tauchen (1992) document several regularities, but the nonparametric methodology of their research does not yield interpretations relevant to the overconfidence hypothesis. Chordia and Swaminathan (2000) examine volume and return cross-autocorrelations at very short (daily) horizons to explore the speed at which information is priced. Statman, Thorley, and Vorkink (2006) test the trading volume predictions of formal overconfidence models and find that share turnover is positively related to lagged returns for many months. Finally, recent research by Cooper (1999); Lee and Swaminathan (2000); Llorente et al. (2002); and Gervais, Kaniel, and Mingelgrin (2001) examines the ability of volume to predict returns instead of the ability of returns to predict volume. Particularly, Lee, and Swaminathan (2000) find that past trading volume predicts both the magnitude and persistence of price momentum.

Besides those in American markets, many empirical studies have been conducted in several other capital markets. In a study of the Malaysian stock market from January 1977 to December 1996, Hameed and Ting (2000) examine the relation between return predictability and the level of trading activity. They find that weekly contrarian profits on actively and frequently traded stocks were significantly higher than those found in low trading activity stocks. Bremer and Hiraki (1999) examine the relation between trading volume of the previous week and the contrarian profits during the subsequent week in the Japanese capital market. Consistent with other studies, price reversals in the following week are reportedly higher in high trading volume stocks. Both of these empirical studies provide evidence that trading volume contains important information for predicting the subsequent stock returns. Recent research by Ding, McInish, and WongChoti (2007) investigates the lead-lag patterns between trading volume and stock price in seven Asia-Pacific markets: Japan, Korea, Taiwan, Hong Kong, Malaysia, Singapore, and Thailand. These authors examine whether behavioral postulations offer any implicit explanation about the countries' varying relations between trading volume and price pattern in short horizons. Their findings lend credence to the Lee and Swaminathan (2000) Momentum Life Cycle explanation and show that trading volume could provide valuable information for the prediction of subsequent stock price. Such an observation is especially pronounced in Hong Kong market.

Despite the increasing importance in the world economy, China's stock markets have received relatively less study, especially in the field of the lead-lag relationship between trading volume and stock returns. Chinese equity markets expanded rapidly in the last decade as the state and individual entrepreneurs tapped investors to help finance the economic restructuring of state-owned enterprises and fund the expansion of privatized firms. Following entry to the WTO and fully opening financial markets, China's equity markets have boomed rapidly. It was said that the Shanghai Stock Exchange would exceed the New York, London, and Hong Kong Stock Exchanges in the number of IPO's issued in 2007 (Great China IPO Watch 2006 Report, PWC; Financial Times, July 2007). Because of the speed of development and China's increasingly important role in the world economy, China's stock markets have not been well studied by the world's academic scholars.

None of the previous research focuses on the intra-market lead-lag patterns between the market trading volume and market return in each of the A share and B share markets of China. Only a few studies have investigated the role of trading volume in predicting the stock returns in the China stock markets. But these studies are focused on the inter-market causal relationships between trading volume and stock returns among China's A share and B share markets and the US and Hong Kong stock markets. Instead of the intra-market lead-lag patterns in each market, Lee and Rui (2000) examine empirical contemporaneous and causal relationships between trading volume, stock returns, and volatility across China's four stock exchanges and the US and Hong Kong stock markets.

As for the cross-market causal relationship in China's stock market, they find evidence of a feedback relationship in returns between Shanghai A share and Shenzhen B share markets, and between Shanghai B and Shenzhen B share markets. Additionally, they find the information contained in returns volatility and volume from financial markets in the US and Hong Kong has very weak predictive power for Chinese financial market variables.

This study seeks to examine empirically the intra-market lead-lag patterns between trading volume and stock return in each of the China A share and B share markets. One way to understand the economics of the relation between trading volume and returns is to investigate it with an existing behavioral model or explanation. In the present study, we first consider the patterns or relations found in each of the China A share and B share markets between 1991 and 2007. Then we compare these relations to the implicit predictions of several behavioral explanations concerning the relation between trading volume and price pattern. To our knowledge, there is no existing study that links all the potential lead-lag patterns between trading volume and stock returns to their corresponding behavioral explanations. We summarize all the potential patterns and link such relations to their corresponding behavioral explanation, especially within the empirical framework of Lee and Swaminathan (2000); Statman, Thorley, and Vorkink (2006); Shefrin and Stateman (1985); Veronesi (2000); and Thaler and Johnson (1990).

Through the Vector Autoregressive (VAR) procedure, we investigate the dynamic relationship between the market trading volume and market stock return in each China stock market. Based on monthly returns of stocks in the China stock market during 1991 to 2007, we find strong monotonic relations between trading volume and stock returns, relations which vary among different kinds of markets, either A share or B share. These differences suggest that the lead-lag patterns need not be the same across different types of stock markets. Particularly, we show that the market trading volume in the A share market contains important information to predict the subsequent stock return, in that the lagged market trading volume is strongly negatively related with subsequent market return. Such lead-lag patterns are consistent and robust when we investigate with different subsamples. According to our assessment, Lee and Swaminathan's (2000) Momentum Life Cycle explanation best describes the relation between trading volume and subsequent stock return patterns in our sample. In particular, late stage momentum performers, including high (low) volume winners (losers), experience price reversals, whereas early stage momentum performers, including low (high) volume winners (losers), experience price momentum. In both cases, high volume would predict a subsequent loser performance, and low volume would predict a subsequent winner performance, which would lead to the negative relation between trading volume and subsequent return. On the other hand, we find evidence that lagged stock returns are positively related with current trading volume in both Shanghai B and Shenzhen B share markets, with the relations being stronger in the Shanghai B share market. Such relations could best be explained by the Statman, Thorley, and Vorkink's (2006) Overconfidence theory that investors are overly confident about the precision of their private information and such biased self-attribution causes the degree of confidence to increase when realized market returns are high, even when those returns are simultaneously enjoyed by the entire market.

The contribution of this article to the literature lies largely in four aspects. First, we systematically summarize all the potential lead-lag patterns between trading volume and stock returns and link them to their corresponding behavioral explanations. Second, we fill in the gap in the literature between the behavioral theories and lead-lag patterns between stock returns and trading volume in China stock markets. Third, through empirical study, we investigate the dynamic relation between trading volume and stock returns in both types of China's stock market by using the Vector Autoregressive model. Finally, we find the different characteristics among the two types of China stock markets: The B share market is more efficient than the A share market in that the B share market's trading volume does not contain important information to predict the subsequent market return. While lagged trading volume is significantly negative related with current market return in A share market, which could be best explained by the Momentum Life Cycle theory, the strong positive relation between lagged return and current trading volume in both B share markets is best explained by the Overconfidence Theory. These findings show that the relation between trading volume and stock returns in each particular market is determined by the market's particular characteristics. The different investor base, trading currency and other characteristics differentiating the A share and B share markets determine the different lead-lag patterns between volume and return and, thus, the underlying behavioral explanations.

In the following section 2.2, all of the potential lead-lag patterns between trading volume and stock returns are summarized and a review of the implications from several behavioral postulations in our investigation are provided. In section 2.3, the data and research methodology used are described. Section 2.4 presents our empirical results and a discussion of the implications of our findings. Finally in section 2.5, we provide our summary and concluding remarks.

2.2 Potential Lead-Lag Patterns and Implicit Behavioral Explanations

There are mainly three categories of relations between trading volume and stock returns: contemporaneous volume and return, current volume and subsequent return, and current return and subsequent volume. The category of lead-lag patterns between trading volume and returns could be further divided into patterns with negative relations and those with positive relations. Since the late 1990s, researchers have developed behavioral models or proposed explanations for the observations of short-to-intermediate-horizon lead-lag patterns between trading volume and stock returns. We believe that some of these models have the potential to explain the relation between trading volume and stock returns. Particularly, we link each potential lead-lag patterns to its corresponding behavioral explanation and empirically test such patterns in the China stock markets.

Lee and Swaminathan (2000) provide a causal theory of the Momentum Life Cycle (MLC) to explain the dynamic relationship between trading volume and price patterns of winner/loser stocks in the US market during 1965 to 1995. In their framework, stocks go through cycles of investor favoritism (high volume and higher number of analysts following) and neglect (low volume and lower number of analysts following). During the periods of favoritism, high volume winners are glamour stocks (growth and low book to market ratio) that are eventually overvalued. After being overvalued, their prices reverse and they enter into the next phase, becoming high volume losers. They are still popular, but their performance declines. Next, as investors reassess these stocks' performance over time, they enter into a period of neglect. These stocks become low volume losers. During this period, they turn into value stocks (high book to market ratio). In the next phase, they become low volume winners that outperform other stocks due to their relatively lower prices and positive surprises. However, they are still not very popular since they are still in a period of neglect (low volume). When they become more popular, their trading volume increases. They then turn back into high volume winners, as their book to market ratio decreases over time. This cycle then repeats itself. Effectively, the MLC labels high (low) volume winners (losers) as late stage momentum stocks that are about to reverse. On the other hand, low (high) volume winners (losers) are categorized as early stage momentum stocks whose momentum is likely to continue, at least in the short horizon.

Lee and Swaminathan (2000) note that the turning points between phases may be at random and are difficult to pinpoint. From the Momentum Life Cycle theory, we can see that high volume winners will reverse in the next stage and become high volume losers, and high volume losers will continue to be low volume losers in the next stage. In both cases of high volume in a current stage, the theory predicts a loser performance in the next stage. The same relation holds in that low volume losers will reverse in the next stage and become low volume winners, and low volume winners will become high volume winners in the next stage. In both cases of low volume in a current stage, the theory predicts a winner performance in the next stage. Under this situation, the lagged trading volume would be negatively related with the current stock return. In other words, high (low) lagged trading volume will predict a low (high) current return if this behavioral explanation is true.

Statman, Thorley, and Vorkink (2006) have developed a model based on investor overconfidence bias. They argue that investors are overly confident about the precision of their private information and that biased self-attribution causes the degree of overconfidence to vary with realized market outcomes. Particularly, the overconfidence is enhanced in investors who experience high returns, even when those returns are simultaneously enjoyed by the entire market. With enhanced overconfidence, investors would be more willing to trade, thus causing subsequent high trading volume. On the other hand, when current realized return is low, the degree of overconfidence of investors would decrease or at least not increase, thus causing subsequent relatively low trading volume. Both situations will lead to a positive relation between the lagged stock return and current trading volume. Consistent with the hypothesis, the authors test the trading volume predictions of formal overconfidence models and find that share turnover is positively related to lagged returns for many months.

Similar to the Overconfidence theory, the disposition effect of Shefrin and Statman (1985) also predicts a positive relation between lagged stock return and current trading volume. The disposition effect describes a desire for investors to realize gains by selling stocks that have appreciated, but to delay the realization of losses. This theory is different from the overconfidence hypothesis in that Overconfidence theory explains the trading activities that relate to investor beliefs about trading in general rather than an attitude about individual stocks they currently hold, as disposition effect theory proposes. Empirical research on behavioral assertions of disposition effects helps us understand the motives of some investors, but it does not address the larger issue of whether these motivations are pervasive enough to impact the structure of the market in terms of realized trading volume and price discovery.

Another implicit behavioral explanation of the relation between trading volume and stock return is based on the market tendency to overreact to bad news and underreact to good news. Veronesi (2000) provides a dynamic, rational expectations equilibrium model of asset prices, in which investors' willingness to hedge against changes in their own uncertainty on the true state makes stock prices overreact to bad news in good times and underreact to good news in bad times. He shows that this model is better able than conventional models to explain features of stock returns. On the other hand, the portfolio rebalancing theory shows that portfolio rebalancing in the wake of large price movements might induce trading activities. With the combination of the market tendency to overreact to bad news and underreact to good news and the portfolio rebalancing, we would expect to see larger (smaller) price volatility on bad news (good news) cause larger (smaller) portfolio rebalancing following bad news (good news). If higher (lower) than expected market return can proxy for the good (bad) news, we would expect to see larger (lower) trading volume following lower (higher) than expected market returns. In other words, if these two theories hold, then lagged market return would be negatively related to the subsequent trading volume. It should be noted, however, that this expectation is contrary to the predictions of Statman, Thorley, and Vorkink (2006) if higher (lower) than expected market return actually represented good (bad) news.

Thaler and Johnson (1990) propose the Try-to-Break-Even Hypothesis, which describes the desire by investors to recoup large losses in one quick long-short investment. This behavior bias predicts that investors who have lost money are more willing to take very high risks to try to recoup the loss immediately. Under this hypothesis, investors experiencing lower than expected returns or losses would possibly trade more than investors experiencing higher than expected returns. The main implications for this effect would be the negative relation between lagged stock return and subsequent trading volume. While both the Try-to-Break-Even effects and the Veronesi (2000) hypothesis predict a negative relation between lagged return and current trading volume, the former relates to investors' beliefs about individual stocks they currently hold, and the latter relates to investors' beliefs about trading in general.

Table 1 summarizes the prediction of the five behavioral explanations for all the potential lead-lag patterns between trading volume and returns. As we can see, Lee and Swaminathan's (2000) MLC hypothesis predicts negative relation between lagged trading volume and subsequent stock return in market level. If MLC hypothesis holds, then trading volume contains important information to predict the subsequent stock return. Statman, Thorley, and Vorkink's (2006) overconfidence hypothesis and Veronesi's (2000) market tendency to overreact on bad news effect provide opposite predictions on the

Table 1
Summary of the Predications of Five Behavior Explanations on the Lead-Lag Patterns Between Trading Volume and Stock Returns

Behavioral Explanations	**Basis**	**Implicit Predictions**
Lee and Swaminathan (2000)	Momentum Life Cycle (MLC)	**High Volume** Winners → High Volume **Losers** **High Volume** Losers → Low Volume **Losers** **Low Volume** Losers → Low Volume **Winners** **Low Volume** Winners → High Volume **Winners** In summary: High Volume followed by Low Returns Low Volume followed by High Returns → Lagged Trading Volume is Negatively Related with the Subsequent Return
Statman, Thorley and Vorkink (2006) Shefrin and Statman (1985)	Investor Overconfidence Hypothesis Disposition Effect	Investors are overly confident about the precision of their private information. Biased self-attribution causes the degree of overconfidence to vary with realized market outcomes. Overconfidence is enhanced in investors that experience high returns, even when those returns are simultaneously enjoyed by the entire market. If overconfidence hypothesis holds: → Lagged Market Returns is Positively Related with Subsequent Market Trading Volume → Both Lagged Individual Stock Return and Lagged Market Return are Positively Related with Subsequent Individual Trading Volume → Lagged Individual Stock Return is Positively Related with Subsequent Individual Trading Volume
Pietro Veronesi (2000) Thaler and Johnson (1990)	Market Tendency to Overreact to Bad News and Underreact to Good News Try-to-Break-Even Hypothesis	If markets tend to over- or underreact to different type of information in that it underreact to good news and overreact to bad news, then investors are more intent to rebalance their portfolio structure on bad performance stocks. The desire by investors to recoup large losses in one quick long-short investment. This behavior bias predicts that investors have lost money are more willing to take very high risk to try to recoup the loss immediately → Lagged Stock Return is Negatively Related with Subsequent Trading Volume

relations between lagged return and subsequent trading volume in market level. While, Shefrin and Statman's (1985) disposition effect and Thaler and Johnson's (1990) Try-to-Break-Even effect predict in the opposite way on the lead-lag patterns between lagged return and trading volume in the individual stock level.

2.3 Data and Methodology

2.3.1 Data Description

This study uses daily return from December 12, 1990 to March, 2007 for the Shanghai A share; From February 21, 1992 to March, 2007 for the Shanghai B share; From September 30, 1992 to March, 2007 for the Shenzhen A share; and from October 6, 1992 to March 2007 for Shenzhen B share. We extract the returns on individual stocks, market returns, risk free rate, number of shares outstanding, number of shares traded, market capitalization and share prices. All the data are getting from the China Stock Market Database from the 'Taiwan Economic Data Bank', TEJ Database of Taiwan Economic Journal Co. Ltd.

Table 2, 3, and 4 summarize the statistical characteristics of both the endogenous and exogenous variables in this study for China A share markets, Shanghai B share market and Shenzhen B share market respectively. In each table, both the whole sample period (1991-2007 for A share markets; 1992-2007 for both B share markets) and four equal length sub sample periods (1991/92-1995, 1995-1999, 1999-2003 and 2003-2007) are analyzed. Figure 1, 2, 3 and 4 plot the market turnover during the whole sample periods for China A share, Shanghai B share and Shenzhen B share market respectively. In each of the figure, the blank and dashed line represents the original time series data of the market turnover, while the solid and red line represents the first differenced natural logged time series data of it. We can see it becomes stationary after the first difference and natural log implement.

Table 2
China Common A Share Market Description Statistics

	Full	A	B	C	D
Period	1991-2007	1991-1995	1995-1999	1999-2003	2003-2007
Observations	194	48	49	48	49
Market Turnover					
Mean	1.9797312	1.9249707	2.6825014	1.4723811	1.8276001
SD	1.6981215	2.4021942	1.7770080	0.9653969	1.0419634
Minimum	0.0023221	0.0023221	0.6565014	0.5176843	0.5901621
Maximum	10.1209561	10.1209561	7.7503754	5.1499172	4.7551389
Logged Market Turnover					
Mean	0.1375883	-0.9266719	0.7687410	0.2305582	0.4579037
SD	1.4546834	2.4368280	0.6827655	0.5384118	0.5397950
Minimum	-6.0652869	-6.0652869	-0.4208304	-0.6583897	-0.5273581
Maximum	2.3146081	2.3146081	2.0477413	1.6389806	1.5592259
First Differenced Market Turnover					
Mean	0.0215936	0.0101655	0.0034389	0.0037690	0.0684040
SD	1.2282947	1.9235383	1.1522305	0.8443767	0.6438722
Minimum	-3.8172234	-3.8172234	-2.6470058	-2.5143160	-1.7857742
Maximum	9.1011817	9.1011817	3.0131635	3.1178149	1.4758056
First Differenced Log Market Turnover					
Mean	0.0346185	0.0953142	0.0060000	0.0050364	0.0327584
SD	0.4932614	0.7065424	0.4409302	0.4129282	0.3503119
Minimum	-1.1297370	-1.1297370	-1.0437034	-0.6698693	-0.5899933
Maximum	2.2950268	2.2950268	0.8562849	1.1230452	0.9398331
Market Return					
Mean	0.0496308	0.1783961	0.0115693	0.0054574	0.0048267
SD	0.4359739	0.8620770	0.0889370	0.0559856	0.0593327
Minimum	-0.3425847	-0.3425847	-0.1828323	-0.1829618	-0.1205855
Maximum	5.8768245	5.8768245	0.2884223	0.1314884	0.1465547
Market Volatility					
Mean	11.3082974	35.8582839	4.5489956	2.7094538	2.4419899
SD	50.5104774	98.2138105	2.7482471	1.3437948	0.7336362
Minimum	0.1233991	0.1233991	1.7497329	1.3176909	1.2827170
Maximum	595.7959640	595.7959640	13.4986754	9.3473391	4.7119984
Dispersion*					
Mean	0.2120973	0.8164575	0.0164237	0.0103427	0.0133818
SD	1.9467830	3.8816338	0.0123873	0.0063806	0.0092290
Minimum	0.0008731	0.0008731	0.0013452	0.0010714	0.0035047
Maximum	25.9496643	25.9496643	0.0625210	0.0276202	0.0374403

*the monthly cross-sectional standard deviation of return (Statman, Thorley, and Vorkink 2006)

Table 3
China Shanghai B Share Market Description Statistics

	Full	A	B	C	D
Period	1992-2007	1992-1995	1995-1999	1999-2003	2003-2007
Observations	181	45	45	45	46
Market Turnover					
Mean	0.5014814	0.3690257	0.3869648	0.8237496	0.4278225
SD	0.6080180	0.3181145	0.2378942	1.0522025	0.3191717
Minimum	0.0024091	0.0024091	0.1319580	0.1045275	0.0979259
Maximum	5.3082675	1.4043182	1.2507186	5.3082675	1.6597390
Logged Market Turnover					
Mean	-1.1353541	-1.6706478	-1.1034057	-0.6871408	-1.0814205
SD	1.0833139	1.6165277	0.5465984	0.9551980	0.6808067
Minimum	-6.0285058	-6.0285058	-2.0252714	-2.2583047	-2.3235445
Maximum	1.6692655	0.3395519	0.2237183	1.6692655	0.5066603
First Differenced Market Turnover					
Mean	0.0042000	0.0046068	0.0040607	-0.0010204	0.0090453
SD	0.4849048	0.2776149	0.2480834	0.8656179	0.2688879
Minimum	-1.5603256	-0.7679047	-0.5273741	-1.5603256	-0.5845508
Maximum	4.8799772	0.8509513	0.6799585	4.8799772	0.9006297
First Differenced Log Market Turnover					
Mean	0.0262165	0.0770826	0.0137189	-0.0027338	0.0170031
SD	0.6521530	0.8191769	0.5328367	0.6858424	0.5512483
Minimum	-1.6196740	-1.3809327	-1.1266142	-1.6196740	-0.9011109
Maximum	2.5806129	2.5806129	1.2634142	2.5172197	1.7246330
Market Return					
Mean	0.0031357	-0.0306614	0.0021672	0.0295425	0.0113130
SD	0.1366233	0.1715244	0.1390442	0.1278119	0.0954541
Minimum	-0.8747987	-0.8747987	-0.2718184	-0.2386781	-0.1813983
Maximum	0.5502937	0.3319962	0.4334753	0.5502937	0.3822881
Market Volatility					
Mean	2.8484618	2.9287231	3.5180147	2.6473993	2.3116394
SD	1.1774331	1.2162876	1.2282769	1.1004499	0.8061920
Minimum	0.5544144	0.9138266	1.8513312	0.5544144	0.9912077
Maximum	7.6271127	6.7535722	7.6271127	5.5467009	4.3219408
Dispersion					
Mean	0.0101459	0.0122998	0.0133392	0.0053342	0.0096220
SD	0.0144138	0.0162051	0.0129663	0.0082053	0.0174864
Minimum	0.0000000	0.0000000	0.0017681	0.0002875	0.0006698
Maximum	0.1170501	0.0785626	0.0549298	0.0495107	0.1170501

*the monthly cross-sectional standard deviation of return (Statman, Thorley, and Vorkink 2006)

Table 4
China Shenzhen B Share Market Description Statistics

	Full	A	B	C	D
Period	1992-2007	1992-1995	1995-1999	1999-2003	2003-2007
Observations	181	45	45	45	46
Market Turnover					
Mean	0.5020346	0.3048261	0.4301916	0.7700412	0.5030570
SD	0.6927435	0.2616332	0.4350848	1.2354517	0.2434093
Minimum	0.0519486	0.0714578	0.0519486	0.1050780	0.1786423
Maximum	7.5673113	1.2653973	1.9636962	7.5673113	1.1193790
Logged Market Turnover					
Mean	-1.0757146	-1.4548649	-1.2890965	-0.7657613	-0.7992787
SD	0.8248399	0.6994913	0.9497016	0.8841947	0.4829480
Minimum	-2.9575012	-2.6386484	-2.9575012	-2.2530523	-1.7223700
Maximum	2.0238378	0.2353862	0.6748285	2.0238378	0.1127741
First Differenced Market Turnover					
Mean	-0.0052488	-0.0164889	-0.0109834	0.0086067	-0.0021974
SD	0.7115352	0.1991679	0.4548412	1.3239610	0.2641576
Minimum	-4.1280443	-0.6247402	-1.4516177	-4.1280443	-0.4724154
Maximum	7.3858327	0.4713482	1.2191789	7.3858327	0.8301170
First Differenced Log Market Turnover					
Mean	-0.0052438	-0.0144766	-0.0210217	0.0178665	-0.0033848
SD	0.6690990	0.5716815	0.7749950	0.7941886	0.5160964
Minimum	-1.9864886	-1.2257965	-1.9864886	-1.5793261	-0.8097770
Maximum	3.7304555	1.4822414	1.7592238	3.7304555	1.5196189
Market Return					
Mean	0.0126011	-0.0016511	0.0131027	0.0303413	0.0086982
SD	0.1546002	0.1527780	0.1640370	0.1990351	0.0848762
Minimum	-0.2410680	-0.1399284	-0.2382372	-0.2410680	-0.1651050
Maximum	1.2095818	0.5899523	0.6010803	1.2095818	0.2395800
Market Volatility					
Mean	3.8907685	6.7048659	3.7415275	2.7455094	2.4042060
SD	6.7058550	12.9809584	1.4235677	1.1025336	0.6566247
Minimum	0.7742725	1.7955298	1.5674937	0.7742725	1.0711493
Maximum	84.0279124	84.0279124	8.2632679	6.2243905	4.0653429
Dispersion*					
Mean	0.0130942	0.0124229	0.0161433	0.0115883	0.0122411
SD	0.0184668	0.0131146	0.0214188	0.0244946	0.0121631
Minimum	0.0004100	0.0031859	0.0011702	0.0004100	0.0010191
Maximum	0.1618149	0.0845596	0.1214732	0.1618149	0.0593220

