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The Effects of Financial Ratios Publication and Bond Rating Announcements on Stock Prices

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Abstract: This thesis consists of two papers in the field of empirical study on stock markets. In the first paper "*An Empirical Study of the Correlation between Financial Ratios and Stock Price Volatility: A Case of China's A-shares 2000-2011*" I study the correlation between five financial ratios and the stock price volatility with a focus on A-class shares in both of the mainland China's stock exchanges namely Shanghai Stock Exchange and Shenzhen Stock Exchange. The data ranges from 2000 to 2011. Empirical results suggest there is a negative correlation between ROA and volatility with slight variation across industries and years depending on the market conditions. In the second paper "The Effects of Bond Rating Announcements on Stock Prices: An Empirical Investigation Using Event Study", I examine whether bond rating changes contain valuable information and hence have significant impact on stock prices with a focus on the US stock market. The standard event study methodology is applied to analyze this issue. Besides t-statistics, a new nonparametric sign test statistics developed by Luoma (2011) is employed to test the null hypothesis of no event effect. The result suggests that stock market reacts positively to downgrades the bonds which are below investment grade prior to rating changes. For downgrades the bonds which are above investment grade, a significant negative market reaction is found. For upgrades, the empirical result shows no significant abnormal stock returns.

Keywords: Financial Ratios, Dynamic Panel Data, Nonparametric Tests, Event Study, Bond Ratings
Supervisor: Assistant Professor Bige Kahraman
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CONTENTS

I. An Empirical Study of the Correlation between Financial Ratios and Stock Price Volatility: A Case of China's A-shares 2000-2011

ABSTRACT

This paper studies the correlation between five financial ratios and stock price volatility with a focus on A-class shares in both of the mainland China's stock exchanges namely Shanghai Stock Exchange and Shenzhen Stock Exchange. The data covers the years from 2000 to 2011. Pooled OLS, Fama-Macbeth and Dynamic Panel Data model are applied and deliver a set of consistent findings. Across all the industries, a significant negative correlation between ROA and volatility is detected with slight variation across different industries and years. During market downturn the correlation between ROA and volatility is vanished. By investigating individual industry, quick ratio is found to be even more significantly related to volatility in certain industries such as financial service and real estate.

Keywords: A-share, volatility, financial ratios, dynamic panel data

Supervisor: Assistant Professor Bige Kahraman

Acknowledgements: I would like to express my since gratitude to my supervisor, Assistant Professor Bige Kahraman, for her kind support and valuable opinions.

1. INTRODUCTION

Throughout the past decades we have witnessed a great deal of financial crisis, such as the one in 1987 October, US subprime mortgage crisis in 2008 and the most recent debt crisis broke out in Europe, while obviously the crisis is not a phenomenaappreciated by us. The most direct phenomenon we can perceive before and during the crisis is the relatively high volatility comparing to what it should be in the usual.[2] Modelling and predicting volatility precisely can help the regulator to better develop relevant regulations when it is necessary. In fact, it is common for a government to take into account the estimated volatility as indicator of the economy and financial markets' stabilization. When formulating its monetary policy, Federal Reserve takes the volatility of various financial tools into consideration (Nasar, Sylvia 1992).

Volatility is one of the key factors when making investment decisions, Investors with different level of risk preference have their own level of risk which they can tolerate. The risk tolerance diverged across different types of investors. There are some sophisticated institutional investors see the increased volatility as an opportunity, while generally the volatility is not favored by majority of the risk-averse retail investors.[3] In that sense, the research on the volatility prediction is very worthy and has attracted lots of financial economists and practioners' devotion to model and forecast the volatility of various financial securities such as options and stocks. But some of the existing researches only focusing modeling the volatility without forecasting. Over the past two decades, Tremendous research is focusing on the US or UK stock markets. Baillie and DeGennaro (1990) explore the dynamic features of expected stock volatility and returns in America's stock markets; Poon

2 Schwert, G W. 1990 investigate the financial crisis throughout the years from 1834 to 1987 and shows that stock volatility tends to increase amid financial crisis.

3 Funds Find Opportunities in Volatility, The New York Times, Mar 17, 2011.

and Taylor (1992) carry out the similar study on UK stock markets. Clustering, persistence and predictability of volatility are revealed by both of the two studies. Lots of financial economists are enthusiastic about investigating the volatility by applying sophisticated econometric models.Cumby, R. et al (1993) use the EGARCH models to forecast the volatility.

Research Motivation

Being launched in late 1990, China's stock exchanges are still in their very early stage and are criticized for various existing defects.[4] An intuitive research with meaningful results might be welcome by the market participants. Unfortunately, there are not many existing researches about volatility of mainland China's stock market. This may probably due to that China's stock exchanges are still in the very early stage and is not that mature as its peers in US and Europe. Information asymmetrywidely exists in China's stock market due to the not well developed regulation system, which makes it hard to obtain complete data for carrying out research. Another noteworthy thing is that the market is dominated by not well educated retail investors, who at the same time are vulnerable to stock market fluctuation. Thus it is worth of conducting anempirical study based on China's stock market to investigate the volatility and hopefully give investors a better guide on investment.

With a focus on the mainland China's stock market A-share stocks, this paper aims to study the correlation between financial ratios and the stock volatility. The data is mainly obtained from Wind information Co., Ltd ranging from 2000 to 2011 covering the 434 stocks listed in both of the stock exchanges in mainland China.[5] A

4 This study is limited to the two stock exchanges in mainland China, Shanghai Stock Exchange (SSE) and Shzhen Stock Exchange (SZSE), for details please refer to the following section.

5 Wind Information Co., Ltd (Wind Info)http://www.wind.com.cn/En/

For the list of stocks please refer to Appendix B simple pooled OLS will be used to provide a preliminary glance of the correlation between variables. Later on, Fama-Macbeth regression will be applied to correct for cross-sectional correlations and any biasedness resulted from OLS. The data is divided into 7 different industrial sectors and estimated by Fama-Macbeth individually to provide an insight into the sector-specific characters. At last, the dynamic panel data model (one-step GMM estimation) will be employed to take into consideration of unobserved heterogeneity in our sample data and provide more accurate estimates of the coefficients.

The rest of this paper is organized as follows: Section 2 reviews the existing related research. Section 3 introduces the current condition of China's stock markets and point out some existing defects. Section 4 describes the data and presents a preliminary descriptive analysis. Section 5 develops the estimation methodologies used in this paper and discusses the empirical findings. This paper concludes in Section 6 and research limitations are also discussed in this section.

2. LITERATURE REVIEW

In this section, only the researched related to stock volatility will be review. Over the past two decades, many financial economists and practioners have conducted research on stock volatility. The mainstream of research methodologies can be summarized in two categories.

2.1 The time series models

Taylor, James (2001) develops a Smooth Transition Exponential Smoothing model to forecast the volatility, which is superior to the traditional exponential weighted moving average (EWMA) method in terms of flexibility. Both the size and the sign can be a proxy of the weights.

Lee,Cheng, F., Chen,Gong-meng.&Rui, Oliver. M, (2001)provide evidence which shows that the volatility is time varying and highly predictable. They use the GARCH and EGARCH models to examine the time series characters of the stock returns and volatility. The data sample focuses on China's stock exchanges. The trading volume is taken as a proxy for information arrival time which finally proved to have no significant power for explaining or predicting the daily returns' conditional volatility.

Some researchers are enthusiastic about even more sophisticated time series models. Examples are Bera, A and Higgins, M(1993) and Lopez, J and Diebold (1995). Engle (1982) first came up with the ARCH (q) model to forecast the volatility. The function is based on the q past squared returns. Later on, Taylor (1986) apply the GARCH(p, q) model in investigating the volatility. By allowing the additional dependency, the model is empirically proved to be more robust than ARCH models. The subsequent researchersdevelop the research methods into an even more sophisticated level. The methodology examples are Exponential GARCH model (Nelson 1991), Quadratic GARCH model Dijk (2000) and so on.

2.2 Models based on derivatives

It is also common to model the volatility using the financial derivatives which are based on the stocks. Option is a class of derivatives most commonly used by the researchers to model and forecast volatility. And the basis for the class of research is mainly based on the work of Black and Scholes (1973), who first derive an valuation formula for the call options based on the stock.

Schmalensee, R and Trippi, Robert.R(1978) use the equilibrium formula derived by Black and Scholes to conduct an empirical study on US markets and propose that the stock volatility can be inferred by the option premia.

2.3 Other models:

Some of the researchers try to investigate the volatility from the perspective of investors' behavior. By formulating the one-period competitive model, Wang,Meijin& Sun,Jianjun(2004) try to explore the influencing factors of stock return and volatility. Both of the returns and volatility are significantly affected by the investors' sentiment.

By investigating in the effective bid-ask spread in the efficient markets, Roll (1984) reveals that the market microstructure has impact on volatility.

Glosten and Milgrom (1985) examine the adverse selection's effect on the market bid-ask spread, implicitly reveals that volatility is partly affected by the liquidity provision process.

Actually, it is very practical to analyze the relationship between financial ratios and stock pricevolatility. Especially for the investors, If any pattern of relationship between a set of financial indice and stock price volatility can be detected, investors can use the public available financial statements of certain companyto inter the risk of the companies. By doing so, investors can choose the portfolio based on the readily avaialble and easily understandable information. What's more, for the managers of companies, when they want to do risk management to control the volatility of their company, they can control their financial index instead.

The rest of this section will review the literatures related to the correlation between financial ratios and stock returns and volatility. There are many financial researchers examining the relation between financial ratios and stock returns. But, unfortunatelyvery limited papers are focusing the correlation between financial ratios and stock price volatility, even less researches on China's stock exchanges can be found.

The financial ratios stated on financial statements are the indicators of a certain company's operating and financial performance. It is worth to research on the financial ratios. Teppo (1995) applied factor analysis method to analyze 28 listed companies in Finland, and he found that the status of cumulative abnormal returns can be partly explained by financial ratios, but across the years the explanation capability is inconsistent.

By investigating the data of listed companies in New York Stock Exchange, Holthausenand Larcker (1992) indicate that there did exist a clear relationbetween some financial ratios (example price to book ratio) and accumulative abnormal returns of stock.

A positive relation between ROE and volatility is detected by Li et al. (1998) whoconducted a cross-sectional research on A-share stocks listed in Shanghai Stock Exchange. The evidence also shows that the volatility is significantly correlated to some other financial ratios such as the dividend and debt related ratios.

However, some other researchers held the slight different view on this issue. Focusing on the 366 listed A-share stocks in Shanghai Stock Exchange, Fu and Chen (2000)they conclude that at least 57% of the volatility can't be explained by financial factors.No more than 43% of volatility can be explained by financial ratios.This may due to the idiosyncratic characters of China's stock market.

Li (2004) carries out a comparison between the Chinese stock market and US stock market, which shows that correlation between financial ratios and volatility in China's stock market is not that significant comparing to that of US market.

Some researchers try to use different sampling method to provide a better view of the correlation between financial ratios and volatility. Yang (2006) conducts the research on a sector by sector base. He use the data of steel industry to examine the correlation. The data only covers the year from 2006 to 2008, while in this study, longer time range will be used to uncover the correlation.

3. INTRODUCTION OF CHINA'S STOCK MARKET

3.1 Fast growing market

Since the Chinese economic reform in 1978, China's economy has experience dramatically change. The market converted from central government planned economy to market orientated economy. Currently, China is the world's second largest economy by nominal GDP and purchasing power parity. 10% average growth rates over the past 30 years makes China become world's fastest growing economy.Being closely related to economy, China's Stock market also experienced tremendous development and growth. As a key component of stock market, China's stock exchanges played a positive role over the past 23 years.

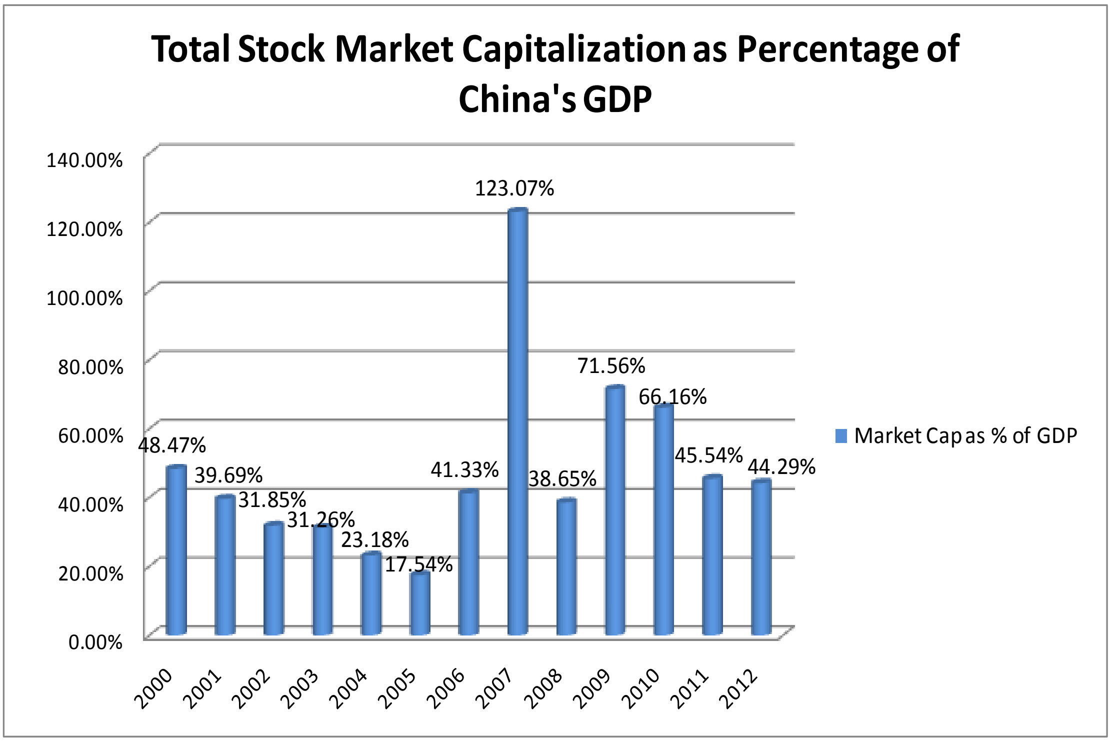
3.2 Two stock exchanges

There are two stock exchanges in China (In this study I mainly focus on the two stock exchanges in Mainland China, Hong Kong Stock Exchange is not covered), Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). Both of them were established in late 1990 and under the supervision of China Securities Regulatory Commission. Since its establishment, the SSE has become the most predominant stock market in Mainland China in terms of various criteria such as total market value, number of listed companies, number of shares listed, securities turnover in value, tradable market value, and the T-bond turnover in value.SZSE is striving to fulfill its commitment to developing China's multi-tiered capital market, contributing to China's economic transformation and development and boosting the nation's independent innovation.

The establishment of these two stock exchanges has been served as an important engine to both China's stock market and economy development. Since 1990, the market capitalization soared up from almost 0 to 23.04 trillion Chinese

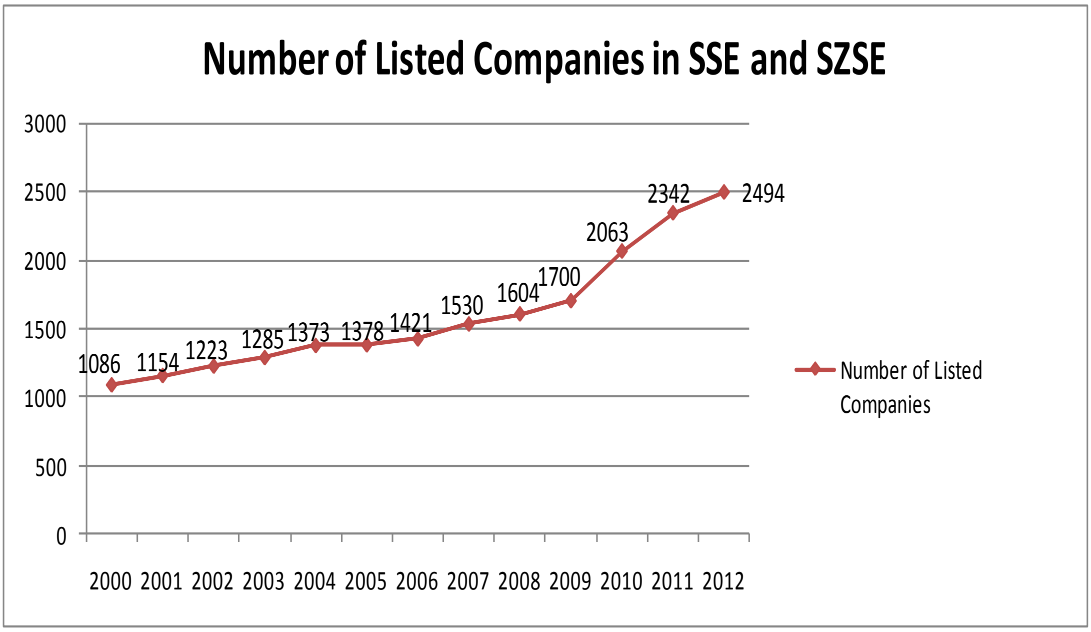
Yuan (abbr. RMB) in 2012, equivalent to 44.29% of the annual GDP of China in 2012.Number of listed companies reached record high of 2494 in 2011. The stock market capitalization as percentage of China's annual GDP from 2000 to 2012 is shown in Graph 1. The growing path of number of listed companies and total market capitalization in both stock exchanges can be observed in Graph 2 and Graph 3.

