THE EFFECT OF BOND RATING CHANGES ON STOCK RETURNS: EVIDENCE FROM THE CHINA & HONG KONG STOCK MARKET

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The Effect of Bond Rating Changes on Stock Returns:
Evidence from the China & Hong Kong Stock Market

by

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Abstract:

Efficient Market Hypothesis has always been a hot topic for empirical study in Finance. In this paper, we examine the efficiencies of Mainland China and Hong Kong markets by analyzing the different reactions of stock price and volatility to credit rating changes. The study of impact of credit rating change also fills a gap of no empirical analysis of credit rating change effect in these two markets.

In a semi-strong efficient market, investors cannot make profit based on public information. In this study, we select Chinese cross-listed A-H share companies as our sample and compare the effects of bond rating changes on A-share stock price and H-share stock price. The differences in the stock return and volatility reactions signify the differences in market efficiency. The results from an event study indicate that neither market is semi-strong efficient and Hong Kong market is more efficient in digesting credit rating change information. Both Mainland China and Hong Kong markets show statistically significant and negative abnormal returns after the annoucement of credit rating downgrades and only Mainland China market shows statistically significant abnormal returns before the annoucement. Hong Kong market shows statistically significant and positive abnormal returns around the announcement of credit rating upgrades and Mainland China market shows no statistically significant abnormal returns around the announcement. Concerning volatility, credit rating downgrades can cause significant positive abnormal volatility around the announcement date in both Mainland

China and Hong Kong markets, while there is no significant abnormal volatility around the announcement of credit rating upgrades.

In the cross-sectional analysis of return reactions to credit rating changes, pre-announcement abnormal returns and whether credit ratings moved to speculative grade have an impact on the abnormal returns during the announcement.

Keywords: Market Efficiency - Credit rating changes – A-H share

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1. Introduction

In finance, the efficient market hypothesis (EMH) asserts that financial markets are "informationally efficient". In semi-strong form efficiency, it is implied that share prices adjust to publicly available new information very rapidly and in an unbiased fashion, such that no excess returns can be earned by trading on that information. Empirical analyses have consistently found problems with the efficient market hypothesis, the most consistent being that stocks with low price to earnings (and similarly, low price to cash-flow or book value) outperform other stocks. However, the efficiency studies have not focused on cross-listed shares.

Two types of stocks are traded in China security market: A-share for local investors and B-share for foreign investors. However, B-share stocks are opened to domestic investors since 2001. In addition, H-share stocks are traded in Hong Kong stock market since 1993. Tsingtao Beer was the first stock which is crossed listed in both Mainland China and Hong Kong stock markets. By the end of 2009, there are over 150 H-share companies listed in Hong Kong Stock exchange, 57 of which were listed in Shanghai or Shenzhen Stock exchange as well.

The reason why so many companies are cross listed is that internationalization of Chinese companies and their development in size and scale have made it difficult for Mainland China stock market to satisfy their funding requirements for rapid development. These companies are facing financing pressures and seek external capital. Moreover, it is also necessary for these companies to expand their shareholders base considering management and strategies. Chang (2000) pointed out that Hong Kong stock market has been the largest source of foreign funds for China and it has been supported by big Chinese companies as well. The existence of dually listed stocks also provides us good evidence for studying relative efficiency of two markets.

Despite the same right for share earnings, there are big differences of prices, yields and volatilities between the two markets. With the expanding of Mainland China stock market, relaxing of the government control over stock listing, implementing the Qualified Foreign Institutional Investors (QFII) program and the Qualified Domestic Institutional Investors (QDII) program, the differences between the two markets are getting smaller.

The aim of this paper is to examine the different stock market reactions to bond rating changes as a test of market efficiency. Perhaps Hong Kong as a mature stock market is more efficient than that of Mainland China in reactions to important information. Then the questions are: Does Hong Kong stock market incorporate the corporate information quicker than Mainland China market and what are the factors fundamentally behind this phenomenon? To answer these questions, we perform both the event study and the cross-sectional analysis of the impact of credit rating changes information on the stock prices.

Bond credit rating is a grade given to bonds that indicate their credit quality. Independent credit rating agencies such as Moody's, Standard and Poor's and Fitch provide these evaluations of a bond issuer's financial strength, or it's the ability to pay a bond's principal and dividend timely. There are two alternative views on the impact of credit rating changes on stock returns. One view is Information Content Hypothesis. It predicts that credit rating changes have an impact on corporation's values. In a credit rating process, credit rating agencies get considerable inside information about the firm. In the stock markets, investors will follow the advice given by credit agencies and credit rating releases cause share price revisions. Moreover, since stocks are residual claimants to the firm's earnings and the bond credit rating provides information about firm value, the stocks of downgraded (upgraded) firms should decrease (increase). Griffin and Sanvicente (1982) are among the first to get this conclusion. The other view is called Wealth Redistribution Hypothesis. It argues that the limited liabilities may encourage stockholders to take on riskier investment strategies to increase their expected returns. This corporate restructuring strategy increases the default risk of outstanding bonds. It leads to a bond downgrade that reduces bond value. Any reduction in bond value is transferred from bondholders to stockholders. The corporate restructuring can also change the firm value. If it also causes a decline in firm value, it makes the probability of default even greater and the outstanding bonds even riskier. In this way, a bond downgrade implies an increase in default risk. If the probability of default risk increases because managers take riskier investment strategies, then the expected return for the stockholders would increase. Thus, the downgrade (upgrade) of bond rating will cause the increase (decrease) of stock returns. Galai and Masulis (1976) extend the principal-agent problem by examning the bondholders and stockholders of a company and get the Wealth Redistribution Hypothesis.

Previous studies only focus on credit rating effect of U.S. and some other developed country markets. For example, Griffin and Sanvicente (1982) find that abnormal reurns for downgrades are statistically significant during the month of annoucement and there is no evidence of abnormal equity returns for upgrades. Mainland China and Hong Kong are two markets in which the topic has not been analyzed. Besides, the comparison of the two market reactions signifies the different efficiencies of the two markets. The crossed listed stocks provide us a perfect sample to analyze the impact of bond rating changes on stock returns and volatilities.

This paper suggests that investors can possibly use the announcement of downgrade (upgrade) to predict future stock price movements. Since credit rating is public information that is available to all investors, this is a violation of semi-strong efficient market hypothesis in both markets. Besides, Hong Kong market is more efficient in digesting corporate information than Mainland China market. Specifically, the 5-day and 10-day post downgrade announcement abnormal returns are negative and statistically significant at 5% level based on the market model whereas there is no significant abnormal positive return around credit rating upgrades except in the largest interval. Additionally, we study the impact of credit rating changes on stock volatility, which is also a meaningful topic and has not been studied. From this part, there is also evidence that the abnormal volatility is positive and statistically significant at 5% level around the announcement of downgrades.

The result of this paper supports and confirms the conclusion reached by Pilar and Dolores (2007) who argue that rating actions cause significant negative abnormal returns in issuing firms around the date of annoucement. This evidence indicates that an informational effect dominated downgrades, which support the hypothesis that credit rating agencies provide inside information that may reduce the problem of asymmetric information. In the case of the upgrades, there are different reactions for Mainland China and Hong Kong stock markets.

