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THE INFORMATION CONTENT OF THE MALAYSIAN CORPORATE BOND RATING CHANGES

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Abstract

This paper aims at investigating the impact of corporate bond rating changes on the common stock returns of the Malaysian corporations for the period spanning from January 1993 up to December 2003 inclusive. The market model with two competing specifications is used to measure the normal returns of firms. These are the standard event study methodology and the ARMA-GARCH lag specification of the market model. The initial finding is that both downgrades and upgrades trigger negative market reaction, albeit with some signs of information leakage. However, with some additional forensics we find that while downgrades elicit negative market response, upgrades induced no market reaction whatsoever. Moreover, the negative reaction following upgrades that we have seen at the initial finding was mainly due to the impact of the South East Asian financial crisis of the 1997/98.

Keywords: Corporate Bond Rating; Malaysia; ARMA-GARCH

1. Introduction

Recently, bond rating agencies have been under increasing scrutiny due to their failure to accurately predict and warn investors of imminent firm-related financial difficulties such as the Enron Corporation bankruptcy[1]. This failure has revived interest among academic circles, investors, and financial analysts to investigate whether announcements by rating agencies contain valuable information. More specifically, the interest has focused on whether rating changes signal the arrival of new information to the capital markets.

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[1] Enron Corporation is one of the biggest US energy corporations. For more on this issue, see: Jennifer (2002).

Several studies have been conducted to ascertain the independent impact of bond ratings on security prices and yields. The thrust of research in this area has focused on the impact of rating changes on stock or bond prices. Among these studies are: Hand, Holthausen and Leftwich (1992); Goh and Ederington (1993); Kliger and Sarig (2000); and Dichev and Piotroski (2001). These studies, however, produced conflicting results.

Some rating revision studies indicate that rating changes provide no new information to the financial markets (Pinches and Singleton, 1978). On the contrary, a number of studies on bond rating changes found that rating reclassifications convey new information to the financial markets. This represents the finding of Ingram, Brooks and Copeland (1983); Hand *et al*. (1992); Barron, Clare and Thomas (1997); and Dichev and Piotroski (2001). These two opposing findings are partially the products of some pre-determined theoretical formulations. However, the theoretical formulations about the informational content of bond ratings and ratings changes are vague because of their dependence on the nature of information obtained by rating agencies. Whether or not rating agencies depend on private as well as public information is not yet so clear. In addition, irrespective of which group spotted the correct guess, countless unanswered questions remain. For instance, what type of private information managers are willing to release to the rating agencies? When do rating agencies receive this information? How long does it take the rating agencies to process this information and come out with the default risk assessment in a timely manner?

A review of literature seems to indicate a consistent transition from using monthly bond yields and common stock returns to the use of daily common stock returns. This is believed to be the case in the empirical studies attempted to examine the information contents of bond rating changes[2]. This shift is partially based on the ground that the stock market is said to be more efficient than the bond market (Katz 1974, and Pinches and Singleton 1978). Moreover, the use of daily data provides more powerful tests, assuming the exact event date can be identified. In addition, it reduces the likelihood that the effect of other disclosures is included in the measured announcement effects (Holthausen and Leftwich, 1986).

Katz (1974) found that no anticipation existed prior to a public announcement of reclassification in the US and he even suggested the existence of six-to-ten- week lags subsequent to the rating reclassification, before total adjustment to the new rating was achieved. This implies that ratings reclassifications do provide surprise information to the market; however, the market itself is inefficient in processing this new information. Davidson and Glascock (1985) examined a slightly different version of the existing literature, namely, the announcement effects of preferred stock rating changes on firm equity returns. The authors found that the market anticipates the re-ratings by 40 days for the complete sample. They suggested further that downgrades for the utility sub-sample do not experience any downward drift after or before the re-

[2] During the 1970s and 1980s, researchers used monthly data. That had changed by using daily stock returns during the 1990s onwards. See for example Hand *et al*. (1992, daily bond returns and daily stock returns); Goh and Ederington (1993, daily stock returns); Matolcsy and Liano (1995, daily stock returns); Nayar and Rozeff (1994, daily stock returns).

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rating. Unlike all the aforementioned studies, which examined the effects of bond ratings changes using data for the United States, Barron *et al*. (1997) presents similar evidence for the United Kingdom. The authors find significant excess stock returns associated with bond rating downgrades, a conclusion consistent with US evidence. Goh and Ederington (1998) found a significant stock market reaction to downgrades but no reaction to upgrades. Moreover, they found that actual earnings fell following downgrades but did not rise following upgrades. The authors believe that the market impounds downgrade information much more quickly and efficiently than analysts do.

Dicheiv and Piotroski (2001) examined the impact of bond rating changes on the common stock returns of large firms' vis-à-vis small firms. Firms are classified yearly as large (small) if their market equity is more (less) than the median market value of equity of all firms that had a Moody's rating change during the year. The authors found no reliable abnormal returns following upgrades but significant negative abnormal returns following downgrades. This effect is visibly more pronounced for the small non-investment-grade firms.