Graph 1: Total Stock Market Capitalization as Percentage of China's annual GDP



Data source: *Shanghai Stock Exchanges, Shenzhen Stock Exchange and National Bureau of Statistics of China*

Graph 2: Number of Listed Companies in China's Stock Exchanges



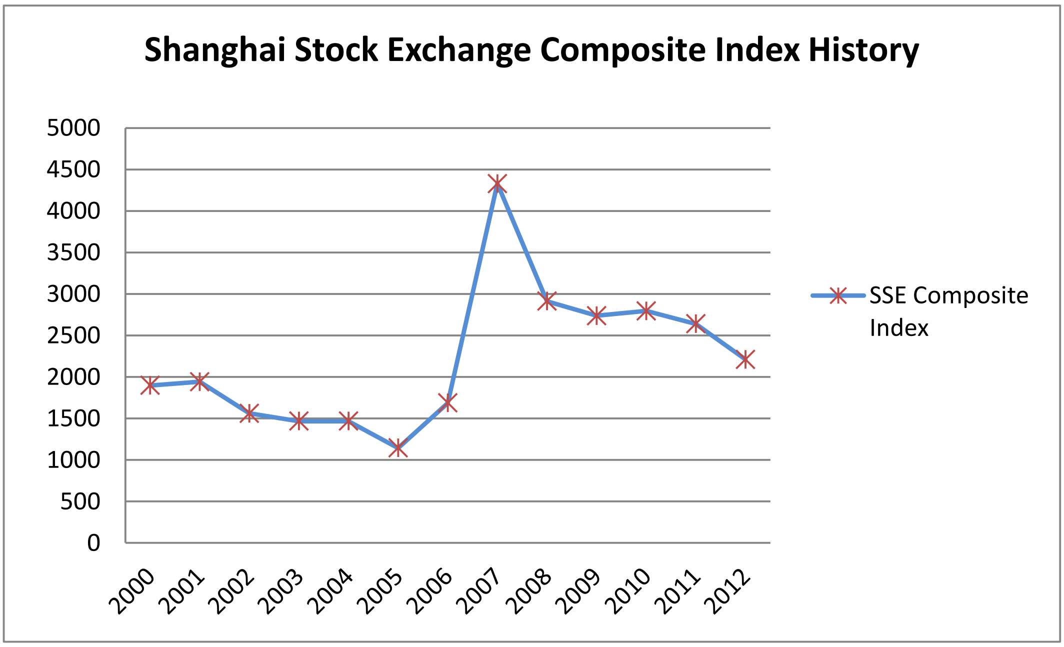
Data source: *Shanghai Stock Exchange and Shenzhen Stock Exchange*

Graph 3: Total Market Capitalization of China's Stock Exchanges (in RMB trillion)

Data source: *Shanghai Stock Exchange and Shenzhen Stock Exchange*

As we can see from above graphs, the number of listed companies is increasing all the way from 2000 to 2012.The macro trend of stock market capitalization is increasing while in the first half of 2000s the capitalization is relatively low comparing to the second half and shrink to 3.24 trillion RMB in the year of 2005, which is equal to 17.54% of the GDP in that year. In the following two years the market experience an unprecedented increasing soaring up to the peak point of 32.71 trillion RMB in the year of 2007 equivalent to 123.07% of GDP of the same year, which iscommonly perceived as the bull market in China. However, China was not able to withstand the global crisis in 2008; the stock market was suffering a downturn. The market capitalization decreases by 62.9%comparing to previous year, which is 12.14 trillion and only 38.65% of GDP of that year. After that, the market capitalization was rebounding. Overall, throughout the past decade, the total market capitalization of China’s stock market increased from almost 0 from the birth to 4.81 trillion RMB in 2000 and further grew to 23.04 trillion in 2012, which is really amazing performance a young stock exchange can ever achieve. The following Graph 4 presents the growing history of Shanghai Stock Exchange Composite Index from 2000 to 2012.

Graph 4: Shanghai Stock Exchange Composite Index History



Data source: *Yahoo Financehttp://finance.yahoo.com/*

3.3 Idiosyncratic features and defects of the two Stock Exchanges

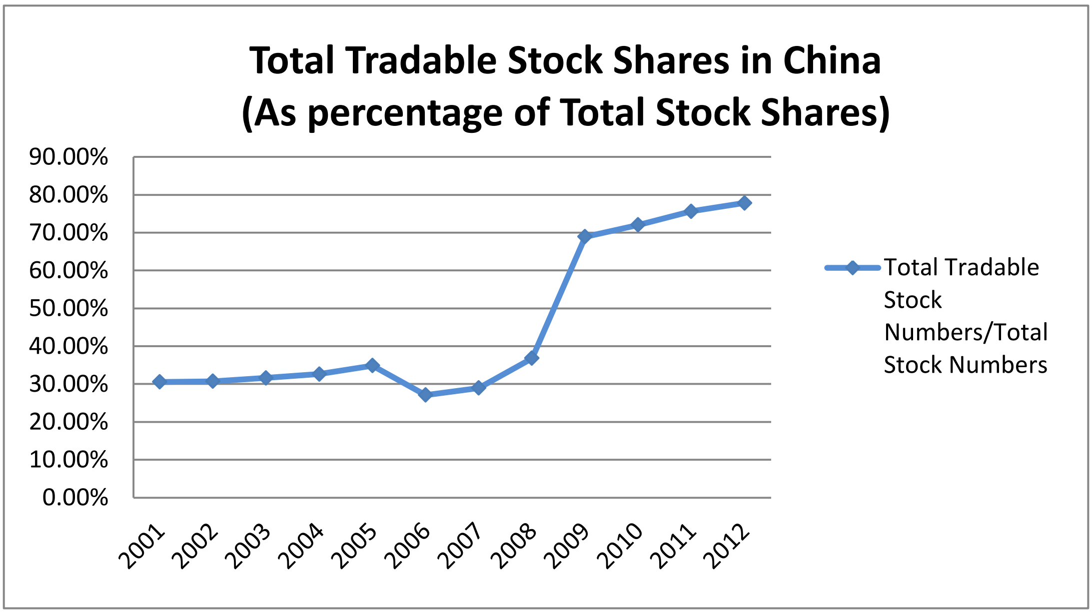
3.3.1 Equity ownership segregation and lack of tradable shares

One of the particular characteristics and problems of China's stock market is the equity ownership segregation and low proportion of tradable shares(abbr.TS) within total stock shares caused by the special stock market structure. As presented by Graph 5 and Graph 6, before 2005, the proportion of tradable shares was extremely low, which is only about 30% of the total stock shares. Non tradable shares (abbr. NTS) dominated the stock market. Even nowadays not all the stocks are tradable.

Graph 5: Total Stock Shares and Tradable Stock Shares in China

Data source: *wind*

Graph 6: Total Tradable Stock Shares as Percentage of Total Stock Shares



***Data source**: wind*

In the initial time, NTS shares were issued to the founders of a corporation, business partners or employees for the following two purposes: First, to maintain the government's control of state-owned companies that were listed in the market; Second, to maximize IPO proceeds and boost the nation's economy. Meanwhile the majority companies in China's stock exchange markets are state-owned companies. This equity structure arrangement resulted in several problems. The stock owners are divided into two major groups: the state-controlled entities and the public individuals. Only the shares held by public individuals are allowed to be traded on the stock exchanges.It was common to see the public companies with shares of different prices, different dividend and different equity. (Xu Xinhua and Chen Jianqing 2011). As the government noticed the defects caused by the large proportion of NTS, from 1997 to 2005 a series of reform was carried out in order to float part of NTS and promote the healthy development of the two stock exchanges, the most pronounced one was in 2005.Depending on lock-up rules, NTS are tradable within a year or two. Shareholders owning 5% or more of a company's outstanding shares can sell after two years, and owners of less than 5% can sell after a year. Many NTS passed their lock-up period in 2008 and 2009. As what we can see from the above two graphs, the percentage of tradable shares increased a lot starting from 2008.

3.3.2 Different share classes

The tradable shares are further classified into four classes: A-shares, B-shares, H-shares and N-Shares. The A-share are restricted to domestic investors and traded in RMB. B-shares are known as officially domestically listed foreign investment shares traded in foreign currencies and are available to both domestic and foreign investors. H-shares are shares of companies incorporated in mainland China traded on Hong Kong Stock exchange and N-shares are shares traded on US Stock Exchanges, including the NYSE and NASDAQ.

In May 2000,strict restriction to A-class shares were partially liberalized, qualified foreign institutional investors (QFII) are allowed to invest in the A-class shares. Since then China experienced tremendous boom. In next year Shanghai Composite Index went up by 130% and Shenzhen Composite Index even more by 197%.[6]

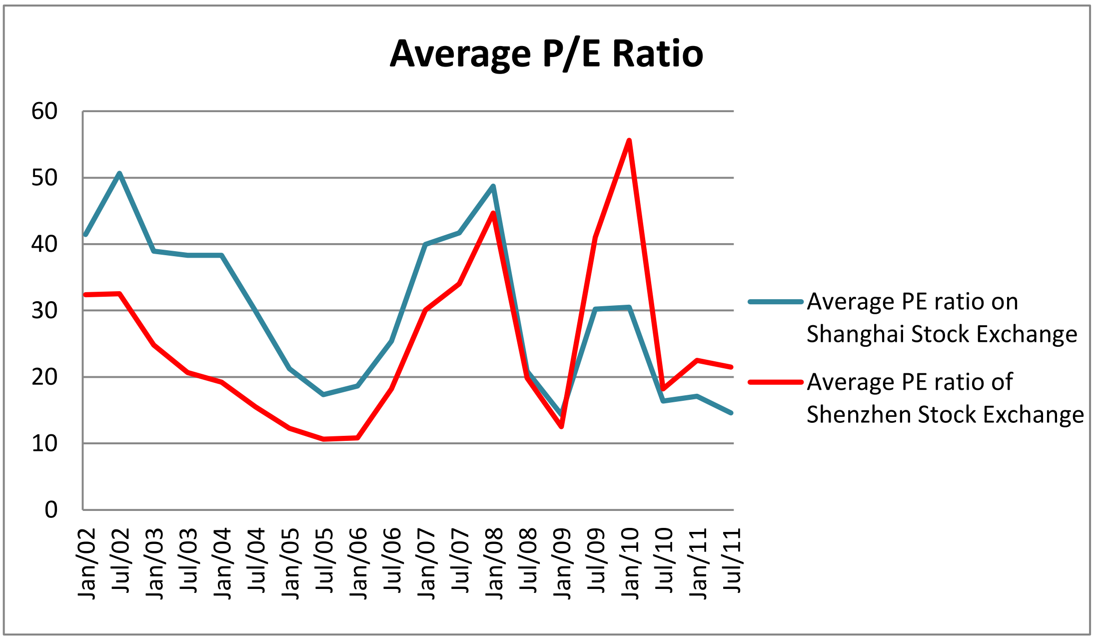
3.3.3 Irrationally high P/E ratios of A-shares

As we can read read from Graph 7, the historically average P/E ratio for China's both stock exchanges are evolving around 30. In 2010 this figure is even greater than 50 for Shenzhen Stock Exchange. While in a mature stock market, this figure tends to be much lower. For example, the historical average U.S. equity P/E ratio from 1900 to 2005 is 14 calculated by geometric mean or 16 calculated by the

6 Data source: Shanghai Stock Exchange and Shenzhen Stock Exchange website

arithmetic meanrespectively. It is suggested that P/E ratio in low twenties is sustainable.[7]

Graph 7: Average P/E ratio on Shanghai and Shenzhen Stock Exchange



Data source: *Wind*

The irrationally high P/E ratio is due to various reasons. The share structure mentioned in previous section is one of them; usually the price for the tradable shares held by public individual is much higher than that of state-owned shares since the tradable shares holder have to pay for the liquidity premium. Therefore it is not uncommon the see the huge price discrepancies between the A shares and the other share classes of the same company. Unbalanced supply and demand is another reason. This unbalance can be sub attribute to different drivers. The NTS suppressed a fraction of capital, reduce supply and push up the price of TS. Furthermore, theChinese government restricts mainland Chinese people from investing abroad,

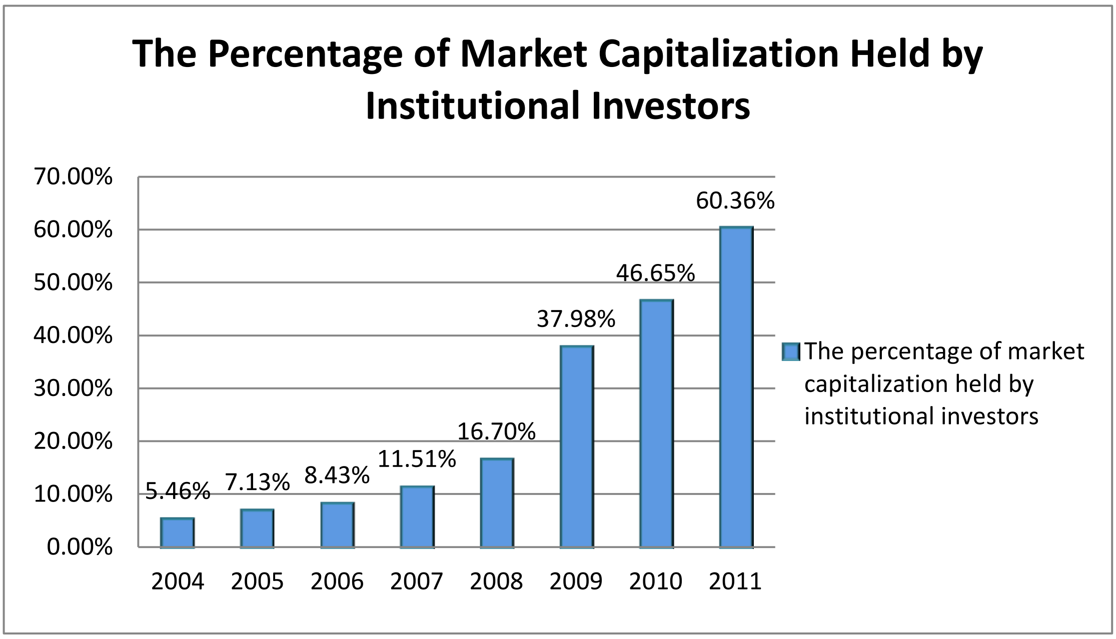
7 Jeremy Siegel, Stocks for the Long Run, (2002 edition)

andthe foreign investors can invest in A-shares only through QFII program set by Chinese government.[8]

3.3.4 Dominated by not well educated retail investors

Stock market in china is dominated by retail investors. Before 2009, holdings of institutions in China are not more than 20% of total market share. While on most stock markets of developed countries, there are 70% or higher percentage of institutional investors.[9] Graph 8 exhibits the participation of institutional investors from 2004 to 2011.

Graph 8: The percentage of market capitalization held by institutional investors



Data source: *PICC Corporation, Research Department*

8 QFII (The Qualified Foreign Institutional Investor) was launched in 2002 in China to allow licensed qualified foreign investors to trade on RMB-denominated A-shares in China's mainland stock exchanges (namely, SSE and SZSE). Mainland China's stock exchanes were

9 Institutional investors include mutual fund, insurance companies, pension funds, Qualified Foreign Institutional Investors (QFIIs), private funds investing in equities and some others.

Odean (1999) states that individual investors tend to trade excessively are more risk-taking and tend to make poor investment decisions. Most of their decisions are based on greater fool theory.[10]

It is assumed that institutional investors can direct the other investors on the right track stabilize the market and share the correct value of investing. Zweig (1973) proposes that institutional investors are “smart money investors”, they can offset retail investors’ irrational trading and thus stabilize asset price.Since on China’s stock market, there are relatively fewer institutional investors comparing to the mature ones, the market tends to be more speculative and volatile

10 The greater fool theory, also known as survivor investing, is the belief held by one who makes a questionable investment and assumes they will be able to sell it to “a greater fool” at higher price. That is to say buying something not because you believe it is worth the price but because you believe that you will be able to sell it at even higher price later

4. DATA

4.1 Data collection

The data used in this study is mainly obtained from Wind information Co., Ltd, a leading integrated service provider of information, financial data, and software.[11] Wind Info covers more than 90% of the financial companies in China's financial market and 75% of the Qualified Foreign Institutional Investors (QFII).

Since the China's stock market are still in its very early stage of development and most of the listed firms didn'tfinish the non-tradable shares reform until 2000. Due to the not well developed reporting regulation and system the data for 2012 is not complete for all the firms in this study. This paper uses the data from 2000 to 2011 which covers the following variables, historic annual volatility quick ratio, return on asset (ROA), asset turnover rate(thereafter abbre. Assettvr), market capitalization (thereafter abbre. MktCap) and growth of operating profit (thereafter abbre. Gro_Ope_Pro).[12] As it is hard to obtain the quarterly or semi-annual data for all the financial ratios, and in order to avoid too small sample size, the annual data is used to carry out this study.

Originally, there are 1085 observations in the sample. Due to that not all the stocks have complete data for all the variables coveringthe intended research time span. After eliminating the observations with incomplete data, 434 stocks remained in the sample.[13] A total of 228 (52.53% of the sample) stocks are listed in SSE and 206 (47.47% of the sample) stocks are listed in SZSE which is parallel with slight

11 Wind Information Co., Ltd (Wind Info)http://www.wind.com.cn/En/

12 Annual market capitalization is simple average of 12 monthly figures within certain year. Wind provides the historic annual volatility calculated from the historic price of corresponding stocks

13 This study is limited to the A-shares in both of the two stock exchanges in mainland China

unbalance compare to the distribution of population. In terms of A-class shares SSE has more listed stocks than that of SZSE which are 944 and 469 respectively.[14]

4.2 Definition of the variables

In this study, there are 6 variables in total, namely volatility (abbre. vol), quick ratio, return on asset (ROA), asset turnover rate (Assettvr), market capitalization (MktCap) and growth of operating profit (Gro_Ope_Pro)

4.2.1 Volatility

Volatility denoted byσ, can be intuitively explained as the uncertainty of magnitude of price movement of asecurity. According to the calculating way, volatility can be classified as historic volatility, implied volatility and etc. Statically the historic volatility is measured by the standard deviation of the security's historical market price (or the deviation from market index), while the implied volatility is derived from certain traded derivatives which are based on the security.[15] In this study, historic annual volatility of stock prices is obtained from wind info, which is calculated as the sample standard deviation.