The rest of this paper is orgnized as follows: the related research and literature is presented in Section 2. Data and sample selection are discribed in Section 3. Section 4 explains the methodology used in the the empirical study. Section 5 presents the results of event study and the analysis of the related results. An conclusion is offered in Section 6.

2. Related Research and Literature

The concept of market efficiency is the foundation for much of the theoretical and empirical research in financial economics. Numerous studies have considered different aspects of market efficiency and relationships of cross-listed shares. Autocorrelation and reaction to information release are two methods that are typically investigated of market efficiency. Fisher (1966) discovers that there is serial autocorrelation in the Dow-Jones and Standard and Poor’s index and uses it as a method of examing market efficiency. In his framework, we can predict prices and returns if there were serial correlation in the index series. Furthermore, this is interpretated as a violation of weak form efficiency which considers that investors can not profit from historical information. Jegadeesh (1990) finds that the negative first-order serial correlation in monthly stock returns is highly significant. Moreover, significant positive serial correlation is found in longer lags, and the twelve-month serial correlation is particularly strong.

Boudoukh et al. (1994) conclude that there are three prevailing views on the cause of autocorrelations in the short-horizon returns: 1) market frictions, 2) microstructure effects, e.g. economic risk premium, 3) over or under reaction to information, e.g. annoucement of earnings, dividends and takeovers. They also find that the effect of nonsynchronous trading has been understated in most literature. Moreover, they study the relationship between the autocorrelations of future's returns and returns on the underlying spot index of two small-firms-based indices and find that, although returns on small-firms-based indices display significant autocorrelation, returns on the corresponding future contracts display almost none.

Jeson (1978) does a literature review of evidence on the reaction of stock prices to earning annoucement which is inconsistent with the Efficient Market Hypothesis (EMH) . He proposes the measurement of abnormal return from financial events as an alternative measurement of market efficiency. Lehmann (1990) tests the market efficiency hypothesis by examining security prices for evidence of unexploited arbitrage opportunities. The results strongly suggest rejection of the efficient markets hypothesis. Andrew and Mackinlay (1990) find that less than 50 percent of the expected profits from a contrarian investment rule may be attributed to overreaction; the majority of such profits are due to the cross effects among securities. The cross effect is the main cause for violation of EMH. Following his suggestion, Jegadeesh and Titman (1995) examine the contribution of stock price overreaction and delayed reation of the profitability of contrarian strategies. The evidence indicates that stock prices overreact to firm-specific information, but react with a delay to common factors. Over and delayed reactions to common factors violate the EMH.

Most efficiency studies have not focused on the cross-listed stocks. However, there is plenty of literature of how American Depository Receipts (ADRs) are priced, the lead-lag relationship of cross-listed stocks and the main effect of cross-listing on stocks in both markets. Foerster and Karolyi (1993) test whether the extent of economic and financial market segmentation between a firm's home country and listing country influences stock price reaction by examining the case of two "similar" countries: the U.S. and Canada. During the 100 days before the week of interlisting in the U.S., stock prices of Canadian firms rise by over 9.4%, rise by 2% around interlisting date, but drop by 9.7% in the 100 days after interlisting. They interpret this evidence to be consistent with the financial market segmentation between Canada and the U.S. Sundaram and Logue (1996) examine post-listing equity price performance of foreign firms which cross-listed sponsored American Depository Receipts on the New York and the American Stock Exchanges during the period 1982-1992. They find positive valuation effects associated with cross-listing for both country-benchmarked and industry-benchmarked price ratios. The results suggest that cross-listing in the U.S. enhances valuation for listing firms by simply reducing the overall effect of segmentation among different national security markets.

Forster (1996) studies the relative variance of "pricing errors" (transitory changes in prices) at the open and close of trading on the NYSE. The variance of pricing errors at the open is greater than at the close for U.S. stocks, whether traded abroad or not, but this is not true of foreign stocks. These differences are explained by a concentration of trading volume at the open relative to the close that is greater for U.S. stocks than foreign stocks. Domowitz et al. (1998) show the effects of cross-listing depend on the quality of intermarket information linkages. They investigate the impact of cross-listing with stocks crossed listed in the Mexico stock market and U.S. stock market. The effects are complex—blancing the costs of order flow migration against the benefits of increased intermarket competition. Wang et al. (2008) examine the impacts of cross-listing on the corporate stocks' risks and returns by studying companies that have issued American Depository Receipts from nine Asian regions in the 1990s. They conclude that the accumulative abnormal returns of international cross-listed high-tech companies are usually higher than those of traditional sectors. Moreover, there are no significant changes in the pattern of risks after international cross-listings.

For the Chinese stocks that are cross-listed in Mainland China and Hong Kong stock markets, there is also plenty of literature studying the A-H share problems, e.g. pricing errors. Wang and Liu (2003) base on the tests of differences between the dual financial reports in 1994-2000 by cross-listed Chinese A-H share compnies in the Mainland China and Hong Kong markets respectively. They find that the new accounting system in 1998 do not reduce the differences notably. They get the implication that the behavior by companies in their accounting and reporting practice before and after 1998 is the real reason resulting in the dual reports disclosure differences. Chen and Wang (2007) explore an empirical research about the impact of cross-listing on A-share market by using a A-H share sample from 1993 to 2006. They find the empirical evidence of the negative net effect to A-share market and A-share listed from the A and H share cross-listing and the investors prefer the A and H cross-listed frims. Pan and Dai (2008) examine the influence of "dual listing" behavior on the level of the companies' financial constraints, providing empirical evidence for the theoritical hypothesis that the instrinsic motive of dual listing is the company's intent to resolve refinancing difficulties. They find that H-share companies face severe refinancing constraints before returning to the domestic market, and threat after dual listing, the sensitivity of corporate investments towards cash flows will sifnificantly drop. Financing constraints will be effectively eased. Moreover, the frequency and amounts of refinancing from the external capital market will significantly increased. Xu (2009) test the factors which result in the price differences between A and H-share of Chinese dual-listed companies and analyszes the effect of QDII and "Through Train" after the share merger reform. The results suggest that the price ratio of A-H share fluctuates during the sample period, but increases as a whole. After the share merger reform, the policy called "Through Train" had an greater effect on the price differences, but QDII does not.

In this paper, we conduct another test of market efficiency. Specifically, we examine different market reactions to credit rating changes for studying the market efficiencies of both markets. Previous studies find that there are abnormally high (low) stock returns around the announcement of credit rating upgrades (downgrades). Most literature focuses on the U.S. market. Pinches and Singleton (1978) find that there is little information in credit rating changes. Therefore, investors cannot make a profit by taking actions based on the annoucement of credit rating changes because it has been already incoroporated into share prices. However, based on the monthly data, Griffin and Sanvicente (1982) suggest that there are negative abnormal returns after the annoucement of rating downgrades while the result of rating upgrades is not statistically significant. The same conclusion is reached by Holthausen and Leftwich (1986). Zaima and McCarthy (1988) conclude that information content of "bad" news dominates firm downgradings, while wealth redistribution effect dominates firm upgradings.