*the monthly cross-sectional standard deviation of return (Statman, Thorley, and Vorkink 2006)

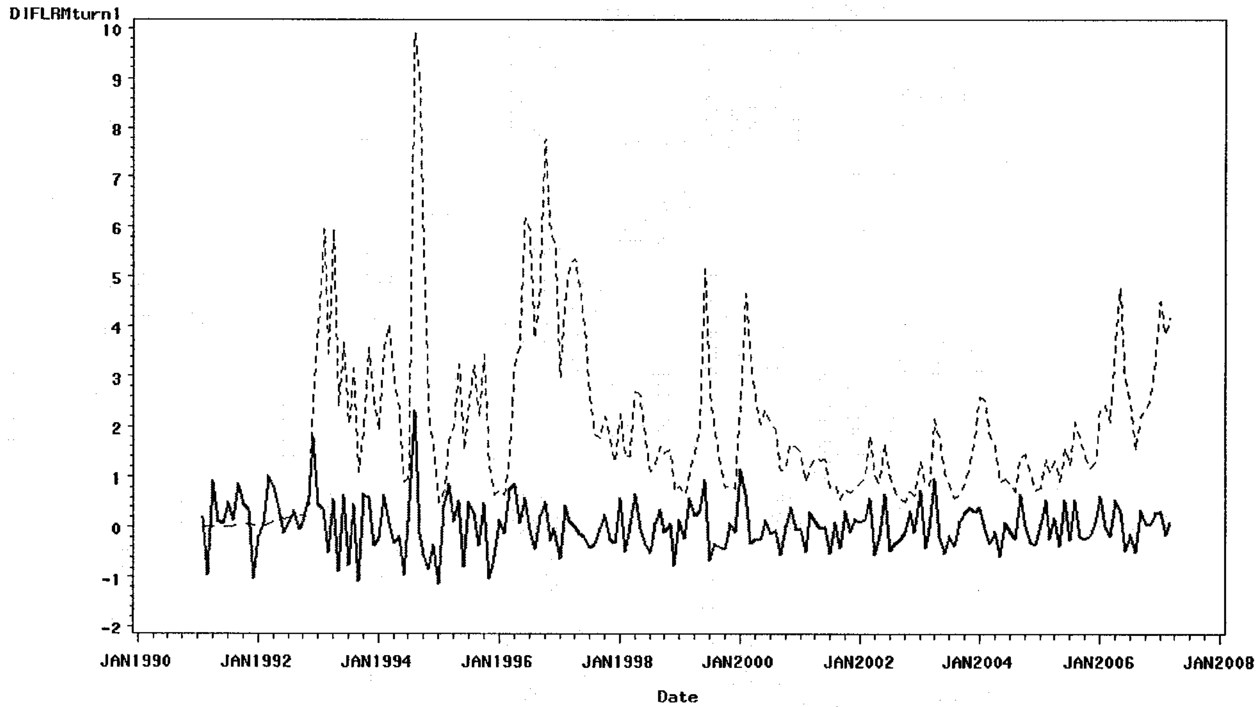


Figure 1. China A Share Market Turnover (Full Sample)

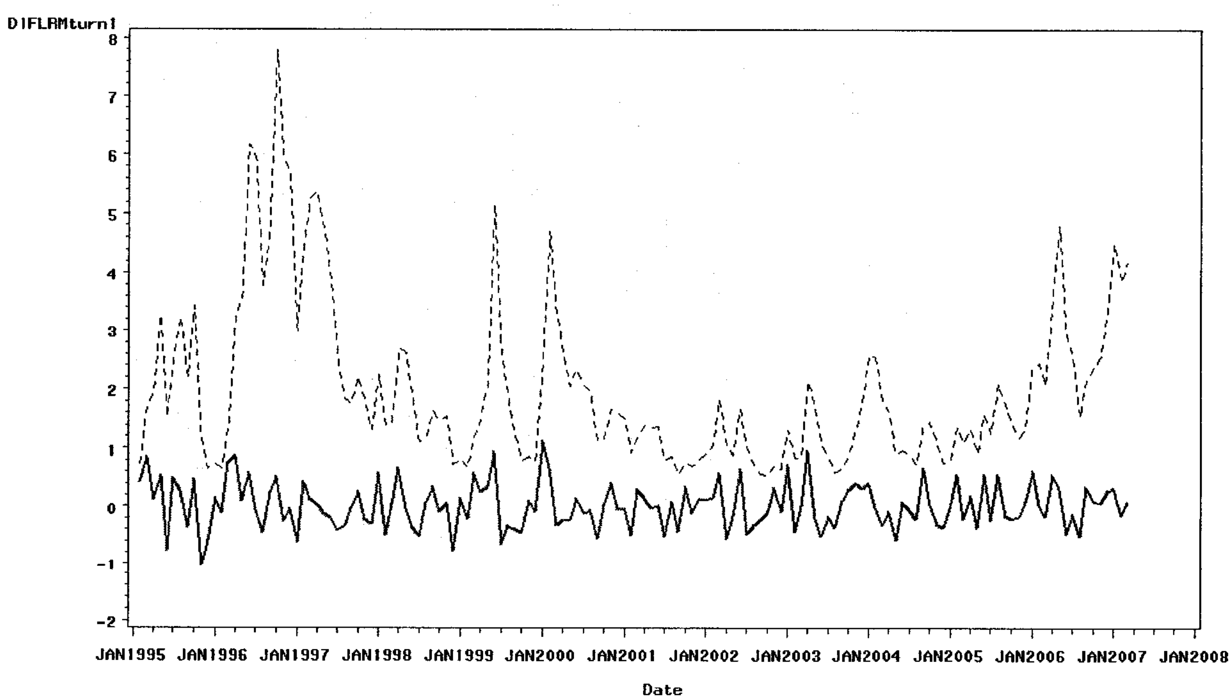


Figure 2. China A Share Market Turnover (1995-2007)

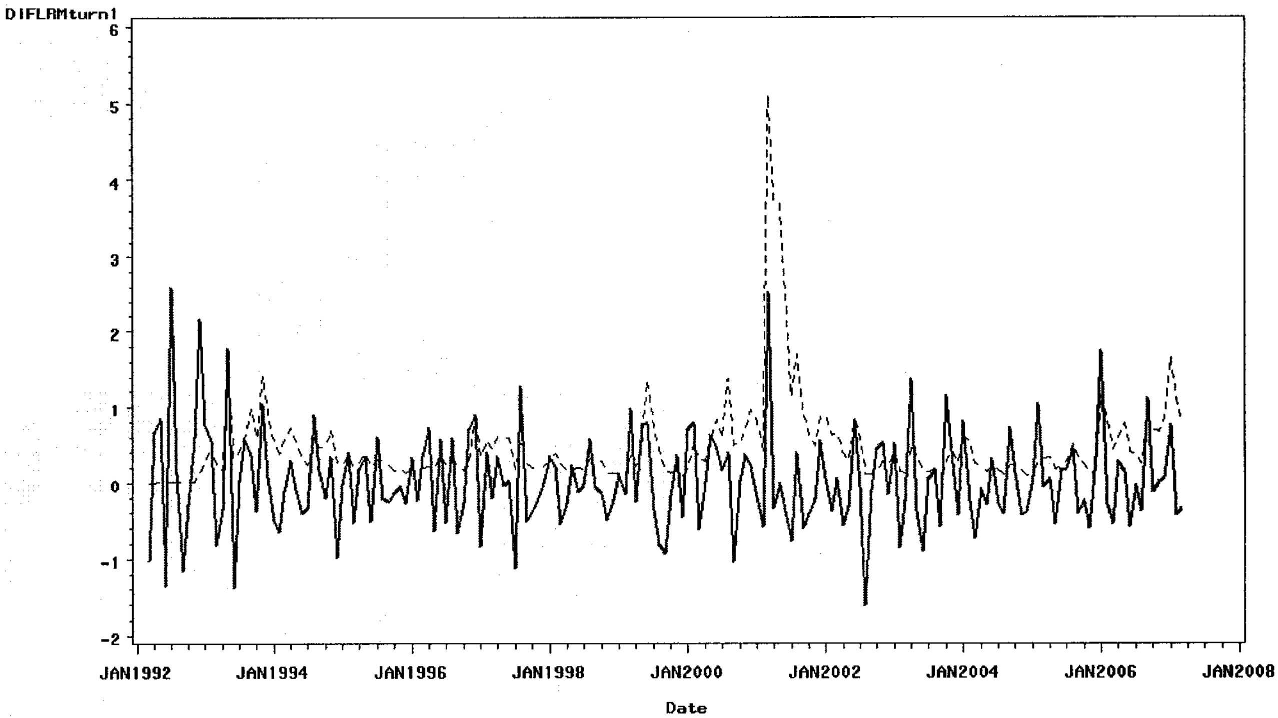


Figure 3. China Shanghai B Share Market Turnover (1992-2007)

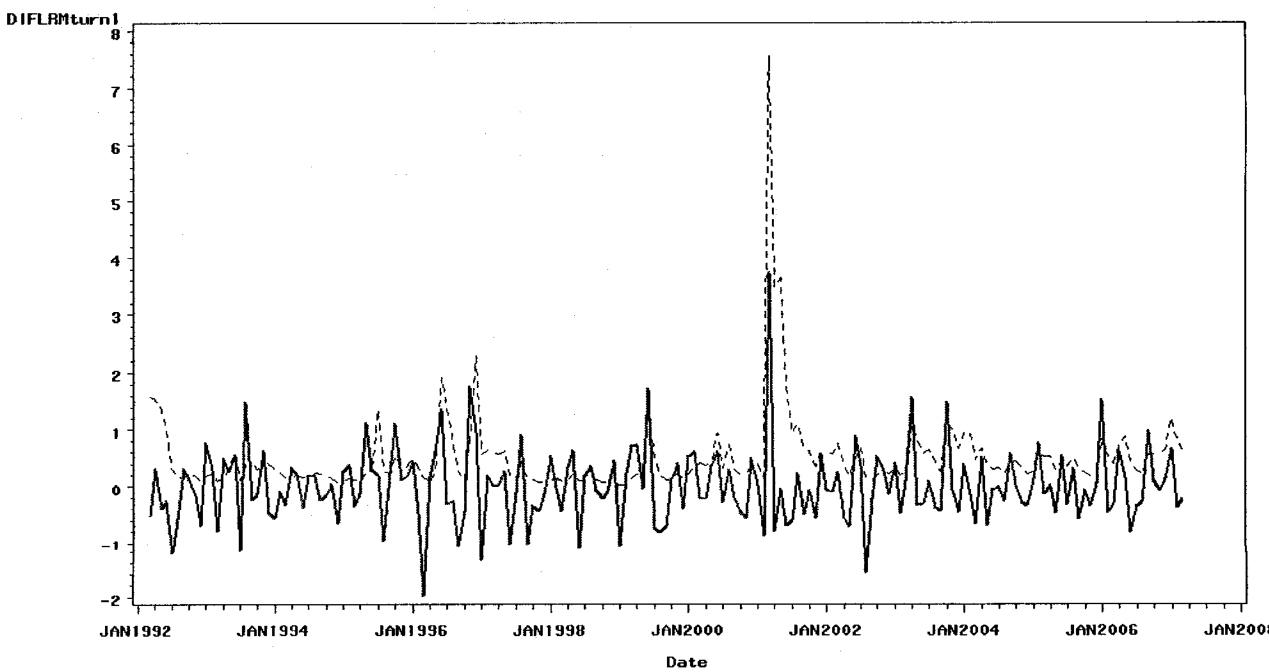


Figure 4. China Shenzhen B Share Market Turnover (1992-2007)

2.3.2 Empirical Methodology

Often, economic or financial variables are not only contemporaneously correlated to each other, they are also correlated to each other's past values. The relationship between market trading volume and market return is very complex, dynamic and also influenced by many variables external to the system under consideration. The Vector Autoregressive (VAR) procedure could be used to model such dynamic relationship between trading volume and market return, with the consideration of external variables influence on such relationship. The general form of the VAR model is:

$$Y_t = \alpha + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{l=0}^{L} B_l X_{t-l} + \varepsilon_t \qquad (1)$$

Where Y_t is a $n \times 1$ vector of period t observations of endogenous variables, for example, market turnover and market return, X_t is a vector of period t observations of the exogenous (i.e., control) variables, and ε_t is a $n \times 1$ residual vector. The regression coefficients, A_k and B_l, estimate the time series relationship between the endogenous and exogenous variables, where K is the number of lagged endogenous observations and L is the number of lagged exogenous observations. The VAR methodology allows for a covariance structure to exist in the residual vector, which captures the contemporaneous correlation between endogenous variables.

Previous literature use optimal number of lagged endogenous and lagged exogenous variables, say K and L based on Schwartz Information Criteria (SIC). Statman, Thorley, and Vorkink (2006) set K=10 and =2 based on the SIC model selection criterion in their study for the investor overconfidence and trading volume. Particularly, in this case, they choose 10 lagged monthly observations of the endogenous variables and use contemporaneous and two lagged monthly observations variables to explain and predict the endogenous variables. As the relationship is dynamic and continuously changing during the time period, the patterns found for some particular 'optimal model' may not be a true underlying pattern. Only the patterns that fit all the different lag models are the most general patterns between the endogenous variables. In our study, we didn't choose the so called optimal lagged numbers of endogenous and exogenous variables, but using 16 different combination of K (=4, 6, 10 or 15) and L (=1, 2, 5, 10) for the VAR model. Particularly, our findings are consistent in all these different VAR models that use different combination of lagged endogenous and exogenous variables. From this aspect, our results are consistent with the selection of different K and L in the VAR model. Particularly, as we are investigating the relationship between the market trading volume and market return, we are using the following market wide VAR model for our study:

$$\begin{bmatrix} mturn_t \\ mret_t \end{bmatrix} = \begin{bmatrix} \alpha_{mturn} \\ \alpha_{mret} \end{bmatrix} + \sum_{k=4,6,10,15}^{K} \begin{bmatrix} mturn_{t-k} \\ mret_{t-k} \end{bmatrix} + \sum_{l=1,2,5,10}^{L} \begin{bmatrix} msig_{t-l} \\ disp_{t-l} \end{bmatrix} + \begin{bmatrix} \varepsilon_{mturn,t} \\ \varepsilon_{mret,t} \end{bmatrix} \quad (2)$$

Where market turnover, *mturn*, is the Hodrick and Prescott (1997) detrended natural log of market turnover. Market return, *mret*, is the monthly value-weighted market return. Market volatility, *msig*, is the French, Schwert, and Stambaugh (1987) monthly volatility measure based on daily return standard deviation. Dispersion, *disp*, is the Statman, Thorley and Vorkink (2006) monthly cross-sectional standard deviation of security returns.

2.4 Empirical Results

We estimate the vector autoregressive models in each of the stock markets of China. Particularly, as Shanghai B share markets use US dollar as the trading currency, while Shenzhen B share markets use Hong Kong dollars as the trading currency, we estimate them separately, instead of combining them together as a whole as we do for the China A share markets (we combine the Shanghai A and Shenzhen A share markets together as China A share market for investigation). The VAR model estimation results for China A share market, Shanghai B share market and Shenzhen B share market are shown in table 5, 7 and 8 respectively. Table 6 is the results also for China A share market, but for the results under a subsample of time period.

Particularly, we estimate the VAR model for the full sample of China A share market with the data ranging from 1991 to 2007. The results are shown in Table 5. As to the number of lagged endogenous and lagged exogenous variables used in the VAR model, we consider 4 different K and 4 different L and, thus, result in totally 16 different combinations of K and L for the VAR model. For this empirical study, we find strong lead-lag patterns between the market trading volume and market stock return and such a pattern is consistent across all the 16 VAR models. Specifically, the one month lagged market trading volume is statistically significantly negative related with the subsequent market return (the significantly level is at 1% for most of the 16 VAR models). On the other hand, there is no significant and consistent relationship between the lagged market return and subsequent market trading volume. Both of these two major findings are consistent through all the different models.

Even though the time series of market trading volume has been stationary through first differencing of the natural log, we can still find some variation of the standard deviation and mean value between the period 91-95 and the remaining period, which could be seen from the Table 2 and Figure1. From Figure1, we can see there is a high volatility period during 91-95 not only for market trading volume, but also for all the endogenous and exogenous variables. Someone may argue that such pattern we find may actually caused by the high volatility in this subperiod of 91-95. in order to investigate this alternative explanation, we re-estimate the relation only in the remaining subperiod, 95-07, and want to examine whether such lead-lag relation still hold. As we can see from both Table2 and Figure1, the subperiod of 95-07 is quite stationary in that the standard deviation and mean value are stable across the three subperiods of 95-99, 99-03, and 03-07. Table 6 shows the results for the VAR estimation in the subperiod of 95-07. It's obviously to see that such lead-lag relationship is still strong and significant. This result strongly support our finding that the lagged market trading volume is strongly related to the subsequent market return in the China A share market.

The finding that trading volume contains important information to predict the future return is an important empirical fact that should be acknowledged by theorists and empirical researchers. According to our assessment, Lee and Swaminathan's (2000) MLC explanation best describes the pattern between trading volume and subsequent stock return in our sample. In particular, late stage momentum performers, including high (low) volume winners (losers), experience price reversals, whereas early stage momentum performers, including low (high) volume winners (losers), experience price momentum. In both cases, high volume would predict a subsequent loser performance and low volume would predict a subsequent winner performance, which would lead to the negative relation between trading volume and subsequent return.

Table 7 and 8 show the estimation results for the Shanghai B and Shenzhen B share markets respectively. Same as in the China A share market study, we also estimate the VAR model by using 16 combinations of different number of lags (K and L) in endogenous and exogenous variables. The results are summarized in the following paragraphs. Its interesting to find that the results are quite similar in these two B share market, even though they use different trading currency. First, the lead-lag pattern appears in the China A share market is not found in both the B share markets. Second, another kind of strong lead-lag patterns between market trading volume and market return is found in both B share markets. Instead of lagged trading volume strongly related with subsequent market return, the lagged market return is significantly positive related with the subsequent market volume. In other words, instead of trading volume has predictive power for subsequent market return as in China A share market, the market returns has predictive power for the subsequent market trading volume in China B share markets. As we can see such patterns also consistent across different VAR models and significant at 1% level in most cases, especially in the Shanghai B share market.

The positive lead-lag pattern found in both the China's B share markets can be best explained by the Statman, Thorley, and Vorkink's (2006) overconfidence theory in the market level, in which market investors are overly confident about the precision of their private information and such biased self-attribution causes the degree of confidence to increase when realized market returns are high, even when those returns are simultaneously enjoyed by the entire market. As Shanghai B share market use US dollar as trading currency, it is interesting to find that the lead-lag patterns in this market are consistent with the findings of Statman, Thorley, and Vorkink's (2006) study in the US stock markets.

Its interesting to find that the two types of stock markets in China (A share and B share markets) have different lead-lag patterns between market trading volume and market return. The different characteristics underlying each type of market might determine the different lead-lag patterns. If these findings are true, we can see that China's A share market is less efficient than its B share market, because the trading volume in A share market contains important information to predict the market return in the subsequent period. It is possible to take advantage of such lead-lag patterns in A share markets to benefit through particular trading strategies. In the next study of this thesis, we further investigate the lead-lag patterns through the aspect of the relation between trading volume and profitability of momentum / contrarian trading strategies. If we could make profits from appropriate trading strategies by taking advantage of such lead-lag patterns between trading volume and subsequent stock return, we would be able to say that such patterns are not only statistically significant but also economically significant.

Table 5

VAR Empirical Results for China A Share Markets (Full Sample, 1991-2007)

Dependent Var		Market Turnover at Time t ($mturn_t$)				Market Return at Time t ($mret_t$)			
		Lagged Market Return		Lagged Market Turnover		Lagged Market Return		Lagged Market Turnover	
		t-1	t-2	t-1	t-2	t-1	t-2	t-1	t-2
P=4	Xlag=1	0.026	0.029	-0.040	-0.1144	-0.085	0.047**	-0.075***	-0.018
		(0.305)	(0.087)	(0.077)	(0.071)	(0.079)	(0.023)	(0.020)	(0.019)
	Xlag=2	0.055	-0.191	-0.044	-0.1290*	-0.105	0.099	-0.072***	-0.017
		(0.310)	(0.310)	(0.078)	(0.077)	(0.081)	(0.081)	(0.020)	(0.020)
	Xlag=5	-0.018	-0.154	-0.021	-0.179**	-0.053	0.147	-0.077***	-0.007
		(0.319)	(0.316)	(0.078)	(0.079)	(0.082)	(0.081)	(0.019)	(0.020)
	Xlag=10	-0.454	-0.661**	-0.090	-0.080	-0.036	0.078	-0.054***	-0.004
		(0.338)	(0.319)	(0.076)	(0.077)	(0.084)	(0.079)	(0.019)	(0.019)
P=6	Xlag=1	0.040	-0.019	-0.060	-0.148**	-0.114	0.099***	-0.066***	-0.007
		(0.312)	(0.105)	(0.079)	(0.075)	(0.079)	(0.0267)	(0.020)	(0.019)
	Xlag=2	0.007	-0.268	-0.057	-0.184**	-0.098	0.124	-0.070***	0.001
		(0.316)	(0.320)	(0.080)	(0.083)	(0.080)	(0.081)	(0.020)	(0.021)
	Xlag=5	0.004	-0.258	-0.043	-0.227***	-0.076	0.151**	-0.072***	0.002
		(0.326)	(0.327)	(0.082)	(0.085)	(0.080)	(0.080)	(0.020)	(0.021)
	Xlag=10	-0.447	-0.737**	-0.117	-0.143*	-0.096	0.076	-0.052***	0.002
		(0.346)	(0.328)	(0.078)	(0.081)	(0.085)	(0.081)	(0.019)	(0.020)
P=10	Xlag=1	0.046	-0.010	-0.067	-0.235***	-0.066	0.116***	-0.068***	-0.008
		(0.336)	(0.105)	(0.083)	(0.076)	(0.087)	(0.027)	(0.021)	(0.020)
	Xlag=2	0.026	-0.019	-0.066	-0.255***	-0.065	0.102	-0.068***	-0.008
		(0.338)	(0.340)	(0.083)	(0.085)	(0.087)	(0.088)	(0.021)	(0.022)
	Xlag=5	-0.059	-0.109	-0.084	-0.275***	-0.050	0.141*	-0.071***	0.001
		(0.350)	(0.345)	(0.085)	(0.088)	(0.085)	(0.084)	(0.021)	(0.021)
	Xlag=10	-0.672*	-0.588*	-0.171**	-0.190**	-0.072	0.084	-0.057***	0.012
		(0.358)	(0.339)	(0.080)	(0.086)	(0.088)	(0.083)	(0.020)	(0.021)
P=15	Xlag=1	0.079	0.060	-0.080	-0.233***	-0.103	0.148***	-0.067***	0.001
		(0.350)	(0.119)	(0.087)	(0.080)	(0.088)	(0.030)	(0.022)	(0.020)
	Xlag=2	0.044	0.171	-0.078	-0.242***	-0.119	0.036	-0.067***	-0.013
		(0.355)	(0.346)	(0.087)	(0.088)	(0.089)	(0.087)	(0.022)	(0.022)
	Xlag=5	-0.084	-0.021	-0.073	-0.270***	-0.177**	0.029	-0.073***	-0.008
		(0.383)	(0.361)	(0.088)	(0.090)	(0.085)	(0.081)	(0.020)	(0.020)
	Xlag=10	-0.358	-0.131	-0.148*	-0.171**	-0.147*	-0.113	-0.061***	-0.004
		(0.393)	(0.384)	(0.089)	(0.089)	(0.088)	(0.086)	(0.020)	(0.020)

(Continue of Table 5. - Exogenous Variables)