4.2.2 Financial ratios

Financial ratios are expressions that give us a comprehensive story of the financial performance of a company by combining the different components from financial statements

14 Data per SSE and SZSE website on May 7th 2013

15 For details please refer to Greg N. Gregoriou. 2009. Stock market volatility:CRC Press

It is widely accepted in considerable literatures and international accounting standards that financial ratios can be mainly classified into following four groups:[16]

Liquidity Ratios: used to measure how capable a company is to pay off its short term debts. The higher is the ratio, the more likely that the company will be able to cover its short-term debts.

Leveraging Ratios: similar to liquidity ratios but measuring the company's ability to replay the long-term debts.

Operating/Efficiency Ratios: indicates how efficient the assets are used by the company in the operating process. Such as the asset turnover rate, inventory turnover rate. etc.

Operating Performance/Profitability Ratios: used to assess the ability of a company to generate the earnings using the cost spent during the operating process.

The following financial ratios are selected to conduct this study:[17]

A. Return on Assets (ROA):

$$\mathrm{ROA} = \frac{\text{Net Income After Tax}}{\text{Average Total Assets}}$$

B. Quick ratio also known as Acid-Test Ratio:

$$\text{Quick Ratio} = \frac{\text{Current Assets} - \text{Inventory} - \text{Cash Equivalent}}{\text{Current Liabilitities}}$$

C. Asset Turnover Rate(Assettvr):

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16 Wiehle U., Diegelmann M., Deter H., Schömig P, Rolf M. July 2005. 100 IFRS Financial Ratios cometis publishing GmbH; 1st edition

Scott Willian R. 2012 Financial accounting theory. Toronto, Pearson Canada

17 For the detailed calculation please refer to GroppelliA., Nikbakht E. 2000. Finance, 4th ed: Barron's Educational Series

$$\text{Asset Turnover Rate} = \frac{\text{Net Sales}}{\text{Average Total Asset}}$$

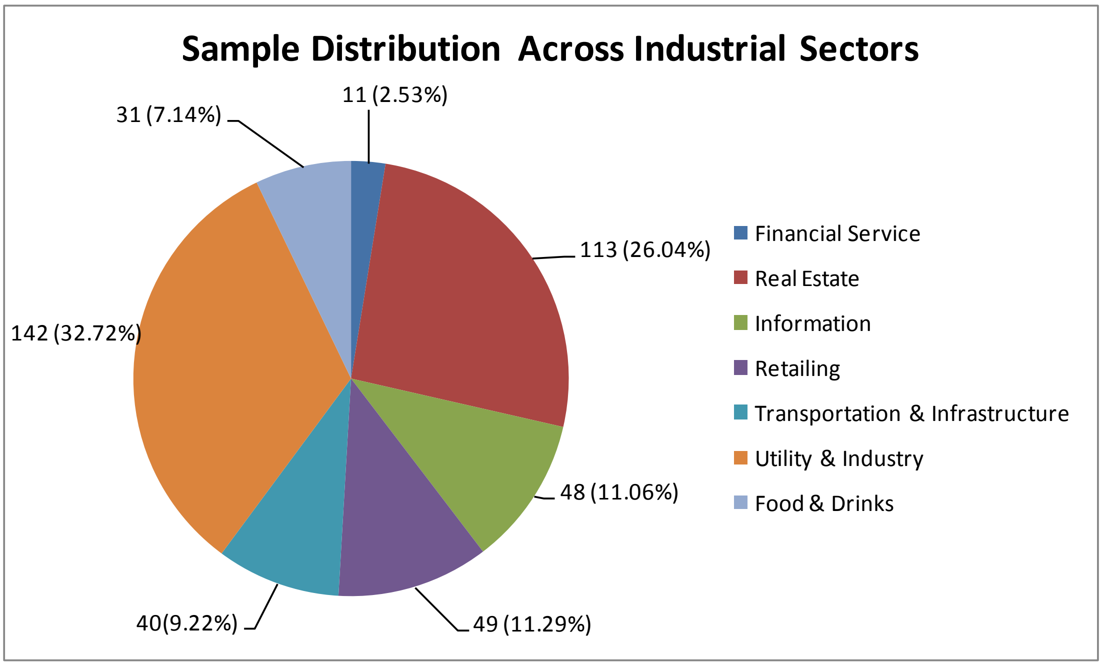
D. Growth of Operating Profit (year –on-year basis, denoted as Gro_Ope_Pro)

$$\text{Growth of Operating profit}_t = \frac{\text{Operating profit}_t - \text{Operating profit}_{t-1}}{\text{Operating profit}_{t-1}}$$

4.3 Descriptive analysis

The 434 observations are further divided into 7 industrial sectors.[18] Financial services, Real estate, Information, Retailing, Transportation & Infrastructure, Utility & Industry and Food & drinks.[19] The pie graph below shows the sample distribution across the seven industries.

Graph 9: Sample distribution across Industrial Sectors



***Data source**: Wind*

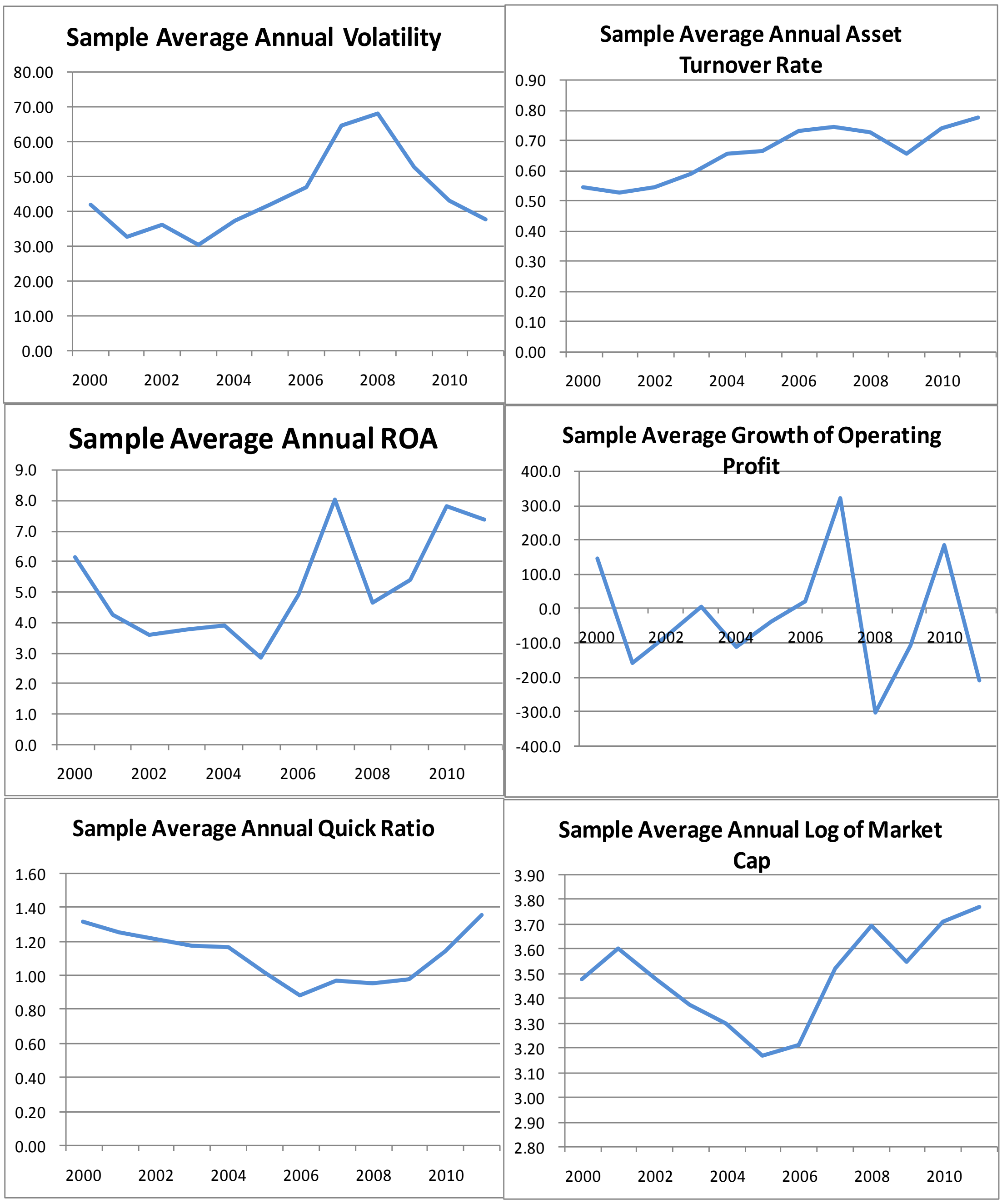
18 the classification is subject to *Guidance for Industry Classification of Listed Companies (2012 revised edition)* released by China Securities Regulatory Commission (CSRC) in Oct 2012.

19 Including oil and chemical, mechanical, food and drinks, coal mining,etc.

The sample distribution reflects the fundamental state of the China's stock markets which are dominated by the companies in utility and real estate industries. Most of the companies operate in utility industry are state-run enterprises with large market capitalization.

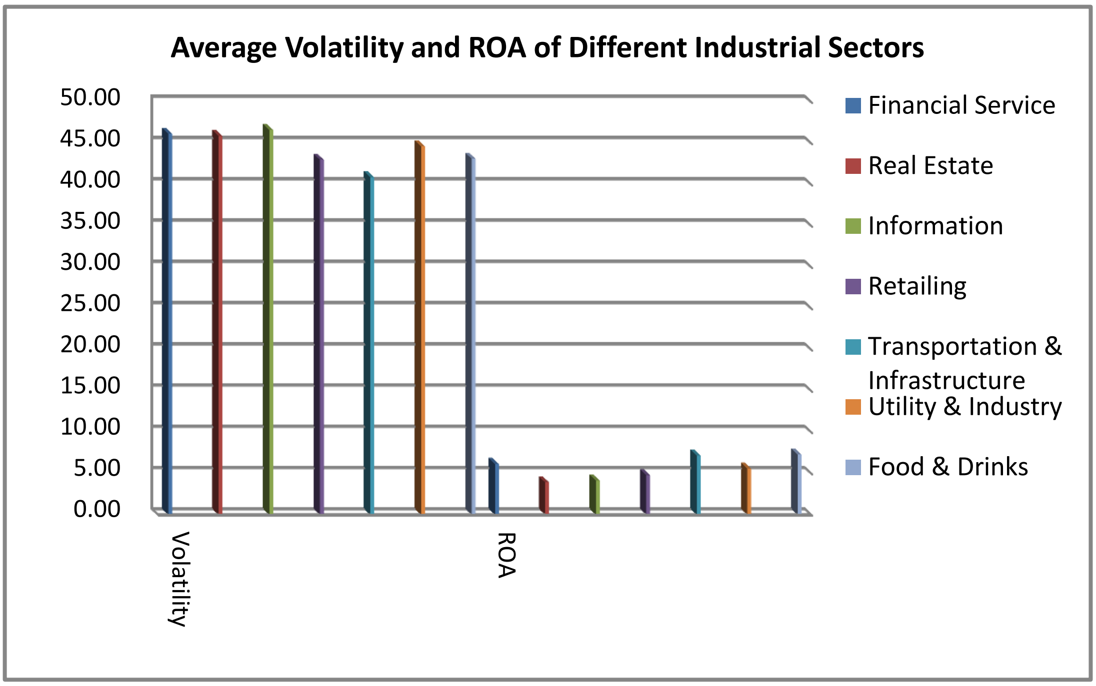
The Graph 10 visually displays the average trend of the 6 variables from 2000 to 2011. As we can see the volatility arrives in the peak point around 2007 and 2008 when the China's stock market was not able to withstand the subprime crisis when was experiencing the turning point from boom market to bear market. An insightful finding is that the ROA is evolving proactively in a similar pattern to volatility. Thus it is reasonable to expect that volatility can be partly predicted by ROA. Generallythe quick ratio has opposite trend as of volatility.

Graph 10: Average of the variables from 2000 to 2011



Data source: *wind*

Graph 11: Average Volatility and ROA of Different Industrial Sectors



Data source: *Wind*

Graph 11 indicates the two chosen variables, volatility and ROA, across different sectors. Generally the three industries with highest volatility are Information, Financial Service and Real Estate industries. Whit the top three industries in terms of ROA are Food & Drinks, Transportation & Infrastructure and Financial Service. The real estate industry in China possesses the China-specific characteristics. As a key engine of China's economic growth, accounts directly for 12% of China's GDP in 2011 (WST, July 2012),real estate is a hot industry and attracts lots of speculative investment. The speculation makes the industry provide its investors with relatively high volatility and low return on asset.

It is worth notice that the transportation & infrastructure and food & drinks deliver relatively high ROA but low volatility.Being closely related to people's daily life and serving the necessity, Food & drinks is more resistant to economic situation. Furthermore as China is on the fast track of developing, disposable income of households is increasing, the high end service providers in food & drinks industry are favored by more and more people. Thus is not surprising to see this industry is with low volatility and high ROA.

Being regarded as the gate of the national economy, majority of the companies in utility sector are owned by the government and do not put profit on the first place of their operating goals. The volatility and ROA in utility industry rank middle among the seven sectors.

5. METHODOLOGY AND EMPIRICAL RESULTS

5.1 Pooled OLS regression

A pooled OLS regression is first deployed to give a preliminary statistical view of the correlation between the variables under study. When applying the pooled OLS regression to the panel data in this case with the following regression equation. The regression is first applied to 7 different sectors individually and later on applied to the whole sample pooling all the sectors.All the observationsin each sample are pooled on sample-wise basis and each individual are assumed to have the same coefficients. The dependent variable should satisfy the exogeneity assumption in order to arrive in unbiased estimates.[20]

$$\begin{aligned}\mathrm{Volatility}_{it} = \alpha + \beta_1 \mathrm{ROA}_{it} + \beta_2 \mathrm{QuickRatio}_{it} + \beta_3 \ln(\mathrm{MktCap})_{it} \\ + \beta_4 \mathrm{Assettvr}_{it} \quad + \beta_5 \mathrm{Gro\_Ope\_Pro}_{it} + \epsilon_{it}\end{aligned} \tag{1}$$

Where i=1, 2….N, t=1, 2…T,

N=434, T=12 (when regression for all 7 sectors)[21]

The regression resultfor sector wise and sample wise are presented in Table 1 and Table 2 respectively. From Table 2 we can observe that for all the 434 stocks in our sample, both ROA and Quick ratio have significantly negative correlation with volatility (significant at 90% and 95% confidence level respectively). The preliminary regression reveals that generally for a certain company from 2000 to 2011 the higher ROA and quick ratio it has, the lower is its stock price volatility. While table 1 gives us more detailed information related to each single sector. It is notable to see that in financial service sector, quick ratio is extremely negatively related to the volatility, significant at 99% confidence level. As financial service is a business with high risk and sensitivity. The investors make the decision is

20 Kim, H.Principle of Economics lecture notes, University of Minnesota

21 When regression is conducted for individual sector, N is equal to the number of stocks in that sector

significantly affected by the financial service company's short-term prospect. If investors perceive that a certain company is not able to repay its short-term debt (low quick ratio), they probably will take action to address on this potential risk, which will finally lead to fluctuatedstock price and increased volatility.

As the pooled OLS regression model assumes that each individual has the same effect on the dependant variable. Even if the individual i has time-invariant effect, if such an effect is distinctive from the other individuals, the estimates is suffering the biasness. It is reasonable to expect that there are some individual stocks which have unique pattern of effect on volatility. So the estimates here is somewhat biased. In the following section, Fama-Macbeth regression model is used to analyze the correlation between variables in each single year and theaverage level from 2000 to 2011.

Table 1: OLS regression for different sectors

	1.Financial Service	2.Real Estate	3.Information	4.Retailing	5.Transportation & Infrastructure	6.Utility	7.Food &Drinks
roa	0.191	0.0117	-0.0428	-0.0834	-0.0951	-0.0744*	0.0513
	-1.19	-0.32	(-1.31)	(-0.80)	(-0.87)	(-2.26)	-0.5
quickratio	-8.724***	-0.368*	0.986	-0.55	-0.407	-0.175*	-3.083*
	(-3.63)	(-2.31)	-1.96	(-0.75)	(-1.54)	(-2.03)	(-2.09)
astvr	-4.16	-1.878	-0.148	0.462	4.009**	1.680*	2.503*
	(-1.14)	(-1.48)	(-0.13)	-0.52	-2.58	-2.42	-2.2
grth_opeprofit	0.00106	0.000407	-0.000226	-0.0000727	-0.000744	-5.49E-05	-0.000287
	-0.59	-1.27	(-1.04)	(-0.19)	(-1.19)	(-0.63)	(-0.40)
lg_mcap	3.634*	0.14	-1.704*	1.635*	-0.364	0.721	-1.049
	-2.2	-0.31	(-2.24)	-2.07	(-0.47)	-1.86	(-1.14)
_cons	25.76	45.83***	59.41***	30.77***	43.48***	38.09***	52.40***
	-1.91	-12.64	-9.61	-5.24	-6.74	-12.4	-7.25
N	132	1357	576	588	480	1703	372

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Fama-Macbeth Regression Model

The two-step Fama-Mecbeth(FM thereafter)regression method (Fama& Macbeth, 1973) was first introduced for estimating the regression coefficients of asset pricing models such as CAPM. Since that, FM model is widely used to handle the financial panel data with multiple observations across a period of time. The first time of FM method being applied rigorously to estimate the factor pricing model is carried out by Shanken (1985). Skoulakis (2005) shows that FM method is as efficient as the generalized method of moments (GMM) approach. Cochrane (2001) demonstrates that, FM model is equivalent to OLS if the dependant variable is imposed with a time-invariant assumption. However, such an assumption is rather unrealistic.

It is worth to mention that FM estimates can correct for cross sectional correlation but not time-series autocorrelation. Fortunately it won't be a problem for applying to the stock data since the stocks are assumed to have weak time-series autocorrelation (Fama, E.F. and French, K.R,1988).

In this section we follow the original two-step procedures same as that in (Coval and Shumway, 2005).[22] They conduct the cross sectional regression on a day-by-day basis and average the coefficients across days. Basically the estimation of original Fama-Macbeth model is done by two steps:

(1) In each time period (in each year in this case), regress all the dependant variables to the independent variables for all the observations (cross-sectional regression);

(2) Derive the estimates simply by averaging the results from first step across the time span (2000-2011 in this case).