Impson et al. (1992) observe that downgrades are accompanied by an increase in beta while upgrades are not found to be associated with such a change. Hand et al. (1992) examine the impact of rating changes and announcement of Standard and Poor's CreditWatch list. They exclude the contaminated samples and find that unexpected downgrades have a negative effect on returns. Goh and Ederington (1993) find that not all credit rating downgrades are bad news for stockholders. In particular, downgrades due to changes in riskier investment strategy reflect the transfer of corporate wealth from bondholders to stockholders. Hence, only downgrades concerned with deterioration in financial outlooks have negative effects. Best (1997) finds the evidence of abnormal returns for both downgrades and upgrades. He concludes that credit rating upgrades (downgrades) are often followed by the positive (negative) abnormal returns. Kliger and Sarig (2000) find that rating information does not affect firm value, but that debt value increases (decreases) and equity value falls (rises) when Moody's announces better- (worse-) than expected ratings. Dichev and Piotroski (2001) use a comprehensive sample that comprises essentially all Moody's bond rating changes between 1970 and 1997 to examine the long-run stock returns following the rating changes. Their main finding is that stocks with upgrades outperform stocks with downgrades for up to one year following the annoucement but they find little or no reliable difference in returns thereafter. The return differnetial between stocks with upgrades and downgrades is on the magnitude of 10 to 14 percent in the year following the annoucement, and is mostly due to the poor performance of the stocks with downgrades. Vassalou and Xing (2004) conclude that if the negative abnormal returns for rating downgrades from the previous studies are adjusted for book-to-market, size and default risk factors, then the abnormal returns will dissipate in a short time horizon.

Some other developed country markets have been discussed in recent years. In the United Kingdom, Barron et al. (1997) find significant negative abnormal returns for long-term debt downgrades during the announcement period, whereas there is no evidence of excess returns for long-term debt upgrades. In Spain, Pilar and Dolores (2007) indicate that rating actions cause significant negative abnormal returns in issuing firms around the date of announcement. This evidence suggests an informational effect related to downgrades, which supports the hypothesis that credit rating agencies provide information that may reduce the asymmetric information problem between firms and investors. In Australia, Chan et al. (2009) classify credit rating agencies into two groups: subscribing and non-subscribing. Investors can access (non-subscribing) credit reports released to the public for no charge, or can subscribe to the fee-paying (subscribing) credit reports from agencies. The result suggests that the information content of non-subscribing credit agencies is very low, whereas, positive excess returns exist after the announcement of upgrades from subscribing agencies.

Some of these studies have also done some cross-sectional analysis in the stock market reaction to downgrades. Holthausen and Leftwich (1986) conclude that downgrades which cross the line between investment grade (Baa and above) and speculative grade (Ba and below) are usually accompanied by larger reactions than downgrades otherwise. However, in the contaminated subsample, Hand et al. (1992) find that the market reaction is stronger for rating changes within the speculative grade than for rating changes within the investment grade. However, the differences are not significant in their contaiminated sample. Goh and Ederington (1999) find that the stock market reactions to bond rating downgrades vary greatly depending on the nature of the downgrade. The stock market reacts more significantly to downgrades at the lower end of the rating scales. They also find that the reactions are stronger if the firm's preannoucement abnormal returns have been negative and large.

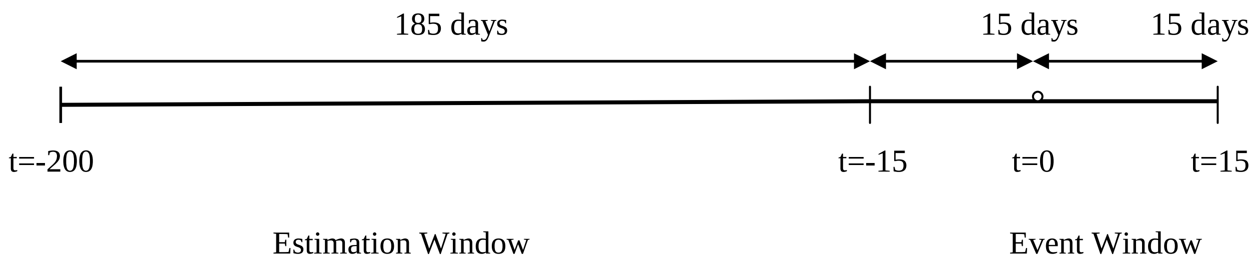
Based on the research before, our study makes three imporatant innovations relative to the early literature. In particular, it tests relative efficiency in Mainland China and Hong Kong markets, which grow fast in the past 30 years. It also studies the reactions of stock returns to rating changes in both markets, which is the first time in Mainland China and Hong Kong markets. Moreover, it focuses on the reations of stock price volatility reaction to rating changes, which is useful for further studying market efficiencies of option/warrant markets.

3. Data and Sample Selection

In this section, we describe the data used in this study. Additionally, we provide the procedures for identifying the firms and the credit rating change events used in this sample. Fifty seven firms are listed crossly in Mainland China and Hong Kong stock markets till 2010/2/28. The time stamps of credit rating data are from 1999/1/1 to 2010/2/28, while daily stock return data is over 1999/1/1 to 2010/2/28 and 5-minute stock data is over 2008/1/1 to 2010/2/28. We collect the credit rating change information from Bloomberg. Directions of credit rating changes are divided into two categories: upgrades and downgrades. The daily stock market return data for Shanghai, Shenzhen and Hong Kong is obtained from RESSET, whereas the 5-minute high frequency data in these markets is from the WSTOCK NET.

Because most credit rating changes happen during the trading period[1], we classify the date of announcement as the event date $t = 0$, and a window of 15 days on both sides of the event as the 'event window'. Each event we selected in our sample has the following characteristics: 1) In the event window, there is no other news that affected the returns and volatilities of the stock. We excluded the credit rating changes that have other important firm-level news released during these 5 days through China Securities Journal and RUN FLUSH software. 2) The daily and 5-minute stock data for Shanghai, Shenzhen and Hong Kong stock markets include the previous 200 days and the following 15 days. Besides, there are at least 100 days for the estimation window and the missing value in the event window (-15, 15) is not allowed. If there are more than one credit rating change for the same company in three months, we only take the first one into account.

[1] 9:30-11:30am and 13:00pm to 15:00pm for Shanghai and Shenzhen Stock Exchange; 10:00am-12:30pm and 14:30pm-16:00pm for Hong Kong Stock Exchange



Ininially we get 234 downgrades and 198 upgrades. After the selection procedure, we finally get 49 downgrades and 63 upgrades. This sample size is obviously smaller than Holthausen and Leftwich (1986) whose sample size is over 1000. But this is comparable to Barron et al. (1997) who get 28 credit rating changes and Matolcsy and Lianto (1995) who get 34 upgrades and 38 downgrades for the Australian market. Therefore, the sample size is enough for our study.

The details of the data is listed in Table 1.