Dependent Var		Market Turnover at Time t ($mturn_t$)					Market Return at Time t ($mret_t$)				
		Constant	Lagged misg		Lagged disp		Constant	Lagged misg		Lagged disp	
		Term	t	t-1	t	t-1	Term	t	t-1	t	t-1
P=4	Xlag=1	0.027	0.004***	-0.002***	0.066***	0.013	0.003	-0.001***	0.001***	0.215***	0.021
		(0.034)	(0.002)	(0.001)	(0.017)	(0.069)	(0.009)	(0.001)	(0.000)	(0.005)	(0.018)
	Xlag=2	0.030	0.004*	-0.002***	0.070***	0.002	0.001	-0.002***	0.001***	0.214***	0.027
		(0.035)	(0.002)	(0.000)	(0.018)	(0.071)	(0.009)	(0.001)	(0.000)	(0.005)	(0.019)
	Xlag=5	0.037	0.004	-0.003	0.068***	0.021	0.003	-0.002***	0.002	0.216***	0.020
		(0.035)	(0.003)	(0.002)	(0.018)	(0.073)	(0.009)	(0.001)	(0.001)	(0.005)	(0.019)
	Xlag=10	0.016	0.013***	-0.004	0.002	0.082	-0.002	-0.006***	0.003***	0.192***	0.038**
		(0.036)	(0.004)	(0.074)	(0.030)	(0.074)	(0.009)	(0.001)	(0.001)	(0.007)	(0.018)
P=6	Xlag=1	0.029	0.007***	-0.004***	0.070***	0.005	0.002	-0.003***	0.001***	0.211***	0.031*
		(0.035)	(0.003)	(0.002)	(0.018)	(0.072)	(0.009)	(0.001)	(0.000)	(0.005)	(0.018)
	Xlag=2	0.028	0.006**	-0.004***	0.075***	0.011	0.003	-0.003***	0.001***	0.209***	0.027
		(0.035)	(0.003)	(0.001)	(0.019)	(0.072)	(0.009)	(0.001)	(0.000)	(0.005)	(0.018)
	Xlag=5	0.040	0.004	-0.003	0.071***	0.022	0.004	-0.003***	0.001	0.209***	0.024
		(0.036)	(0.003)	(0.003)	(0.019)	(0.074)	(0.009)	(0.001)	(0.001)	(0.005)	(0.018)
	Xlag=10	0.024	0.012***	-0.004	-0.010	0.093	-0.001	-0.006***	0.001	0.193***	0.043***
		(0.036)	(0.038)	(0.004)	(0.032)	(0.074)	(0.009)	(0.001)	(0.001)	(0.008)	(0.018)
P=10	Xlag=1	0.019	0.007**	-0.003	0.074***	0.006	0.006	-0.004***	0.002**	0.213***	0.024
		(0.034)	(0.003)	(0.003)	(0.019)	(0.075)	(0.009)	(0.001)	(0.001)	(0.005)	(0.019)
	Xlag=2	0.018	0.006**	-0.003	0.079***	0.013	0.006	-0.004***	0.002**	0.212***	0.023
		(0.035)	(0.003)	(0.003)	(0.020)	(0.076)	(0.009)	(0.001)	(0.001)	(0.005)	(0.020)
	Xlag=5	0.018	0.007**	-0.005	0.091***	0.043	0.006	-0.004***	0.001*	0.209***	0.020
		(0.035)	(0.003)	(0.003)	(0.021)	(0.079)	(0.009)	(0.001)	(0.001)	(0.005)	(0.019)
	Xlag=10	0.034	0.015***	-0.005	0.011	0.098	-0.001	-0.006***	0.001	0.184***	0.034*
		(0.037)	(0.004)	(0.004)	(0.035)	(0.075)	(0.009)	(0.001)	(0.001)	(0.009)	(0.018)
P=15	Xlag=1	0.012	0.005	-0.005	0.068***	-0.003	0.003	-0.005***	0.002**	0.208***	0.034*
		(0.035)	(0.004)	(0.004)	(0.020)	(0.077)	(0.009)	(0.001)	(0.001)	(0.005)	(0.019)
	Xlag=2	0.008	0.005	-0.007	0.073***	0.009	0.003	-0.006***	0.002**	0.210***	0.038**
		(0.035)	(0.004)	(0.004)	(0.020)	(0.078)	(0.009)	(0.001)	(0.001)	(0.005)	(0.020)
	Xlag=5	0.009	0.003	-0.008*	0.090***	0.048	0.001	-0.006***	0.001	0.205***	0.050***
		(0.035)	(0.004)	(0.005)	(0.022)	(0.085)	(0.008)	(0.001)	(0.001)	(0.005)	(0.019)
	Xlag=10	-0.014	0.012**	-0.006	0.041	0.080	0.016*	-0.004***	0.002	0.158***	0.039**
		(0.042)	(0.005)	(0.005)	(0.046)	(0.080)	(0.009)	(0.001)	(0.001)	(0.010)	(0.018)

Table 6

VAR Empirical Results for China A Share Markets (Sub Sample, 1995-2007)

Dependent Var		Market Turnover at Time t ($mturn_t$)				Market Return at Time t ($mret_t$)			
		Lagged Market Return		Lagged Market Turnover		Lagged Market Return		Lagged Market Turnover	
		t-1	t-2	t-1	t-2	t-1	t-2	t-1	t-2
P=4	Xlag=1	0.880	0.447	-0.016	0.010	-0.109	0.092	-0.050***	-0.012
		(0.598)	(0.505)	(0.089)	(0.090)	(0.110)	(0.093)	(0.110)	(0.016)
	Xlag=2	0.729	0.752	-0.048	0.018	-0.123	0.123	-0.062***	-0.009
		(0.613)	(0.573)	(0.105)	(0.091)	(0.113)	(0.105)	(0.019)	(0.017)
	Xlag=5	0.552	0.484	-0.093	-0.066	-0.125	0.065	-0.064***	-0.023
		(0.646)	(0.640)	(0.110)	(0.116)	(0.118)	(0.117)	(0.020)	(0.021)
	Xlag=10	0.943	1.201	-0.099	0.002	-0.039	-0.067	-0.052***	-0.032
		(0.762)	(0.757)	(0.121)	(0.123)	(0.135)	(0.134)	(0.021)	(0.022)
P=6	Xlag=1	0.936	0.209	0.019	-0.063	-0.135	0.061	-0.062***	-0.018
		(0.651)	(0.538)	(0.099)	(0.102)	(0.122)	(0.101)	(0.019)	(0.019)
	Xlag=2	0.832	0.499	-0.015	-0.045	-0.150	0.096	-0.070***	-0.015
		(0.668)	(0.653)	(0.113)	(0.105)	(0.125)	(0.122)	(0.021)	(0.019)
	Xlag=5	0.686	0.259	-0.073	-0.122	-0.184	0.072	-0.079***	-0.033
		(0.691)	(0.679)	(0.120)	(0.126)	(0.129)	(0.126)	(0.022)	(0.023)
	Xlag=10	0.857	0.765	-0.114	-0.099	-0.073	-0.029	-0.062***	-0.030
		(0.807)	(0.783)	(0.134)	(0.140)	(0.146)	(0.142)	(0.024)	(0.025)
P=10	Xlag=1	0.810	0.226	-0.083	-0.111	-0.055	0.047	-0.044**	-0.009
		(0.701)	(0.549)	(0.106)	(0.107)	(0.125)	(0.098)	(0.019)	(0.019)
	Xlag=2	0.687	0.613	-0.127	-0.086	-0.054	0.067	-0.048**	-0.068
		(0.722)	(0.692)	(0.119)	(0.112)	(0.129)	(0.123)	(0.021)	(0.019)
	Xlag=5	0.561	0.516	-0.158	-0.137	-0.091	0.038	-0.059***	-0.033
		(0.766)	(0.731)	(0.126)	(0.135)	(0.134)	(0.128)	(0.022)	(0.024)
	Xlag=10	-0.046	0.671	-0.205	-0.185	0.121	-0.066	-0.037*	-0.031
		(0.818)	(0.779)	(0.135)	(0.144)	(0.144)	(0.137)	(0.024)	(0.025)
P=15	Xlag=1	0.770	0.533	-0.107	-0.088	0.010	0.015	-0.039**	-0.016
		(0.753)	(0.605)	(0.113)	(0.114)	(0.133)	(0.106)	(0.019)	(0.020)
	Xlag=2	0.489	0.998	-0.139	-0.063	0.037	0.018	-0.046**	-0.014
		(0.778)	(0.740)	(0.126)	(0.118)	(0.137)	(0.129)	(0.022)	(0.021)
	Xlag=5	0.400	0.861	-0.174	-0.192	0.005	-0.005	-0.056**	-0.029
		(0.803)	(0.774)	(0.134)	(0.141)	(0.143)	(0.137)	(0.024)	(0.025)
	Xlag=10	0.054	0.781	-0.208	-0.211	0.128	-0.053	-0.039	-0.028
		(0.866)	(0.850)	(0.149)	(0.158)	(0.157)	(0.154)	(0.027)	(0.029)

(Continue of Table 6. - Exogenous Variables)

Dependent Var		Market Turnover at Time t ($mturn_t$)					Market Return at Time t ($mret_t$)				
		Constant	Lagged misg		Lagged disp		Constant	Lagged misg		Lagged disp	
		Term	t	t-1	t	t-1	Term	t	t-1	t	t-1
P=4	Xlag=1	0.024	0.107***	-0.095***	2.762	-8.132*	-0.016	-0.012***	0.008**	3.112***	-0.463
		(0.067)	(0.020)	(0.019)	(3.813)	(4.291)	(0.012)	(0.004)	(0.004)	(0.701)	(0.789)
	Xlag=2	0.032	0.108***	-0.092***	2.348	-5.659	-0.011	-0.011***	0.011***	3.050***	-0.216
		(0.070)	(0.021)	(0.0220)	(3.842)	(4.822)	(0.013)	(0.004)	(0.004)	(0.705)	(0.885)
	Xlag=5	0.065	0.110***	-0.088***	2.903	-6.270	-0.007	-0.009***	0.011**	3.054***	-0.387
		(0.076)	(0.022)	(0.025)	(4.093)	(5.020)	(0.014)	(0.004)	(0.004)	(0.747)	(0.915)
	Xlag=10	0.013	0.123***	-0.048	1.535	-5.195	-0.005	-0.011	0.007	3.502***	-1.115
		(0.085)	(0.029)	(0.033)	(4.446)	(5.463)	(0.015)	(0.005)	(0.006)	(0.789)	(0.969)
P=6	Xlag=1	0.028	0.112***	-0.100***	2.660	-7.756*	-0.023*	-0.011***	0.009**	3.093***	-0.405
		(0.071)	(0.022)	(0.022)	(3.788)	(4.339)	(0.013)	(0.004)	(0.004)	(0.709)	(0.812)
	Xlag=2	0.037	0.113***	-0.093***	2.277	-6.086	-0.020	-0.011***	0.011**	3.037***	-0.211
		(0.074)	(0.022)	(0.026)	(3.841)	(4.846)	(0.014)	(0.004)	(0.005)	(0.718)	(0.906)
	Xlag=5	0.059	0.122***	-0.092***	3.798	-6.894	-0.013	-0.009**	0.014***	2.985***	-0.231
		(0.077)	(0.024)	(0.027)	(4.039)	(5.014)	(0.0143)	(0.004)	(0.005)	(0.751)	(0.932)
	Xlag=10	0.025	0.129***	-0.056	1.287	-4.530	-0.010	-0.010**	0.009	3.525***	-1.019
		(0.085)	(0.029)	(0.035)	(4.399)	(5.559)	(0.015)	(0.005)	(0.006)	(0.797)	(1.007)
P=10	Xlag=1	-0.014	0.138***	-0.111***	3.121	-7.732*	-0.020	-0.016***	0.012***	3.006***	-0.582
		(0.078)	(0.026)	(0.026)	(3.898)	(4.530)	(0.014)	(0.005)	(0.005)	(0.693)	(0.805)
	Xlag=2	-0.000	0.137***	-0.097***	2.775	-6.060	-0.018	-0.016***	0.014***	2.985***	-0.557
		(0.082)	(0.026)	(0.032)	(3.936)	(4.961)	(0.015)	(0.005)	(0.006)	(0.701)	(0.884)
	Xlag=5	0.021	0.144***	-0.095***	3.359	-6.526	-0.008	-0.013***	0.016***	2.908***	-0.560
		(0.088)	(0.028)	(0.034)	(4.212)	(5.168)	(0.015)	(0.005)	(0.006)	(0.739)	(0.907)
	Xlag=10	0.032	0.114***	-0.071**	3.322	-0.408	-0.011	-0.009*	0.012**	2.887***	-1.409
		(0.086)	(0.029)	(0.034)	(4.333)	(5.452)	(0.015)	(0.005)	(0.006)	(0.763)	(0.959)
P=15	Xlag=1	-0.016	0.131***	-0.113***	2.316	-6.812	-0.024	-0.011**	0.011***	3.119***	-1.179
		(0.085)	(0.029)	(0.027)	(4.213)	(4.837)	(0.015)	(0.005)	(0.005)	(0.742)	(0.852)
	Xlag=2	-0.016	0.128***	-0.111***	1.852	-3.638	-0.019	-0.011**	0.016***	3.191***	-1.449
		(0.088)	(0.029)	(0.034)	(4.223)	(5.332)	(0.015)	(0.005)	(0.006)	(0.741)	(0.936)
	Xlag=5	0.030	0.146***	-0.117***	2.165	-4.239	-0.012	-0.009*	0.018	3.242***	-1.510
		(0.094)	(0.032)	(0.036)	(4.505)	(5.555)	(0.017)	(0.006)	(0.006)	(0.799)	(0.986)
	Xlag=10	0.057	0.124***	-0.099***	1.265	1.598	-0.016	-0.008	0.014**	2.934***	-1.721
		(0.095)	(0.034)	(0.038)	(4.978)	(6.268)	(0.017)	(0.006)	(0.007)	(0.903)	(1.137)

Table 7

VAR Empirical Results for China Shanghai B Share Market (Full Sample, 1992-2007)

Dependent Var		Market Turnover at Time t ($mturn_t$)				Market Return at Time t ($mret_t$)			
		Lagged Market Return		Lagged Market Turnover		Lagged Market Return		Lagged Market Turnover	
		t-1	t-2	t-1	t-2	t-1	t-2	t-1	t-2
P=4	Xlag=1	0.642**	-0.728**	-0.235***	-0.219***	0.137*	-0.030	0.009	0.009
		(0.044)	(0.016)	(0.001)	(0.002)	(0.087)	(0.688)	(0.634)	(0.636)
	Xlag=2	0.619**	-0.654**	-0.237***	-0.202***	0.132*	-0.001	0.005	0.014
		(0.053)	(0.042)	(0.003)	(0.007)	(0.102)	(0.986)	(0.817)	(0.456)
	Xlag=5	0.614**	-0.720**	-0.276***	-0.283***	0.128	-0.003	-0.001	0.003
		(0.042)	(0.016)	(0.001)	(0.001)	(0.117)	(0.969)	(0.965)	(0.898)
	Xlag=10	0.612**	-0.689**	-0.317***	-0.188**	0.102	-0.021	0.0162	0.002
		(0.040)	(0.018)	(0.001)	(0.021)	(0.168)	(0.767)	(0.403)	(0.911)
P=6	Xlag=1	0.847***	-0.753***	-0.262***	-0.242***	0.096	0.013	0.010	0.003
		(0.006)	(0.007)	(0.001)	(0.001)	(0.246)	(0.865)	(0.637)	(0.848)
	Xlag=2	0.867***	-0.649**	-0.304***	-0.227***	0.097	0.035	0.007	0.008
		(0.005)	(0.028)	(0.001)	(0.001)	(0.244)	(0.660)	(0.741)	(0.676)
	Xlag=5	0.806***	-0.667**	-0.350***	-0.283***	0.091	0.035	0.006	0.003
		(0.01)	(0.024)	(0.001)	(0.001)	(0.280)	(0.658)	(0.792)	(0.879)
	Xlag=10	0.719***	-0.597**	-0.345***	-0.201***	0.077	-0.010	0.019	0.001
		(0.019)	(0.041)	(0.001)	(0.001)	(0.319)	(0.895)	(0.382)	(0.950)
P=10	Xlag=1	0.698**	-0.862***	-0.264***	-0.159**	0.084	-0.038	0.027	0.017
		(0.021)	(0.004)	(0.001)	(0.032)	(0.261)	(0.600)	(0.14)	(0.340)
	Xlag=2	0.701**	-0.713**	-0.320***	-0.104	0.080	-0.021	0.027	0.021
		(0.02)	(0.020)	(0.001)	(0.184)	(0.283)	(0.778)	(0.182)	(0.275)
	Xlag=5	0.691**	-0.662**	-0.353***	-0.175**	0.0811	-0.011	0.020	0.011
		(0.023)	(0.030)	(0.001)	(0.040)	(0.287)	(0.889)	(0.248)	(0.596)
	Xlag=10	0.658**	-0.502	-0.335***	-0.177**	0.086	0.019	0.020	0.009
		(0.035)	(0.111)	(0.001)	(0.052)	(0.280)	(0.816)	(0.361)	(0.695)
P=15	Xlag=1	1.088***	0.057	-0.375***	-0.378***	0.121	0.036	0.015	0.013
		(0.004)	(0.874)	(0.001)	(0.001)	(0.204)	(0.696)	(0.497)	(0.590)
	Xlag=2	1.101***	0.094	-0.423***	-0.324***	0.100	0.059	0.019	0.017
		(0.004)	(0.799)	(0.001)	(0.001)	(0.306)	(0.531)	(0.426)	(0.501)
	Xlag=5	1.172***	0.262	-0.497***	-0.459***	0.113	0.079	0.010	0.001
		(0.002)	(0.485)	(0.001)	(0.001)	(0.257)	(0.425)	(0.677)	(0.967)
	Xlag=10	1.094***	0.368	-0.469***	-0.436***	0.112	0.079	0.008	0.008
		(0.005)	(0.338)	(0.001)	(0.001)	(0.279)	(0.448)	(0.759)	(0.799)

(Continue of Table 7. - Exogenous Variables)

Dependent Var		Market Turnover at Time t ($mturn_t$)					Market Return at Time t ($mret_t$)				
		Constant	Lagged misg		Lagged disp		Constant	Lagged misg		Lagged disp	
t-1		Term	t	t-1	t	t-1	Term	t	t-1	t	
P=4	Xlag=1	-0.088	0.211***	-0.212***	10.717***	2.914	-0.059*	0.022**	-0.006	2.609***	-1.058
		(0.496)	(0.001)	(0.001)	(0.001)	(0.368)	(0.071)	(0.053)	(0.575)	(0.001)	(0.197)
	Xlag=2	-0.092	0.215***	-0.203***	10.657	2.880	-0.054	0.023**	-0.001	2.563***	-1.073
		(0.511)	(0.001)	(0.001)	(0.001)	(0.376)	(0.132)	(0.040)	(0.911)	(0.002)	(0.192)
	Xlag=5	0.030	0.238***	-0.154***	10.844***	3.492	-0.022	0.028**	0.0036	2.411***	-1.060
		(0.839)	(0.001)	(0.001)	(0.001)	(0.261)	(0.576)	(0.017)	(0.767)	(0.004)	(0.208)
	Xlag=10	-0.086	0.249***	-0.146***	10.033	3.317	-0.036	0.016	-0.002	3.510***	-1.113
		(0.589)	(0.001)	(0.001)	(0.001)	(0.279)	(0.356)	(0.132)	(0.887)	(0.001)	(0.145)
P=6	Xlag=1	-0.252**	0.232***	-0.170***	10.746***	-0.067	-0.041	0.019*	-0.012	2.812***	-0.140
		(0.041)	(0.001)	(0.001)	(0.001)	(0.983)	(0.214)	(0.080)	(0.260)	(0.001)	(0.868)
	Xlag=2	-0.185	0.245***	-0.144***	10.404***	-0.299	-0.041	0.020*	-0.009	2.791	-0.145
		(0.159)	(0.001)	(0.002)	(0.001)	(0.924)	(0.242)	(0.080)	(0.450)	(0.001)	(0.864)
	Xlag=5	-0.031	0.266***	-0.108**	10.371***	-0.061	-0.019	0.022**	-0.005	2.626***	-0.311
		(0.827)	(0.001)	(0.002)	(0.001)	(0.985)	(0.622)	(0.055)	(0.691)	(0.001)	(0.718)
	Xlag=10	-0.154	0.268***	-0.115***	10.474***	0.209	-0.033	0.016	-0.004	3.599***	-0.881
		(0.328)	(0.001)	(0.014)	(0.001)	(0.948)	(0.416)	(0.130)	(0.720)	(0.001)	(0.286)
P=10	Xlag=1	-0.266**	0.243***	-0.178***	10.295***	0.664	-0.031	0.016*	-0.010	3.677***	-1.322*
		(0.024)	(0.001)	(0.001)	(0.001)	(0.833)	(0.300)	(0.101)	(0.296)	(0.001)	(0.090)
	Xlag=2	-0.180	0.262***	-0.136***	9.686***	0.440	-0.031	0.016	-0.008	3.662***	-1.322*
		(0.149)	(0.001)	(0.002)	(0.001)	(0.888)	(0.325)	(0.111)	(0.442)	(0.001)	(0.092)
	Xlag=5	-0.055	0.274***	-0.106**	9.363***	0.143	-0.007	0.017*	-0.004	3.466***	-1.284*
		(0.688)	(0.001)	(0.021)	(0.002)	(0.964)	(0.840)	(0.090)	(0.716)	(0.001)	(0.104)
	Xlag=10	-0.150	0.263***	-0.091**	11.282***	-1.691	-0.029	0.016	-0.002	3.758***	-1.519*
		(0.345)	(0.001)	(0.056)	(0.001)	(0.614)	(0.471)	(0.133)	(0.869)	(0.001)	(0.079)
P=15	Xlag=1	-0.312***	0.227***	-0.150***	13.363***	-2.909	-0.029	0.008	-0.003	4.389***	-1.524*
		(0.008)	(0.001)	(0.001)	(0.001)	(0.389)	(0.317)	(0.452)	(0.752)	(0.001)	(0.079)
	Xlag=2	-0.236**	0.241***	-0.113***	13.065***	-2.935	-0.033	0.007	-0.004	4.428***	-1.471*
		(0.059)	(0.001)	(0.016)	(0.001)	(0.384)	(0.309)	(0.489)	(0.753)	(0.001)	(0.091)
	Xlag=5	-0.073	0.243***	-0.069	12.995***	-2.689	-0.009	0.005	0.003	4.405***	0.012
		(0.581)	(0.001)	(0.145)	(0.001)	(0.420)	(0.799)	(0.624)	(0.798)	(0.001)	(0.338)
	Xlag=10	-0.042	0.239***	-0.064	13.873***	-3.467	-0.025	0.005	0.005	4.522***	-1.537*
		(0.781)	(0.001)	(0.200)	(0.001)	(0.324)	(0.539)	(0.662)	(0.706)	(0.001)	(0.107)

Table 8

VAR Empirical Results for China Shenzhen B Share Market (Full Sample, 1992-2007)

Dependent Var		Market Turnover at Time t ($mturn_t$)				Market Return at Time t ($mret_t$)			
		Lagged Market Return		Lagged Market Turnover		Lagged Market Return		Lagged Market Turnover	
		t-1	t-2	t-1	t-2	t-1	t-2	t-1	t-2
P=4	Xlag=1	0.595	-0.222	-0.301***	-0.304***	0.157**	0.033	0.001	-0.012
		(0.165)	(0.493)	(0.001)	(0.001)	(0.058)	(0.602)	(0.942)	(0.435)
	Xlag=2	0.624	-0.319	-0.301***	-0.314***	0.168	-0.002	0.001	-0.016
		(0.153)	(0.419)	(0.001)	(0.001)	(0.045)	(0.975)	(0.999)	(0.321)
	Xlag=5	0.609	-0.139	-0.316***	-0.345***	0.170**	-0.014	-0.001	-0.013
		(0.168)	(0.750)	(0.001)	(0.001)	(0.047)	(0.872)	(0.935)	(0.440)
	Xlag=10	0.578	-0.357	-0.316***	-0.345***	0.169**	-0.027	0.005	-0.015
		(0.21)	(0.436)	(0.001)	(0.001)	(0.059)	(0.758)	(0.786)	(0.408)
P=6	Xlag=1	0.546	0.071	-0.338***	-0.391***	0.161	0.030	-0.001	-0.013
		(0.199)	(0.839)	(0.001)	(0.001)	(0.057)	(0.662)	(0.951)	(0.428)
	Xlag=2	0.561	0.006	-0.337***	-0.397***	0.173**	-0.011	-0.002	-0.017
		(0.195)	(0.989)	(0.001)	(0.001)	(0.045)	(0.894)	(0.899)	(0.332)
	Xlag=5	0.626	-0.143	-0.341***	-0.381***	0.172**	-0.022	-0.003	-0.013
		(0.155)	(0.749)	(0.001)	(0.001)	(0.047)	(0.803)	(0.838)	(0.472)
	Xlag=10	0.517	-0.219	-0.348***	-0.388***	0.186**	-0.043	0.001	-0.014
		(0.259)	(0.636)	(0.001)	(0.001)	(0.037)	(0.635)	(0.980)	(0.452)
P=10	Xlag=1	0.759*	-0.056	-0.345***	-0.376***	0.181**	0.006	0.004	-0.007
		(0.082)	(0.875)	(0.001)	(0.001)	(0.039)	(0.927)	(0.834)	(0.714)
	Xlag=2	0.781*	-0.133	-0.343***	-0.381***	0.193**	-0.033	0.003	-0.009
		(0.080)	(0.763)	(0.001)	(0.001)	(0.031)	(0.704)	(0.872)	(0.589)
	Xlag=5	0.840*	-0.265	-0.344***	-0.374***	0.188**	-0.033	0.002	-0.009
		(0.067)	(0.563)	(0.001)	(0.001)	(0.039)	(0.717)	(0.931)	(0.649)
	Xlag=10	0.783*	-0.301	-0.362***	-0.360***	0.207**	-0.047	0.002	-0.008
		(0.101)	(0.526)	(0.001)	(0.001)	(0.029)	(0.616)	(0.899)	(0.658)
P=15	Xlag=1	0.829*	-0.128	-0.351***	-0.359***	0.198**	0.013	0.008	-0.007
		(0.089)	(0.745)	(0.001)	(0.001)	(0.034)	(0.858)	(0.640)	(0.699)
	Xlag=2	0.888*	-0.247	-0.348***	-0.370***	0.216**	-0.035	0.008	-0.011
		(0.078)	(0.620)	(0.001)	(0.001)	(0.024)	(0.711)	(0.646)	(0.577)
	Xlag=5	0.953*	-0.436	-0.344***	-0.368***	0.216**	-0.051	0.006	-0.009
		(0.066)	(0.405)	(0.001)	(0.001)	(0.026)	(0.602)	(0.730)	(0.630)
	Xlag=10	0.906*	-0.451	-0.364***	-0.364***	0.235**	-0.055	0.008	-0.009
		(0.093)	(0.412)	(0.001)	(0.001)	(0.020)	(0.589)	(0.649)	(0.646)