The regression result in each individual year and the average level from 2000 to 2011 is presented in Table 2. Interpreting from the perspective of significance

22 the regression equation is the same as the equation (1).

level, the variables which correlated with volatility are ROA and log of market cap. Both of them have significant negative relation with volatility in 6 years out of 12 in total and mostly significant on a confidence level of 99% or 95%.

ROA is negatively related to volatility at confidence level of 99% from 2001 to 2005, and has no relation with volatility throughout the years from 2006 to 2009. A similar pattern can be observed for the variable ln(MktCap). It is reasonable to expect that in a relative stable market condition (2001-2005), a company with higher ROA usually have lower volatility of stock price. Since the market is without turmoil and a company with strong ability to generate profit, which makes the investors believe that there is little space for speculation. Thus the stock price volatility tends to be lower. 2006 and 2007 China's stock market was experiencing an unprecedented booming years. The NT reform was in progress, the number of tradable socks was increasing. SSE Composite Index soared up and reached a record high in the year of 2007 (Graph 4). The average P/E ratio for both stock exchanges also reached the peak point in 2007 (Graph 7). As discussed in previous sector, the investor in China's stock market is dominated by not well educated retail investors who are more likely to see the booming market as an opportunity of speculation. In such a period, irrational investment decisions are more likely to be made. Thus the ROA lose its predicting ability. Similar thing in the year from 2008 onwards, China was not able to stand clear from the sub-prime crisis. The SSE Composite Index dropped down all the way from 2007 to2010 and no rebounding was detected until 2011 (Graph 4). Even now, the market is still on the process of recovery.

ROA and market capitalization have relatively strong prediction power in a stable market condition and will lose the power upon an abnormally unstable market.

Table 2: Pooled OLS and Fama-MacBeth regression results

	(OLS)	2000	2001	2002	2003	2004	2005
QuickRatio	-0.207**	-0.497	0.0999	-0.09	-0.0824	-0.112	0.0366
	(-2.95)	(-1.52)	-0.78	(-0.66)	(-0.57)	(-0.90)	-0.15
ROA	-0.0455*	-0.0897	-0.145***	-0.135***	-0.163***	-0.131***	-0.178***
	(-2.56)	(-1.85)	(-3.95)	(-3.91)	(-4.31)	(-4.12)	(-3.45)
AsTvr	0.709	-1.35	-0.418	-3.046***	0.735	-1.246	-1.622
	-1.9	(-1.69)	(-0.70)	(-4.15)	-1	(-1.76)	(-1.67)
Grth_OpePro	-5.89E-05	0.0000551	-0.000207	-6.18E-08	0.000193	-0.000345	0.000113
	(-0.78)	-0.47	(-1.52)	(-0.00)	-0.59	(-0.92)	-0.17
ln_MCap	0.202	-1.337**	-0.507	-2.205***	-0.919	-1.606***	-3.190***
	-0.89	(-2.75)	(-1.35)	(-4.65)	(-1.85)	(-3.36)	(-4.94)
_cons	42.99***	54.75***	37.73***	56.14***	37.94***	51.19***	66.98***
	-23.68	-14.24	-12.14	-14.65	-9.83	-14.2	-14.4
N	5208	434	434	434	434	434	434

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	2006	2007	2008	2009	2010	2011	Fama-MacBeth
QuickRatio	-0.414	-0.0951	0.178	-0.39	-0.0679	-0.0325	-0.122
	(-0.90)	(-0.15)	-0.62	(-1.30)	(-0.72)	(-0.61)	(-2.03)
ROA	0.0162	-0.0422	-0.0496	0.00699	-0.0456*	0.00953	-0.0788**
	-0.28	(-0.60)	(-1.43)	-0.17	(-2.20)	-0.39	(-3.87)
AsTvr	-0.287	1.199	-2.433**	-0.803	-0.481	-0.0341	-0.816*
	(-0.34)	-0.74	(-2.88)	(-1.23)	(-0.90)	(-0.06)	(-2.32)
Grth_OpePro	0.000289	0.0000479	-0.000136	-6.88E-05	0.0000866	-0.000188**	-1.33E-05
	-0.31	-0.19	(-0.69)	(-0.77)	-0.55	(-2.69)	(-0.25)
ln_MCap	0.472	-1.942	0.734	-1.223**	-0.591	-1.358**	-1.139**
	-0.77	(-1.94)	-1.39	(-3.02)	(-1.51)	(-3.11)	(-3.61)
_cons	43.91***	80.17***	63.76***	63.77***	49.00***	49.53***	54.57***
	-9.98	-9.95	-14.29	-19.25	-14.61	-13.11	-15.11
N	434	434	434	434	434	434	5208

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

However, nosignificant correlation between the other financial variables and volatilityis found under FM regression. Asset turnover rate is only negatively correlated with volatility in the year of 2002 and 2008 which doesn't provide any intuitive meaning. Meanwhile it is surprisingly to see that Quick ratio is not related to volatility at all. The growth of operating profit has relationship with volatility only in the year of 2011, it seems when the market approaching the mature status, the investors are more likely to make rational investment decisions based on the profit and growing potential of the company. Yet we still need data starting from 2012 to confirm this hypothesis.

Since only ROA and market capitalization significantlycorrelated with volatility, Dynamic panel data will be applied to the delta figure of the two variables together with the quick ratio. Since it is worth of further research on whether the change of quick ratio has any correlation with volatility.

5.3 Dynamic Panel Data Model

Many financial economists are confronted with panel data when carrying our research. The purpose to combine the time series and cross sectional data into a set of panel data is to uncover any potentially unobserved individual effect which is correlated to dependant variable. If estimated by OLS or GLS methods will result in biased estimates, as Hausman,J. A. & Taylor ,W. E. (1981) argue in their paper.[23] Since the OLS estimation is unbiased when a strict assumption was imposed, which is that each individuali has time-invariant and effect on dependant variable and such an effect is identical for different individuals. And as discussed in previous section, even though Fama-Macbeth is slightly superior to OLS by correcting for the cross sectional correlation, it still suffers from the similar drawbacks as OLS. Therefore in this section, dynamic panel data model is used to deal with the unobserved heterogeneity in our sample data.[24]

23 Jerry A. Hausman& William E. Taylor. 1981
24 For detailed inference please refer to Baltagi, B. H 2005

Dynamic panel data models are widely applied to different areas of study. Gari, T (2006) applies the model to examine the international tourism in Canary Islands. Bond et al. (2002) study on a sample consisted of 703 UK listed companies ranging from 1987 to 2000 to uncover the correlation between the company's gross investment expenses and its equity value. Arellano and Bond (1991) apply the dynamic model to the annual data of 140 UK firms from 1976 to 1984 trying to reveal which variables can affect optimal employment level.[25]

The general panel data model appears with following form with a lagged term of dependant variable:

$$y_{it} = \delta y_{i,t-1} + x_{it}\beta + \xi_{it} \text{where } i = 1, \dots, N \;\; t = 1, \dots, T \tag{2}$$

$$\xi_{it} = \mu_i + v_{it}$$

Whereμ_i stands for the individual effect, which usually are unobservable and v_{it} denotes the error term following i.i.d $(0,\sigma_v^2)$ distribution.

Also it is possible to add the time effect, lagged term of independent variables and/or additional lags of y. According to the assumptions imposed above, independent variable is independent of the error term.[26] By the construction of equation, y_{it} and its lagged term are supposed to be correlated with the individual effectμ_i

Existing textbooks and research papers have discussed extensively of performance of different estimating methods to dynamic models.[27] When the heterogeneous effect is fixed effect, even though we can eliminate the individual effect term μ_i, by taking the first difference and the disturbance term v_{it} is not serially correlated, a correlation between dependent variable and disturbance term

25 The variables covered in this research are one-period lagged employment wages, output demand, equity value and etc.

26 But it is still possible that independent variable is correlated with the unobserved individual effect μ_i or time effect if we included in.

27 Baltagi, B. H 2005. Econometric Analysis of Panel Data

exist.[28] Thus the OLS estimate is biased but consistent when $T \rightarrow \infty$. The Random Effect Model, which assume μ_i is following a normal distribution with mean zero and is independent of v_{it}. The Random Effect Model is suitable case that when we randomly draw N individuals from a large population. Since the estimation arrangement introduces the correlation between repressors and individual effect terms, the GLS estimates are also biased.

In this paper, the one-step first-differenced Generalize Method of Moments estimator is used (thereafter GMM).Hansen, L.P. (1982) is the first one who came up with the GMM. Later on Holtz-Eakin, D., Newey, H.E and Rosen (1988) developed the first-differenced GMM, which are designed for "a sample with large N butt small T". Arellano and Bond (1991) conducted a rigorous survey on different estimators and conclude that GMM can correct for the biasness discussed above. Two-step GMM is proved to be only marginally improved comparing to one-step GMM.[29] The magnitude of estimated coefficients is almost the same only the standard error is slightly decreased. Thus the two-step GMM only provides some improvement in precision when there is heteroskedastic error term.

The one-step GMM idea is as following. Firstly, get rid of the individual effect term $\mu_i$and any time invariant component in the repressorsby the differencing. Secondly, incorporate all the past information of dependant variable y_i by using it as instruments. Finally, arrange the disturbance term and infer the estimates. The process also gets rid of the endogeneity that may be resulted from the correlation of individual effects and the independent variables on the right hand side of equation. The moment conditions utilize the orthogonality conditions between the lagged terms and differenced errors of the dependent variable.

28 Bond, S. 2002. Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice, working paper, the Institute for Fiscal Studies
29 Windmeijer. 2000

In this paper the following equationsare estimated:[30]

$$\text{Volatility}_{it} = \delta_{it}\text{Volatility}_{i,t-1} + \beta_{it}\text{ROA}_{it-1} + \gamma_{it}\,\text{QuickRatio}_{it} + \theta_{it}\ln(\text{MktCap})_{it} + \lambda_{it}\text{Assettvr}_{it} + \Phi_{it}\text{Gro\_Ope\_Pro}_{it} + \mu_i + v_{it} \quad (3)$$

Where i=1, 2….N, t=1, 2…T, μ_i is the individual effect

The GMM estimation result for the whole sample and some selective estimates for different sectors are presented in Table 3.[31]

Table 3: GMM estimation result[32]

GMM	N=4340				
L.Volatility	L.ROA	ln_MCap	QuickRatio	AsTvr	Grth_OpeProfit
0.476***	-0.120*	-2.013*	-1.766	35.52***	0.000883
(8.89)	(-2.18)	(-2.42)	(-1.32)	(4.5)	(1.2)

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 3, L.Volatilityand L.ROA stands for the one-period lagged term of volatility and ROA respectively. The first line of numbers shows the estimated coefficient, the corresponding t-statistics is in parentheses under. With the GMM estimation, lagged ROA has significant negative correlation with volatility on 90% confidence level, which means that a firm with higher ROA tends to be followed by lower stock price volatility. Since the higher ROA strengthen the investors' confidence in certain company's fugure performance and attracts the investors to stay stable relatively longer with the company. Thus the volatility is stabilized. When a lower ROA is perceived by investor, divergent investment decisions arose among investors. Some risk seeking investors are willing to take a speculative position in the

30 Estimation is achieved in Stata with xtabond2 command
31 For sample code please refer to Appendix A
32 for detailed results please refer to Appendix A

company’s stocks while those risk-averse people would probably clear their position in that company. Such noisytrades will lead to an increased volatility.

Another noteworthy point is that the volatility is highly positively correlated with asset turnover rate. As Fairfield, P.M &Yohn, T (2001) propose that if a company has a asset turnover ratehigher than the industry average, it may indicate thatgiven the asset invested, the firm does not generate a sufficient volume of sales comparing to tis peers. Thus a low profit marginal can be reasonably expected. So this estimated coefficient results is consistent with that of ROA, when a company has higher asset turnover rate (lower potential profit margin), its stock volatility tends to be higher.

As concluded by Bond, S(2002) the GMM estimates is with somewhat biased downwards, therefore the true value of coefficient should be slightly higher than the estimates presented in table 3

6. CONCLUSION

This paper has studied on the correlation between financial ratios and stock price volatility with the focus of A-share stocks listed in Shanghai and Shenzhen Stock Exchange ranging from 2000 to 2011. OLS, Fama-McBethand Dynamic Panel Data Model (GMM estimation) are used to estimate the coefficients. Consistent estimation results with slight variation are achieved with above mentioned estimation methods,. All estimations indicate that ROA is negatively correlated with stock price volatility, while the magnetite and precision of the coefficient is slightly different according to different methodology, which is in line with what has been proved by precedent researchers. The overall empirical evidence gives a good sign showing that healthy fundamental performance is one of the most important key considerations for A-share investors when making investment decisions. A company with higher ROA is potentially to deliver a lower volatility of its stock price.

However this correlation is subject to market condition. The predicting power is strong when the market is in a stable condition but vanished when the market is in downturn

The growth of operating profit does not appear to have significant relationship with volatility. But the correlation turns to be significant in the most recent year within the sample. It shows that a company with higher capability to generate profit is favored by the investors.

The quick ratio is unexpectedly to be without clear correlation with volatility on the sample wise basis, but the correlation is found in certain industries such as financial service, real estate, utility and food & drinks and is extremely significant in financial service.

The dynamic panel data model reveals that there is a significant positive relationship between asset turnover rate and volatility, which can indirectly reflect the effect of profitability on the stock volatility.

Research Limitations

The paper has some innovative achievements, in addition to the OLS and Fama-Macbeth regression method, dynamic panel data is used and estimation results are compared. But still there are some limitations need to be pointed out. First, the data is limited due to the unavailability. There might have more plausible results if larger sample size with more frequent (semi-annually or quarterly) data is used. Second, volatility might have been affected by some other non-financial factors, investors'behavior is one of the example. But it is hard to introduce such and variable and quantify it.

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APPENDIX I

GMM regression results

Dynamic panel-data estimation, one-step difference GMM

Group variable: Code		Number of obs =	4340
Time variable : Year		Number of groups =	434
Number of instruments = 110		Obs per group: min =	10
F(5, 433) =	18.56	avg =	10.00
Prob > F =	0.000	max =	10

Volatility	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
Volatility L1.	.4764939	.0536189	8.89	0.000	.3711083	.5818796
ROA L1.	-.120303	.0550782	-2.18	0.029	-.2285569	-.0120492
ln_MCap	-2.013442	.830581	-2.42	0.016	-3.645914	-.3809705
QuickRatio	-1.765704	1.335128	-1.32	0.187	-4.389841	.8584328
AsTvr	35.51778	7.889936	4.50	0.000	20.01044	51.02511
Grth_OpeProfit	.0008831	.0007337	1.20	0.229	-.0005589	.0023251
Year	.1191504	.2793598	0.43	0.670	-.4299193	.6682202

Instruments for first differences equation
GMM-type (missing=0, separate instruments for each period unless collapsed)
L(1/.).(L.Volatility L.ROA)

APPENDIX II

List of sample stocks (denoted by stock code)