Table 1 Credit Rating Changes Information

Year	Rating changes		Total
	Upgrade	Downgrade	
2000	0	0	0
2001	0	2	2
2002	0	0	0
2003	2	5	7
2004	0	1	1
2005	5	1	6
2006	7	5	12
2007	11	5	16

2008	18	12	30
2009	20	12	32
2010	0	6	6
Total	63	49	112

In the volatility part, we take 44 ups and downs both for Mainland China and Hong Kong markets. The reason why we choose 5-minute stock price data to construct the realized volatility is because more frequent data will incorporate big influence of microstructure of the stock market. Anderson, Bollerslev, Diebold and Labys[2] (1999) point out that the optimal sampling frequency will not be the highest available, but rather some intermediate value, ideally high enough to produce a volatilty estimate with negligible sampling variation, yet not enough to avoid microstructure bias. Bandi (2006) simulates the microstructure in the market and gets the conclusion that the optimized frequency of data is determined by signal-to-noise ratio. Through the simulation, he suggests that the best frequency is between 0.4-minute and 13.8-minute, approximately 3.4-minute. Yacine and Jacod (2009) simulate the microstructure and jumps and get the similar conclusion.

For Chinese stock market, Tang (2006) tries to minimize the error term of Realized Volatility minus Integrated Volatilty and concludes that the optimal sampling intervel is between 5 to 15 minute in China stock market. ABDL (1999) develop a simple and direct grahplical tool called "volatility signiture plot". They manifest microstructure bias as sampling frequency increases by distorting the average realized volatility. Thus, they plot average volatility against sampling interval. The vertical axis is $\overline{RV} = \frac{1}{n}\sum_{t=1}^{n} RV_t$, while the horizental axis is sampling interval f. When the averge volatility begins to get stable, the corresponding interval is the optimal sampling interval.

[2] We use ABDL for short.

In figure 1, we select the 1-minute Shanghai A-share Index data from 2005/1/1 to 2006/1/2. In this interval, there are 243 trading days and 240*243=58320 samples. Because the high frequency data is uniformly-spaced, we can get 17 sampling intervals. We do the volatlity signiture plot following the steps of ABDL (1999). At the smallest sampling intervals, the volatility measures are the highest. This can be explained by the negative serial correlation in returns, which are most likely induced by bid-ask bounce in microstructure noise. As returns are aggregated through larger intervals, the overall volatility is lower. The volatility signature stabilizes at about f=5. Although high-frequency microstructrue effects will be samller for sampling intervals larger than f=5, realized volatility estimates will begin to suffer from higher sampling error. Therefore, we would choose f=5 minute, which represents an optimal sampling interval for China stock market.

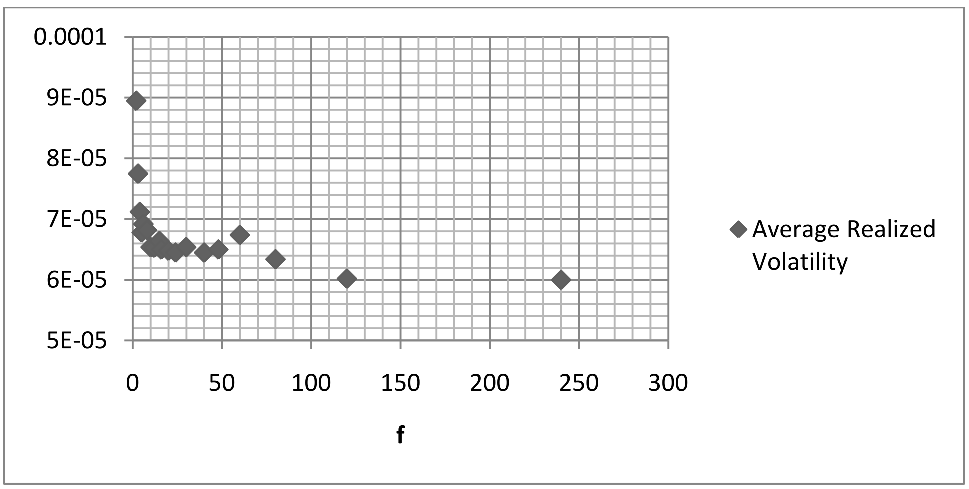


Figure 1 Volatility Signature Plot for Shanghai A-share Index

4. Methodology

4.1 Market Efficiency Comparision: Stock Return Reaction to Rating Changes

In the case of stock returns, we estimate a standard market model using daily returns in the estimation window. For each event i, the daily (log-differenced) stock price return for the company R_{it} is regressed on the market return $R_{\mathrm{M},t}$ using ordinary least squares:

$$R_{it} = \hat{\alpha}_i + \hat{\beta}_i R_{\mathrm{M},t} + \varepsilon_{it} \tag{1}$$

where $\mathrm{R}_{\mathrm{M,t}}$ is the Market Capitalization Weighted Daily Return from RESSET database.

Brown and Warner (1986) use simulation procedures with actual daily data and examine how the particular characteristics of daily stock return data affect event study methodologies. The problems inclue non-normality of returns and excess returns, non-synchronous trading and autocorrelation in the daily excess returns and volatility clustering in the daily data. The results from simulations with daily data generally indicate that methodologies based on the OLS market model and using standard parametric tests are well-specified uder a variety of conditions.

Abnormal returns AR_{it} are then defined as the difference between actual returns and the returns predicted by the market model:

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{\mathrm{M},t} \tag{2}$$

After the calculation of abnormal return for each stock at date t, we need to aggregate the abnormal return both in the dimensions of cross-sectional and time series. Cumulative Abnormal Return $CAR_i(t_1, t_2)$ is then caculated by summing the abnormal return for stock i over time period t_1 to t_2, whereas Cumulative Average Abnormal Return $CAAR(t_1, t_2)$ within the event window is defined as the sum of cumulative abnormal returns across the n events.

Under the null hypothesis, $CAAR(t_1, t_2)$ is normally distributed with zero mean, which requires that the influence of the event is independent among the companies. We use both parametric and nonparametric tests to test the reactions of stock return and volatility.

The parametric test is

$$T_1 = \frac{CAAR(t_1, t_2)}{\sigma(t_1, t_2)} \sim^a N(0,1) \tag{3}$$

where

$$\sigma^2(t_1, t_2) = \frac{1}{N^2} \sum_{i=1}^{N} Var(CAR(t_1, t_2)) = \frac{1}{N^2} \sum_{i=1}^{N} (\sum_{t=t_1}^{t_2} Var(\varepsilon_{it})) \tag{4}$$

assuming ε_{it} and CAR_t are independent and identically distributed (iid) within the event period L. $\sigma^2(t_1, t_2)$ is the aggregate variance for CAAR during the period (t_1, t_2).