(Continue of Table 8. - Exogenous Variables)

Dependent Var		Market Turnover at Time t ($mturn_t$)					Market Return at Time t ($mret_t$)				
		Constant Term	Lagged misg t	Lagged misg t-1	Lagged disp t	Lagged disp t-1	Constant Term	Lagged misg t	Lagged misg t-1	Lagged disp t	Lagged disp t-1
P=4	Xlag=1	-0.217***	0.002	-0.008	19.868***	-0.437	-0.048***	0.001	-0.001	5.673***	-1.286
		(0.003)	(0.791)	(0.176)	(0.001)	(0.896)	(0.001)	(0.842)	(0.764)	(0.001)	(0.047)
	Xlag=2	-0.235***	0.002	-0.008	19.816***	-0.524	-0.053	0.001	-0.001	5.637***	-1.314
		(0.005)	(0.802)	(0.179)	(0.001)	(0.876)	(0.001)	(0.764)	(0.756)	(0.001)	(0.043)
	Xlag=5	-0.102	0.001	-0.008	19.341***	-0.478	-0.039*	0.001	-0.001	5.596***	-1.331**
		(0.349)	(0.963)	(0.218)	(0.001)	(0.888)	(0.065)	(0.879)	(0.815)	(0.001)	(0.044)
	Xlag=10	-0.073	0.001	-0.007	18.858***	0.016	-0.030	0.001	-0.001	5.559***	-1.418**
		(0.574)	(0.904)	(0.262)	(0.001)	(0.996)	(0.231)	(0.739)	(0.855)	(0.001)	(0.036)
P=6	Xlag=1	-0.205***	0.001	-0.007	18.979***	-0.183	-0.049***	0.001	-0.001	5.694***	-1.257**
		(0.004)	(0.862)	(0.229)	(0.001)	(0.956)	(0.001)	(0.769)	(0.744)	(0.001)	(0.058)
	Xlag=2	-0.219***	0.001	-0.008	18.976***	-0.219	-0.054***	0.001	-0.001	5.565***	-1.278**
		(0.009)	(0.902)	(0.231)	(0.001)	(0.948)	(0.001)	(0.676)	(0.719)	(0.001)	(0.055)
	Xlag=5	-0.143	-0.001	-0.008	18.649***	-0.234	-0.048**	0.001	-0.001	5.638***	-1.255**
		(0.207)	(0.999)	(0.208)	(0.001)	(0.945)	(0.032)	(0.871)	(0.844)	(0.001)	(0.059)
	Xlag=10	-0.097	0.001	-0.007	18.454***	0.277	-0.022	-0.001	-0.001	5.608***	-1.407**
		(0.476)	(0.933)	(0.269)	(0.001)	(0.936)	(0.403)	(0.983)	(0.964)	(0.001)	(0.037)
P=10	Xlag=1	-0.184***	0.003	-0.007	18.555***	-1.524	-0.044***	0.001	-0.001	5.599***	-1.490**
		(0.012)	(0.677)	(0.246)	(0.001)	(0.652)	(0.003)	(0.571)	(0.564)	(0.001)	(0.029)
	Xlag=2	-0.205***	0.002	-0.007	18.566***	-1.556	-0.049***	0.001	-0.001	5.558***	-1.519**
		(0.015)	(0.769)	(0.241)	(0.001)	(0.647)	(0.004)	(0.509)	(0.540)	(0.001)	(0.027)
	Xlag=5	-0.148	0.001	-0.008	18.197***	-1.573	-0.040*	0.001	-0.001	5.542***	-1.498**
		(0.197)	(0.826)	(0.247)	(0.001)	(0.650)	(0.077)	(0.677)	(0.772)	(0.001)	(0.030)
	Xlag=10	-0.205	0.002	-0.008	18.927***	-1.418	-0.016	0.001	-0.001	5.581***	-1.618**
		(0.166)	(0.721)	(0.276)	(0.001)	(0.686)	(0.589)	(0.867)	(0.976)	(0.001)	(0.021)
P=15	Xlag=1	-0.178**	0.004	-0.008	18.344***	-2.098	-0.036***	0.001	-0.002	5.461***	-1.674**
		(0.024)	(0.515)	(0.217)	(0.001)	(0.565)	(0.017)	(0.719)	(0.215)	(0.001)	(0.016)
	Xlag=2	-0.205**	0.004	-0.009	18.290***	-2.281	-0.043***	0.001	-0.002	5.427***	-1.73***
		(0.025)	(0.592)	(0.207)	(0.001)	(0.535)	(0.013)	(0.695)	(0.193)	(0.001)	(0.014)
	Xlag=5	-0.132	0.004	-0.009	17.763***	-2.331	-0.032	0.001	-0.001	5.376***	-1.75***
		(0.290)	(0.599)	(0.185)	(0.001)	(0.533)	(0.171)	(0.819)	(0.384)	(0.001)	(0.013)
	Xlag=10	-0.203	0.004	-0.009	18.639***	-2.022	-0.010	-0.001	-0.001	5.409***	-1.85***
		(0.195)	(0.619)	(0.211)	(0.001)	(0.593)	(0.725)	(0.985)	(0.439)	(0.001)	(0.009)

2.5 Conclusions and Future Research

This study seeks to examine empirically the lead-lag patterns between the trading volume and stock return in China's A share and B share markets. Through the Vector Autoregressive procedure, we investigate the dynamic relationship between the market trading volume and market stock return in China A share and B share markets. Particularly, we show that the market trading volume in the A share market contains important information to predict the market stock return, in that the lagged market trading volume is strongly negatively related to subsequent market return. Such lead-lag patterns are consistent and robust when we investigate with different subsamples, as well as when using different VAR models with lagged endogenous and lagged exogenous variables. In general, Lee and Swaminathan's (2000) Momentum Life Cycle theory could best explain such strong negative relations between lagged trading volume and subsequent return. While we can find no evidence that such a pattern also exists in the two segmented B share markets, we show that another kind of lead-lag pattern does exist in both B share markets. It is shown that lagged market returns are significantly positively related with the subsequent market trading volume in both B share markets and such patterns could best be explained by Statman, Thorley, and Vorkink's (2006) Overconfidence theory. Our study shows that China's A share and B share markets behave differently in terms of the lead-lag patterns between the market trading volume and market return and, therefore, exhibit differences in market efficiency. If such strong lead-lag relations do exist in the China A share market, it is possible to benefit through appropriate trading strategy by taking advantage of such lead-lag patterns in those markets.

Further studies should be conducted to investigate whether an appropriate trading strategy could be used to taking advantage of the statistically significant, as well as economically significant, profits in the China A share market. On the other hand, as we have shown that overconfidence bias holds for the China B share markets on the market level, further study should be conducted to see whether such investor attitude bias also holds for stocks on individual level in these markets. In other words, further study could be conducted particularly on testing Shefrin and Statman's (1985) disposition effect on individual stock in China's two B share markets.

Chapter 3

Behavioral Explanations of Trading Volume and Stock Return Patterns: An Investigation on Trading Strategies

3.1 Introduction

Through empirical study, we have found very interesting lead-lag relations between trading volume and stock return patterns in Chinese A share and B share markets respectively. Particularly, we find significant negative relations between the lagged trading volume and subsequent stock returns for Chinese A shares by using Vector Autoregressive methods. If such relation holds, then it would mean that trading volume contains important information to predict the China A share market return. Even though we have shown that such statistically significant relations in the A share market could best be explained by Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis compared with other theories, no studies have ever been done to investigate the appropriate trading strategy that could take advantage of such relations and make economic profits from them.

Trading strategies investigation based on the relation between trading volume and the subsequent stock return pattern are well documented for many capital markets. Conrad, Hameed, and Niden (1994) tested Compbell, Grossman, and Wang's (1993) model on US weekly returns to determine whether the winner/loser contrarian strategy is a profitable one. They find the strategy to be profitable only for high-transaction securities, for which price reversals are experienced. For low-transaction securities, returns were positively autocorrelated, suggesting the dominance of a momentum strategy (price continuation). Hameed and Ting (2000) find that weekly contrarian profits on actively and frequently traded stocks were significantly higher than those for low trading activity stocks. They also find that such differences in behavior of price reversals between high volume and low volume stocks were not entirely subsumed by a size effect. The authors attribute their findings to the institutional arrangements in Malaysia. Through investigation of seven Pacific Basin stock markets - Japan, Korea, Taiwan, Hong Kong, Malaysia, Thailand and Singapore - during the period 1990 to 2000, Ding, McInish, and Wongchoti (2007) examine whether behavioral postulations offer any implicit explanation of the countries varying relations between trading volume and price pattern among short-horizon winners/losers. Their findings show that Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis best explains the relations, in that high (low) volume winners (losers) are more likely to experience price reversals, thus being suitable for contrarian strategy, whereas high (low) volume losers (winners) are more likely to experience price momentum, thus being suitable for momentum strategy. Their observation is especially pronounced in Hong Kong. Other models, such as those based on an information diffusion process and investors' overconfidence in glamour stocks, offer limited explanations for the relations.

Besides directly investigating the lead-lag patterns, another way to understand the economics of the relation between trading volume and stock return patterns is to investigate the profitability of appropriate trading strategies with an existing behavioral model or explanation. Compared with Statman, Thorley, and Vorkink's (2006) Overconfidence theory; Shefrin and Statman's (1985) disposition effect; Pietro Veronesi's (2000) market tendency to overreact to bad news and underreact to good news effect; and Thaler and Johnson's (1990) Try-to-Break-Even hypothesis, in our previous study, Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis best explains the significant negative relations between the lagged trading volume and subsequent stock returns in China's A share market. In the present study, we further investigate such patterns, first, by examining the profitability of trading strategies based on Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis to show that such a relation is not only statistically significant but also economically significant. Then, we compare the profitability of trading strategies to the implicit prediction of MLC and the other two behavioral explanations about the relation between trading volume and stock return. To our best knowledge, there is no existing study that links such profitability of trading strategies to behavioral explanations for the China stock market, especially in the empirical framework of Lee and Swaminathan (2000); Daniel, Hirshleifer, and Subrahmanyam (1998); and Hong and Stein (1999).

Based on monthly, quarterly, half yearly, and yearly returns of stocks in the China A share market during 1991 to 2007, we find monotonic relations between trading volume and stock return patterns from the aspect of profitability of trading strategies, which vary both across different horizons and among winners/losers. These differences suggest that the relation between trading volume and stock return pattern need not be the same across different horizons, thus allowing us to conduct different trading strategies under different horizons. Confirming our previous findings, Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis best describes the relation between trading volume and stock return patterns in our sample. In particular, late stage momentum performers, including high (low) volume winners (losers), experience price reversal and, thus, are profitable in contrarian strategy, whereas early stage momentum performers, including low (high) volume winners (losers), experience price momentum and, thus, are profitable in momentum strategy. Even though our results are not perfectly consistent across all horizons and winners/losers studied, the behavioral postulation of Momentum Life Cycle hypothesis offers the best explanatory power concerning the dynamic relation between trading volume and stock return patterns in the China A share market. Our findings are stronger in the longer horizon cases. At the same time, the implicit predictions based on Hong and Stein's (1999) information diffusion effect and Daniel, Hirshleifer, and Subrahmanyam's (1998) overconfidence in glamour stocks theory are limited.

The contribution of this article to the literature lies largely in four aspects. First, we confirm the findings of the former empirical studies on the lead-lag relations between trading volume and stock return patterns from the aspect of profitability of appropriate trading strategies, demonstrating that Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis best explains not only the lead-lag patterns between trading volume and stock return but also the profitability of appropriate trading strategies in China A share market. Second, this study shows that such lead-lag patterns are not only statistically significant but also economically significant. The trading volume in China's A share market contains important information to predict its market return. Third, through the investigation of the relations in different horizons, this study provides valuable information on profitable trading strategies under different horizons. Fourth, combined with the previous work, this study contributes as a complementary component of the framework of a systematically behavioral finance study on China's stock market. We investigate both streams of behavioral finance literature and find the best behavioral theory that explains not only from the aspect of lead-lag patterns between trading volume and return but also from the aspect of profitability of appropriate trading strategies.

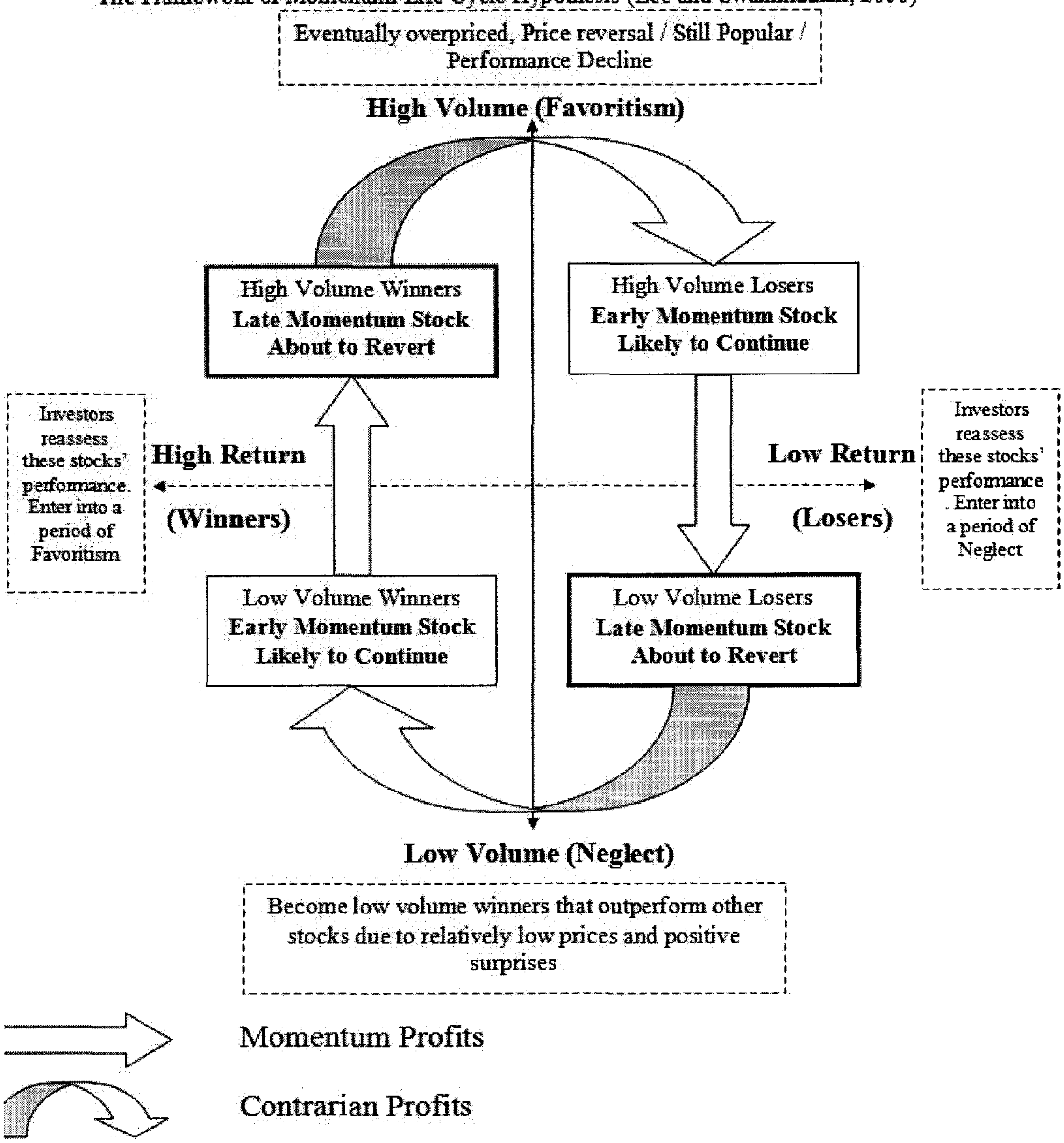
The rest of this chapter is organized as follows. In section 3.2, we provide a review of the implications of several behavioral theories in terms of our investigation of the aspect of profitability and appropriateness of trading strategies. In section 3.3, we describe the data used and research methodology employed. Section 3.4 presents our empirical results and a discussion of the implications of our findings. Finally, in section 3.5, we provide our summary and concluding remarks.

3.2 Implicit Behavioral Explanations

In the previous literature, researchers have developed behavioral models or proposed explanations for the observations of short-to-intermediate-horizon return momentum profits and long-run return contrarian profits. We investigate whether some of these models have the potential to explain the relation between trading volume and price momentum/reversals. Lee and Swaminathan (2000) provide a causal theory of the Momentum Life Cycle (MLC) hypothesis to explain the dynamic relationship between trading volume and stock return patterns of winner/loser stocks in the US market during

1965 to 1995. Figure 5 shows the framework of their hypothesis from the aspect of momentum and contrarian profits for winner/loser stocks with different levels of volumes.

Figure 5
The Framework of Momentum Life Cycle Hypothesis (Lee and Swaminathan, 2000)



In this framework, stocks go through a life cycle of investor favoritism (high trading volume and higher number of analysts following) and neglect (low trading volume and lower number of analysts following). During the period of favoritism, high trading volume winners are glamour stocks (growth stock with low B/M ratio) that are eventually overvalued. After overvaluing, their returns reverse, and they enter into the next phase, becoming high volume losers. At this moment, they are still popular, but their performance declines. In the next period, as investors reassess these stocks' performance over time, they enter into a period of neglect. These stocks become low trading volume losers. During this period, they turn into value stocks (high B/M ratio). In the next phase, they become low trading volume winners that outperform other stocks due to their relatively lower prices and positive surprises. However, at the moment, they are still not very popular as they are still in a period of neglect (low trading volume). When they become more popular, their trading volume increases. They then turn back into high trading volume winners as their B/M ratio decreases over time. This cycle then repeats itself. Effectively, the MLC labels high (low) trading volume winners (losers) as late stage momentum stocks that are about to reverse, thus becoming profitable in contrarian strategy. On the other hand, low (high) trading volume winners (losers) are categorized as early stage momentum stocks whose momentum is likely to continue, at least in the short run, thus becoming profitable in momentum strategy.

Daniel, Hirshleifer, and Subrahmanyam (1998) have developed a model based on overconfidence bias. In their analysis, overconfidence, together with attribution bias, generates shorter (longer) term price momentum (reversal). They argue that overconfidence is more likely to happen in stocks that are more difficult to evaluate. One important proxy for such valuation uncertainty is the growth (or glamour) characteristic. Essentially, prices of these stocks are more likely to overreact to news concerning a company's fundamentals and tend to deviate from their intrinsic value. But, ultimately, the prices would revert back to their fundamental values. Some previous studies have documented the relation between trading volume and growth characteristics. Lee and Swaminathan (2000) show that high trading volume stocks are characterized as growth stocks in their US sample. As a result, if high trading volume stocks proxy for growth stocks, as in Lee and Swaminathan's (2000) study, they should produce higher short-horizon momentum profits as well as higher long-horizon contrarian profits than low trading volume stocks.

Another implicit behavioral explanation of the relation between trading volume and stock return patterns from the aspect of profitability of trading strategies is based on the information diffusion process. Hong and Stein (1999) provide a model based on the interactions between two types of biased investors: news-watchers and momentum traders. News-watchers continually update their news and information about stock but are conservative when it comes to trading. Thus, they underreact to new information, and their stock prices do not reflect their intrinsic values. Instead, momentum traders follow the trend or initial movement and trade accordingly, adding extra momentum to stock prices and enhancing momentum patterns in the short run. However, momentum traders tend to overtrade and move prices away from their intrinsic values, leading to overreaction and price reversals in the long run. One of the main implications of the

Hong and Stein model is the effect of the rate of information flow. The slower the rate of information diffusion across investors, the more pronounced the short-term momentum and long-term contrarian profits. Another implication is that such firms experience a slower adjustment rate to new information. Hong and Stein show that short horizon price momentum holds not only for private information but also with public information. In their study, firms with a lower information diffusion rate include smaller firms and less-analyst-followed firms. Hong, Lim, and Stein (2000) test this suggested relationship based on a stock's size and residual analyst coverage, confirming their predictions. Chordia and Swaminathan (2000) find a lead-lag effect across firms with different levels of trading volume, even after controlling for a possible size effect. For short-term horizons of both weekly and daily date, the returns of their high trading volume stocks led the returns of the low trading volume stocks. They also show that low volume stocks have a lower rate of adjustment to public information, such as market returns. Combining these results with the implications of the Hong and Stein (1999) model, it can be predicted that, in the short horizon, momentum profits are higher for low volume stocks. In the long horizon, contrarian profits should also be higher for low trading volume stocks. It should be noted, however, that these expectations are contrary to the predictions of Daniel, Hirshleifer, and Subrahmanyam's (1998) overconfidence bias theory if high volume stocks actually proxy the growth stocks.

Table 9 summarizes the predictions of the three behavioral explanations for the relation between trading volume and stock returns from the aspect of profitability of appropriate trading strategies.

Table 9

Summary of the Predications of Three Behavior Explanations on the Relation between Trading Volume and Profitability of Contrarian or Momentum Profits from the Aspect of Profitability of Appropriate Trading Strategies

Behavioral Explanations	**Basis**	**Implicit Predictions**
Lee and Swaminathan (2000)	Momentum Life Cycle (MLC)	Winners: High Volume = Contrarian Profits Low Volume = Momentum Profits Losers: High Volume = Momentum Profits Low Volume = Contrarian Profits
Daniel, Hirshleifer and Subrahmanyam (1998)	Overconfidence Bias in Glamour Stocks	Short-horizon Momentum Profits will be Higher for Stocks in the Trading Volume Group That have Stronger 'Growth / Glamour' Characteristics (No Separation of Winners from Losers) If High Volume Stocks Proxy for Growth Stocks Then, High Volume Stocks Have: Higher Short-Term Momentum Profits Higher Long-Term Contrarian Profits
Hong and Stein (1999)	Under/Overreaction is Stronger in Stocks that Adjust More Slowly to News and Markets	If High Volume Stocks Adjust to News and Information Faster than Low Volume Stocks, Then Momentum Profits will be Higher in Low Volume Stocks. (No Separation of Winners from Losers) Low Volume Stocks Have: Higher Short-Term Momentum Profits Higher Long-Term Contrarian Profits

3.3 Data and Methodology

3.3.1 Data Description

This study uses daily return from December 12, 1990 to March, 2007 for the Shanghai A Index; From February 21, 1992 to March, 2007 for the Shanghai B Index; From September 30, 1992 to March, 2007 for the Shenzhen A Index; and from October 6, 1992 to March 2007 for Shenzhen B Index. We extract the returns on individual stocks, market returns, risk free rate, number of shares outstanding, number of shares traded, market capitalization and share prices. Same to the previous study on lead-lag patterns on China stock market, all market data (stock price, return, trading volume, turnover, outstanding shares) are obtained from the China Stock Market Database from the 'Taiwan Economic Data Bank', TEJ Database of Taiwan Economic Journal Co. Ltd. The accounting data (book value of equity) is obtained from the Chinese Stock market and Accounting Research Database (CSMAR). Followed on Wang (2004), we use China's monthly yield of 3-month household deposit interest rate as the proxy for the risk free rate of China. The data of monthly yield of 3-month household deposit interest rate is obtained from The People's Bank of China (the central bank of China, http://www.pbc.gov.cn/).

Table10 summarize the statistical characteristics of the China A share and B share markets. The number of stocks in our sample ranges from 7 in 1991 to 1247 in March 2007. In terms of the number of listings and market capitalization, the Shanghai Stock Exchange is larger than the Shenzhen Stock Exchange. The highest average return on the overall market was 5.9% (excluding the 3 months average return in 2007).