Financial Service	Real Estate		Information	Retailing	Transportation & Infrastructure	Utility			Food & Drinks
N=11	N=113		N=48	N=49	N=40	N=142			N=31
000415.SZ	000002.SZ	000809.SZ	000021.SZ	000056.SZ	000022.SZ	000059.SZ	000825.SZ	000831.SZ	000019.SZ
000563.SZ	000005.SZ	000838.SZ	000032.SZ	000058.SZ	000088.SZ	000060.SZ	000830.SZ	000835.SZ	000568.SZ
000623.SZ	000006.SZ	000897.SZ	000034.SZ	000062.SZ	000089.SZ	000407.SZ	600784.SH	000859.SZ	000596.SZ
600635.SH	000009.SZ	000909.SZ	000035.SZ	000301.SZ	000421.SZ	000420.SZ	600792.SH	000878.SZ	000716.SZ
600643.SH	000011.SZ	000918.SZ	000063.SZ	000416.SZ	000429.SZ	000422.SZ	600803.SH	000898.SZ	000729.SZ
600733.SH	000014.SZ	000926.SZ	000066.SZ	000417.SZ	000507.SZ	000426.SZ	600808.SH	000906.SZ	000752.SZ
600739.SH	000024.SZ	000931.SZ	000070.SZ	000419.SZ	000520.SZ	000510.SZ	600810.SH	000912.SZ	000796.SZ
600747.SH	000029.SZ	000961.SZ	000503.SZ	000501.SZ	000548.SZ	000523.SZ	600844.SH	000928.SZ	000799.SZ
600783.SH	000031.SZ	000965.SZ	000504.SZ	000516.SZ	000582.SZ	000525.SZ	600871.SH	000932.SZ	000848.SZ
600816.SH	000036.SZ	000979.SZ	000555.SZ	000560.SZ	000594.SZ	000552.SZ	600882.SH	000933.SZ	000858.SZ
600830.SH	000040.SZ	600007.SH	000561.SZ	000564.SZ	000828.SZ	000553.SZ	600888.SH	000936.SZ	000895.SZ
	000042.SZ	600052.SH	000586.SZ	000679.SZ	000886.SZ	000554.SZ	600889.SH	000937.SZ	000929.SZ
	000043.SZ	600053.SH	000665.SZ	000715.SZ	000900.SZ	000565.SZ	600769.SH	000949.SZ	600059.SH
	000046.SZ	600064.SH	000673.SZ	000753.SZ	000905.SZ	000571.SZ	600780.SH	000950.SZ	600073.SH
	000069.SZ	600067.SH	000682.SZ	000759.SZ	000916.SZ	000584.SZ	600782.SH	000953.SZ	600084.SH
	000090.SZ	600082.SH	000748.SZ	000785.SZ	600009.SH	000589.SZ	600623.SH	000959.SZ	600090.SH
	000402.SZ	600113.SH	000793.SZ	000829.SZ	600077.SH	000599.SZ	600636.SH	000960.SZ	600132.SH
	000502.SZ	600136.SH	000839.SZ	000861.SZ	600087.SH	000602.SZ	600652.SH	000962.SZ	600186.SH
	000505.SZ	600158.SH	000851.SZ	000882.SZ	600106.SH	000603.SZ	600673.SH	000968.SZ	600197.SH
	000511.SZ	600159.SH	000917.SZ	000889.SZ	600115.SH	000612.SZ	600688.SH	000969.SZ	600199.SH
	000514.SZ	600162.SH	000938.SZ	600122.SH	600119.SH	000615.SZ	600711.SH	000970.SZ	600238.SH
	000526.SZ	600173.SH	000948.SZ	600628.SH	600125.SH	000627.SZ	600714.SH	000973.SZ	600300.SH
	000534.SZ	600175.SH	000977.SZ	600655.SH	600153.SH	000629.SZ	600721.SH	000976.SZ	600600.SH
	000537.SZ	600185.SH	600076.SH	600682.SH	600190.SH	000630.SZ	600722.SH	600005.SH	600616.SH
	000540.SZ	600193.SH	600088.SH	600693.SH	600221.SH	000635.SZ	600725.SH	600061.SH	600702.SH
	000546.SZ	600208.SH	600100.SH	600694.SH	600269.SH	000637.SZ	600727.SH	600063.SH	600779.SH
	000558.SZ	600215.SH	600105.SH	600697.SH	600611.SH	000655.SZ	600731.SH	600074.SH	600809.SH
	000567.SZ	600223.SH	600149.SH	600704.SH	600650.SH	000662.SZ	600740.SH	600075.SH	600866.SH
	000573.SZ	600239.SH	600198.SH	600712.SH	600662.SH	000677.SZ	600746.SH	600078.SH	600872.SH
	000608.SZ	600240.SH	600601.SH	600723.SH	600676.SH	000683.SZ	600768.SH	600091.SH	600873.SH
	000609.SZ	600266.SH	600637.SH	600729.SH	600692.SH	000687.SZ	600230.SH	600096.SH	600887.SH
	000616.SZ	600606.SH	600680.SH	600738.SH	600708.SH	000697.SZ	600231.SH	600111.SH	
	000628.SZ	600614.SH	600718.SH	600774.SH	600717.SH	000698.SZ	600256.SH	600117.SH	
	000667.SZ	600615.SH	600728.SH	600778.SH	600751.SH	000703.SZ	600299.SH	600121.SH	
	000668.SZ	600620.SH	600756.SH	600785.SH	600787.SH	000707.SZ	600618.SH	600123.SH	
	000671.SZ	600621.SH	600757.SH	600790.SH	600794.SH	000708.SZ	000795.SZ	600126.SH	
	000691.SZ	600634.SH	600764.SH	600814.SH	600798.SH	000709.SZ	000807.SZ	600139.SH	
	000711.SZ	600638.SH	600775.SH	600821.SH	600834.SH	000717.SZ	000818.SZ	600141.SH	
	000718.SZ	600639.SH	600776.SH	600824.SH	600896.SH	000723.SZ	000819.SZ	600145.SH	
	000736.SZ	600641.SH	600797.SH	600827.SH	600897.SH	000731.SZ	000822.SZ	600146.SH	
	000797.SZ	600647.SH	600804.SH	600828.SH		000737.SZ	000780.SZ	600155.SH	
	000803.SZ	600648.SH	600825.SH	600838.SH		000751.SZ	000782.SZ	600157.SH	
	600736.SH	600649.SH	600831.SH	600856.SH		000755.SZ	000791.SZ	600160.SH	
	600743.SH	600657.SH	600832.SH	600858.SH		000758.SZ	000792.SZ	600176.SH	
	600745.SH	600658.SH	600845.SH	600859.SH		000761.SZ	600227.SH	600179.SH	
	600748.SH	600663.SH	600850.SH	600861.SH		000762.SZ	600228.SH	600182.SH	
	600753.SH	600665.SH	600855.SH	600865.SH		000778.SZ	600229.SH		
	600759.SH	600675.SH	600880.SH	600891.SH		600219.SH	600188.SH		
	600766.SH	600679.SH		600898.SH					
	600767.SH	600683.SH							
	600773.SH	600684.SH							
	600777.SH	600687.SH							
	600791.SH	600696.SH							
	600807.SH	600716.SH							
	600823.SH	600732.SH							
	600890.SH	600734.SH							
		600895.SH							

II. The Effects of Bond Rating Announcements on Stock Prices: An Empirical Investigation Using Event Study

ABSTRACT

This thesis examines whether bond rating changes contain valuable information and hence have significant impact on stock prices with a focus on the US stock market. Rating changes announced by Standard & Poor's are classified into four sub groups by whether the rating change is upgrade or downgrade and whether the bond is above or below investment grade prior to rating changes. The standard event study methodology is applied to analyze this issue. Besides t-statistics, a new nonparametric sign test statistics developed by Luoma (2011) is employed to test the null hypothesis of no event effect. The result from event study suggests that stock market reacts positively to downgrades the bonds which are below investment grade prior to rating changes. For downgrades the bonds which are above investment grade, a significant negative market reaction is found. For upgrades, the empirical result shows no significant abnormal stock returns.

Supervisor: Professor Massimo Guidolin

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1. INTRODUCTION

In 1970s the credit rating industry switched from investor-pay model to issuer-pay model. If bond issuer solicits a rating, it provides the rating agency with private information and pays the rating service fees. A lot of bond issuers pay to be rated by qualified credit rating agencies aiming to convey firm-specific information to investors and facilitate the firms' financing needs, even though the rating service is usually costly. It is for this reason, the credit rating agencies are supposed to provide impartial ratings based on the information received from issuers and other public available sources. However, one of the potential problems is that issuers may be reluctant to make all their private information public. In this case, rating agencies will not be able to provide investors sufficient information to make well informed investment decisions (Deb and Murphy, 2009).

Even though credit rating agencies clearly declare that bond ratings are primarily intended to provide information about the relative credit risk of issuers and do not necessarily constitute investment advice, bond ratings are largely used by both institutional and individual investors across the world as a major factor for making investment decisions (Lal and Mitra, 2011). Given the concerns about the informational content of bond ratings and the heavy reliance of investors on bond ratings, whether bond ratings contain valuable information is worth being studied. If bond rating changes have impact on stock market, how do stock prices react to rating announcements?

This thesis aims to shed light on the above research questions which have been examined by tremendous researchers, but the results of extant studies are conflicting. Pinches and Singleton (1978) and Wakeman (1981) study the behaviour of stock prices during the period surrounding rating change announcements and find no evidence of price change. Weinstein (1977) and Wakeman (1981) state that rating agencies only summarize public information; hence, the rating changes do not contain any valuable information. Accordingly, no reaction of stock prices should be expected surrounding raging changes.

However, other researchers argue that rating agencies have privileged access to private information and stock market reacts significantly to the unexpected information released by rating change announcements. Wansley and Clauretie (1985), Cornell *et al*. (1989) and Holthausen and Leftwich (1992) explore the effect of bond rating changes on stock prices with a focus on the US markets and find evidence of negative stock prices reaction to bond downgrading announcements, while no evidence of reaction is found for upgrading announcements. This finding is evidenced by studies on other stock markets, for instance, the Spanish stock market (Romero and Fernandez, 2006).

Different methods are used by researchers to explore the effect of rating changes on stock prices. Romero and Fernandez (2006) use an extended Dummy Variable Regression (DVR) to assess the effect of bond rating changes in Spanish stock market. Poon and Chan (2008) use a full information maximum likelihood (FIML) simultaneous equation model to examine whether credit ratings affect Chinese stock market. Tremendous of these studies are conducted using event studies with parametric test methods which are based on stringent assumptions about return distributions (e.g., Goh and Ederington, 1993; Li, Visaltanachoti and Kesayan, 2004 and Choy, Gray and Ragunathan, 2006). However, Fama (1976) suggests that the distributions of daily stock returns are fat-tailed comparing to the standard normal distribution.

In this thesis, rating changes are further classified into four sub groups by whether the rating is upgrade or downgrade and whether the bond is above or below investment grade prior to rating change announcement. The standard event study methodology is used to examine whether bond rating announcements convey new information which hasn't been anticipated by investors in the US stock market. The null hypothesis of no event effect is tested by new nonparametric sign test statistics developed by Luoma (2011) and compared to traditional t-statistics results. Consideration is only given to rating change announcements made by the rating agency Standard & Poor's.

The rest of this thesis is organized as follows: Section 2 reviews a few empirical studies. Section 3 introduces the development and general steps of an event study. Section 4 describes the data. Section 5 presents basic notation and the estimation of abnormal returns and cumulative abnormal returns. Section 6 introduces the widely used parametric and nonparametric test statistics and the two test statistics employed in this thesis. Section 7 presents the empirical results. Section 8 concludes and summarizes the study.

2. LITERATURE REVIEW

Whether bond rating change announcements convey any valuable information to stock market participants is a long debated and inconclusive issue. There are two divergent views on this issue. Weinstein (1977) and Pinches and Singleton (1978) point out that bond rating changes do not contain any valuable information since rating agencies only act as outside auditors and summarize public information. Therefore, no response in stock market should be expected upon rating change announcements. Wakeman (1981) does not find excess monthly stock returns at the time of rating changes. Kapland and Urwitz (1979) develop a simple linear model using total asset, systematic risk, firm specific leverage and subordination dummy as regressors to measure a sample of bonds. They find the statistical model can predict the credit risk of bonds better than rating agencies. Whether bond rating changes have valuable information is doubted as there is no evidence showing rating agencies outperform the regression model.

However, these early studies are criticized for not being able to isolate the effect of bond rating changes from other relevant information being made public to the market around the rating change date. In order to find more conclusive evidence on the effect of bond rating changes on stock prices, Griffin and Sanvicente (1982), Holthausen and Leftwich (1986) and Hand *et al.* (1992) use daily data to conduct the investigation. They find a significant negative response to downgrades. However, no significant reactions to upgrades are found in their studies. Zaima and McCarthy (1988) propose a wealth hypothesis which suggests that bond downgrades result in wealth being transferred from bond holders to shareholders, and significant effect should be expected after bond downgrades but not upgrades.

Dichev and Piotroski (2001) and Barber and Lyon (1996) study long-run stock returns following bond rating changes using the rating changes announced by

Moody's during the year 1970 to 1997. Both the buy-and-hold returns and cumulative abnormal returns are examined. There is no significant reaction after upgrades, while there are significant negative abnormal returns right following downgrades. The effect is even more significant for those small and low-credit-quality firms.

The detailed reactions of stock prices after bond rating changes are further studied by a number of researchers. Goh and Ederington (1993) classify downgrades by the underlying reason for downgrades and state that not all downgrades are bad news for investors. For instance, downgrades due to increased leverage generally lead to positive stock market reaction, and downgrades due to re-evaluation of the firm's financial prospects cause negative stock prices response.

Glascock *et al.* (1987) point out that Moody's announces rating changes and their underlying reasons in two different days. After examining the stock movement surrounding bond rating changes, they find there is a negative response to downgrades and a return reversal after the underlying reasons being published.

Elayan *et al.* (1990) analyze the common stock response to false signals from Credit Watch placements. The empirical results suggest that there is no response for positive placements. There is a negative stock market response to negative placements which followed by rating affirmation. No evidence shows a response to negative placements which followed by rating downgrades.

Tremendous studies have examined the effect of bond rating changes in several different stock markets across the world such as US, New Zealand, Australia, Spain, UK and emerging markets. Choy, Gray and Ragunathan (2006) examine a sample of Australian domiciled companies rated by Standard & Poor's and Moody's from 1989-2003. Their finding is consistent with that documented by US-based studies. Barron *et al.* (1997) carry out this study based on the UK stock market. They examine the daily stock returns around Credit Watch or rating changes announced during the period from 1984 to 1992. They find downgrades and positive Credit Watch announcements are followed by significant positive stock market response. Lal and Mitra (2011) examine the effects of bond rating changes on Indian stock market over the period from April 2002 to March 2008. The empirical evidence from event study shows no response to bond upgrades or downgrades, which indicates the information was already anticipated by the Indian market before rating change announcements.

The majority of the above studies are conducted using event study methods. While most of event studies rely on parametric test statistics to test the null hypothesis, such as t-statistics and Z-statistics which require stringent assumptions about the probability distribution of returns, usually a normal distribution is assumed. Dichev and Piotroski (2001) use t-statistics to test the effects and try to use the Fama-MacBeth regressions to account for the problem of cross-sectional dependence.

However, Fama (1976) suggests that the distribution of daily stock returns is fat-tailed comparing to the normal distribution. The sample problems existed for the daily excess returns (Brown and Warner, 1985), which imply that parametric test statistics may not be the most appropriate ones to be used for testing the null hypothesis of no event effect. Significant research has been performed in order to compare the performance of parametric and nonparametric test statistics used in event studies. It is widely agreed that nonparametric test statistics are superior to parametric ones. Luoma (2011) conducts simulation and compares the power and rejection rates between parametric test statistics and the widely used nonparametric sign and rank statistics. The study finds that t-tests tend to over reject null hypotheses when event clustering exists. A set of new nonparametric sign and rank test statistics tackling the deficiencies contained by above mentioned test statistics are developed. Similar findings can also be found in Kolari and Pynnonen (2011) and Corrado and Zivney (1992). However, there is an ongoing debate as to which of the two methods is the superior one. Berry *et al.* (1990) argues that the residuals from OLS regression are well conditioned for student t-test statistics, whose sampling distribution and Type I error is appropriate. The nonparametric statistics has superior testing power but the sampling distribution is inappropriately specified.

3. INTRODUCTION TO EVENT STUDY METHODS

3.1 History of Event Study Methods

The long history of event study methods has been well summarized by Mckinley (1997). The first published event study might be James and Dolley (1933) who examine the change of nominal stock prices after stock splits. Since then, event study methods have become more sophisticated with the ability to separate out confounding events. Typical examples are Myers and Bakay (1948) and Ashley (1962). The standard methods we are using today are basically the same as what were introduced in Ball and Brown (1968) and Fama *et al*. (1969).

A number of further improvements have been developed. The data used in event studies is sampled at a daily interval instead of monthly interval (Brown and Warner, 1980 and 1985). Some statistical assumptions are relaxed in order to accommodate more specific hypotheses. For instance, the original hypothesis of event studies is no event effect, which means either a mean effect or a variance effect will violate the null. However, testing for a mean effect might be the only interest in some studies. In order to meet tailored study objective, the original hypothesis of no event effect is expanded to allow for increasing variances surrounding event day. Boehmer, Musumeci and Poulsen (1991) propose a method to accommodate changing variance by removing the reliance on past returns when estimating the variance of abnormal returns.

As the basic ideas behind event study methods are intuitive and simple, event study methods have been frequently used by economists when confronted with the problem of measuring the effects of an economic event. Kothari and Warner (2007) summarize that from 1974 to 2000 there are 565 papers reporting event study results published on the five major finance journals.[33] Tremendous researchers have introduced event study methods to a broad area of accounting, financial economists and politics (e.g., Schwert, 1981; Mitchell and Netter, 1994).

3.2 General Steps of an Event Study

Though event studies have been improved a lot to accommodate different events, the general steps of an event study basically remain the same as what were introduced in Ball and Brown (1968) and Fama et al. (1969). As summarized by Mckinley (1997) the starting point is defining an event of interest, hence event day and event window. For example, if someone is interested in the market reaction to a new regulation, the event will be the announcement of this regulation. Security prices surrounding the event day will be examined.[34] The event window can be customized to include days prior to or after event. The second step is to decide a series of sample selection criteria.

The next step is measuring abnormal returns of securities over the defined event window. The underlying idea of measuring Abnormal Returns (ARs) is subtracting normal returns from the ex-post actual returns of securities. For company i, the abnormal return at day τ is

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_{\tau}) \qquad (1)$$

where $(R_{i\tau}|X_{\tau})$ are the normal returns conditioning on τ and X_{τ}. The normal returns are defined as the expected returns if there were no event and can be estimated by two types of model, constant mean return model or the market model.

33 Journal of Business, Journal of Finance, Journal of Financial Economics, Journal of Financial and Quantitative Analysis and the Review of Financial Studies.

34 For more detailed introduction please refer to Campbell and MacKinlay (1997) *The Econometrics of Financial Markets.* Edition: Princeton, NJ.

By assuming the mean return (X_τ) for a security i is constant, the AR for a certain security can be obtained by subtracting its mean return from the ex-post actual return. This is a very simple and straightforward method which can generate similar result as those sophisticated models (Brown and Warner, 1980). Market model is achieved by regressing security returns to returns of market portfolio (X_τ represents market returns in this model) over the estimation window and taking the predicted disturbance term in the event window as the estimate of abnormal return.[35] By eliminating the part of security returns which is attributed to the market dynamics and reducing the variance of abnormal returns, the market model generally has superior ability to detect event effects. The next step is designing a framework for testing event effects. This includes defining a null hypothesis, aggregating abnormal returns across time and firms and building tailored test statistics. The final step is presenting the empirical results. In some cases it would be more insightful to present detailed diagnostics. For instance, when the sample size is small, empirical results may be largely driven by certain firms. In such case, a thorough analysis into individual firm will provide a more correct view of the results.

35 Typically the estimation window is days prior to event window, though some of the researchers use the post event days (Hand, Holthausen and Leftwich, 1992). An array of indices can be used as proxy of market portfolio return such as the Dow Jones Industrial Average, S&P500, and a weighted average of these indices. For detailed derivation please refer to the following section of methodology.

4. DATA DESCRIPTION

A total of 3086 actual bond rating announcements made by Standard and Poor's, from 1987 to 2010 are collected, including the details pertaining to the rating such as notches, upgrade or downgrade, and prior and after rating announcements. Ratings are expressed as letter grades which range from 'AAA' to 'D'. To facilitate the empirical study in this thesis, ratings are converted to numbers ranging from 1 to 22.[36] For example, the highest rating 'AAA' is converted to number 1 and the lowest rating 'D' is converted to number 22. 'BBB-' (converted to number 10) is the lowest investment grade.