A weakness of the parametric test is the hypothesis that abnormal returns or volatility yield a normal distribution. To overcome this weakness, Corrado (1989) proposed a nonparametric rank test to test the abnormal performance in event studies. This test presents the advantage of being robust to variance changes in the event window. Take the event window (-15,15) for example. For each stock i, we sort the 216 days of abnormal returns (volatilities) in ascending order. We define K_{it} as the rank of abnormal returns (volatilities) in date t. Day 0 indexes the event date. The mean estimate is

$$\mu(K) = \frac{1}{N} \sum_{i=1}^{N} (\sum_{t=-15}^{15} (K_{it} - 108.5)) \tag{5}$$

and the standard deviation

$$\sigma(\mathrm{K}) = \sqrt{\frac{31}{216}\sum_{t=-200}^{15}\left(\frac{1}{N}\sum_{i=1}^{N}(\mathrm{K}_{it} - 108.5)\right)} \tag{6}$$

The Corrado(1989) test statistic is

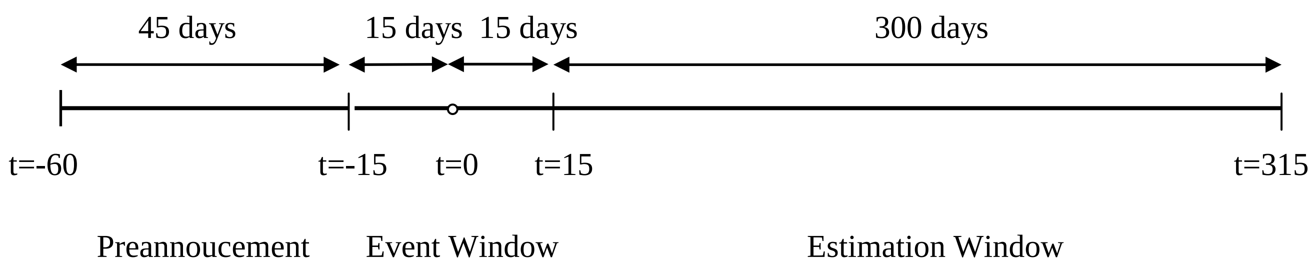
$$\mathrm{T}_2 = \frac{\mu(\mathrm{K})}{\sigma(\mathrm{K})} \tag{7}$$

4.2 Cross Sectional Analysis

We are now paying attention to how the market reactions to a rating change vary across ratings and stocks. Since there are both rating downgrades and upgrades, we separately study the cross sectional effect of credit rating changes. We do exactly the same analysis as Goh and Ederington (1999) on Mainland China and Hong Kong markets. They hypothesize that the market reaction depends on two factors: (1) whether or not the downgrade is a surprise, and (2) the intrinsic importance of credit rating information if the rating changes are suruprises.

They utilize the pre-annoucement returns as measure for surprise of credit raitng changes. If the pre-annoucement abnormal returns (volatilities) are significant, then it seems that the following credit rating changes are largely anticipated. Therefore, the surprise hypothesis implies a negative correlation between pre-annoucement and annoucement period returns. On the other hand, if the pre-annoucement abnormal returns (volatilities) are not significant, then the changes are surprises. Besides, correlation hypothesis insists that there is usually a positive correlation between pre-annoucnement and annoucenment period returns.

To test these two hypotheses, we regress the event window CAR on the 45-day pre-annoucement CAR, CAR(-60,-16). As the utilization of pre-annoucement returns, we use post annoucment period (16, 315) as the estimation period.



We also relate the reaction to credit rating changes to (1) the number of grades the rating is changed and (2) the dummy variable whether the credit rating moves a bond to the speculative grade from below or above. For example, NUM_GRD=3 for change from Aa1 to A1 and NUM_GRD=1 for change from Aa1 to Aa2.

The regressions are estimated separately for downgrades and upgrades for Shanghai, Shenzhen and Hongkong markets.

$$\mathrm{CAR_i} = \alpha + \beta_1 \mathrm{CAR_i}(-60, -16) + \beta_2 \mathrm{NUM\_GRD_i} + \beta_3 \mathrm{SPEC\_GRD}_{\ \mathrm{i}} \tag{8}$$

where $\mathrm{CAR_i}$ is the event i cumulative abnormal returns for event window; $\mathrm{CAR_i}(-60, -16)$ is the event i pre-annoucement cumulative abnormal returns; $\mathrm{NUM\_GRD_i}$ is the number of credit rating changed; $\mathrm{SPEC\_GRD}_i$ is a dummy variable which equals to 1 if the rating changes moves a bond to speculative grade.

4.3 Market Efficiency Comparision: Stock Volatility Reaction to Rating Changes

In recent years, realized volatility has been argued that it has the comparative advantage over Autoregressive Conditional Heteroskedasticity (ARCH) or Stochatic Volatility (SV) type models. First, RV overcomes the well known curse-of-dimension problem in multivariate GARCH and SV models. Second, RV provides a more reliable estimate of integrated volatility according to the stochastic process theory.

The theoretical verification of realized volatility as a measure of volatility comes from the stochastic process theory that quadratic variation converges to integrated volatility as the sampling frequency goes to infinity (ABDL, 2001). Furthermore, ABDL (2003) show that a long memory VAR model for the logarithmic daily realized volatility provides more accurate forecasts than the GARCH (1, 1) model and Risk Metrics model. In this sense, we use ARFIMA model to estimate the influence of bond credit rating change.

The RV is defined by

$$RV_t = \sqrt{\sum_{i=2}^{N}(lnp_{it} - lnp_{it-1}]^2} \quad (9)$$

where p is the stock price and N is 72 in daily realized volatility construction for 5 minute data. The logarithmic transformation is used since the distribution of log realized volatility, but not of realized volatility is approximately normal.

Table 2 The statistics of realized volatility and log-realized volatility

Company_id	variable	Mean	Std	Skewness	Kurtosis	JB test
HK 02628	RV	0.0013	0.0014	4.0167	24.8661	0.0000
	Log-RV	-7.0492	0.8139	0.3748	3.3379	0.0064
HK 00386	RV	0.0013	0.0013	2.7478	14.4051	0.0000
	Log-RV	-7.0218	0.8460	0.1305	2.6011	0.0853
HK 03968	RV	0.0013	0.0031	17.5007	359.3699	0.0000
	Log-RV	-7.0258	0.7812	0.6026	4.8405	0.0000
HK 00670	RV	0.0025	0.0030	3.1114	16.1183	0.0000
	Log-RV	-6.5075	1.0127	0.0616	2.6155	0.2020
HK 03328	RV	0.0010	0.0010	4.1690	28.1358	0.0000
	Log-RV	-7.1829	0.7408	0.2451	3.6350	0.0091
HK 00991	RV	0.0014	0.0015	2.4368	10.3182	0.0000
	Log-RV	-7.0025	0.9424	0.0850	2.4539	0.0301
HK 02600	RV	0.0018	0.0016	2.2456	9.9110	0.0000
	Log-RV	-6.6459	0.8074	-0.0122	2.7082	0.3964
HK 01071	RV	0.0013	0.0014	3.4174	19.2398	0.0000
	Log-RV	-7.0681	0.9049	0.1011	2.5567	0.0764
HK 02883	RV	0.0012	0.0013	3.3367	20.7418	0.0000
	Log-RV	-7.0392	0.8254	0.1268	2.9558	0.4889

ARFIMA (1, d, 1) model for the log RV is defined by

$$(1-\beta_1 L)(1-L)^d(\ln RV_t-\mu)=(1-\alpha_1 L)\varepsilon_t \tag{10}$$

where ε_t is a sequence of independent $N(0,{\sigma_\epsilon}^2)$ distributed random variables. The degree of fractional integration d, obtained using Robinson test. If $0 < d < 0.5$, the time series exhibits long memory effect.

We also use event study to estimate the abnormal volatiilty in this part. The abnormal voaltility is defined as the difference between actual log-realized volatility and the log- realized volatility predicted by ARFIMA model. Cumulative Abnormal Volatility $CAV_i(t_1, t_2)$ is then caculated by summing the abnormal volatility for stock i over time period t_1 to t_2, whereas Cumulative Average Abnormal Volatility $CAAV(t_1, t_2)$ within the event window is defined as the sum of cumulative abnormal volatilities across the n events.Additionally, we use two statistical tests in section 4.1 to test the significance of the abnormal volatility.