Table 10

Summary Statistics for China A Share Markets Characteristics

Figures reported are the values over the period from 1991 to 2007. The number of stocks refers to the total number of firms that have data available for our analysis. The returns for individual stock exchange are the monthly average returns on the Shanghai Stock Exchange (SHSE) or Shenzhen Stock Exchange (SZSE) composite index, in percent. Market Capitalization is the Monthly average Market Capital on the stock in each stock exchange. BM in year t is the ratio of book value to market value of equity measured at the end of December of year t-1. The returns (BM ratios) for the whole market are the equal-weighted average returns on the two market indexes (Average BM ratios of all stocks

	No. of Stocks			Return			Market Capitalization			BM		
	SHSE	SZSE	Whole	SHSE	SZSE	Whole	SHSE	SZSE	Whole	SHSE	SZSE	Whole
1991	7	0	7	0.057	-	0.057	20630.45	-	20630.45	0.006	-	0.006
1992	7	4	11	0.046	0.076	0.057	41495.03	2394.34	27276.59	0.051	0.449	0.196
1993	29	22	51	0.023	-0.014	0.007	2376.87	2056.80	2238.80	0.635	0.596	0.618
1994	101	75	176	-0.009	-0.061	-0.031	1656.53	1071.49	1407.23	1.387	1.684	1.514
1995	168	115	283	-0.006	-0.024	-0.013	1465.08	761.64	1179.23	1.707	2.427	2.000
1996	183	124	307	0.029	0.103	0.059	1824.20	1289.50	1608.23	1.659	2.142	1.854
1997	286	224	510	0.008	-0.003	0.003	2390.06	2078.32	2253.14	1.130	1.003	1.074
1998	370	343	713	0.006	-0.003	0.001	2619.14	2286.69	2459.21	1.053	1.033	1.043
1999	423	395	818	0.022	0.019	0.021	2968.38	2449.02	2717.59	1.053	1.129	1.090
2000	468	447	915	0.031	0.033	0.032	4096.99	3676.72	3891.68	0.834	0.847	0.840
2001	554	496	1050	-0.024	-0.028	-0.026	4341.39	3721.56	4048.59	0.782	0.835	0.807
2002	630	495	1125	-0.010	-0.008	-0.009	3951.39	2903.71	3490.41	1.035	1.165	1.092
2003	699	489	1188	-0.016	-0.016	-0.016	3598.50	2610.92	3192.00	1.286	1.439	1.349
2004	761	486	1247	-0.023	-0.021	-0.022	3557.12	2459.09	3129.18	1.598	1.825	1.687
2005	818	481	1299	-0.007	-0.008	-0.008	2626.03	1819.57	2327.41	2.519	2.991	2.694
2006	813	474	1287	0.033	0.035	0.034	3372.56	2280.56	2970.38	2.265	2.668	2.414
2007	799	448	1247	0.216	0.234	0.223	5866.70	4136.04	5244.94	1.499	1.703	1.572

Table 11

Summary Statistics for China B Share Markets Characteristics

Figures reported are the values over the period from 1992 to 2007. The number of stocks refers to the total number of firms that have data available for our analysis. The returns for individual stock exchange are the monthly average returns on the Shanghai Stock Exchange (SHSE) or Shenzhen Stock Exchange (SZSE) composite index, in percent. Market Capitalization is the Monthly average Market Capital on the stock in each stock exchange. The returns for the whole market are the equal-weighted average returns on the two market indexes.

	No. of Stocks			**Return**			**Market Capitalization**		
	SHSE	SZSE	Whole	SHSE	SZSE	Whole	SHSE	SZSE	Whole
1992	9	9	18	-0.162	-0.010	-0.086	1151.924	527.954	839.939
1993	21	19	40	0.067	0.036	0.052	65.443	307.778	180.553
1994	34	24	58	-0.023	-0.040	-0.030	50.242	298.761	153.078
1995	36	34	70	-0.023	-0.027	-0.025	39.513	220.125	127.239
1996	42	43	85	0.028	0.126	0.078	37.241	308.977	174.707
1997	50	51	101	-0.033	-0.040	-0.036	60.622	483.914	274.364
1998	52	54	106	-0.036	-0.051	-0.044	34.988	269.935	154.678
1999	54	54	108	0.045	0.058	0.051	31.349	255.845	143.597
2000	55	59	114	0.091	0.042	0.066	49.243	341.732	200.619
2001	55	59	114	0.062	0.096	0.080	139.484	852.154	508.322
2002	54	58	112	-0.024	-0.022	-0.023	127.243	705.771	426.838
2003	54	57	111	-0.019	0.005	-0.007	103.014	723.434	421.608
2004	54	57	111	-0.023	-0.023	-0.023	90.361	832.608	471.515
2005	54	56	110	-0.013	-0.016	-0.014	65.539	759.175	418.663
2006	54	55	109	0.061	0.047	0.054	96.244	1001.981	553.267
2007	54	54	108	0.152	0.147	0.150	169.548	1670.684	920.116

3.3.2 Methodology

To facilitate the comparison of return patterns among stocks with different levels of trading volume across different horizons in China A share market, we classify the stocks into three groups. Following Ding, McInish, and Wongchoti's (2007) method, for each year *t*, the sample stocks in each country are divided into three volume categories of high, medium and low according to their daily average turnover during the previous year *t-1*. In order to minimize the potential effects of trading volume categorization method on the final results, we use three schemes to categorize the stocks into high, medium and low level of trading stocks. First, for the equally divided way, the top, medium and bottom one-third are classified as high, medium and low trading volume group, respectively. Second way, we classified the extreme top and bottom of 20% and remaining medium 60% as high, low and medium trading volume group, respectively. Third way, we categorize by the extreme top and bottom of 10% and remaining 80% for high, low and medium trading volume respectively. We would compare the results getting from different trading volume categorization methods and see whether the results are robust on the volume classification method. Following other studies in the area, such as Ding, McInish, and Wongchoti (2007); Hameed and Ting (2000); and Lee and Swaminathan (2000), we use turnover ratio, obtained by taking the number of shares traded divided by the number of shares outstanding, as the proxy for trading volume and believe that the turnover ratio helps extricate the firm size effect embodied in pure trading volume that is expressed in dollars or the number of shares traded. Trading volume categorization in several other studies is designed to capture the arrival of news and information. For example, in an attempt to test the Campbell, Grossman, and Wang (1993) model, Conrad, Hameed, and Niden (1994) categorized stocks into high and low trading volume groups by comparing the formation-period trading volume to its historical average. Under a monthly formation period scheme, a stock presented as belonging to a high (low) trading volume group is one that is heavily (thinly) traded during the month of the arrival of news and information.

3.3.2.1 Lead-Lag Patterns Reflected in Profitability of Trading Strategy

Following Ding, McInish, and Wongchoti's (2007), we use trading profits on portfolios formed with a weighted relative strength scheme (WRSS) portfolio method (Lo and MacKinlay, 1990) as the indicator of a stock return pattern. Under the WRSS method, investors follows the investment strategy of buying (selling) stocks in proportion to their return performance over the formation period. Stocks with positive excess returns during the ranking period will be bought with a higher weight placed on the top performers. On the other hand, stocks with negative excess returns during the same period will be sold, at the same time, with a higher weight placed on the worst performers. Different from the previous study, we use two methods to categorize the winners and losers stocks. Stocks that outperform (underperform) the market are classified as winners (losers). Normally there are mainly two methods to calculate the market return: the value-weighted market return and equal-weighted market return. In order to minimize the potential effects of market return calculation on the investigation results, we use both value-weighted and equal-weighted market return to categorize the winner and loser stocks. As a result, during each formation period t, the weight assigned to an individual stock in a WRSS portfolio is

$$w_{i,t} = \frac{1}{N}(r_{i,t-1} - \overline{r_{t-1}}) \tag{3}$$

where $r_{i,t-1}$ is the return of stock i during the ranking/formation period *t-1*, $\overline{r_{t-1}}$ is the market return in period *t-1* either value-weighted or equal-weighted market return, and N is the number of stocks in the whole sample. The momentum profit, denoted as, can be measured as

$$\pi_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t}(r_{i,t-1} - \overline{r_{t-1}}) \tag{4}$$

According to equation (4), a positive (negative) result represents momentum (contrarian) profits, and hence, price momentum (reversals). The higher its magnitude, the stronger is the price pattern. For better presentation, we multiply the profits by a factor of 1000. Then we evaluate the performance of the WRSS momentum trading strategy over each of the eight subsequent periods (in our study, we investigate monthly, quarterly, half yearly and yearly horizons). The momentum (contrarian) profit during observation period k (k=8) is

$$\pi_{j,t}(k) = \frac{1}{N}\sum_{i=1}^{N_j} W_{i,t} r_{i,t+k-1} \tag{5}$$

where j=L, W, and A (loser, winner and all portfolio, respectively), represents the weight of individual stocks in the WRSS portfolio, while denotes the number of stocks included in a WRSS portfolio during the formation period t. Importantly, the price pattern found in the contemporaneous observation period is prone to misinterpretation since it might reflect thin trading (Ding, McInish and Wongchoti, 2007). Lo and MacKinlay (1999) point out that non-synchronous trading problems can become serious, especially for studies that evaluate a short-horizon price pattern. To be conservative, we present and investigate results eight periods beyond the formation period.

Different from the previous study in the similar research, we are using a relative measure of profits instead of absolute ones in order to minimize the effects of trading volume and winner/loser categorization on the final results. Particularly, for each horizon investigation, we have three different methods of trading volume categorization and two different methods of winner/loser categorization (value- and equal-weighted), thus totally six categories of final results. We average the portfolio results from the six categories and subtract the corresponding averaged value from the absolute profits of winner and losers under each level of trading volumes, high, medium and low. The relative profits getting from such way are robust to the potential effects of trading volume and winner/loser categorization methods.

3.3.2.2 Glamour Characteristics and HML Loadings

In order to investigate the Danuel, Hirshleifer, and Subrahmanyam's (1998) investor overconfidence bias hypothesis, it is important to test whether high or low trading volume stocks exhibit stronger 'growth' or 'glamour' characteristics. If high trading volume stocks can proxy growth stocks or valuation uncertainty, then short-term momentum profits and long-term contrarian profits would be higher for high trading volume stocks. We value the high volume and low volume stocks' characteristics by implementing the Fama and French (1993) three factor model on momentum/contrarian profits of high and low trading volume stocks respectively. The positive value loading on HML represents value characteristics, whereas the negative value loading on HML represents the opposite, growth characteristics. A portfolio with positive (negative) factor lading represents one of high (low) B/M ratio and is a value (glamour) stock.

Following Fama and French (1993) three factor model, we regress excess return of a portfolio of interest during each corresponding period on market premium ($r_{m,t} - r_{f,t}$), size premium (SMB), and value premium (HML) as follows:

$$r_{P,t} - r_{f,t} = \alpha_{i,t} + \beta_i (r_{m,t} - r_{f,t}) + \gamma_i SMB + \upsilon_i HML + \varepsilon_{i,t} \quad (6)$$

Where $r_{P,t}$ = monthly return of portfolio P; $r_{m,t}$ = monthly return of the market; $r_{f,t}$ = monthly risk free rate, assuming to be stable during each year. Following Wang (2004), we use monthly China three-month household deposit rate as proxy for the risk free rate of China. SMB= the monthly average return on portfolios of small firms minus the monthly average return on portfolio of large stocks. Here, we calculate SMB as 1/3(Small Value + Small Neutral + Small Growth) – 1/3(Big Value + Big Neutral + Big Growth). And HML = the monthly average return on portfolios of value firms minus the monthly average return of growth/glamour stocks. Here, we calculate HML as ½ (Small Value + Big Value) – ½ (Small Growth + Big Growth).

Following Ding, McInish, and Wongchoti, (2007), within each horizon, from July through June (i.e. July year *t* to June year *t+1*), size and value categorization is undertaken as follows. A firm with market value above (below) the mean of the whole sample during June year *t* is categorized as big (small) stocks. At the same time, value categorization is based on book-to-market ratio of an individual firm in December of the previous year (year *t-1*). The top, medium and bottom of one-third represent value, neutral and growth stocks, respectively. In this study, our interest lies in the value/growth characteristics of the winner and loser portfolios with different levels of trading volumes.

3.3.2.3 Speed of Public Information Diffusion

In order to investigate the Hong and Stein's (1999) information diffusion model, it is important to test whether high or low trading volume stocks have a slower speed of adjustment to the public information in China A share market. Following Ding, McInish, and Wongchoti, (2007) and Chordia and Swaminathan (2000), we use Dimson beta regression to test whether high volume stocks adjust to public information faster than low volume stocks. We use the Dimson beta regression to analyze the information diffusion speed relative to a single common benchmark, the market returns. The idea is based on the evaluation of a zero net investment portfolio O that is long in high trading volume portfolio and short in low trading volume portfolio. The monthly returns on portfolio O are regressed on three period leads and lags (k=3) of the market return as follows:

$$r_{O,t} = \alpha_O + \sum_{-K}^{K} \beta_{O,K} r_{M,t-K} + \varepsilon_{O,t} \tag{7}$$

To test whether high trading volume portfolio adjust to market return faster than low trading volume portfolio, one can simply test whether $\beta_{O,0}$>0 and $\sum_{k=-1}^{K} \beta_{O,k} < 0$, where $\beta_{O,0}$ is the contemporaneous beta of portfolio O, and $\sum_{k=-1}^{K} \beta_{O,k}$ is the sum of the lagged beta of portfolio O. As indicated by Chordia and Swaminathan (2000), the speed of adjustment to public information can also depend on the firm size. Thus following the design of Ding, McInish, and Wongchoti, (2007), we investigate the information diffusion speed under different firm size categories and see whether the difference in the speed of adjustment among stocks with different trading volume persists within all group sizes. All stocks in the sample are categorized into big and small sizes based on their market value during the previous year of their formation period. Big sized stocks refer to those with a market value higher than the mean value and small sized stocks refer to those with market value smaller than the mean value. Particularly, we run the Dimson beta regressions in three categories, in order to test whether high volume stocks across all group sizes adjust faster to market information than low trading volume stocks. The three Dimson beta regressions are as follow:

(1). All sizes category: A zero net investment of being long in high-volume stocks and short in low-volume stocks;

(2). Big size category: A zero net investment of being long in high-volume big-sized stocks and short in low-volume big-sized stocks;

(3). Small Size category: A zero net investment of being long in high-volume small sized stocks and short in low-volume small sized stocks.

3.4 Empirical Results

3.4.1 Profitability of Momentum/Contrarian Strategies under Different Horizons

Table 11 to 16 illustrates the relation between trading volume and relative profitability of WRSS contrarian / momentum strategies based on different horizons (monthly, quarterly, half yearly and yearly) of formation period in China A share market. Particularly, table 11, 12, 13 illustrate the results when winners/losers are divided based on value-weighted market return and when levels of trading volumes of high/low/medium are categorized by equally one-third, extreme 20% for high and low, and extreme 10% for high and low, respectively. Similarly, table 14, 15, 16 illustrate the results when winners/losers are divided based on equal-weighted market return and when levels of trading volumes of high/low/medium are categorized by equally one-third, extreme 20% for high and low, and extreme 10% for high and low, respectively. Through these results based on different methods of categorization on winners/losers and levels of trading volumes, we were able to see whether the lead-lag patterns between trading volume and stock returns are robust to the choice of these categorization methods. To give a better and visual illustration, we plot graphs for each cumulative momentum/contrarian profits over the subsequent eight observation periods for winner and loser and for different horizons. Figure 6 and 7 illustrate the monthly results based value-weighted and equal-weighted winner/loser categorization method, respectively. Within each figure, Panel A to Panel C illustrate the results based on different trading volume categorization methods. Similarly, Figure 8 and 9, Figure 10 and 11, Figure 12 and 13 illustrate the paired results for quarterly, half yearly and yearly, respectively.

In general, we find that the horizon has more obvious effects on the relations between trading volume and stock returns than other factors like trading volume and winner/loser categorization methods. Particularly, the relation between trading volume and profitability of WRSS contrarian/momentum profit become more obvious when horizons are longer. We find monotonic relation between trading volume and profitability of contrarian/momentum profit only for losers in equal-weighted case, when horizon is monthly, whereas more obvious monotonic relations could be found for longer horizons. Consistent with former empirical study (Ding, McInish, and Wongchoti, 2007), we find that losers and winners seem to exhibit a different subsequent price pattern, implying that there is an asymmetric reaction to good and bad news. Such situation holds for different horizons.

Taken value-weighted quarterly winners as example, as shown in panel A of Figure 8, we can see obviously that the low volume winner continue to be winner and high volume winner reverse to become loser in the post formation period 4 to 9. In panel B, when we use another method of trading volume categorization, the same pattern between trading volume and momentum/contrarian profit still consist. In panel C, the same pattern consists for all the post formation period of eight quarters. According to our assessment, Lee and Swaminathan's (2000) Momentum Life Cycle explanation best describes such relation in our quarterly sample. In particular, late stage momentum performers, including high volume winners experience price reversals thus profitable in contrarian strategy, whereas early stage momentum performers, including low volume winners experience price momentum thus profitable in momentum strategy. On the other hand, taken equal-weighted monthly losers as example, as shown in panel C of Figure 7, we can see clearly that the low volume losers reverse to become winners and high volume losers continue to be losers in the whole post formation period of eight months. The similar pattern are also found in panel A and panel B of Figure 7, when we considering different trading volume categorization methods, even though the other two cases are not as obviously as the one in panel C. When we consider value-weighted case, the pattern is still consistent. These results show that the relation between trading volume and profitability of momentum/contrarian profits for monthly losers is robust to the choice of trading volume and winner/loser categorization methods. This pattern could also be best explained by Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis in that late stage momentum performers, including low volume losers experience price reversals thus profitable in contrarian strategy, whereas early stage momentum performers, including high volume losers experience price momentum thus profitable in momentum strategy.

Under the same way, we summarize all the relations between trading volume and profitability of momentum/contrarian profits on whether they are consistent or inconsistent with the Momentum Life Cycle expectations in Table 17. From the summarized results we can see that Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis has a great explanation power on our samples. Particularly 21 patterns out of 48 cases are consistent with the expectations of the Momentum Life Cycle postulation. On the other hand, we could see that the explanation power of Momentum Life Cycle hypothesis increases in longer horizon cases. We can see for monthly horizon only equal-weighted losers are consistent with the MLC hypothesis, whereas for half yearly and yearly horizons both losers and winners in equal-weighted cases are consistent with the MLC hypothesis. Particularly, the number of consistency cases for MLC for different horizons of monthly, quarterly, half yearly and yearly are 3, 5, 7 and 6 respectively. And in the consistency cases the winners to losers ratio is 15:6.

Table 12
Relative Relation between Trading Volume and Stock Return Patterns based on **Value-Weighted** Winner/Loser Division and **Equally Divided** High/Medium/Low Trading Volume Method

This table presents the relation between trading volume and return patterns in horizons of monthly, quarterly, half yearly and yearly in China A share market. Negative numbers represent relative WRSS contrarian profits (price reversal); Positive numbers represents relative WRSS momentum profits (price momentum).

		Observation Intervals (K)							
		2	3	4	5	6	7	8	9
Panel A: Monthly Interval									
Winner	High	-0.012	-0.020	-0.002	-0.009	-0.005	-0.022	-0.009	-0.030
	Medium	0.021	0.018	0.008	0.024	0.023	0.029	0.007	0.014
	Low	-0.041	-0.063	-0.009	-0.038	-0.017	-0.020	-0.016	-0.031
Loser	High	-0.028	-0.027	-0.039	-0.033	-0.033	-0.017	-0.023	-0.006
	Medium	-0.005	-0.001	0.008	-0.008	-0.005	-0.014	-0.001	-0.005
	Low	-0.141	0.001	-0.056	-0.017	-0.069	-0.030	-0.028	-0.012
Panel B: Quarterly Interval									
Winner	High	0.011	0.008	-0.040	-0.007	-0.032	-0.025	-0.022	-0.004
	Medium	0.008	0.012	-0.004	-0.003	-0.006	-0.009	-0.007	-0.026
	Low	-0.026	-0.021	-0.016	0.007	-0.003	0.011	-0.001	0.026
Loser	High	-0.034	-0.028	-0.007	-0.022	-0.012	-0.015	-0.012	0.030
	Medium	-0.011	-0.013	-0.001	-0.006	-0.001	0.003	0.004	0.115
	Low	-0.096	-0.029	-0.008	-0.020	0.002	-0.015	-0.002	0.080
Panel C: Half Year Interval									
Winner	High	-0.239	-0.305	-0.518	-0.309	-0.347	-0.119	-0.081	-0.017
	Medium	-0.125	-0.091	-0.230	-0.084	-0.021	0.042	0.030	0.032
	Low	-0.114	-0.167	-0.013	-0.059	0.066	0.013	-0.051	-0.104
Loser	High	-0.190	-0.120	-0.103	-0.004	-0.133	-0.129	0.011	0.020
	Medium	-0.109	0.111	0.300	-0.001	0.022	-0.056	0.018	-0.035
	Low	-0.256	0.012	-0.187	0.049	-0.001	0.008	-0.015	-0.118
Panel B: Yearly Interval									
Winner	High	0.296	-0.536	-0.912	-0.176	-0.192	-0.181	-0.105	0.412
	Medium	-1.712	-1.597	-0.326	-0.244	-0.315	-0.321	-0.230	0.177
	Low	-1.486	-0.738	0.294	0.236	-0.118	0.082	-0.378	0.217
Loser	High	1.784	0.410	0.493	0.109	0.072	0.197	-0.067	-0.158
	Medium	0.059	1.471	-0.461	0.200	0.538	0.555	0.030	0.410
	Low	2.055	0.794	0.693	-0.862	0.440	-0.009	-0.189	0.561

*To better illustrate, the numbers are all scaled by 100 times

Table 13

Relative Relation between Trading Volume and Stock Return Patterns based on **Value-Weighted** Winner/Loser Division and Divided High/Medium/Low Trading Volume by **20% Extreme Values**.

This table presents the relation between trading volume and return patterns in horizons of monthly, quarterly, half yearly and yearly in China A share market. Negative numbers represent relative WRSS contrarian profits (price reversal); Positive numbers represents relative WRSS momentum profits (price momentum).

		Observation Intervals (K)							
		2	3	4	5	6	7	8	9
Panel A: Monthly Interval									
Winner	High	0.016	0.006	0.020	0.019	0.030	-0.001	0.023	-0.012
	Medium	0.009	0.006	0.005	0.013	0.008	0.015	0.004	0.008
	Low	0.052	-0.068	0.026	-0.039	0.014	-0.016	-0.012	-0.034
Loser	High	-0.014	-0.004	-0.024	-0.020	-0.025	0.003	-0.022	0.026
	Medium	-0.005	-0.004	-0.001	-0.009	-0.006	-0.009	0.007	-0.001
	Low	-0.114	0.034	-0.051	0.010	-0.067	-0.028	-0.030	-0.005
Panel B: Quarterly Interval0									
Winner	High	0.038	0.030	-0.022	-0.002	-0.019	-0.008	-0.007	-0.021
	Medium	0.008	0.008	-0.010	0.006	-0.002	-0.004	-0.004	-0.008
	Low	0.029	-0.006	0.001	0.021	-0.002	0.025	-0.002	-0.002
Loser	High	-0.031	-0.009	0.009	-0.016	-0.001	-0.001	-0.001	0.021
	Medium	-0.011	-0.013	0.004	-0.002	0.005	0.003	0.008	0.090
	Low	-0.068	-0.018	0.001	-0.017	0.007	-0.010	-0.012	0.047
Panel C: Half Year Interval									
Winner	High	0.021	-0.106	-0.400	-0.231	-0.208	0.041	-0.099	-0.037
	Medium	0.023	-0.148	-0.210	-0.063	0.017	0.029	0.001	0.028
	Low	-0.253	-0.092	0.182	0.011	-0.020	0.029	0.033	-0.017
Loser	High	-0.111	0.147	0.124	0.268	0.149	-0.024	0.053	0.043
	Medium	0.001	0.061	0.181	0.045	0.002	0.002	0.016	-0.017
	Low	-0.183	-0.028	-0.226	-0.001	-0.018	-0.013	0.031	-0.037
Panel B: Yearly Interval									
Winner	High	0.001	-0.413	-0.447	-0.184	-0.192	-0.073	-0.215	0.150
	Medium	-1.278	-1.259	-0.110	-0.220	-0.305	-0.389	-0.293	0.060
	Low	-1.638	-0.833	-0.125	1.354	-0.218	0.318	0.166	0.363
Loser	High	-0.847	0.438	0.797	0.157	0.058	0.145	0.088	-0.170
	Medium	1.532	1.274	0.409	0.226	0.376	0.311	0.121	0.135
	Low	2.099	-0.049	-0.150	-0.950	0.276	-0.062	-0.570	0.463

*To better illustrate, the numbers are all scaled by 100 times

Table 14

Relative Relation between Trading Volume and Stock Return Patterns based on **Value-Weighted** Winner/Loser Division and Divided High/Medium/Low Trading Volume by **10% Extreme Values.**

This table presents the relation between trading volume and return patterns in horizons of monthly, quarterly, half yearly and yearly in China A share market. Negative numbers represent relative WRSS contrarian profits (price reversal); Positive numbers represents relative WRSS momentum profits (price momentum).