Daily stock market returns (holding period return) from January 1980 to December 2011 for all companies received rating changes announced by Standard and Poor's are retrieved from CRSP (the Center for Research in Security Prices). Corrado and Truong (2005) advocate that an equal weighted index provides a better test specification when using the market model to calculate the abnormal returns. In this thesis, an index which is weighted average of the five market groups of securities are retrieved from CRSP US indices database and security portfolio assignment module.[37] Two samples are selected from the 3086 rating change records.

4.1 Sample 1

After counting the number of rating changes announced on different dates, the most event-rich date is sorted out. A total of 57 rating changes were made on the same date, March 19, 2008.[38] To avoid any information contamination, the observations which received multiple rating changes surrounding March 19, 2008

36 Refer to Table I in Appendix VI for detailed conversion.

37 The market groups of securities for which indices are calculated are the individual NYSE, AMEX, NASDAQ markets,NYSE/AMEX and NYSE/AMEX/NASDAQ market combinations. Ppublished S&P 500 and NASDAQ Composite Index Dataare also included.

38 Refer to Appendix I for the number of rating changes on different dates.

are deleted. Any observations whose returns for that period are not available in CRSP or return data is missing on event day are deleted.[39] After performing these data cleaning processes, 36 observations are left, among which 29 are upgrades, 7 are downgrades. Sample 1 is designed expressly for testing the performance of the t-statistics and the new sign test statistics provided by Luoma (2011), which is SIGN-GSAR-T.

4.2 Sample 2

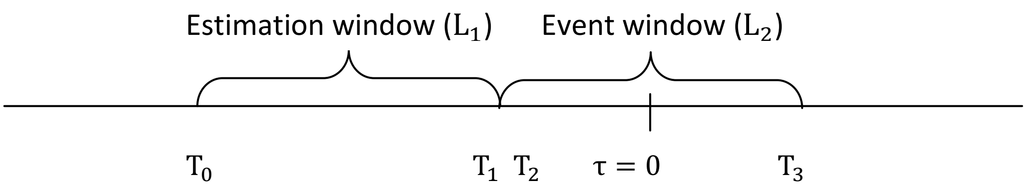
Sample 2 originally consists of 71 observations which only received rating changes once throughout the whole data file. Any observations whose returns are not available in CRSP for the period of interest or return data is not available on event day are deleted from the sample, which leaves a total of 51 observations, within which 25 are upgrades and 26 are downgrades. Sample 2 is built in purpose of eliminating any confounding events surrounding event day and significant event clustering effect.

39 The return data ranging from half year prior to and after the event day is required in this event study design.

5. METHODOLOGY

5.1 Notation

The standard procedures of event study presented by Mackinley (1997) will be employed in this study. To facilitate future measurements and presenting the empirical results, some notations are defined first. $\tau = 0$ is the event day. The estimation window starts from $\tau = T_0$ to $\tau = T_1$ with length of L_1 days. Event window starts from $\tau = T_1 + 1$ (i.e T_2) ends at $\tau = T_3$ with a length of L_2 days.



For Sample 1, the cumulative abnormal returns in the following event windows will be examined: single event day window, (-1, 1), (-3, 3), (-5, 5), (-10, 10), (-3, 10), and (-3, 20). A similar set of event windows will be examined for the Sample 2.

5.2 Estimating Abnormal Returns and Cumulative Abnormal Returns

The following market model will be used to estimate abnormal returns:

$$R_{i\tau} = \alpha_i + \beta_i R_{m\tau} + \epsilon_{i\tau} \tag{2}$$

$$E[\epsilon_{i\tau}] = 0, \qquad Var[\epsilon_{i\tau}] = \sigma^2_{\epsilon_{i\tau}}$$

where R_{it} is daily stock return, R_{mt} is return on market index, which is return on the equal weighted indices in this thesis. ϵ_{it} is the disturbance term with zero mean, which is used as estimates of abnormal returns in event window. ϵ_{it} is not correlated with R_{mt}, α_i, β_i and $\sigma^2_{\epsilon_{it}}$ are the parameters estimated from the market model. Thus abnormal return is equal to the difference of realized and predicted return on day τ in the event window.

It is noteworthy that when $\beta_i = 0$, the market model is equivalent to the constant mean return model. By eliminating the portion of return which is related to the market portfolio return, the market model provides a potential improvement over the constant mean return model. The improvement can be measured by the R^2 of the regression. The larger the R^2, the greater is the reduction of the variances of abnormal returns, which can increase the power of detecting abnormal returns.

The focus of this thesis is to examine the relationship between abnormal return ϵ_{it} and the bond rating changes over several different event windows, which are consisted of days surrounding the event day. Though events usually occur on one date, it is typical to extend event windows to more than one day in order to ensure returns in event windows incorporate the information conveyed by events.

For the Sample 1, two estimation windows are used whose lengths are 35 days and 235 days respectively. The two estimation windows served as a comparison exhibiting how the t-statistics works under short and long estimation windows.

According to different event windows, a set of cumulative abnormal returns (CARs) are calculated.

$$CAR_i(T_2, \tau) = \sum_{\tau=T_2}^{\tau} AR_{i\tau} \tag{3}$$

CARs of each single company for $\tau = T_2 + 1, T_2 + 2 \ldots T_3$ are calculated, which express cumulative abnormal returns at different time point in event window. When $\tau = T_3$, $CAR_i(T_2, \tau)$ represents cumulative abnormal returns accumulated for the whole event window for company i.

T_2 is not necessary the same for all event windows. For example the T_2 is one day before event day ($\tau = 0$) for an event window of (-1, 1) and three days before event day for the event windows of (-3, 3), (-3, 10) and (-3, 20). Thus the T_0 and T_1 will be different accordingly with the condition of same estimation window length.

Cumulative abnormal returns are first cumulated for all days in event window and for each individual company in Sample 1 then averaged across companies separately for the two sub groups (upgrades and downgrades) on a daily basis throughout the event window. The average CARs at each time point in event window are presented in equation (4). The average cumulative abnormal returns for the two sub groups are tested by the t-statistics and SIGN-GSAR-T, which will be presented in the following section.

$$\overline{\mathrm{CAR}}(\mathrm{T}_2, \tau) = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{CAR}_{\mathrm{i}}(\mathrm{T}_2, \tau) \tag{4}$$

where N is the number of firms in each sub groups. That means N=29 and N=7 for upgrades and downgrades group in Sample 1 respectively. $\tau = T_2 + 1, T_2 + 2 \ldots T_3$, which are time points in event window. When $\tau = T_3$, equation (4) provides the average CARs throughout whole event window for each sub group.

As stated previously, Sample 1 is designed with a special intention to exhibit the performance of the two test statistics which will be used in this thesis. After the data cleaning, Sample 2 consists of 51 observations which received rating changes on different dates and only received rating change once during the whole period under concern. The procedure for estimating abnormal returns and cumulative abnormal returns are the same as that for Sample 1. But only an estimation window of 235 days will be used in Sample 2.

6. TEST STATISTICS

6.1 General Background on Parametric and Nonparametric Tests

Parametric tests are based on a set of stringent assumptions about return distributions. One of the key assumptions is a standard normal distribution. These strict assumptions usually lead to misspecification when conducting research on stock returns at short term interval, as Fama (1976) proposes that the distributions of daily stock returns depart from normality more than the monthly returns do. Evidence shows that daily stock returns are fat-tailed rather than normally distributed, and these parametric tests are usually prone to misspecification.

Nonparametric tests usually require much less stringent assumptions, many of which are based on rank or sign without requirements on the underlying distribution of data generating process. For example, when applying a rank test, we only need to know the rank which can be easily obtained by sorting the observations from lowest to highest in value and assigning a rank to them. The sign test only requires the values of the observations to be compared to a benchmark, which is either the mean or median of the data set.

6.2 Widely Used Parametric Test Statistics in Event Studies

Perhaps the t-statistics inferred by Patell (1976) is the most widely used parametric test applied to examining the significance of abnormal returns. The key assumptions of Patell's test are that abnormal returns are normally distributed and cross-sectional independent. A lot of researchers have reported that t-statistics tend to over reject the null hypothesis when conducting research on stock returns. Campbell and Wasley (1993) support this proposition after conducting research using NASDAQ stock returns. Over-rejecting the null is more common for the less frequently traded securities. This has been echoed by Maynes and Rumsey (1993) who report the same problem by testing on the most illiquid one-third of stocks traded on Toronto Exchange and Pynnönen (2010) also supports this point and concludes that the t-statistics is easily affected by event-induced volatility. Luoma (2011) designs a simulation to compare the performance of t-statistic and nonparametric SIGN-GSAR-T statistics when the event days are clustered. The event windows range from one day to 21 days. The Type I error of t-statistics is higher than that of SIGN-GSAR-T over every event window. The difference is greater for longer event windows. Since the Type I error is equivalent to rejection rate, this result means the t-statistics generally over rejects the null hypothesis compared to the SIGN-GSAR-T statistics. The SIGN-GSAR-T statistics performs considerably stable and rejects the null close to the nominal rejection rate over every event window, though there is a slight increase in longer event windows. To correct the misspecification of t-statistics, Boehmer *et al*. (1991) introduce a modified version of Patell's test statistics which corrects for the increased variance of stock returns around the event date.

6.3 Nonparametric Tests in Event Studies

Daily stock returns are frequently used in event studies; however, conducting event studies with parametric tests is prone to cross-sectional correlation among abnormal returns especially when the event day is the same for firms in the sample. Kolariand and Pynnonen (2010) state that even a small cross-correlation may bias the test results if it is not properly accounted for.

There are two broad types of nonparametric tests, rank and sign tests. Based on standardized returns, Corrado (1989) proposes a rank test which has been proved to have better performance than parametric tests. This test has been further improved by Corrado and Zivney (1992) based on re-standardized returns in the event window, which was proved to be robust against the cross-correlation caused by event day clustering and event induced volatility.

Corrado and Zivney (1992) introduce a sign test statistics based on standardized excess returns without assuming a zero median. The sign of excess returns over the event window is calculated based on the median of sample excess return. Corrado (2010) states that when confronted with non-normally distributed data, the nonparametric sign and rank tests are recommended for evaluating the statistical significance.

6.4 Tests Used in This Thesis

6.4.1 T-statistics

In this thesis, the t-statistics defined as follows is used for testing null hypothesis:

$$\mathrm{t-statistics} = \frac{\overline{\mathrm{CAR}}(\mathrm{T_2,T_3})}{\sqrt{\mathrm{V}(\overline{\mathrm{CAR}}(\mathrm{T_2,T_3}))}} \sim \mathrm{N}(0,1) \tag{5}$$

where $\overline{\mathrm{CAR}}(\mathrm{T_2,T_3})$ is the same as in equation (4) when $\tau = \mathrm{T_3}$.

$$\mathrm{V}(\overline{\mathrm{CAR}}(\mathrm{T_2,T_3})) = \frac{\mathrm{L_2}}{\mathrm{N^2}} \sum_{\mathrm{i=1}}^{\mathrm{N}} \hat{\sigma}_{\epsilon,\mathrm{i}}^2 \tag{6}$$

$$\hat{\sigma}_{\epsilon,\mathrm{i}}^2 = \frac{1}{\mathrm{L_1}-2} \sum_{\tau=\mathrm{T_0}}^{\mathrm{T_1}} \mathrm{AR}_{\mathrm{i}\tau}^2 \tag{7}$$

$\mathrm{L_1}$ and $\mathrm{L_2}$ are the length of estimation and event windows respectively. $\mathrm{L_1} - 2$ is a correction for degrees of freedom. If the raw return is used instead of abnormal return, this correction should be changed to $\mathrm{L_1} - 1$.

To calculate the error variance $\sigma^2_{\epsilon,i}$, abnormal returns from the estimation window is used, which is the residual of the market model regression using the data in estimation window shown in equation (8):

$$AR_{i\tau} = R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau}, \text{ where } \tau \in [T_0, T_1] \tag{8}$$

If the event effect exists, returns tend to be fluctuating around event day, thus the variance of returns is greater than it was in estimation window. Standardizing by the ARs in estimation window instead of that in event window avoids the potential excess effect of the stocks with large return standard deviation in the event window, thus the power of the test is improved.

This formulating is supported by the proposition in Patell (1976). In his research Patell presents a test statistics which the ARs in an event window were standardized by the standard deviation of the ARs in estimation window. Due to its improved power, the standardized test statistics of Patell (1976) is more popular than the conventional non-standardized test statistics in testing the effect of events.

6.4.2 SIGN-GSAR-T statistics

The SIGN-GSAR-T statistics was first proposed by Luoma (2011) and is based on generalized standardized abnormal returns (GSARs). To derive the final test statics, a series of components need to be calculated beforehand. The following is the calculation for SIGN-GSAR-T. The first step is to calculate the standardized abnormal returns (SAR) and standardized cumulative abnormal returns (SCAR) which are defined as follows:

$$SAR_{i\tau} = \frac{AR_{i\tau}}{S(AR_{i\tau})} \tag{9}$$

$S(AR_{i\tau})$ is the standard deviation of the residuals from the market model regression defined in equation (8).

$$SCAR_{i,T_2,T_3} = \frac{CAR_{i,T_2,T_3}}{S(CAR_{i,T_2,T_3})} \tag{10}$$

where the $S(CAR_{i,T_2,T_3})$ is the standard deviation of the prediction errors in the cumulative abnormal returns computed as in Campbell *et al.* (1997 Section 4.4.3) adjusted for forecast errors.

$$S(CAR_{i,T_2,T_3}) = \sqrt{\frac{1}{L_1 - 2}\sum_{\tau=T_2}^{T_3} AR_{i\tau}^2} \tag{11}$$

Under the null hypothesis of no event effect, the standardized cumulative abnormal returns follows student t distribution with $L_1 - 2$ degrees of freedom, 0 mean and a variance of $(\frac{L_1-4}{L_1-2})$. For a large estimation window (when L_1>30) the distribution of standardized cumulative abnormal returns will be approximately standard normal (Campbell and MacKinlay, 1997 Section 4.4.3).

Re-standardized SCAR is defined as follows:

$$SCAR'_{i,T_2,T_3} = \frac{SCAR_{i,T_2,T_3}}{S(SCAR_{T_2,T_3})} \tag{12}$$

As proposed by Kolari and Pynnonen (2010) that test statistics are prone to even a small cross-correlation. In order to account for the potential volatility induced by this event, same as Boehmer *et al*. (1991), Kolariand and Pynnonen (2011) further re-standardize the SCARs using its cross-sectional standard deviation to get the re-standardized SCARs, which is presented in equation (12). $S\left(SCAR_{T_2,T_3}\right)$ is the cross-sectional standard deviation of $SCAR_{i,T_2,T_3}$s and is calculated as follows:

$$S\left(SCAR_{T_2,T_3}\right) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(SCAR_{i,T_2,T_3} - \overline{SCAR_{T_2,T_3}})} \tag{13}$$

$$\overline{\mathrm{SCAR}_{\mathrm{T}_2,\mathrm{T}_3}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} (\mathrm{SCAR}_{\mathrm{i},\mathrm{T}_2,\mathrm{T}_3}) \tag{14}$$

N represents the number of observations within each sub group. Similar to other standardized abnormal returns like $\mathrm{SCAR}_{\mathrm{i},\mathrm{T}_2,\mathrm{T}_3}$, $\mathrm{SCAR}'_{\mathrm{i},\mathrm{T}_2,\mathrm{T}_3}$ is a standard normal random variable.

Similar to the definition in Kolariand andPynnonen (2011), $\mathrm{SCAR}'_{\mathrm{i},\mathrm{T}_2,\mathrm{T}_3}$ is used as the abnormal return to define the generalized standardized abnormal return (GSAR) as follows:

$$\mathrm{GSAR}_{\mathrm{i}\tau} = \begin{cases} \mathrm{SCAR}'_{\mathrm{i}}, & \text{in event window} \\ \mathrm{SAR}_{\mathrm{i}\tau}, & \text{otherwise} \end{cases} \tag{15}$$

where the $\mathrm{SCAR}'_{\mathrm{i}}$is defined in equation (12) and $\mathrm{SAR}_{\mathrm{i}\tau}$ is defined in equation (9).

It is noteworthy that the event window in equation (15) is considered to be a point in time in which the GSAR equals the re-standardized SCAR as defined in equation (12), and for the rest of the time points the GSAR equals the usual standardized abnormal return defined in equation (9). $\mathrm{SCAR}'_{\mathrm{i}}$ in essence, is equal to the cumulative abnormal return. $\mathrm{GSAR}_{\mathrm{i}\tau}$ has $\mathrm{L}_1 + 1$ observations of which L_1 are abnormal returns in the estimation window and the last one is the abnormal return cumulated across the event window and indicated by $\mathrm{SCAR}'_{\mathrm{i}}$.

In the top part of equation (15), the days in event window is compressed to a point in time, which is the last day of event window. Therefore the potential event effect that happened across event window fromT_2 to T_3 is to be summarized into the single number $\mathrm{SCAR}'_{\mathrm{i}}$, which under the null hypothesis of no event effect, follows a distribution similar to the other standardized returns. The $\mathrm{SCAR}'_{\mathrm{i}}$ starts to deviate from the other standardized returns when the effect of the event takes place in the case when the null hypothesis fails to be true. This deviation can be utilized to develop sign or rank tests. Kolari and Pynnonen (2011) suggest that the sign test presented in Corrado and Zivney (1992) can be extended by utilizing GSARs for testing CARs.