5. Results and Analysis

In this part, we compare Mainland China and Hong Kong market efficiencies by analyzing the reactions of stock returns and volatilities to credit rating changes. We study the upgrades and downgrades separately for Mainland China and Hong Kong markets. As for the event window, we first choose the date of annoucement as the event widow. Besides, we pick three symmetric windows (-

15,15)、(-5,5)、(-1,1) as well as four asymmetric windows (-10,-1)、(-5,-1)、(1,5) and (1,10). For credit rating's impact on returns, we also do the cross sectional study following the event study.

5.1 Market Efficiency Comparision: Stock Return Reaction to Rating Downgrades

In order to study the different market effciencies, we compare the abnormal returns caused by the same credit rating changes in Mainland China and Hong Kong stock markets. As we see from Table 3, both Mainland China and Hong Kong markets show statistically significant and negative abnormal returns after the annoucement of credit rating downgrades and only Mainland China market shows statistically significant abnormal returns before the announcement. This indicates that Credit rating downgrades do include some inside information for stockholders and the annoucement has an impact on the return of the stock. Therefore, investors could make a profit from the strategy based on the credit rating announcements.

Furthermore, Shanghai and Shenzhen markets show longer impact than Hong Kong market, Their post-annoucement 10-day abnormal return is still statistically significant, whereas the post-annoucement 10-day abnormal return is not significant in Hong Kong market. Since investors can make a profit by strategies based on rating downgrades, the existence of arbitrage opportunity is a violation of semi-strong form market efficiency in both markets. Hong Kong stock market is more efficient by digesting the information quicker than Mainland China stock market.

This conclusion is supported by Kliger and Sarig (2000), who have discovered that information content hypothesis dominates the downgrades case. Furthermore, the differences between the reactions of Mainland China and Hong Kong markets are suggestive of the relative efficiency of Hong Kong stock market.

Table 3 Cumulative average abnormal return for rating downgrades

Market	Event Window	CAAR (%)	Test 1	Test 2
Shanghai and Shenzhen	(-15,15)	-2.423	-0.49	0.601
	(-5,5)	-1.787	-1.612*	-0.782
	(-3,3)	-0.788	-0.965	-1.236
	0	0.313	1.806**	0.576
	(-10,-1)	-1.027	-1.08	-0.738
	(-5,-1)	-0.956	-1.343*	-1.608*
	(1,10)	-1.511	-1.941**	-1.915**
	(1,5)	-0.889	-1.257	-1.664*
Hong Kong	(-15,15)	-1.829	-0.079	0.229
	(-5,5)	-0.622	-0.427	-0.807
	(-3,3)	-0.68	-1.854**	-1.861**
	0	-0.267	-1.182	-1.479*
	(-10,-1)	-0.66	-0.41	0.461
	(-5,-1)	0.347	0.524	0.271
	(1,10)	-1.141	-0.942	-0.534
	(1,5)	-1.066	-1.975**	-1.703**

*、**、*** denote statistical significance at 10%, 5% and 1% significance levels

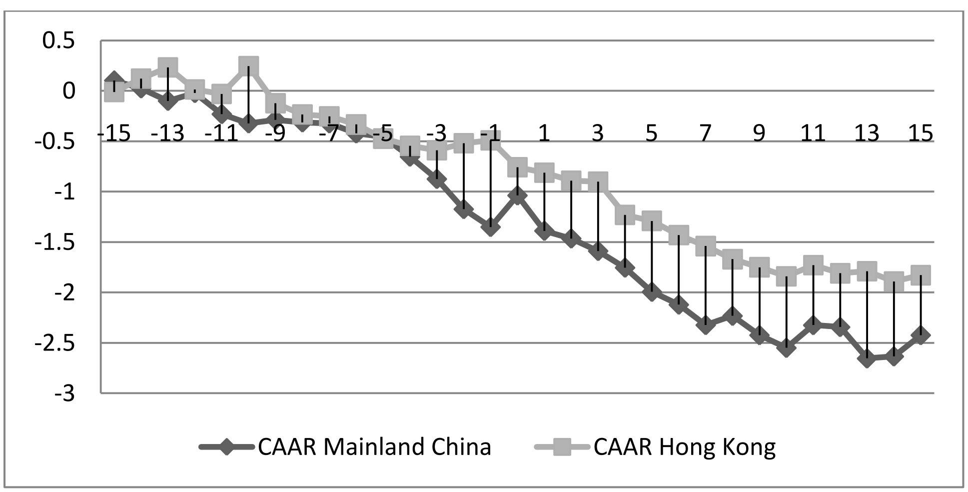


Figure 2 Cumulative average abnormal return for rating downgrades

In Table 4, we do the cross-sectional analysis of credit rating downgrades. The coefficient of CAR(-60, -16) is positive and significant in both Mainland China and Hong Kong stock markets, which implies that the reaction to the credit rating downgrades annoucement is greater if the firm has already had negative abnormal returns. This is the confirmation of correlation hypothesis not the surprise hypothesis. Negative pre-annoucement returns seem to indicate more negative returns during the annoucement period.

However, the coefficient of NUM_GRD is not significant, and even has a positive sign. This phenomenon implies that the number of credit rating changes does not matter for stock market. The market reactions to Aa1 to Aa2 and Aa1 to Aa3 are roughly the same. The coefficient of SPEC_GRD is negative and significant, which implies that the reaction to credit rating downgrades is larger in the speculative grade. The situation in Shanghai, Shenzhen and Hong Kong stock markets are approximately the same as Goh and Ederington (1999) ‘s conclusion in U.S. market.

Table 4 Cross-sectional analysis of return reactions to downgrades

Variable	Shanghai and Shenzhen	Hong Kong
Intercept	-0.014	-0.030
	(-0.67)	(-1.02)
CAR(-60,-16)	0.052	0.140
	(2.25)**	(2.54)***
NUM_GRD	0.011	0.030
	(0.60)	(1.24)
SPEC_GRD	-0.006	-0.052
	(-2.22)**	(-1.80)**

*、**、*** denote statistical significance at 10%, 5% and 1% significance levels

5.2 Market Efficiency Comparision: Stock Return Reaction to Rating Upgrades

To study different market effciencies, we further compare the abnormal return reactions to the same credit rating upgrades in Mainland China and Hong Kong stock markets. As we see from Table 5, Hong Kong market show statistically significant and positive abnormal returns around the announcement of credit rating upgrades and Mainland China market shows no statistically significant abnormal returns around the announcement. Besides, Shanghai and Shenzhen markets show significant negative abnormal returns in the largest event window (-15, 15) which supports the Wealth Redistribution Hypothesis. In Hong Kong market, there is no significant abnormal return after the annoucement.

Similar to credit rating downgrades, Shanghai and Shenzhen markets show longer impact than Hong Kong market. Their post-annoucement 10-day abnormal return is statistically significant, whereas the abnormal return is only significant for (-10, -1) in Hong Kong market. Since investors can only make profit by strategies based on the rating upgrades in Mainland China stock market, the existence of arbitrage opportunity is a violation of semi-strong form market efficiency in Mainland China stock market. Hong Kong stock market is more efficient by digesting the information quicker than Mainland China stock market.