		Observation Intervals (K)							
		2	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Panel A: Monthly Interval									
Winner	High	0.060	0.061	0.063	0.045	0.042	0.017	0.069	0.013
	Medium	0.006	0.001	0.006	0.013	0.009	0.013	0.005	0.009
	Low	0.304	-0.067	0.115	-0.021	0.127	0.015	0.015	-0.039
Loser	High	-0.001	0.002	0.006	0.012	0.007	0.034	-0.006	0.039
	Medium	-0.005	-0.001	-0.007	-0.011	-0.009	-0.008	0.004	0.006
	Low	-0.022	0.133	-0.012	0.097	-0.050	0.002	-0.010	0.040
Panel B: Quarterly Interval									
Winner	High	0.079	0.033	-0.001	0.012	-0.015	-0.015	0.020	0.006
	Medium	0.009	0.012	-0.008	0.009	0.001	0.010	-0.005	-0.022
	Low	0.192	0.037	0.040	0.052	0.018	0.008	0.019	0.017
Loser	High	-0.040	-0.022	0.026	0.008	0.036	0.033	0.019	0.037
	Medium	-0.008	-0.008	0.011	-0.002	0.010	0.003	0.007	0.072
	Low	-0.002	0.029	0.006	-0.010	-0.009	0.003	-0.006	0.0002
Panel C: Half Year Interval									
Winner	High	0.322	0.001	0.027	-0.006	-0.021	0.202	-0.025	-0.016
	Medium	0.023	-0.138	-0.235	-0.052	0.019	0.059	-0.016	0.015
	Low	0.116	0.266	0.799	0.121	0.004	0.035	0.190	0.224
Loser	High	-0.001	0.102	0.669	0.349	0.641	0.209	0.185	0.075
	Medium	0.024	0.089	0.118	0.134	0.013	0.024	0.018	0.013
	Low	0.178	0.236	-0.097	-0.103	0.023	-0.070	0.093	-0.004
Panel B: Yearly Interval									
Winner	High	-1.589	-0.227	-0.867	-0.102	-0.063	-0.058	-0.307	-0.002
	Medium	-1.057	-1.243	0.007	-0.054	-0.350	-0.251	-0.201	0.005
	Low	-1.845	-0.217	0.019	2.786	-0.216	-0.112	0.459	0.366
Loser	High	-0.337	0.209	0.743	0.071	0.396	0.324	0.485	0.016
	Medium	1.289	0.907	0.603	0.263	0.277	0.173	0.011	-0.027
	Low	0.764	0.613	-0.815	-1.185	-0.114	-0.012	-0.417	0.615

*To better illustrate, the numbers are all scaled by 100 times

Table 15
Relative Relation between Trading Volume and Stock Return Patterns based on **Equal-Weighted** Winner/Loser Division and **Equally Divided** High/Medium/Low Trading Volume Method

This table presents the relation between trading volume and return patterns in horizons of monthly, quarterly, half yearly and yearly in China A share market. Negative numbers represent relative WRSS contrarian profits (price reversal); Positive numbers represents relative WRSS momentum profits (price momentum).

		Observation Intervals (K)							
		2	3	4	5	6	7	8	9
Panel A: Monthly Interval									
Winner	High	-0.012	-0.016	-0.002	-0.010	-0.012	-0.031	-0.016	-0.041
	Medium	0.028	0.012	0.005	0.022	-0.001	0.018	-0.002	-0.004
	Low	-0.027	-0.070	-0.033	-0.055	-0.014	-0.031	-0.018	-0.025
Loser	High	-0.038	-0.038	-0.046	-0.039	-0.033	-0.020	-0.034	-0.019
	Medium	-0.023	-0.009	-0.001	-0.015	0.003	-0.019	-0.012	-0.007
	Low	-0.162	0.006	-0.042	-0.010	-0.052	-0.001	-0.004	0.001
Panel B: Quarterly Interval									
Winner	High	0.008	0.011	-0.026	-0.008	-0.023	-0.026	-0.021	-0.027
	Medium	0.016	0.012	-0.011	-0.007	-0.012	-0.013	-0.006	-0.089
	Low	-0.063	-0.018	-0.021	-0.004	-0.018	0.001	-0.007	-0.028
Loser	High	-0.029	-0.027	-0.006	-0.008	-0.005	-0.005	-0.011	-0.021
	Medium	-0.010	-0.008	0.007	-0.001	-0.001	0.002	0.004	-0.004
	Low	-0.066	-0.029	-0.012	-0.023	0.004	-0.017	-0.005	-0.002
Panel C: Half Year Interval									
Winner	High	-0.159	-0.114	-0.432	-0.286	-0.447	-0.107	-0.012	-0.013
	Medium	0.014	0.057	-0.242	-0.117	-0.015	-0.025	-0.018	-0.004
	Low	0.213	-0.179	-0.055	-0.081	0.026	0.059	-0.087	-0.048
Loser	High	-0.263	-0.117	-0.151	-0.014	-0.140	-0.221	-0.067	-0.014
	Medium	-0.038	-0.003	0.286	-0.040	0.008	-0.067	-0.037	-0.048
	Low	-0.360	-0.066	-0.204	0.019	0.007	-0.013	-0.050	-0.143
Panel B: Yearly Interval									
Winner	High	0.712	-0.701	-0.937	-0.147	-0.377	-0.292	-0.038	0.327
	Medium	-1.372	-1.742	-0.320	-0.330	-0.453	-0.399	-0.055	-0.132
	Low	-1.139	-0.699	0.391	0.166	-0.184	0.027	-0.022	-0.554
Loser	High	1.875	0.649	0.244	-0.010	-0.041	0.018	-0.067	-0.145
	Medium	-0.121	1.401	-0.553	0.066	0.370	0.238	0.149	0.390
	Low	1.595	0.866	0.723	-1.102	0.369	0.142	0.170	-0.346

*To better illustrate, the numbers are all scaled by 100 times

Table 16

Relative Relation between Trading Volume and Stock Return Patterns based on **Equal-Weighted** Winner/Loser Division and Divided High/Medium/Low Trading Volume by **20% Extreme Values.**

This table presents the relation between trading volume and return patterns in horizons of monthly, quarterly, half yearly and yearly in China A share market. Negative numbers represent relative WRSS contrarian profits (price reversal); Positive numbers represents relative WRSS momentum profits (price momentum).

		Observation Intervals (K)							
		2	3	4	5	6	7	8	9
Panel A: Monthly Interval									
Winner	High	0.012	0.017	0.020	0.020	0.0220	-0.010	0.017	-0.024
	Medium	0.015	0.001	-0.001	0.011	-0.008	0.006	-0.004	-0.005
	Low	0.075	-0.081	-0.006	-0.065	0.026	-0.030	-0.010	-0.021
Loser	High	-0.019	-0.024	-0.030	-0.023	-0.022	0.001	-0.034	-0.015
	Medium	-0.022	-0.012	-0.010	-0.017	-0.002	-0.014	-0.002	0.004
	Low	-0.139	0.055	-0.021	0.024	-0.037	0.024	0.009	0.018
Panel B: Quarterly Interval									
Winner	High	0.037	0.030	-0.009	-0.001	-0.014	-0.007	-0.009	-0.036
	Medium	0.004	0.009	-0.013	-0.001	-0.004	-0.009	-0.006	-0.067
	Low	-0.013	-0.001	0.001	0.010	-0.021	0.013	0.001	-0.045
Loser	High	-0.035	-0.010	0.014	0.002	0.014	0.009	-0.001	-0.009
	Medium	-0.003	-0.010	0.009	0.002	0.002	0.004	0.004	-0.016
	Low	-0.028	-0.017	-0.012	-0.020	0.018	-0.013	-0.002	-0.028
Panel C: Half Year Interval									
Winner	High	0.121	0.078	-0.297	-0.196	-0.326	0.038	-0.042	-0.050
	Medium	0.169	-0.043	-0.222	-0.084	-0.011	0.013	-0.016	0.019
	Low	0.119	-0.046	0.169	-0.014	-0.042	0.068	0.004	0.060
Loser	High	-0.044	0.128	0.050	0.068	0.129	-0.125	-0.043	0.009
	Medium	-0.075	0.002	0.166	0.069	0.008	-0.019	-0.027	-0.037
	Low	-0.202	-0.147	-0.241	0.010	-0.036	-0.057	-0.027	-0.061
Panel B: Yearly Interval									
Winner	High	0.022	-0.765	-0.477	-0.113	-0.372	-0.201	-0.197	0.018
	Medium	-0.799	-1.339	-0.076	-0.192	-0.455	-0.456	-0.070	-0.286
	Low	-1.259	-0.689	-0.069	0.990	-0.237	0.243	0.481	-0.408
Loser	High	-0.823	0.634	0.770	0.004	-0.004	-0.035	0.074	-0.196
	Medium	1.389	1.123	0.186	0.088	0.215	0.192	0.257	-0.059
	Low	1.589	0.612	0.025	-1.203	0.236	-0.101	-0.167	-0.449

*To better illustrate, the numbers are all scaled by 100 times

Table 17

Relative Relation between Trading Volume and Stock Return Patterns based on **Equal-Weighted** Winner/Loser Division and Divided High/Medium/Low Trading Volume by **10% Extreme Values.**

This table presents the relation between trading volume and return patterns in horizons of monthly, quarterly, half yearly and yearly in China A share market. Negative numbers represent relative WRSS contrarian profits (price reversal); Positive numbers represents relative WRSS momentum profits (price momentum).

		Observation Intervals (K)							
		2	3	4	5	6	7	8	9
Panel A: Monthly Interval									
Winner	High	0.053	0.076	0.065	0.040	0.038	0.005	0.067	0.007
	Medium	0.010	-0.002	-0.001	0.010	-0.005	0.004	-0.004	-0.006
	Low	0.350	-0.088	0.069	-0.059	0.154	-0.003	0.030	0.002
Loser	High	-0.008	-0.018	-0.008	0.003	0.010	0.033	-0.022	0.023
	Medium	-0.019	-0.009	-0.012	-0.018	-0.008	-0.012	-0.004	-0.001
	Low	-0.063	0.169	0.042	0.133	0.023	0.109	0.075	0.094
Panel B: Quarterly Interval									
Winner	High	0.076	0.050	0.018	0.008	0.005	-0.007	0.021	-0.012
	Medium	0.007	0.011	-0.010	0.004	-0.003	0.003	-0.007	-0.072
	Low	0.102	0.053	0.046	0.038	-0.016	0.001	0.023	-0.036
Loser	High	-0.041	-0.029	0.027	0.035	0.046	0.054	0.023	0.013
	Medium	-0.005	-0.005	0.010	0.002	0.010	0.003	0.007	-0.026
	Low	0.089	0.028	0.023	-0.012	0.009	0.001	-0.018	-0.034
Panel C: Half Year Interval									
Winner	High	0.618	0.190	0.210	0.045	-0.144	0.240	0.087	0.010
	Medium	0.122	-0.028	-0.203	-0.072	-0.019	0.051	-0.009	0.007
	Low	0.850	0.286	0.460	0.118	-0.020	0.040	-0.025	0.334
Loser	High	0.012	0.147	0.659	0.377	0.608	0.094	0.063	0.037
	Medium	0.005	0.022	0.093	0.091	0.015	-0.010	-0.031	-0.009
	Low	-0.039	0.094	-0.150	-0.012	-0.011	-0.093	0.047	-0.024
Panel B: Yearly Interval									
Winner	High	-1.537	-0.012	-1.011	-0.095	-0.238	-0.221	-0.279	-0.043
	Medium	-0.738	-1.392	0.057	-0.072	-0.488	-0.327	0.006	-0.401
	Low	-0.765	-0.146	0.020	2.487	-0.229	-0.153	0.766	-0.223
Loser	High	-0.324	0.266	0.500	-0.045	0.316	0.129	0.443	-0.030
	Medium	1.171	0.989	0.492	0.103	0.148	0.058	0.151	-0.266
	Low	-0.125	0.705	-0.724	-1.429	-0.172	-0.048	0.099	-0.467

*To better illustrate, the numbers are all scaled by 100 times

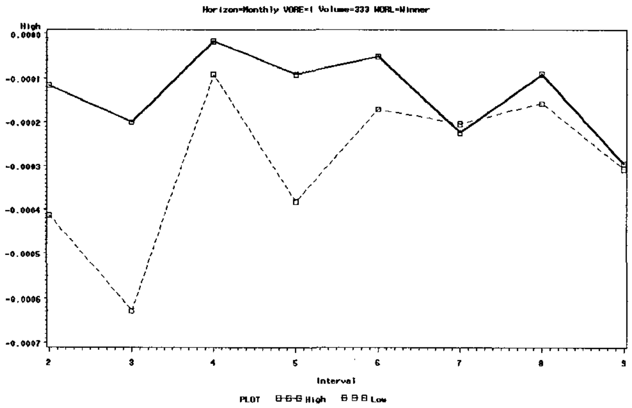
Figure 6

Accumulate Contrarian/Momentum Profit over the Observation Interval (Monthly)

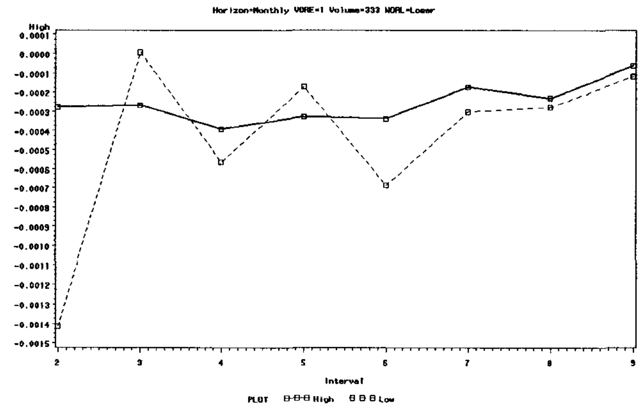
The following graphs display relative accumulate price reversals (negative numbers) and price momentum (positive numbers) of winners and loser stocks with different trading volume during the observation months, using **Value-Weighted** way to distinguish winner/loser

Panel A: High/Med/Low Volume is Equally Divided

Winner

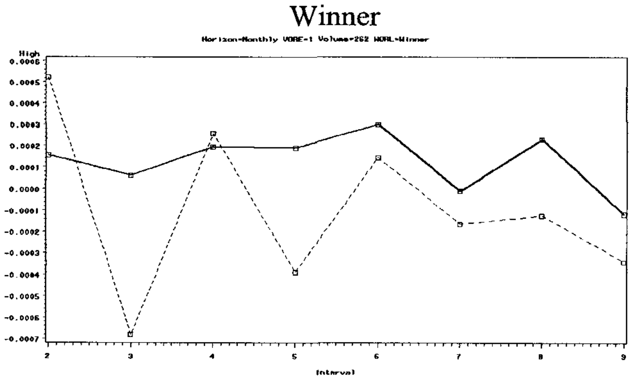


Loser

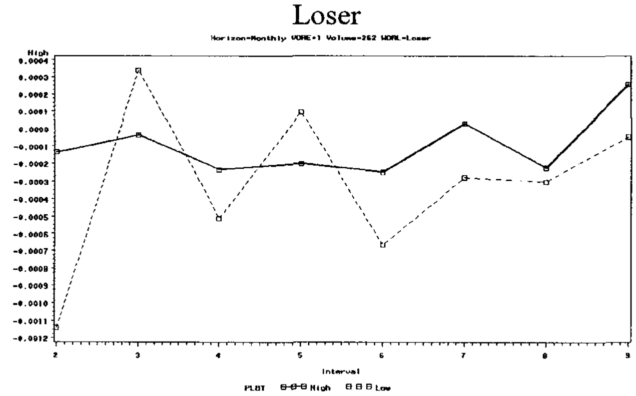


Panel B: Using 20% Extreme Values as High/Low Volumes

Winner

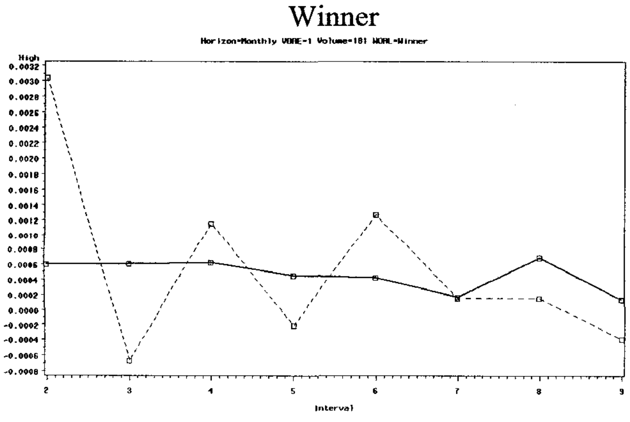


Loser



Panel C: Using 10% Extreme Values as High/Low Volumes

Winner



Loser

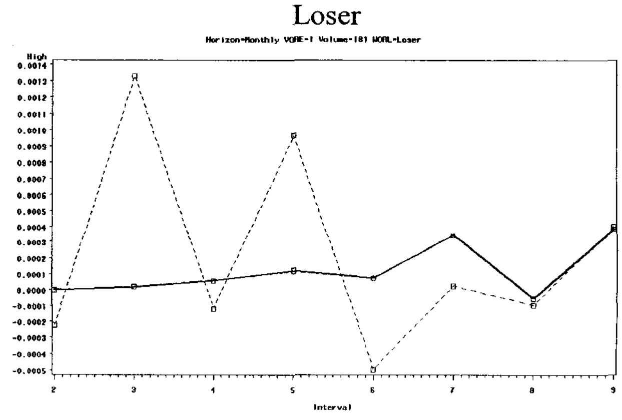


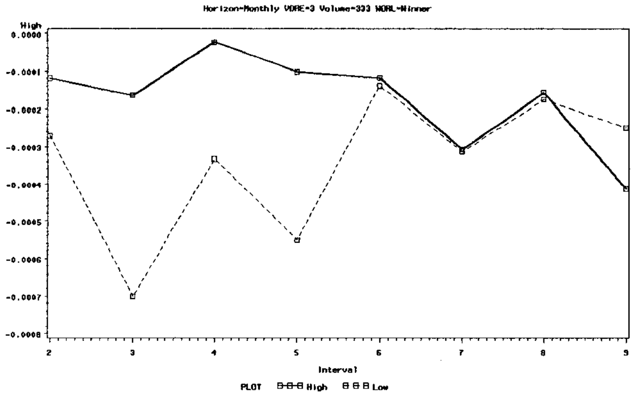
Figure 7

Accumulate Contrarian/Momentum Profit over the Observation Interval (Monthly)

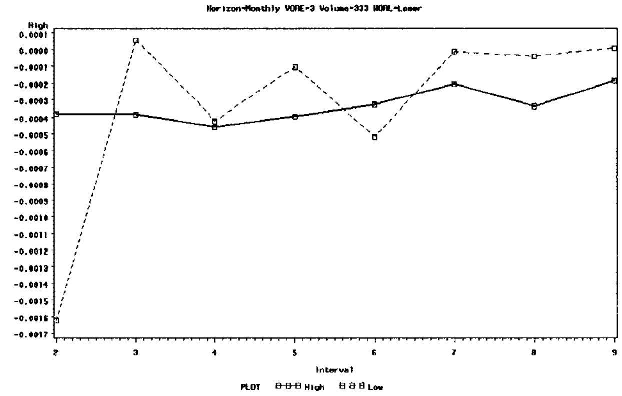
The following graphs display relative accumulate price reversals (negative numbers) and price momentum (positive numbers) of winners and loser stocks with different trading volume during the observation months, using **Equal-Weighted** way to distinguish winners/losers

Panel A: High/Med/Low Volume is Equally Divided

Winner

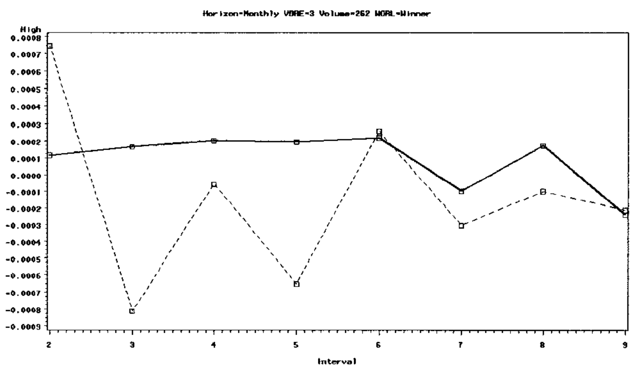


Loser

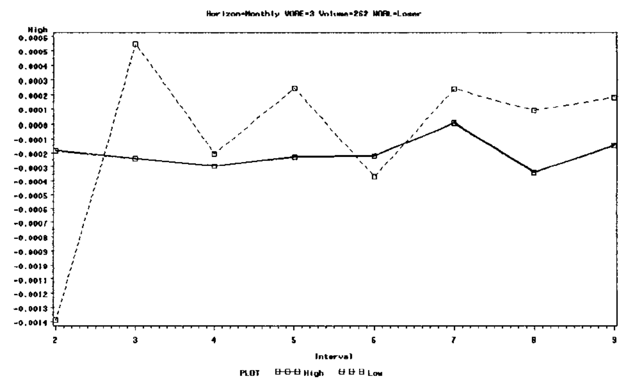


Panel B: Using 20% Extreme Values as High/Low Volumes

Winner

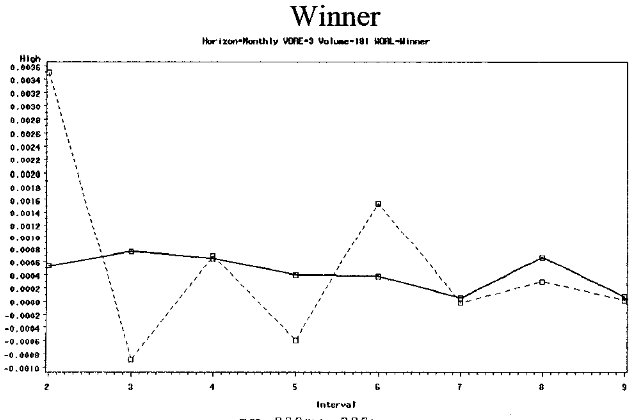


Loser



Panel C: Using 10% Extreme Values as High/Low Volumes

Winner



Loser

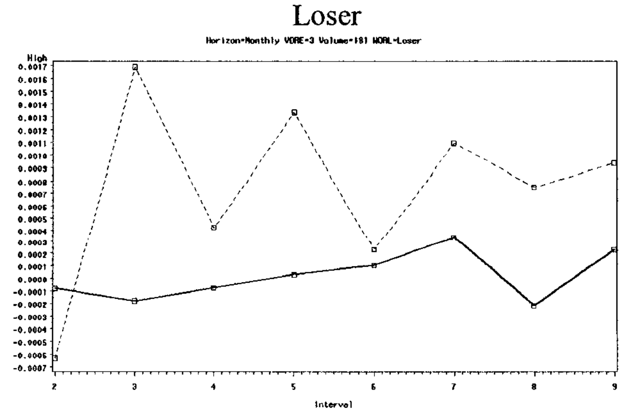


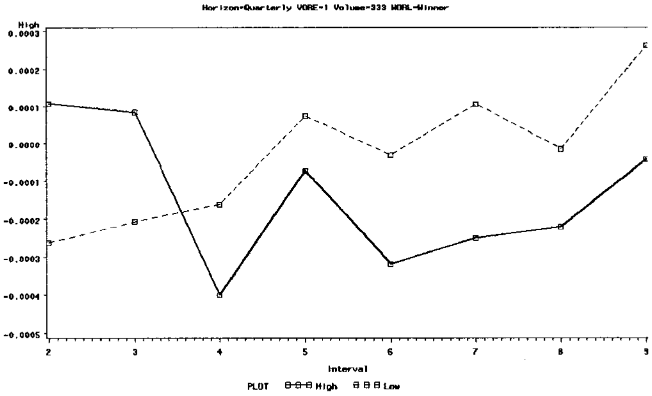
Figure 8

Accumulate Contrarian/Momentum Profit over Observation Interval (Quarterly)

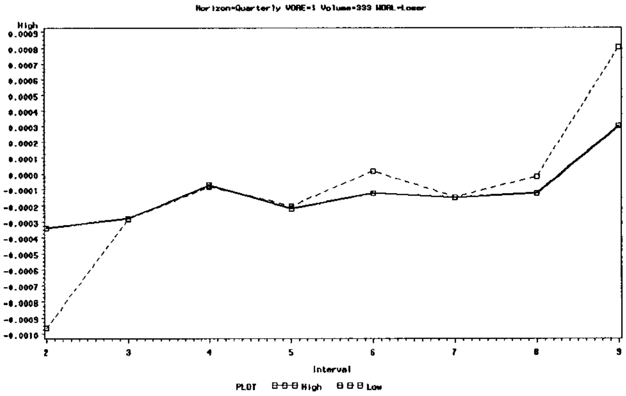
The following graphs display relative accumulate price reversals (negative numbers) and price momentum (positive numbers) of winners and loser stocks with different trading volume during the observation months, using **Value-Weighted** way to distinguish winner/loser