To achieve the extension, the sign($G_{i\tau}$) of the generalized standardized abnormal return is defined as follows:

$$G_{i\tau} = \mathrm{sign}[\mathrm{GSAR}_{i\tau} - \mathrm{median}(\mathrm{GSAR}_i)] \tag{16}$$

$$G_{i\tau} = \begin{cases} +1, & \text{if } \mathrm{GSAR}_{i\tau} > median(\mathrm{GSAR}_i) \\ 0, & \text{if } \mathrm{GSAR}_{i\tau} = \mathrm{median}(\mathrm{GSAR}_i) \\ -1, & \text{if } \mathrm{GSAR}_{i\tau} < median(\mathrm{GSAR}_i) \end{cases} \tag{17}$$

For the detailed properties of $G_{i\tau}$ please refer to Appendix II.

$$\overline{G}_\tau = \frac{1}{n_t} \sum_{i=1}^{n_t} G_{i\tau} \tag{18}$$

where the n_t is the number of available returns data across the n-firms on day τ. Thus n-n_t is the number of missing returns in the cross-section of n-firms on the same day.

$$S(G) = \sqrt{\frac{1}{T} \sum_{\tau \in L_1+1} \frac{n_t}{n} \overline{G}_\tau^2} \tag{19}$$

$L_1 + 1$ is the same as what is defined in equation (15) which consists of L_1 time points in estimation window $[T_0, \ T_1]$, plus one time point which is the last day in the event window.

$$Z = \frac{\overline{G}_0}{S(G)} \tag{20}$$

Z in equation (20) is the test statistics used for testing single event-day abnormal returns, which is derived by Corrado and Zivney (1992)

The SIGN-GSAR-T is defined as:

$$\text{SIGN-GSAR-T} = \frac{Z\sqrt{T-2}}{\sqrt{T-1-Z^2}}$$

$$= \frac{\frac{\bar{G}_0}{S(G)}\sqrt{T-2}}{\sqrt{T-1-(\frac{\bar{G}_0}{S(G)})^2}} \tag{21}$$

7. EMPIRICAL RESULTS

7.1 Empirical Results for Sample 1

Sample 1 is deliberately set up for testing and comparing the performance of two test statistics. In Sample 1 there are 29 companies that received upgrade rating announcements and 7 companies that were downgraded by Standard & Poor's. All the rating announcements in Sample 1 were made on the same date, March 19, 2008.

Average CARs and t-statistics for a set of different event windows ranging from a single event day to 24 event days were calculated. The t-statistics is defined in equation (5). It follows standard normal distribution asymptotically under the null hypothesis of no event effect.

As exhibited in Table 1, column 3 shows the results when the estimation window is 35 days and column 4 shows the results when the estimation window length is expanded to 235 days. I just see rejection of null hypothesis in one case. With L1=35 days, event window (-3, 10) is the only case where the t-statistics indicates a significant event effect at 90% confidence level in the downgrade group, while the null hypothesis is not rejected with L1=235 days. So there is almost no evidence for abnormal return and the result of longer estimation window is more robust. In fact according the earlier suggestions in various research papers such as Corrado and Truong (2005) and Luoma (2011), if the data is available, a relatively long estimation window length is required for generating reliable results. Usually an estimation window with at least 230 days can ensure reliable results. Therefore, going forward the estimation window with 235 days will be employed in this study.

The next comparison shows the performance of t-statistics and SIGN-GSAR-T when the estimation window length L1 equals 235 days. The comparison result presented in Table 2 is similar to the proposition in Luoma (2011) in which the simulation results find that the t-test tends to over reject the null hypothesis when event clustering exists.[40] Also the simulation results show that SIGN-GSAR-T performs better than the widely used t-statistics, and the nonparametric sign test statistic derived by Cowan when the event days are clustered.

The event days are clustered when every company in the sample has the same or almost the same event day. This is exactly the case in Sample 1, where every company received the rating announcements on the same date March 19, 2008. Hence it is reasonable to apply the SIGN-GSAR-T test.

G0 in the last column of Table 2 is defined in equation (18) for companies either in downgrade group or upgrade group when $\tau = 0$ which is the one time point the event window compressed to. From Table 2 we can see that, again, none of the results is statistically significant, which means that abnormal return can be barely detected. Notice that the fact the higher p-value in the t-test than that in SIGN-GSAR-T test is consistent with the simulation results of Luoma (2011).

An ex ante comparison of the performance of different test statistics is meaningful for further test design. The similar comparison and evaluation of test statistics can be seen in tremendous earlier researches such as Brown and Warner (1985) which evaluate the performance of Patell (1976) test using the daily stock returns, Lee and Varela (1997), Corrado and Zivney (1992), Boehmer, Musumeci and Poulsen (1991) and Giacotto and Sfridis (1996).

40 Refer to Appendix III for detailed results including the power properties of SIGN-GSAR-T across different event window lengths.

7.2 Empirical Results for Sample 2

Sample 2 consists of 51 companies which received rating changes on different dates ranging from February 1997 to June 2010.[41] There are 25 companies that received upgrade rating announcements and 26 companies were downgraded by Standard & Poor's.

The t-statistics and SIGN-GSAR-T are used to examine whether bond rating changes have effect on stock returns. Test results are presented in Table 3. Overall the results generated by t-statistic are in line with those generated by SIGN-GSAR-T except for the event window (-3, 20) in which the t-statistic shows that downgrades have positive effect on stock returns and is significant at 90% confidence level but no effect is found according to test statistics SIGN-GSAR-T. Both tests do not find any significant stock market response to bond upgrades.

As indicated by SIGN-GSAR-T statistics, only downgrading announcements have significant effect on stock returns but this effect does not always exist over every event window. For example, in the case of single event day window, SIGN-GSAR-T suggests that downgrades cause stock returns decrease, which is significant at the 95% confidence level, while no significant effect is found in the event window (-1, 1), (-3, 3) and (-3, 20). As for the single event day window, according to the t-statistic result, the average stock returns decreased by 2.17% and is significant at 98% confidence level. It is worth noting that stock returns react positively to downgrades in longer event window (-3, 10).

The inconsistent effect of bond downgrades on stock returns across different event windows is worth further investigation. The next step is to further divide

41 Refer to Appendix IV for further details including the company names and rating date of each company

Sample 2 into the following 4 sub groups: Below Investment Grade Downgrades, Below Investment Grade Upgrades, Above Investment Grade Downgrades and Above Investment Grade Upgrades. There are 14, 17, 12 and 8 companies falling into the above 4 sub groups respectively.[42] The Below Investment Grade Downgrades group includes those companies whose bonds were previously rated at below investment grade and were further downgraded by Standard and Poor's on event day.

The empirical results of the 4 sub groups over event windows of single event day, (-3, 10), (0, 10) and (-3, 20) are presented in Table 4. Overall, the results generated by both test statistics are in line with each other. From Table 4, we can see that downgrades on those rated at above investment grade bonds have significant negative effect on stock returns only in the case of single event day. This effect is not found in the other event windows which are longer than one day.

Figure 1 visually exhibits how the average abnormal returns for the Above Investment Grade Downgrades group changes since 250 days prior to the event day. Before event day, the average abnormal returns are fluctuating around 0. Average abnormal returns drop by 2.91% on the event day, which is significant at 98% confidence level. This effect is only found in the case of single event window but not in longer windows of (0, 10), (-3, 10) or (-3, 20). Apparently, stockholders do not expect the bonds rated at above investment grade would be downgraded by rating agency, and there is no information leakage prior to the event day. In this case, stockholders within this sub group perceive the downgrades as bad news. From Table III in Appendix V we can see that except for the company 33, all the other 11 companies within this sub group are downgraded by only 1 grade. Even 1 grade change can drastically decrease stockholders' sentiment and overall stock returns.

42 Refer to Appendix V for the details of sub groups.

A positive stock market reaction is found in the Below Investment Grade Downgrades group. This effect is significant across the event window (-3, 10), (0, 10) and (-3, 20) when tested by t-statistics, but only significant under the event window (-3, 10) and (0, 10) if measured by SIGN-GSAR-T statistics.

Figure 2 and 3 reveal how the average abnormal returns and average CARs of the stocks in Below Investment Grade Downgrades Group develop prior to and throughout the event window (0, 10). The average CARs increase by 10.49% across the event window.

From Table I in Appendix V we can see that except for the company 45, the other 13 companies in this group are downgraded by only 1 grade. The positive effects may be because stockholders were anticipating more extreme downgrades, when it turns out to be downgraded by only 1 notch, investor confidence is restored and stock returns increased gradually.

8. CONCLUSION

The empirical result of Sample 1 is consistent with the simulation results of Luoma (2011) in which the simulation results find that the t-test tends to over reject the null hypothesis when event clustering exists. Hence it is reasonable to apply the SIGN-GSAR-T test when event days are clustered (Kolariand and Pynnonen, 2011). Result of longer estimation window (235 days) is more robust. If the data is available, a relatively long estimation window length is required for generating reliable results. Usually an estimation window of at least 230 days can ensure reliable results.

The empirical results of Sample 2 suggest that there is no evidence of stock market response to upgrades in bond ratings. This result is consistent with previous studies (e.g., Wansley and Clauretie, 1985; Holthausen and Leftwitch, 1986). There are significant stock market reactions to bond downgrades. However, the reactions are mixed. To analyze the mixed reactions, Sample 2 is further divided into 4 sub groups by whether the rating is upgrade or downgrade and whether the bond is above or below investment grade prior to rating change announcement. Downgrades on those rated at above investment grade bonds have significant negative effect on stock returns on event day. Average abnormal returns drop by 2.91% on the event day. This may be because the downgrades on the bonds rated at above investment grade are not anticipated by stockholders. Hence, the sudden downgrades are perceived as bad news for stockholders within this sub group.

Downgrades those bonds rated at below investment grade have a positive effect on stock returns. This effect is significant across the event windows (-3, 10) and (0, 10) if tested by SIGN-GSAR-T statistics. Stockholders hold an overly negative view of the bonds rated at below investment grade, so when they are only downgraded by 1 notch, stockholders were positively surprised and returns increased.

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APPENDIX I

Find the most rating-rich date

Rating Date	Number of Companies Rated
19-Mar-08	57
22-Sep-06	19
19-Dec-08	19
27-Sep-06	16
23-Mar-10	16
26-Sep-06	15
3-Mar-07	15
21-Sep-06	14
14-Feb-07	14
19-Sep-06	13
20-Nov-07	13
15-Feb-02	12
12-Dec-08	12
17-Jun-09	12
7-Jun-02	10
26-Nov-02	10
28-Sep-06	10
9-Nov-07	10
15-Nov-07	10
15-Sep-08	10
27-Feb-09	10
18-Dec-00	9
8-Nov-01	9

APPENDIX II

Properties of $G_{i\tau}$

If $T = L_1 + 1$ is even:

$$\Pr[G_{i\tau} = 1] = \Pr[G_{i\tau} = -1] = \frac{1}{2}$$

$$\Pr[G_{i\tau} = 0] = 0$$

$$E[G_{i\tau}] = 0$$

$$\mathrm{Var}[G_{i\tau}] = 1$$

$$\mathrm{Cov}[G_{i\tau}, G_{is}] = -\frac{1}{T-1}$$

where $i = 1,2, \dots. N$, and $\tau \neq s$

If $T = L_1 + 1$ is odd:

$$\Pr[G_{i\tau} = 1] = \Pr[G_{i\tau} = -1] = \frac{T-1}{2T}$$

$$\Pr[G_{i\tau} = 0] = \frac{1}{T}$$

$$E[G_{i\tau}] = 0$$

$$\mathrm{Var}[G_{i\tau}] = \frac{T-1}{T}$$

$$\mathrm{Cov}[G_{i\tau}, G_{is}] = -\frac{1}{T}$$

where $i = 1,2, \dots. N$, and $\tau \neq s$

APPENDIX III

The performance of T-statistics, SIGN-COWAN and SIGN-GSAR-T

This is a simulation results conducted by Luoma, T (2011) which shows the performance of the three test statistics when the event days are clustered. There are 1000 portfolios with 50 stocks in the simulation.

Tables 1-4 report the Type I error and power results of the test statistics with clustered event days. The zero abnormal return line in each table indicates the Type I error rates. The rest of the lines of the tables indicate the rejection rates for the respective abnormal returns shown in the first column. For AR(0) the abnormal performance is artificially introduced by adding the indicated percentage (a constant) to the day-0 return of each security. While for event window (-1,1), (-5,5) and (-10,10), the abnormal performance is introduced by selecting one day of the eventwindow at random and adding the particular level of abnormal performance to that days return.

For almost all event windows the test statistic SIGN-GSAR-T reject close to the nominal rate with rejection rates that are well within the approximate 99 percent confidence interval of [0.032,0.068]. The ordinary t-test statistic and the sign test statistic derived by Cowan seem to over-reject for all CAR-windows. Also SIGN-GSAR-T seems to somewhat over-reject for the longest event window of (-10,10), but clearly not as much as the other test statistics.

Table I: Single event day AR(0)

Abnormal return	ORDIN	SIGN-COWAN	SIGN-GSAR-T
3,0	1,000	0,999	0,996
2,0	0,987	0,995	0,981
1,0	0,824	0,927	0,788
0,0	**0,096**	**0,137**	**0,058**
-1,0	0,821	0,903	0,843
-2,0	0,991	0,992	0,987
-3,0	0,998	1,000	0,998

Table II: Event window (-1,1)

Abnormal return	ORDIN	SIGN-COWAN	SIGN-GSAR-T
3,0	0,979	0,992	0,962
2,0	0,889	0,962	0,849
1,0	0,468	0,656	0,368
0,0	**0,113**	**0,114**	**0,042**
-1,0	0,488	0,596	0,477
-2,0	0,876	0,929	0,888
-3,0	0,968	0,981	0,967

Table III: Event window (-5, 5)

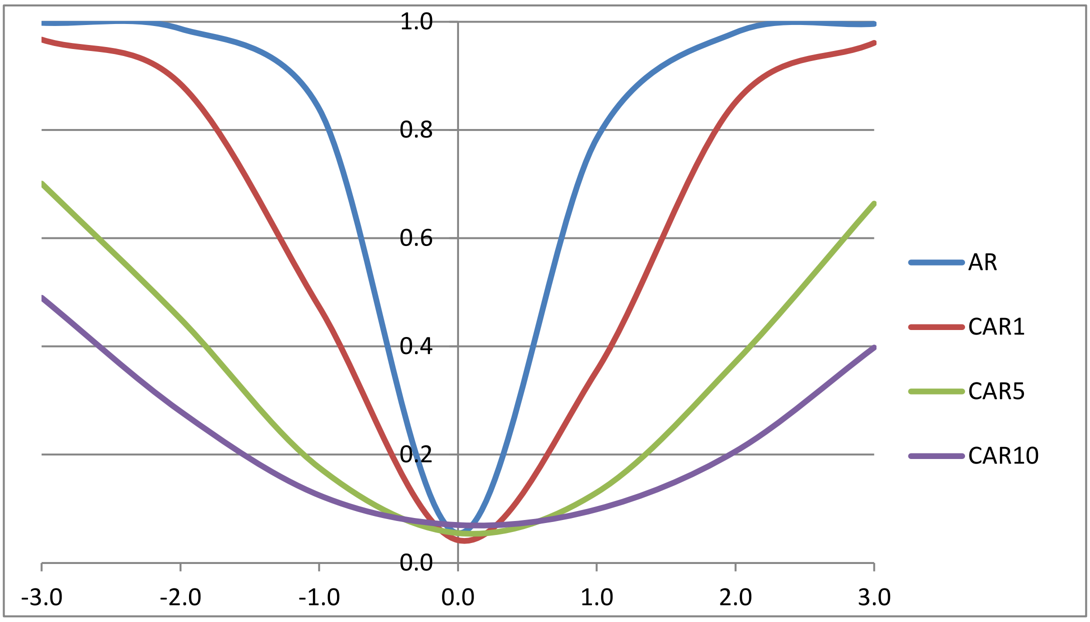
Abnormal return	ORDIN	SIGN-COWAN	SIGN-GSAR-T
3,0	0,740	0,863	0,669
2,0	0,497	0,672	0,377
1,0	0,242	0,342	0,136
0,0	**0,162**	**0,145**	**0,059**
-1,0	0,273	0,274	0,178
-2,0	0,538	0,565	0,461
-3,0	0,761	0,793	0,709

Table IV: Event window (-10,10)

Abnormal return	ORDIN	SIGN-COWAN	SIGN-GSAR-T
3,0	0,524	0,700	0,405
2,0	0,035	0,467	0,210
1,0	0,217	0,259	0,102
0,0	**0,172**	**0,158**	**0,069**
-1,0	0,235	0,201	0,129
-2,0	0,398	0,374	0,284
-3,0	0,581	0,602	0,497

The power properties of the test statistic SIGN-GSAR-T are also graphically depicted in Graph 1. As can be seen the power of the test statistic decreases when the length of the event window increases from single event day to 10 event days.