Table 5 Cumulative average abnormal return for rating upgrades.

Market	Event Window	CAAR (%)	Test 1	Test 2
Shanghai and Shenzhen	(-15,15)	0.0185	0.040	-1.501*
	(-5,5)	0.1224	0.659	-0.118
	(-3,3)	-0.124	-0.897	-1.025
	0	0.069	0.011	0.042
	(-10,-1)	0.2796	1.538*	1.582*
	(-5,-1)	0.011	0.124	0.516
	(1,10)	-0.032	-1.338*	-1.492*
	(1,5)	-0.125	-1.402*	-0.791
Hong Kong	(-15,15)	0.8335	1.653*	2.232**
	(-5,5)	0.2492	0.951	1.982**
	(-3,3)	-0.087	-0.465	0.580
	0	-0.038	-1.077	0.903
	(-10,-1)	0.62	2.519**	1.545*
	(-5,-1)	0.104	0.675	1.234
	(1,10)	0.0713	0.259	1.146
	(1,5)	0.0749	0.360	0.757

*、**、*** denote statistical significance at 10%, 5% and 1% significance levels

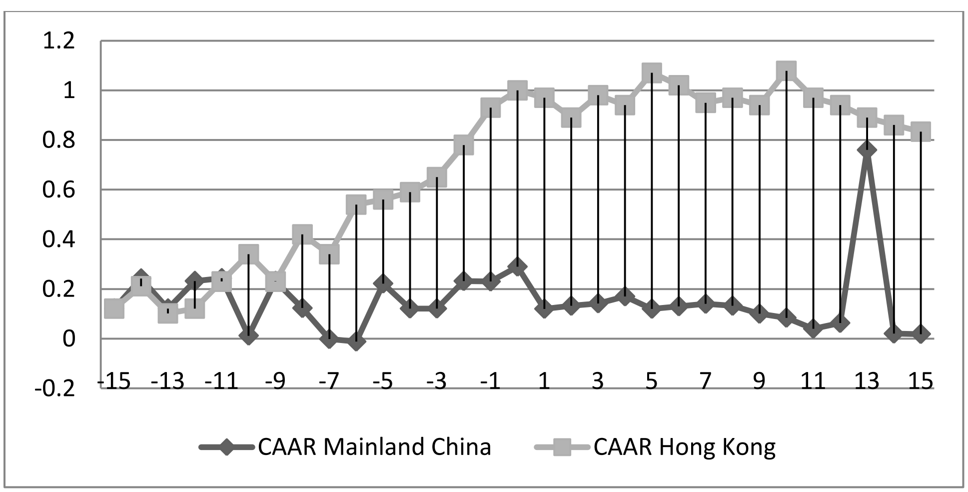


Figure 3 Cumulative average abnormal return for rating upgrades

In Table 6, we do the cross-sectional analysis of credit rating upgrades. The result is almost the same as the credit rating downgrades. The coefficient of CAR(-60, -16) is positive and significant in both Mainland China and Hong Kong stock markets, which implies that the reaction to the credit rating upgrades annoucement is greater if the firm has already had positive abnormal returns. This is the confirmation of correlation hypothesis not the surprise hypothesis. Positive pre-annoucement returns seem to indicate more positive returns during the annoucement period.

However, the coefficient of NUM_GRD is not significant. This phenomenon implies that the number of credit rating changes does not matter for stock market. The market reaction to Aa2 to Aa1 and Aa3 to Aa1 is roughly the same. The coefficient of SPEC_GRD is positive and significant, which implies that the reaction to credit rating upgrades is larger in the speculative grade.

Table 6 Cross-sectional analysis of return reactions to upgrades

Variable	Shanghai and Shenzhen	Hong Kong
Intercept	-0.0195	0.010
	(-2.44)**	(1.14)
CAR(-60,-16)	0.096	0.547
	(3.04)***	(4.20)***
NUM_GRD	-0.001	-0.0195
	(-0.09)	(-1.25)
SPEC_GRD	0.0006	1.12
	(1.41)*	(1.57)*

*、**、*** denote statistical significance at 10%, 5% and 1% significance levels

5.3 Market Efficiency Comparision: Stock Volatility Reaction to Rating Downgrades

We first take Robinson test to test the long memory of the realized volatility data series. The results in table 5 show that most stocks in the sample have long memory characteristics. They are estimated using ARFIMA(1,d,0).

Table 7 Robinson test for sample stocks

Company_id	Est. d	T test
HK 00902	0.4041	10.5386***
HK 01071	0.3935	8.9869***
HK 00386	0.3892	8.1088***
HK 03968	0.3213	8.2460***
HK 01398	0.4124	9.5983***
HK 02600	0.4485	11.0573***
HK 02628	0.3944	9.8114***
HK 00857	0.3603	8.8981***
HK 00939	0.3961	9.5046***
HK 03988	0.3979	10.0204***
HK 00991	0.4176	10.2154***
HK 00998	0.3837	9.4947 ***

*、**、*** denote statistical significance at 10%, 5% and 1% significance levels

Table 8 presents the cumulative abnormal volatility for credit rating downgrades in Mainland China and Hong Kong markets. Almost all the test statistics are significant, which means that credit rating downgrades cause statistically significant abnormal volatility. This suggests that investors in the Shanghai, Shenzhen and Hong Kong markets can make a profit in the corresponding warrants or options with the strategy based on credit rating downgrades. Additionally, both the pre and post periods show significant abnormal volatility, which means that investors can predict part of the information contained in the credit rating downgrades.

Since investors can make a profit by strategies based on the rating downgrades in both warrant markets, the existence of arbitrage opportunity is a violation of semi-strong form market efficiency in Mainland China and Hong Kong warrant markets.

Table 8 Cumulative average abnormal volatility for rating downgrades

Market	Event Window	CAAV (%)	Test 1	Test 2
Shanghai and Shenzhen	(-15,15)	5.495	3.559***	3.708***
	(-5,5)	2.423	2.578***	3.155***
	(-3,3)	1.658	3.578***	3.501***
	0	0.331	3.338***	2.379**
	(-10,-1)	2.252	2.376**	2.646***
	(-5,-1)	1.464	1.025	2.601***
	(1,10)	1.469	3.130***	2.098**
	(1,5)	0.653	2.933***	1.898**
Hong Kong	(-15,15)	6.116	3.578***	3.648***
	(-5,5)	1.746	2.683***	2.683***
	(-3,3)	1.305	3.608***	1.950**
	0	0.099	0.625	0.481
	(-10,-1)	2.031	1.342*	2.902***
	(-5,-1)	1.122	2.683***	1.979**
	(1,10)	1.873	3.970***	2.084**
	(1,5)	0.703	1.917**	1.670*