Panel A: High/Med/Low Volume is Equally Divided

Winner

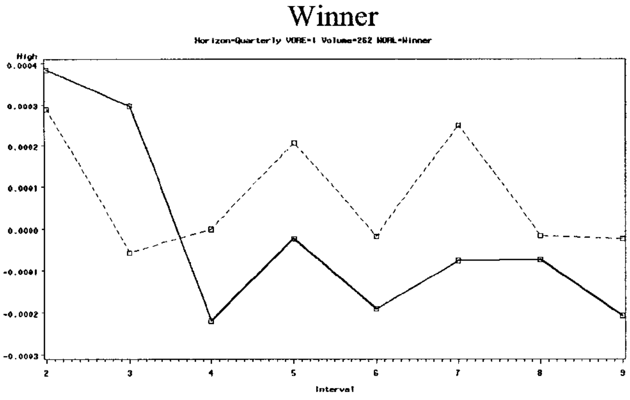


Loser

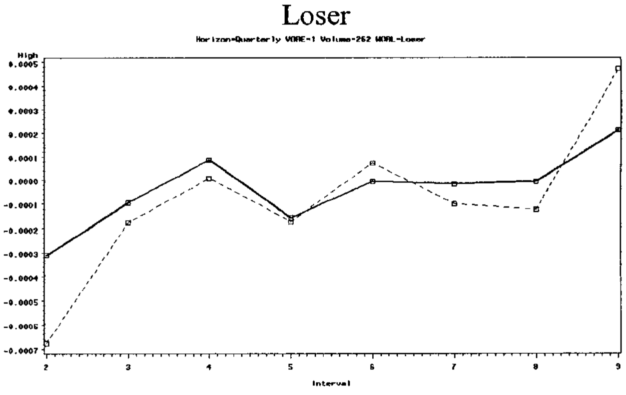


Panel B: Using 20% Extreme Values as High/Low Volumes

Winner

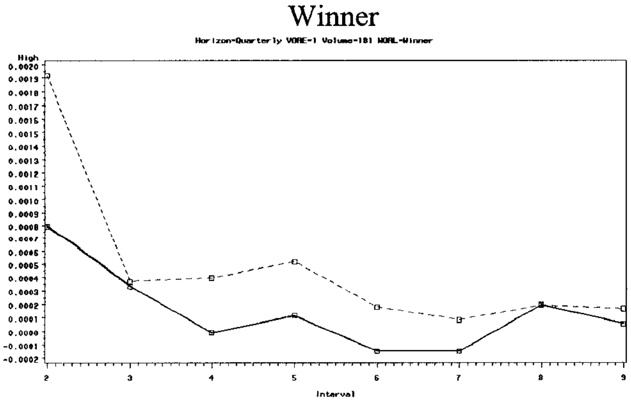


Loser



Panel C: Using 10% Extreme Values as High/Low Volumes

Winner



Loser

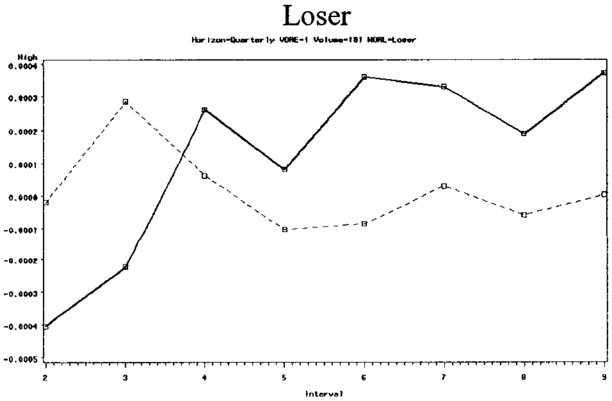


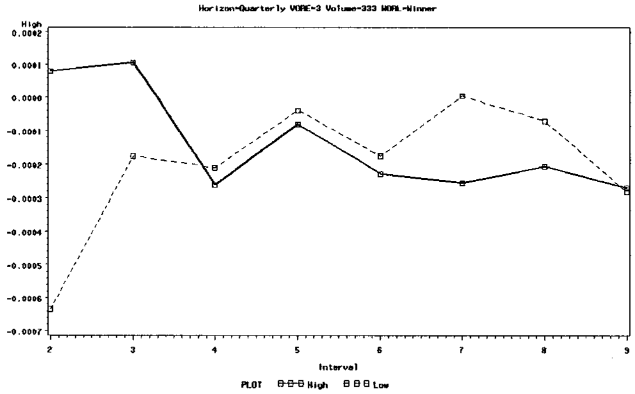
Figure 9

Accumulate Contrarian/Momentum Profit over Observation Interval (Quarterly)

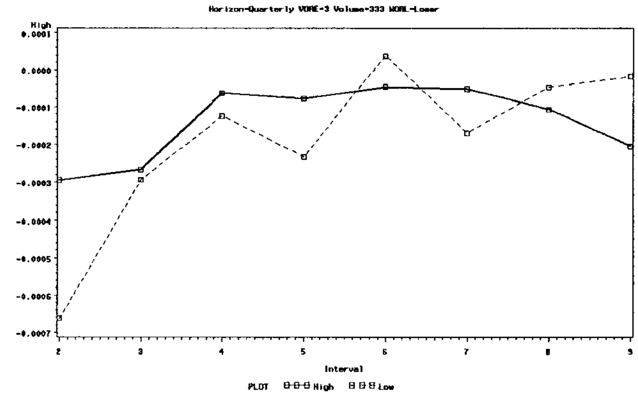
The following graphs display relative accumulate price reversals (negative numbers) and price momentum (positive numbers) of winners and loser stocks with different trading volume during the observation months, using **Equal-Weighted** way to distinguish winner/loser

Panel A: High/Med/Low Volume is Equally Divided

Winner

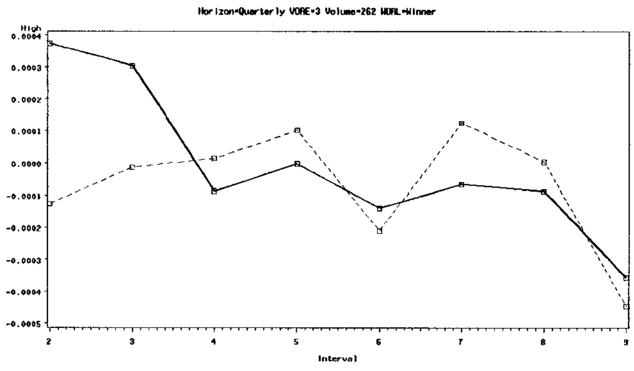


Loser

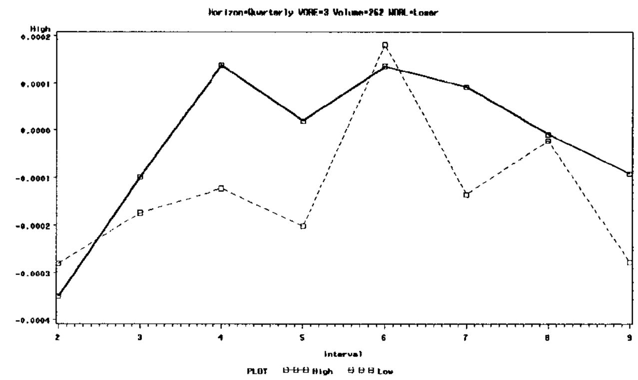


Panel B: Using 20% Extreme Values as High/Low Volumes

Winner

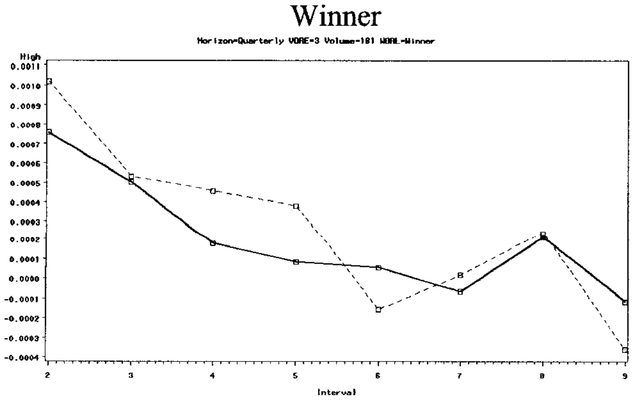


Loser



Panel C: Using 10% Extreme Values as High/Low Volumes

Winner



Loser

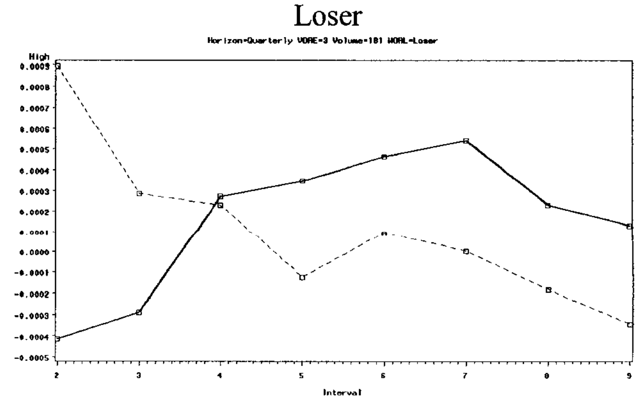


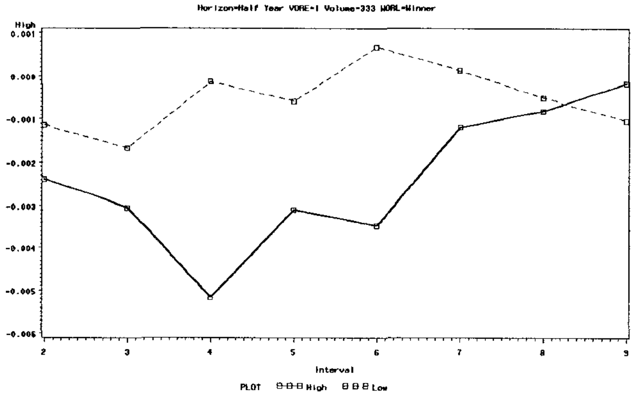
Figure 10

Accumulate Contrarian/Momentum Profit over Observation Interval (Half Yearly)

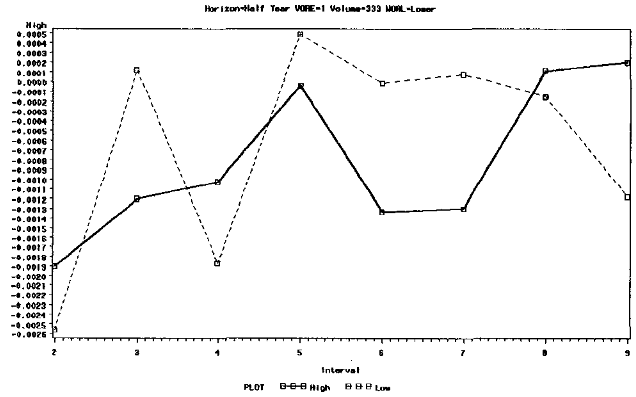
The following graphs display relative accumulate price reversals (negative numbers) and price momentum (positive numbers) of winners and loser stocks with different trading volume during the observation months, using **Value-Weighted** way to distinguish winner/loser

Panel A: High/Med/Low Volume is Equally Divided

Winner

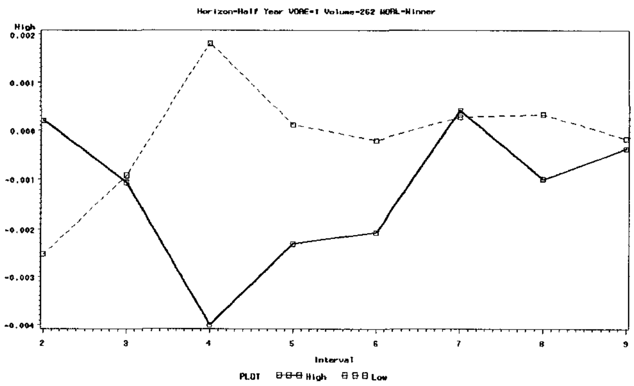


Loser

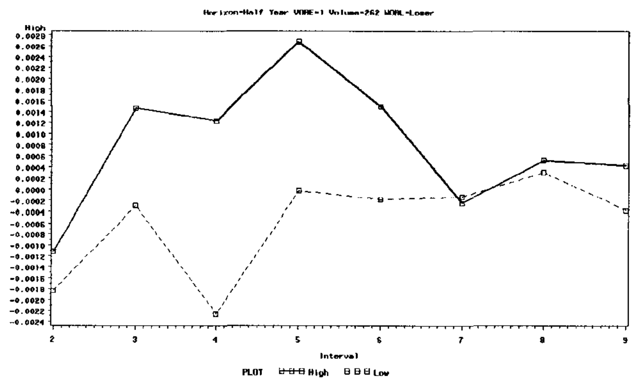


Panel B: Using 20% Extreme Values as High/Low Volumes

Winner

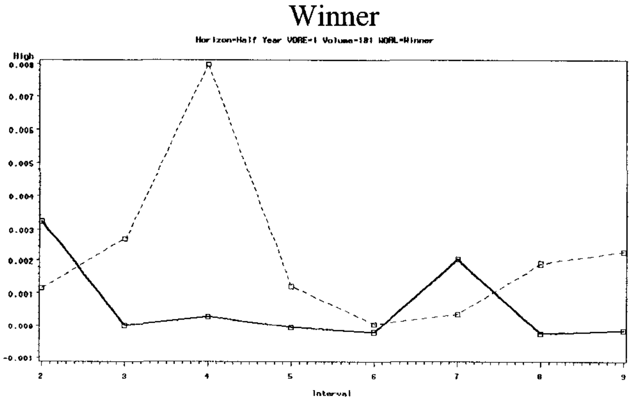


Loser



Panel C: Using 10% Extreme Values as High/Low Volumes

Winner



Loser

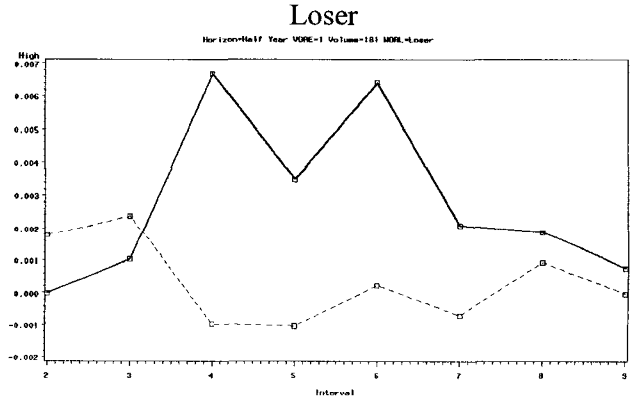


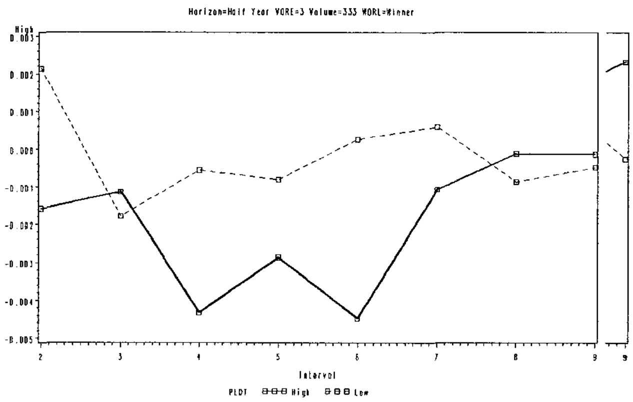
Figure 11

Accumulate Contrarian/Momentum Profit over Observation Interval (Half Yearly)

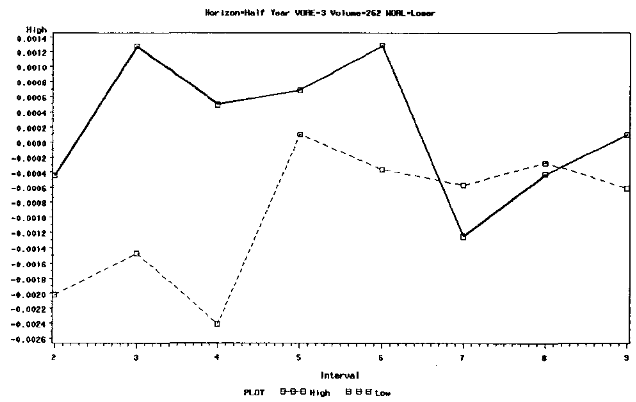
The following graphs display relative accumulate price reversals (negative numbers) and price momentum (positive numbers) of winners and loser stocks with different trading volume during the observation months, using **Equal-Weighted** way to distinguish winner/loser

Panel A: High/Med/Low Volume is Equally Divided

Winner

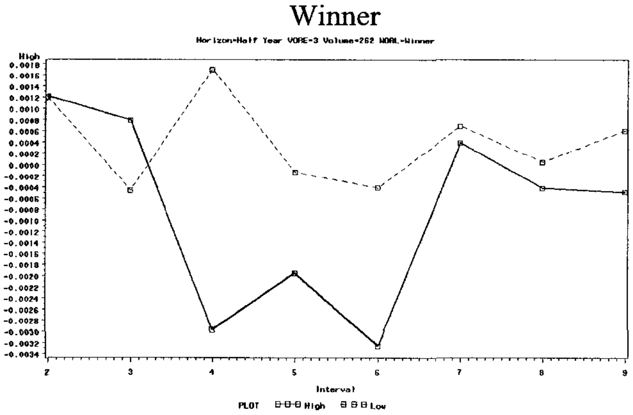


Loser

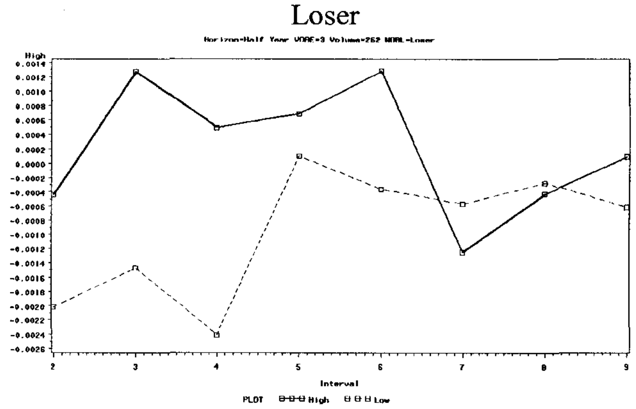


Panel B: Using 20% Extreme Values as High/Low Volumes

Winner

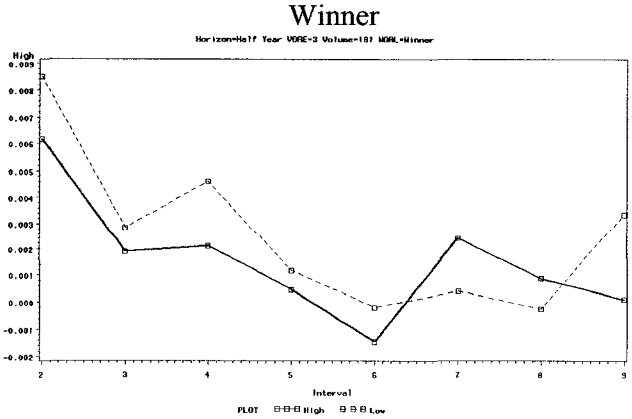


Loser



Panel C: Using 10% Extreme Values as High/Low Volumes

Winner



Loser

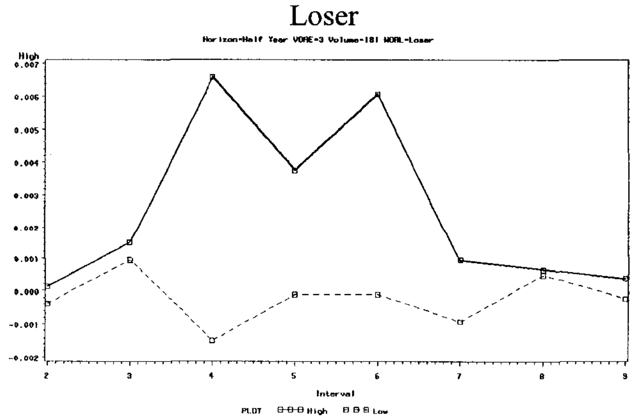


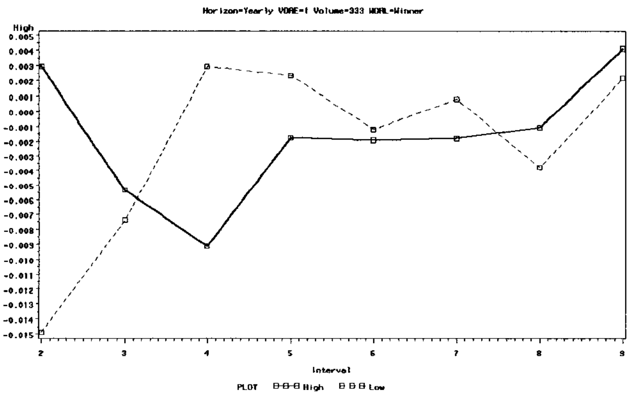
Figure 12

Accumulate Contrarian/Momentum Profit over Observation Interval (Yearly)

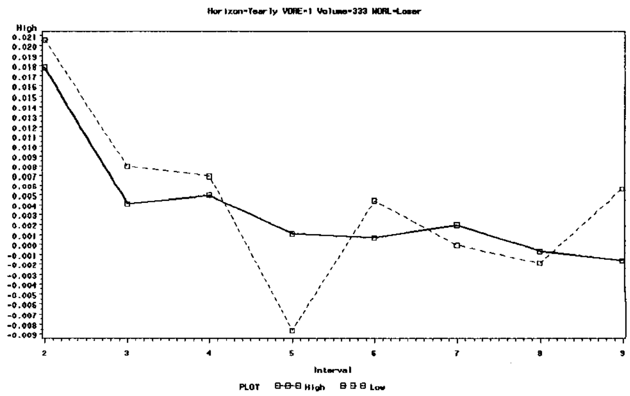
The following graphs display relative accumulate price reversals (negative numbers) and price momentum (positive numbers) of winners and loser stocks with different trading volume during the observation months, using **Value-Weighted** way to distinguish winner/loser

Panel A: High/Med/Low Volume is Equally Divided

Winner

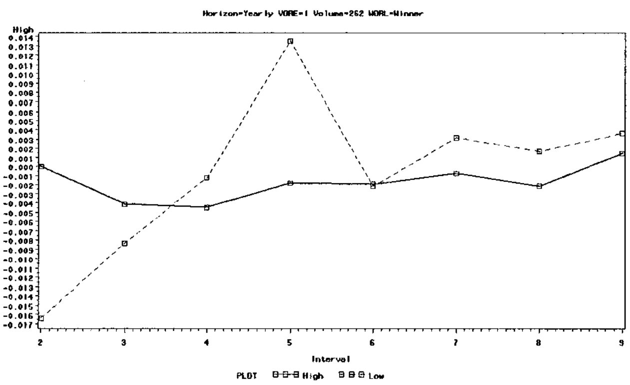


Loser

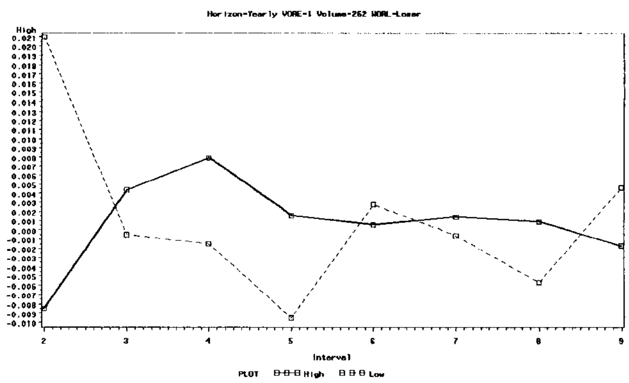


Panel B: Using 20% Extreme Values as High/Low Volumes

Winner

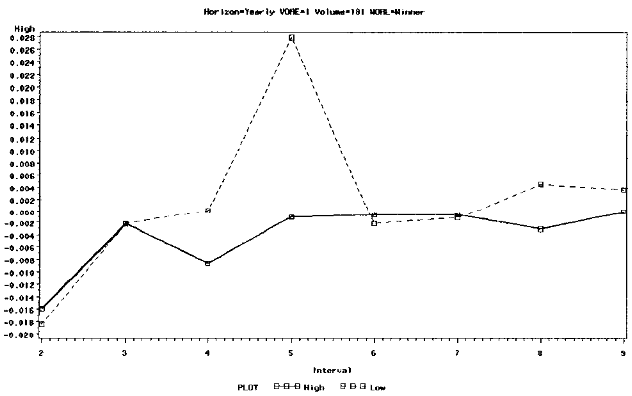


Loser



Panel C: Using 10% Extreme Values as High/Low Volumes

Winner



Loser

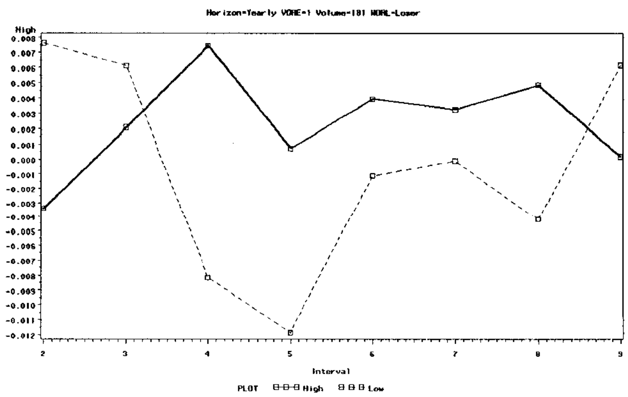


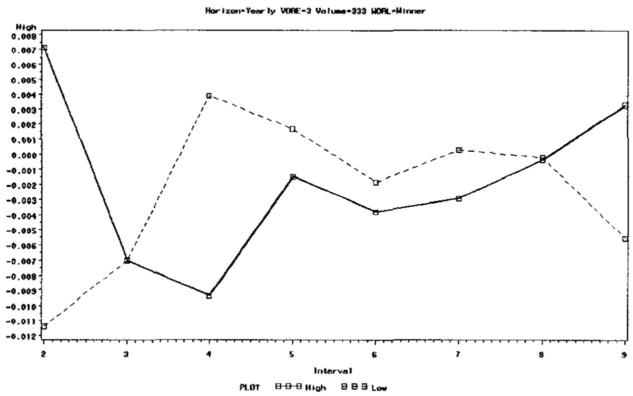
Figure 13

Accumulate Contrarian/Momentum Profit over Observation Interval (Yearly)