Figure I: The power results of the test statistic SIGN-GSAR-T



APPENDIX IV

Event day for Sample 2

Table I: Upgrade Group in Sample 2

Observation	Company Name	Rating Date
1	CARBIDE/GRAPHITE GROUP INC	28-Feb-97
2	COOPER COMPANIES INC	22-Jan-10
3	ENGLE HOMES INC	7-Jun-00
4	ROWAN COS INC	4-Nov-97
5	PENN NATIONAL GAMING INC	4-Nov-98
6	COINSTAR INC	28-May-10
7	CHATTEM INC	9-Nov-04
8	CHOICE HOTELS INTL INC	28-Feb-05
9	SONIC AUTOMOTIVE INC -CL A	29-Jan-10
10	ITT CORP	25-Sep-01
11	CHARLES RIVER LABS INTL INC	22-Feb-08
12	MCMORAN EXPLORATION CO	8-Aug-08
13	CHEMED CORP	24-Jan-05
14	ASPEN INSURANCE HOLDINGS LTD	27-May-05
15	FISHER COMMUNICATIONS INC	22-Feb-08
16	AXIS CAPITAL HOLDINGS LTD	2-Feb-09
17	WELLPOINT INC	20-Nov-07
18	AMERIPRISE FINANCIAL INC	10-Jul-08
19	ST JUDE MEDICAL INC	1-May-08
20	PETROHAWK ENERGY CORP	18-Oct-07
21	H&E EQUIPMENT SERVICES INC	19-Mar-08
22	PETROLEUM DEVELOPMENT CORP	19-Mar-08
23	BIOGEN IDEC INC	4-Dec-08
24	BILL BARRETT CORP	8-Jan-10
25	ALPHA NATURAL RESOURCES INC	4-Aug-09

Table II: Downgrade Group in Sample 2

Observation	Company Name	Rating Date
26	AMERICAN TELECASTING INC	16-Apr-98
27	CINTAS CORP	2-Oct-09
28	HUNTINGTON BANCSHARES	6-Apr-05
29	SYSCO CORP	27-Feb-04
30	TEKTRONIX INC	22-Feb-00
31	YOUNG BROADCASTING-CL A	18-Apr-05
32	CORPORATE EXPRESS INC	24-Mar-99
33	GREEN MOUNTAIN POWER CORP	11-Jun-98
34	AGCO CORP	7-Apr-04
35	CARLISLE COS INC	19-Jul-01
36	WALLACE COMPUTER SVCS INC	17-May-00
37	MEDIACOM COMMUNICATIONS CORP	30-Sep-04
38	LIZ CLAIBORNE INC	23-Mar-10
39	TERADYNE INC	13-Dec-02
40	ARCH COAL INC	1-Oct-09
41	FBL FINANCIAL GROUP INC-CL A	20-Feb-09
42	NOBLE ENERGY INC	17-May-05
43	BARRICK GOLD CORP	7-Feb-06
44	HORNBECK OFFSHORE SVCS INC	8-Jun-10
45	ATP OIL & GAS CORP	8-Jun-10
46	TIME WARNER CABLE INC	27-Mar-09
47	EPICOR SOFTWARE CORP	19-Dec-07
48	L-1 IDENTITY SOLUTIONS INC	12-Jan-10
49	NATIONAL SEMICONDUCTOR CORP	10-Dec-08
50	HERCULES OFFSHORE INC	8-Jun-10
51	WESTERN REFINING INC	9-Mar-10

APPENDIX V

Sub groups for Sample 2

Table I: Below Investment Grade Downgrades (N=14)

Obs	Company Name	Rating	Rating Number	Notches	Previous Rating	Below Downgrades
26	AMERICAN TELECASTING INC	CCC	18	1	17	1
31	YOUNG BROADCASTING -CL A	B-	16	1	15	1
32	CORPORATE EXPRESS INC	B-	16	1	15	1
34	AGCO CORP	BB-	13	1	12	1
37	MEDIACOM COMMUNICATIONS CORP	B	15	1	14	1
38	LIZ CLAIBORNE INC	CCC+	17	1	16	1
39	TERADYNE INC	B+	14	1	13	1
40	ARCH COAL INC	BB-	13	1	12	1
44	HORNBECK OFFSHORE SVCS INC	B+	14	1	13	1
45	ATP OIL & GAS CORP	CCC+	17	2	15	1
47	EPICOR SOFTWARE CORP	B	15	1	14	1
48	L-1 IDENTITY SOLUTIONS INC	B+	14	1	13	1
50	HERCULES OFFSHORE INC	B-	16	1	15	1
51	WESTERN REFINING INC	CCC+	17	1	16	1
Total						14

Table II: Below Investment Grade Upgrades (N=17)

Obs	Company Name	Rating	Rating Number	Notches	Previous Rating	Below Upgrades
1	CARBIDE/GRAPHITE GROUP INC	BB	12	-2	14	1
2	COOPER COMPANIES INC	BB	12	-1	13	1
3	ENGLE HOMES INC	B+	14	-1	15	1
4	ROWAN COS INC	BB	12	-2	14	1
5	PENN NATIONAL GAMING INC	B+	14	-1	15	1
6	COINSTAR INC	BB+	11	-1	12	1
7	CHATTEM INC	BB-	13	-1	14	1
9	SONIC AUTOMOTIVE INC -CL A	B-	16	-3	19	1
11	CHARLES RIVER LABS INTL INC	BB+	11	-2	13	1
12	MCMORAN EXPLORATION CO	B-	16	-1	17	1
13	CHEMED CORP	B	15	-1	16	1
15	FISHER COMMUNICATIONS INC	B	15	-1	16	1
20	PETROHAWK ENERGY CORP	B	15	-1	16	1
21	H&E EQUIPMENT SERVICES INC	BB-	13	-1	14	1
22	PETROLEUM DEVELOPMENT CORP	B+	14	-2	16	1
24	BILL BARRETT CORP	BB-	13	-1	14	1
25	ALPHA NATURAL RESOURCES INC	BB	12	-3	15	1
Total						**17**

Table III: Above Investment Grade Downgrades (N=12)

Obs	Company Name	Rating	Rating Number	Notches	Previous Rating	Above Downgrades
27	CINTAS CORP	A-	7	1	6	1
28	HUNTINGTON BANCSHARES	BBB+	8	1	7	1
29	SYSCO CORP	A+	5	1	4	1
30	TEKTRONIX INC	BB+	11	1	10	1
33	GREEN MOUNTAIN POWER CORP	BBB	9	2	7	1
35	CARLISLE COS INC	BBB	9	1	8	1
36	WALLACE COMPUTER SVCS INC	BBB	9	1	8	1
41	FBL FINANCIAL GROUP INC-CL A	BBB-	10	1	9	1
42	NOBLE ENERGY INC	BBB-	10	1	9	1
43	BARRICK GOLD CORP	A-	7	1	6	1
46	TIME WARNER CABLE INC	BBB	9	1	8	1
49	NATIONAL SEMICONDUCTOR CORP	BBB-	10	1	9	1
Total						12

Table IV: Above Investment Grade Upgrades (N=8)

Obs	Company Name	Rating	Rating Number	Notches	Previous Rating	Above Upgrades
8	CHOICE HOTELS INTL INC	BBB	9	-1	10	1
10	ITT CORP	BBB+	8	-1	9	1
14	ASPEN INSURANCE HOLDINGS LTD	BBB+	8	-1	9	1
16	AXIS CAPITAL HOLDINGS LTD	A-	7	-1	8	1
17	WELLPOINT INC	A-	7	-1	8	1
18	AMERIPRISE FINANCIAL INC	A	6	-1	7	1
19	ST JUDE MEDICAL INC	A-	7	-1	8	1
23	BIOGEN IDEC INC	BBB+	8	-1	9	1
Total						8

APPENDIX VI

Table I: Standard and Poor's Rating Number Conversion

Rating	**Rating Number**
AAA	1
AA+	2
AA	3
AA-	4
A+	5
A	6
A-	7
BBB+	8
BBB	9
BBB-	10
BB+	11
BB	12
BB-	13
B+	14
B	15
B-	16
CCC+	17
CCC	18
CCC-	19
CC	20
C	21
D	22

Note: BBB- (rating number 10) is the lowest investment grade

TABLES AND FIGURES

Table 1: Summary of t-statistics for Sample 1 with different estimation window lengths

Event Window	Ratings	Average CAR (T-statistics) L1=35 days	Average CAR (T-statistics) L1=235 days
Single Event day	Upgrade	-0.55% (-0.99302404)	-0.24% (-0.68881134)
	Downgrade	-1.04% (-0.90972523)	-0.72% (-0.77608291)
(-1,1)	Upgrade	-1.37% (-1.4227231)	-0.72% (-0.84793617)
	Downgrade	-0.47% (-0.23674448)	0.47% (0.1942735)
(-3,3)	Upgrade	-1.35% (-0.89647667)	-0.37% (-0.69017846)
	Downgrade	-4.18% (-1.3533615)	-1.18% (-0.48324809)
(-5,5)	Upgrade	-1.79% (-0.92594855)	-0.08% (-0.44894151)
	Downgrade	-4.66% (-1.1566988)	-0.69% (-0.22616766)
(-10,10)	Upgrade	-4.80% (-1.7859886)	0.34% (1.15284416)
	Downgrade	-2.72% (-0.49128221)	2.41% (0.31114551)
(-3,10)	Upgrade	-1.20% (-0.56332328)	0.78% (0.42631439)
	Downgrade	-9.08% (-2.0799794)*	-2.65% (-1.46972709)
(-3,20)	Upgrade	-2.99% (-1.0759783)	0.61% (0.95372149)
	Downgrade	-9.24% (-1.6154822)	-2.26% (0.50064176)

***p<0.02 **p<0.05 *p<0.1 Test Statistics in parenthesis
29 observations in upgrade group, 7 observations in downgrade group

Table 2: Summary of t-statistics and SIGN-GSAR-T for Sample 1

Event Window	Ratings	Average CAR (T-statistics) L1=235 days	G0 (SIGN-GSAR-T) L1=235 days
Single Event day	Upgrade	-0.24% (-0.68881134)	-0.1034483 (-0.4881666)
	Downgrade	-0.72% (-0.77608291)	-0.1428571 (-0.3418412)
(-1,1)	Upgrade	-0.72% (-0.84793617)	-0.1034483 (0.4910522)
	Downgrade	0.47% (0.1942735)	0.1428571 (0.0425232)
(-3,3)	Upgrade	-0.37% (-0.69017846)	-0.1034483 (0.4883868)
	Downgrade	-1.18% (-0.48324809)	-0.1428571 (0.3425232)
(-5,5)	Upgrade	-0.08% (-0.44894151)	-0.0344828 (0.2609898)
	Downgrade	-0.69% (-0.22616766)	-0.4285714 (-0.097995)
(-10,10)	Upgrade	0.34% (1.15284416)	0.1034483 (1.021558)
	Downgrade	2.41% (0.31114551)	0.1428571 (-0.1986419)
(-3,10)	Upgrade	0.78% (0.42631439)	0.1724138 (0.2132476)
	Downgrade	-2.65% (-1.46972709)	-0.4285714 (-1.025532)
(-3,20)	Upgrade	0.61% (0.95372149)	0.1724138 (0.7165636)
	Downgrade	-2.26% (0.50064176)	-0.1428571 (0.3418412)

***p<0.02 **p<0.05 *p<0.1 Test Statistics in parenthesis
29 observations in upgrade group, 7 observations in downgrade group

Table 3: Summary of t-statistics and SIGN-GSAR-T for Sample 2

Event Window	Ratings	Average CAR (T-statistics) L1=235 days	G0 (SIGN-GSAR-T) L1=235 days
Single Event day	Upgrade	0.26% (0.44457689)	0.28 (0.790844)
	Downgrade	-2.17% (-3.1274849)***	-0.1538462 (-2.2294637)**
(-1,1)	Upgrade	-0.80% (-0.79224826)	-0.12 (-0.6469644)
	Downgrade	-0.88% (-0.73500206)	0.0769231 (0.4151922)
(-3,3)	Upgrade	-0.51% (-0.82676717)	0.12 (0.6470589)
	Downgrade	-0.66% (-1.46082096)	0.2307692 (1.266281)
(-3,10)	Upgrade	1.04% (0.77264547)	0.12 (0.6412002)
	Downgrade	4.29% (1.7548871)*	0.3846154 (2.115406)**
(-3,20)	Upgrade	-3.35% (-1.1686183)	-0.12 (-0.643784)
	Downgrade	5.91% (1.7424172)*	0.1538462 (0.8440307)

***p<0.02 **p<0.05 *p<0.1 Test Statistics in parenthesis

25 observations in upgrade group, 26 observations in downgrade group

Table 4: Summary of t-statistic and SIGN-GSAR-T for sub groups in Sample 2

Event Window	Sub groups (N)	Average CAR (T-statistics) L1=235 days	G0 (SIGN-GSAR-T) L1=235 days
Single Event day	Below Investment grade downgrade (14)	-1.54% (-1.5638733)	-0.1428571 (-1.3354956)
	Below Investment grade upgrade (17)	0.04% (0.44805123)	0.1764706 (0.2398504)
	Above Investment grade downgrade (12)	-2.91% (-4.0220918)***	-0.1666667 (-2.586184)**
	Above Investment grade upgrade (8)	0.73% (1.2194578)	0.5 (1.0312842)
(-3,10)	Below Investment grade downgrade (14)	11.11% (2.6244498)***	0.8571429 (3.346081)***
	Below Investment grade upgrade (17)	-2.42% (-0.80280967)	-0.2352941 (-0.9887131)
	Above Investment grade downgrade (12)	-3.66% (-1.3679611)	-0.1666667 (-0.5910951)
	Above Investment grade upgrade (8)	1.90% (0.78054238)	0.75 (1.272317)
(0,10)	Below Investment grade downgrade (14)	10.49% (2.7943017)***	0.7142857 (2.677373)***
	Below Investment grade upgrade (17)	-0.9% (-0.33666979)	-0.0588235 (-0.2458216)
	Above Investment grade downgrade (12)	-4.42% (-1.3424376)	-0.5 (-1.049663)
	Above Investment grade upgrade (8)	2.28% (1.0551258)	0.5 (1.531282)
(-3,20)	Below Investment grade downgrade (14)	12.74% (2.2992726)**	0.4285714 (1.667849)
	Below Investment grade upgrade (17)	-4.97% (-1.2602178)	-0.1764706 (-0.7447336)
	Above Investment grade downgrade (12)	-2.05% (-0.58474739)	-0.1666667 (-0.5910951)
	Above Investment grade upgrade (8)	0.08% (0.02578404)	0.25 (0.7575726)

***p<0.02 **p<0.05 *p<0.1 Test Statistics in parenthesis

Figure 1: Average ARs for Above Investment Grade Downgrades Group

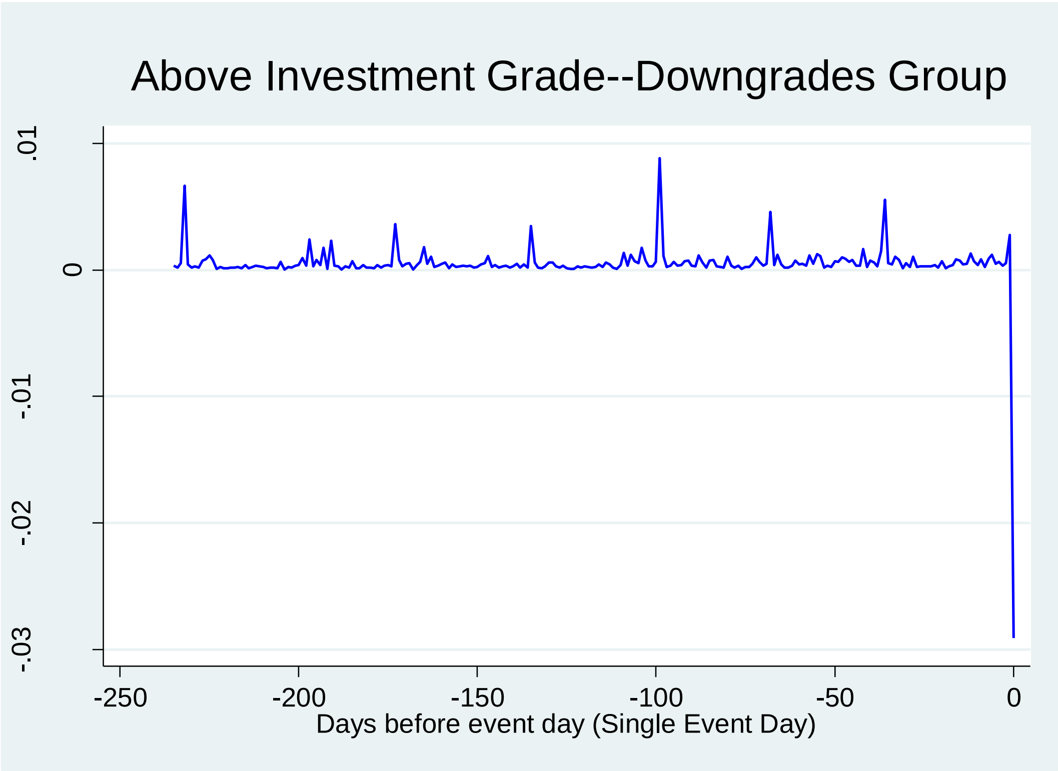


Figure 2: Average ARs for Below Investment Grade Downgrades Group

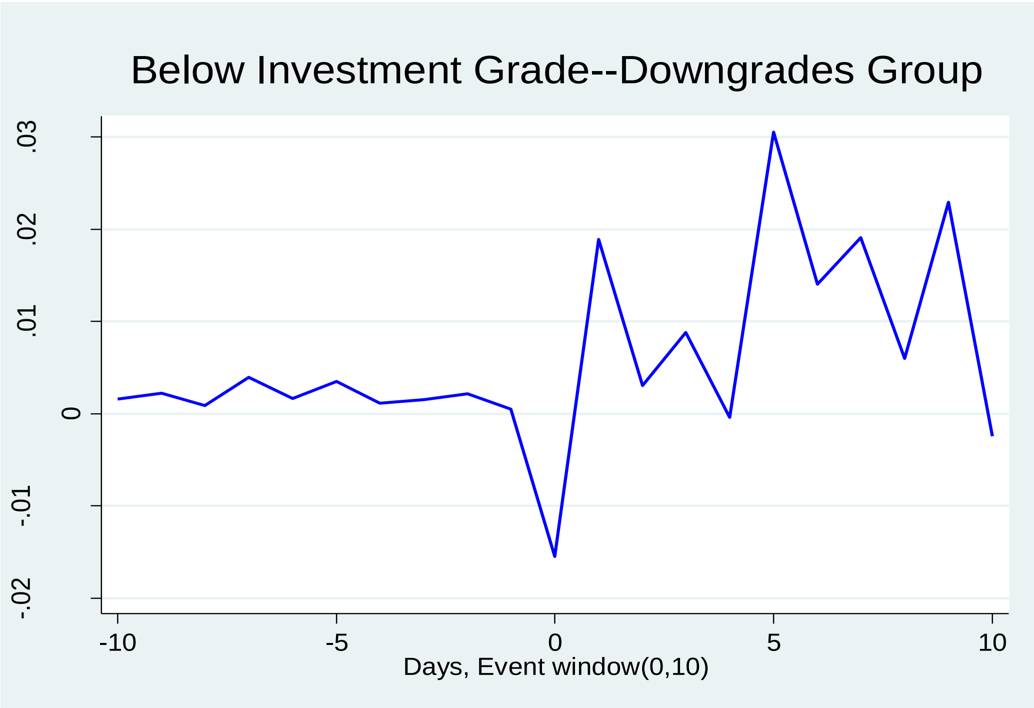


Figure 3: Average CARs for Below Investment Grade Downgrades Group