*、**、*** denote statistical significance at 10%, 5% and 1% significance levels

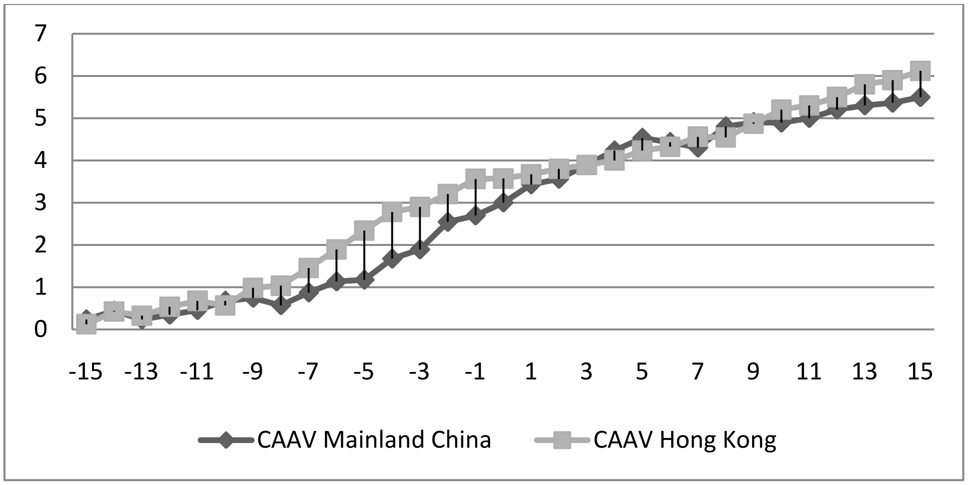


Figure 4 Cumulative average abnormal volatility for rating downgrades

5.4 Market Efficiency Comparision: Stock Volatility Reaction to Rating Upgrades

Table 9 presents the cumulative average abnormal volatility for credit rating upgrades in Mainland China and Hong Kong markets. For Shanghai and Shenzhen markets, there is only significant abnormal volatility in the largest event window (-15, 15). In Hong Kong market, there is no significant abnormal volatility around the announcement of credit rating upgrades. These results support the hypothesis that stock market reacts little to credit rating upgrades since firms are tending to release good news to the market.

Since investors cannot make a profit by strategies based on the rating upgrades in both warrant markets, we can not reject the semi-strong market efficiency in Mainland China and Hong Kong warrant markets.

Table 9 Cumulative average abnormal volatility for rating upgrades

Market	Event Window	CAAV (%)	Test 1	Test 2
Shanghai and Shenzhen	(-15,15)	1.071	1.561*	2.528***
	(-5,5)	0.067	0.167	0.855
	(-3,3)	0.231	0.959	1.001
	0	-0.124	-1.070	-0.158
	(-10,-1)	0.637	1.949**	2.266**
	(-5,-1)	0.218	0.940	1.510*
	(1,10)	0.323	0.704	1.145
	(1,5)	-0.189	-0.597	-0.110
Hong Kong	(-15,15)	0.529	0.733	0.322
	(-5,5)	0.307	0.685	0.907
	(-3,3)	-0.224	-0.749	0.079
	0	0.093	0.505	0.531
	(-10,-1)	0.370	0.825	1.308*
	(-5,-1)	0.339	1.299	1.440*
	(1,10)	-0.388	-0.863	-0.893
	(1,5)	-0.309	-0.829	-1.450**

*、**、*** denote statistical significance at 10%, 5% and 1% significance levels

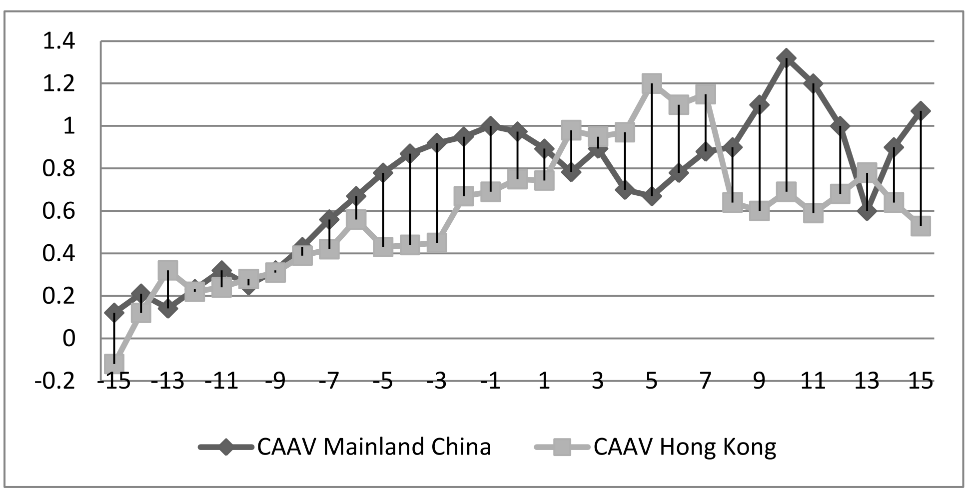


Figure 5 Cumulative average abnormal volatility for rating upgrades

6. Summary and Conclusions

In this paper, we analyze relative efficiency of Mainland China versus Hong Kong stock exchanges. We examine the firms that are dual-listed on Mainland China and Hong Kong stock exchanges from 1999 to 2010. We find that there are evidences that both Mainland China and Hong Kong stock markets are not semi-strong efficient, and Hong Kong market is more efficient in digesting credit rating change information than Mainland China market. The detailed results can be summarized as follows:

(1) Both Mainland China and Hong Kong markets show statistically significant and negative abnormal returns after the annoucement of credit rating downgrades and only Mainland China market shows statistically significant abnormal returns before the annoucement. This indictates that credit rating downgrades do include some inside information for stockholders and the annoucement has an impact on the return of the stock. Therefore, investors can make a profit from the strategy based on the credit rating downgrade annoucements. Moreover, Hong Kong stock market is more efficient in digesting rating downgrade information. For the cross-sectional analysis, pre-annoucement negative returns and speculative grade are separately positively and negatively correlated to the abnormal returns during the annoucement of credit rating downgrades.

(2) Hong Kong market shows statistically significant positive abnormal returns around the announcement of credit rating upgrades and Mainland China market shows no statistically significant abnormal returns around the announcement. Besides, Shanghai and Shenzhen markets show significant negative abnormal returns after the annoucement which supports the Wealth Redistribution Hypothesis. In Hong Kong market, there is no significant abnormal return after the upgrade annoucement.

Therefore, Hong Kong market is also more efficient in digesting rating upgrade information. For the cross-sectional analysis, pre-annoucement negative returns and speculative grade are both positively correlated to the abnormal returns during the annoucement of credit rating upgrades.

(3) Credit rating downgrades cause statistically significant and positive abnormal volatility. The results suggest that investors in Shanghai and Shenzhen markets can make a profit in the corresponding warrant or option markets with the strategy based on the credit rating downgrades. This is a violation of semi-strong efficient market hypothesis in both markets.

(4) Credit rating upgrades do not cause statistically significant abnormal volatility. This is comparative to the case in return reactions and suggests that the strategy based on credit rating upgrades cannot make a profit in the warrant/option investment.

To conclude, Both Mainland China and Hong Kong stock markets are not semi-strong efficient, and Hong Kong market is more efficient in digesting rating change information. There is evidence that credit rating changes especially downgrades do provide inside information about the corresponding stock, not only at the return level but also at the volatility level. Anyone who takes on the stock investment recommendations should also considers the firm's bond credit rating changes as well.

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