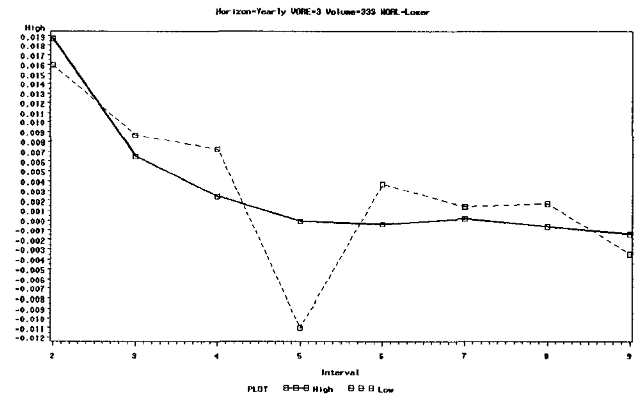
The following graphs display relative accumulate price reversals (negative numbers) and price momentum (positive numbers) of winners and loser stocks with different trading volume during the observation months, use **Equal-Weighted** to distinguish winner/loser

Panel A: High/Med/Low Volume is Equally Divided

Winner

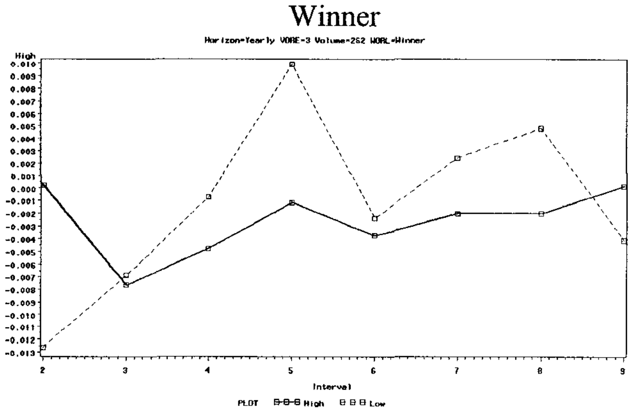


Loser

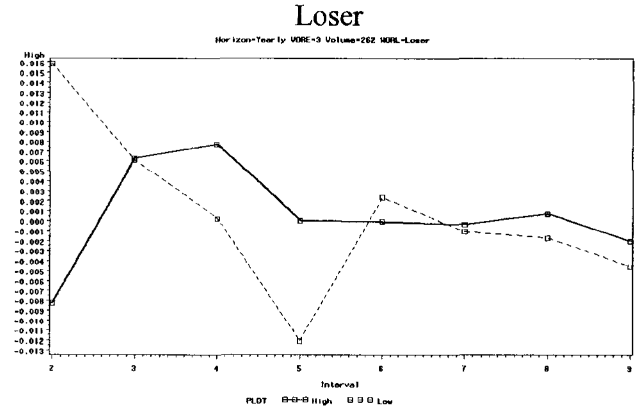


Panel B: Using 20% Extreme Values as High/Low Volumes

Winner

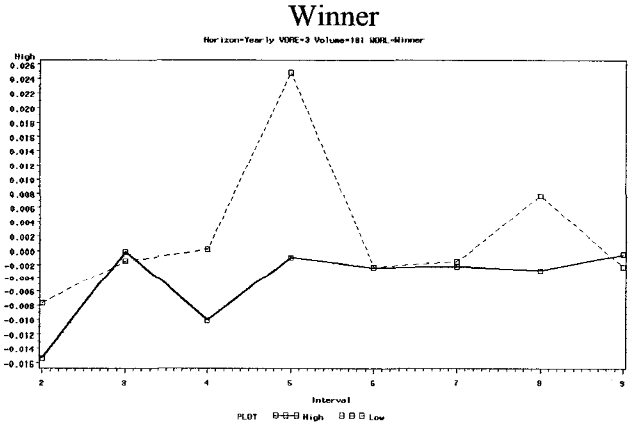


Loser



Panel C: Using 10% Extreme Values as High/Low Volumes

Winner



Loser

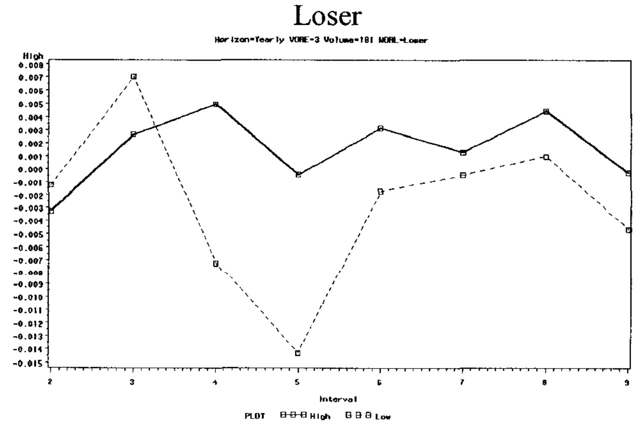


Table 18

Summary Findings on Whether the Relations between Trading Volume and Stock Return Patterns are Consistent with the Momentum Life Cycle Hypothesis

	Value-Weighted Method to Distinguish Winner/Loser		Equal-Weighted Method to Distinguish Winner/Loser	
	Winner	**Loser**	**Winner**	**Loser**
Panel A: Equally Divided for High, Low and Medium Trading Volumes				
Monthly Horizon	High Volume Continue Low Volume Convert [Inconsistent]	High Volume Convert Low Volume Continue [Inconsistent]	High Volume Continue Low Volume Convert [Inconsistent]	High Volume Continue Low Volume Convert **[Consistent]**
Quarterly Horizon	High Volume Convert Low Volume Continue **[Consistent]**	Mixed Result [Inconsistent]	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]
Half Yearly Horizon	High Volume Convert Low Volume Continue **[Consistent]**	Mixed Result [Inconsistent]	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Continue Low Volume Convert **[Consistent]**
Yearly Horizon	Mixed Result [Inconsistent]	High Volume Continue Low Volume Convert **[Consistent]**	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Continue Low Volume Convert **[Consistent]**
Panel B: Use Extreme 20% for High and Low Trading Volumes				
Monthly Horizon	High Volume Continue Low Volume Convert [Inconsistent]	Mixed Result [Inconsistent]	High Volume Continue Low Volume Convert [Inconsistent]	High Volume Continue Low Volume Convert **[Consistent]**
Quarterly Horizon	High Volume Convert Low Volume Continue **[Consistent]**	Mixed Result [Inconsistent]	Mixed Result [Inconsistent]	High Volume Convert Low Volume Continue [Inconsistent]
Half Yearly Horizon	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]
Yearly Horizon	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]

(Continue with Table 17)

	Value-Weighted Method to Distinguish Winner/Loser		Equal-Weighted Method to Distinguish Winner/Loser	
	Winner	**Loser**	**Winner**	**Loser**
Panel C: Use Extreme 10% for High and Low Trading Volumes				
Monthly Horizon	Mixed Result [Inconsistent]	Mixed Result [Inconsistent]	Mixed Result [Inconsistent]	High Volume Continue Low Volume Convert **[Consistent]**
Quarterly Horizon	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]
Half Yearly Horizon	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]
Yearly Horizon	Mixed Result [Inconsistent]	High Volume Convert Low Volume Continue [Inconsistent]	High Volume Convert Low Volume Continue **[Consistent]**	High Volume Convert Low Volume Continue [Inconsistent]

3.4.2 Value Characteristics of Trading Volume

We investigate the value loading of momentum/contrarian profits of stocks in different trading volume groups by implementing the Fama and French (1993) 3-factor Model, and present the results in Table 18. These results are only for short horizon of monthly case and we categorize the level of trading volume by equally one-third method. We analyze the returns occurring in the second observation month from the WRSS portfolios formed with monthly returns. Thus, following Ding, McInish, and Wongchoti (2007), we make an implicit assumption that the glamour characteristic of a given stock is reasonably stable in the short run. Contrary to Ding, McInish, and Wongchoti's (2007) findings on seven other Asian markets, the Fama and French (1993) three-factor model has a very strong explanatory power on momentum returns in the China A share markets. For both value-weighted and equal-weighted cases, all performers exhibits value characteristic, except low-volume winners (HML loading of -0.007 in value-weighted case and -0.042 and significant for equal-weighted case). As a result, the Daniel, Hirshleifer, and Subrahmanyam's (1998) overconfidence bias model implicitly predicts a higher short-horizon momentum profits for low-volume winner stocks. However, we find that price momentum in China A share market is displayed only by low-volume winners when equal-weighted and extreme trading volume categorization methods are used (one out of six case) and it increases with trading volumes in all cases. Panel A of Figure 6 shows that low-volume stocks generate contrarian profits during the whole observation periods and high-volume winners always outperforms low-volume winners in the whole process. Hence the indirect link between trading volume and short-horizon price pattern through an overconfidence bias model fails to explain what happened in China A share market.

Table 19

Three Factor Regression Coefficients of Monthly Contrarian/Momentum Returns of Stocks with Different Levels of Trading Volume

Portfolio	α	β	γ SMB Loading	υ HML Loading	Adjust R-Square
Panel A Using Value-Weighted Market Return to Distinguish Winners/Losers					
High-Winner	0.086***	0.569***	-0.418***	0.048***	0.022
	(0.001)	(0.001)	(0.001)	(0.006)	
High-Loser	-0.075***	-0.047***	-0.298***	0.123***	0.016
	(0.001)	(0.001)	(0.001)	(0.001)	
Total	0.003***	0.022***	0.083***	0.068***	0.003
	(0.009)	(0.001)	(0.001)	(0.001)	
Med.-Winner	0.082***	0.062***	-0.421***	0.071***	0.022
	(0.001)	(0.001)	(0.001)	(0.001)	
Med.-Loser	-0.070***	-0.056***	-0.453***	0.124***	0.037
	(0.001)	(0.001)	(0.001)	(0.001)	
Total	0.003***	0.006	-0.113***	0.126***	0.002
	(0.009)	(0.247)	(0.001)	(0.001)	
Low-Winner	0.074***	0.057***	-0.484***	-0.007	0.039
	(0.001)	(0.001)	(0.001)	(0.690)	
Low-Loser	-0.065***	-0.050***	-0.425***	0.027**	0.044
	(0.001)	(0.001)	(0.001)	(0.022)	
Total	-0.002**	-0.016***	-0.232***	0.055***	0.005
	(0.044)	(0.002)	(0.001)	(0.001)	
Panel B Using Equal-Weighted Market Return to Distinguish Winners/Losers					
High-Winner	0.088***	0.069***	-0.066***	0.040**	0.006
	(0.001)	(0.001)	(0.005)	(0.017)	
High-Loser	-0.074***	-0.041***	-0.001	0.093***	0.007
	(0.001)	(0.001)	(0.985)	(0.001)	
Total	0.003***	0.022***	0.083***	0.068***	0.003
	(0.009)	(0.001)	(0.001)	(0.001)	
Med.-Winner	0.084***	0.077***	-0.032	0.052***	0.008
	(0.001)	(0.001)	(0.179)	(0.003)	
Med.-Loser	-0.069***	-0.047***	-0.153***	0.107***	0.009
	(0.001)	(0.001)	(0.001)	(0.001)	
Total	0.003***	0.006	-0.113***	0.126***	0.002
	(0.009)	(0.247)	(0.001)	(0.001)	
Low-Winner	0.076***	0.070***	-0.075***	-0.042***	0.009
	(0.001)	(0.001)	(0.001)	(0.015)	
Low-Loser	-0.065***	-0.043***	-0.129***	0.019	0.008
	(0.001)	(0.001)	(0.001)	(0.119)	
Total	-0.002**	-0.016***	-0.232***	0.055***	0.005
	(0.043)	(0.002)	(0.001)	(0.001)	

3.4.3 Speed of Adjustment to Public Information

We present the results of the Dimson beta regressions in Table 19. Based on Chordia and Swaminathan (2000), when high volume stocks adjust faster to public information than low volume stocks, we are expected to see that the contemporaneous beta and sum of lagged betas are positive and negative, respectively. Panel A and B present the results for value- and equal-weighted market return respectively. When we consider stocks of all size group in value-weighted case, the contemporaneous beta and sum of lagged betas are -0.08487 and -0.18831 respectively. Even though the sign of contemporaneous beta is not as expected, it is not significant, whereas the coefficient for sum of lagged betas is significantly negative as expected. Consistent with Chordia and Swaminathan (2000), our results shows that the speed of adjustment to public information influenced by size effect. In both value- and equal-weighted cases, when we consider stocks of small size group, the contemporaneous beta and sum of lagged betas are all in expected sign as well as significant, which strongly confirm the prediction that high volume stocks adjust faster to public information than low volume stocks especially for small group. In summary, though the results for big size group are mixed, in general, we still could regard that high volume stocks adjust faster to public information than low volume stocks in China A share market. According to the implicit predictions of Hong and Stein (1999) model, the above findings would suggest that momentum profits should be higher for low-volume stocks, especially for small stocks in China A share markets. Refer to panel A of Table 15 and 16, momentum profits are found only in loser stocks in equal-weighted cases. On balance, we can conclude that, of all the 12 monthly results, the information diffusion behavioral explanation yields the right prediction for loser stocks only in two cases.

Table 20

Dimson Beta Regressions for China A Share Markets

We perform Dimson beta regressions: $r_{O,t} = \alpha_O + \sum_{-K}^{K} \beta_{O,K} r_{M,t-K} + \varepsilon_{O,t}$ to examine the hypothesis that high trading volume stocks adjust to market information (as proxied by market returns) faster than low trading volume stocks. Portfolio O has a long (short) position in high (low) volume stocks. The weekly returns on portfolio O are regressed on leads and lags (k=3) of the market returns. The hypothesis can not be rejected if we find significant positive contemporaneous beta and negative sum of lagged beta. H (L) represents returns on portfolios of high (low) volume stocks.

Panel A: Using Value-Weighted Market Returns

	Contemporaneous Beta	Sum of Lagged Beta	Sum of Lead Beta	Adj R Square
High - Low (All Size)	-0.08487	-0.18831 ***	0.0522	0.11
	(0.1274)	(0.0010)	(0.1312)	
High -Low (Big Size)	-0.25895 ***	-0.28752 ***	0.11685 **	0.13
	(0.0030)	(0.0012)	(0.0303)	
High - Low (Small Size)	0.08921 **	-0.0891 **	-0.01245	0.12
	(0.0260)	(0.0285)	(0.6145)	

Panel B: Using Equal-Weighted Market Returns

	Contemporaneous Beta	Sum of Lagged Beta	Sum of Lead Beta	Adj R Square
High - Low (All Size)	-0.16441 ***	-0.10832 **	0.0327	0.09
	(0.0038)	(0.0549)	(0.3192)	
High -Low (Big Size)	-0.4497 ***	-0.14231 *	0.09008 *	0.17
	(0.0001)	(0.0914)	(0.0675)	
High - Low (Small Size)	0.12089 ***	-0.07432 *	-0.02469	0.11
	(0.0027)	(0.0632)	(0.2891)	

*, **, *** represent significant level at 10%, 5% and 1% respectively.

3.4.4 Summary on the Comparison among Three Behavioral Models

Lee and Swaminathan's (2000) Momentum Life Cycle (MLC) explanation for the relation between trading volume and profitability of momentum / contrarian strategies is the most causal of behavioral postulations tested in out study. However, it turns out to be the most effective one in explaining the relation between trading volume and stock return patterns in the China A share market during the period from 1991 to 2007. Recall, that the Momentum Life Cycle expects that high (low) volume winners (losers) will experience price reversal thus profitable in contrarian strategy, while high (low) volume losers (winners) will experience price momentum thus profitable in momentum strategy. Among totally 48 results based on different horizons and categorization methods for winner/loser and trading volume, Momentum Life Cycle hypothesis best explain 21 cases for the relations between trading volume and profitability of momentum/contrarian strategies. On one hand, MLC does reasonably well in justifying high volume contrarian return and low volume momentum return of winners stocks in 15 out of 24 cases. On the other hand, we detect a consistent projection with the MLC for low-volume contrarian and high volume momentum profits of loser stocks in 6 out of 24 cases.

Particularly, for short-term horizon of monthly results, we compare the explanation power of Momentum Life Cycle hypothesis with Daniel, Hirshleifer, and Subrahmanyam's (1998) overconfidence bias in glamour stocks and Hong and Stein's (1999) information diffusion process. Table 20 summarizes the comparison results for these 3 behavioral postulations. Even though MLC is more pronounced in explaining

Table 21
Comparisons of Results to the Predictions of Three Behavioral Explanations

	Our Monthly Results				Consistency with Behavioral Explanations		
	Winners	Losers	Volume Group with Strongest Growth Characteristics	High Volume Adjust Faster to Low Volume?	Overconfidence Bias Daniel et al. (1998)	Information Diffusion Hong and Stein (1999)	MLC Lee and Swaminathan (2000)
Value-Weighted W/L Equally Divide for Level of Trading Volume H/M/L	Mixed (H>L)	Contrarian (Unclear)	Low-Volume Winners	Yes (Especially for Small Stocks)	No	No	No
Value-Weighted W/L Use Extreme 20% for Level of Trading Volume H/L	Momentum: High Contrarian: Low	Contrarian (Unclear)			No	No	No
Value-Weighted W/L Use Extreme 10% for Level of Trading Volume H/L	Momentum (Unclear)	Contrarian: High Mixed: Low			Inconclusive	Inconclusive	Inconclusive
Equal-Weighted W/L Equally Divide for Level of Trading Volume H/M/L	Contrarian (Unclear)	Contrarian (L>H)			No	Inconclusive	Yes (Partially on Losers)
Equal-Weighted W/L Use Extreme 20% for Level of Trading Volume H/L	Momentum: High Contrarian: Low	Contrarian: High Momentum: Low			No	Yes (Partially on Losers)	Yes (Partially on Losers)
Equal-Weighted W/L Use Extreme 10% for Level of Trading Volume H/L	Momentum (Unclear)	Mixed: High Momentum: Low			No	Yes (Partially on Losers)	Yes (Partially on Losers)

relations between trading volume and profitability of momentum/contrarian profits in longer horizons, it still outperforms the other two behavioral theories in monthly horizon. The comparison results reconfirm the explanation power of Momentum Life Cycle hypothesis for the China A share market.

3.5 Conclusions

The relation between trading volume and stock return patterns is among the more well-documented phenomena in financial research. At the same time, there have been several behavioral explanations that may provide a rationale for this relation, especially from the aspect of profitability of momentum/contrarian strategies. Despite the growing importance of China's economy, relatively little study has been done to justify these implications in a systematic framework. With data on the China A share market from 1991 to 2007, we examine the cross-horizon implications of three behavioral explanations and validate their implicit predictions. In general, Lee and Swaminathan's (2000) Momentum Life Cycle (MLC) explanation provides the best explanatory power for the relation between trading volume and stock returns found in the China A share market. This result reconfirms the findings of an earlier study on the negative lead-lag relations between lagged trading volume and subsequent stock returns in that such a pattern is not only statistically significant but also economically significant. The Momentum Life Cycle hypothesis provides the strongest explanatory power not only for the lead-lag patterns but also for the profitability of momentum/contrarian strategies in various horizons. However, the results are not fully consistent across the horizons studied. Specifically, while MLC can nicely explain most of the results of both winner and loser stocks patterns in quarterly, half yearly and yearly horizons, it can only explain the loser stock in equal-weighted monthly results. Even though Momentum Life Cycle hypothesis has stronger explanatory power for longer horizons (quarterly, half yearly and yearly), it still outperforms the other behavioral models in monthly horizon. The implications of Daniel, Hirshleifer, and Subrahmanyam's (1998) overconfidence bias in glamour stocks can explain the relation between trading volume and stock returns only among loser stocks when winner/loser is based on equal-weighted market return. On the other hand, none of the results could be explained by expectations based on Hong and Stein's (1999) information diffusion effect.

This study compares only the explanatory power of these three behavioral models in short-term horizons (monthly). Further study should be done to investigate and compare these models in longer horizons. There are still some cautions that should be noted in terms of this study. First, trading volume as referred to by Lee and Swaminathan (2000) represents trading activity during the formation period. In this study, we make an implicit assumption that trading volume will continue at a similar level in the following periods. This assumption could misrepresent trading volume, especially in the late half of the observation periods. Second, in Daniel, Hirshleifer, and Subrahmanyam's (1998) model, glamour characteristics within a particular trading volume group, whether high or low, may not be an absolute proxy for valuation uncertainty; thus, the explanatory power of this model might not be fully tested. A better or more suitable proxy should be used for further investigation.

Chapter 4

Summary and Conclusions

This study systematically investigated the lead-lag relations between the trading volume and stock return patterns in China A share and B share markets through two streams of behavioral postulations. On the one hand, we summarized all the potential lead-lag patterns between trading volume and stock returns and linked them to the corresponding behavioral explanations. In particular, Lee and Swaminathan's (2000) Momentum Life Cycle theory predicts a negative relation between lagged trading volume and subsequent return; Statman, Thorley, and Vorkink's (2006) overconfidence hypothesis predicts a positive relation between lagged return and subsequent trading volume in market level; Shefrin and Statman's (1995) disposition effect also predicts a positive relation between lagged return and subsequent trading volume, but in individual stock level; Veronesi's (2000) market tendency to overreact to bad news and underreact to good news effect; and Thaler and Johnson's (1990) Try-to-Break-Even hypothesis predict a negative relation between lagged stock return and subsequent trading volume in market and individual levels respectively. On the other hand, we further investigated such relations from the aspect of profitability of momentum/contrarian strategies under different behavioral models, especially within the empirical framework of Lee and Swaminathan (2000); Daniel, Hirshleifer, and Subrahmanyam (1998); and Hong and Stein (1999). Particularly, Lee and Swaminathan's (2000) Momentum Life Cycle predicts that late stage momentum performers, including high (low) volume winners (losers), will experience price reversals, thus becoming profitable in contrarian strategy, whereas early stage momentum performers, including low (high) volume winners (losers), will experience price momentum, thus being profitable in momentum strategy; Daniel, Hirshleifer, and Subrahmanyam's (1998) overconfidence bias on glamour stocks predicts that high volume stocks produce higher short-term momentum profits as well as higher long-horizon contrarian profits than low volume stocks, if high volume stocks really proxy for growth stocks; conversely, Hong and Stein's (1999) information diffusion process expects low volume stocks to produce higher short-term momentum profits and higher long-term contrarian profits if low volume stocks really adjust more slowly to public information than high volume stocks.

Using such a systematic framework of behavioral study on the trading volume and stock return patterns, we find some very interesting results as follows. First, we find strong but very different lead-lag relations between trading volume and stock returns in China's A share and B share markets. Particularly, we find strong negative relations between lagged trading volume and subsequent market return in the A share market, whereas we find positive relations between lagged market return and subsequent trading volume in both Shanghai B and Shenzhen B share markets, though the relations in the former market are stronger. These findings indicate that the relation between trading volume and stock returns in each particular market is determined by that market's particular characteristics. The different investor base, trading currency, and other characteristics of the A share and B share markets determine the different lead-lag patterns between volume and return and, thus, the underlying behavioral explanations. These findings also show that China's A share market is less efficient than its B share markets in that trading volume in the A share market contains important information to predict the subsequent market return. Second, we find that Lee and Swaminathan's (2000) Momentum Life Cycle hypothesis can best explain not only the strong negative lead-lag relations between lagged trading volume and subsequent return but also the profitability of momentum/contrarian strategies for different volume levels' winner and loser stocks in the China A share market (particularly, the contrarian profit for late stage momentum performers and momentum profit for early stage momentum performers). This finding demonstrates that the strong negative lead-lag patterns are not only statistically significant but also economically significant, in that such patterns can be taken advantage of in order to make profits under appropriate trading strategies. Third, we documented a material and statistically significant tendency for market-wide turnover to increase in the months following high market returns, after accounting for contemporaneous and lagged volatility associations, in China's two B share markets (especially in the Shanghai B share market). Our finding of a positive lead-lag relationship between lagged market return and subsequent turnover confirms the conventional wisdom of market making professionals as well as formal theories of investor overconfidence.

In summary, the findings that there exist strong lead-lag patterns between trading activities and market return, no matter whether the relation is between lagged trading volume and subsequent return or between lagged return and subsequent trading activity, are all important empirical facts, independent of the individual's interpretation, that should be acknowledged by theorists and empirical researchers.

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