Empirical evidence on the effect of bond rating changes on stock returns in Malaysia is rather limited. Kesavan (1999) investigated the impact of the Malaysian corporate bond rating changes on common stock returns for the period from 1994 to 1999. She used the market model of the standard event study methodology to estimate the normal performance model. She then concluded that for upgrades, there are negative abnormal returns for the both the pre-and-post event window for long-term bonds. However, there is no abnormal stock performance during the announcement window. For downgrades announcements, the author finds that there are significant abnormal returns for both the long-term and short-term bonds. It is interesting to find that upgrades produce negative reaction in the stock market, because this conclusion defies conventional wisdom and common observations. However, some factors like the model used, the event window employed or the quality of data used[3] might have led to this unique finding. However, Yusop and Omar (2002) concluded that downgrades produced significant negative abnormal returns on the event day, while upgrades do not cause any significant change in the behavior of the stock market. They used daily data on stock returns and a one-event day window for the period from August 1997 to June 2001. This study utilized an uncontaminated data set of 38 rating changes (6 upgrades and 32 downgrades).

There is no doubt that the findings of different studies with different specifications are contradictory. Accordingly, it is widely believed that factors like the frequency of observations (daily, weekly, or monthly), differences in bond market coverage, contamination with news, and differing sample periods are responsible for this contradiction (Barron, Clare and Thomas, 1997). It is also believed that there are two competing views that shape the investors' response to credit ratings changes. Proponents of the first view claim that rating agencies provide information that is already being discounted by investors, and hence rating changes do not signal the arrival of any new information to the market. On the other hand, proponents of the competing view believe that rating agencies base their judgment on private

[3] The authors did not control for data contamination by other confounding events issued by or about the firms in the sample.

information that is so confidential for the public to know. Therefore, any announcement of rating change would be reflected in the asset prices, assuming market efficiency.

To our knowledge, the impact of bond rating changes on stock returns and bond yields has not been comprehensively tested using data for Malaysia. It is worth noting that since the adoption of the industrialization policies in the mid-80s, Malaysia has witnessed significant progress in the financial market. The progress of the stock and bond markets is widened by Islamic bonds. With this setting, it provides us with the motivation to test whether the results that have been recorded globally applies to Malaysia. Thus, the primary focus of this research is to answer the empirical question, 'Do bond rating changes affect stock returns in Malaysia?' More specifically, this study aims to establish evidence on the impact of corporate bond upgrades and downgrades on stock returns. Additionally this study will also investigate the impact of bond rating changes on stock returns pre- and post- South-East Asia financial crisis in 1997/1998. Unlike earlier studies which used OLS market model only, this study utilizes both OLS market model and the bivariate Autoregressive Moving Average-General Autoregressive Conditional Heteroscedasticity or ARMA-GARCH[4] lag specification which was developed by Solibakke (2002) to enhance the performance of the market model. The rest of the paper is organized as follows. Section 2 describes the empirical models and data used in this study. Section 3 discusses the results while Section 4 concludes the study.

2. Empirical Model and Data

We employ an event study methodology[5] to measure the impact of bond rating changes on stock returns. The choice of this methodology flows from the fact that the effects of an event would immediately be reflected in the security prices given market efficiency. These effects are examined through calculating the difference between the actual returns of a security around the event period and the normal returns that would have been observed had the event not occurred during the said period. This difference is called abnormal returns. In this event study, we choose an estimation period that ranges from 250 days up to 300 days ending 90 days prior to the event period. In other words, T_0 ranges from 340 days to 390 days prior to the event date 0, with $T_1 = -90$, and $T_2 = +90$.

The estimation period would be used to estimate the predicted returns during the event window which is then subtracted from the actual returns during the same window with the aim of detecting abnormal returns. We use continuously compounded returns in log form as follows:

$$R_{it} = \log[P_t / P_{t-1}] \tag{1}$$

[4] Auto-regressive Heteroscedasticity (ARCH) model was first introduced in 1982 by Robert Engle. The model is further refined and extended into GARCH by Tim Bollerslev in 1986 and 1987.
[5] Event studies are widely used in economics and finance. Since the early 1930s, they have been applied to a number of firm specific and economic wide events.

where R_{it} is the return at time t. Returns normally include both the price changes and dividends. P_t is the asset price plus dividends at time t.

The market model with two competing specifications is used to measure the normal performance of firms. This model relates the return of a security to the return of the corresponding market index.

The Standard Event Study Methodology

We use the Single Index Market Model (SIMM)[6] to estimate the normal returns. The SIMM is extensively used by empirical researchers[7] especially, those aiming at evaluating the impact of an event on the shareholders' wealth. This model is shown below:

$$R_{it} = \alpha_i + \beta_i(R_{mt}) + \varepsilon_{it}\,, \tag{2}$$

where R_{it} = return on asset i at time t,
α_i = the constant term for asset $i's$ regression equation,
β_i = the slope term,
R_{mt} = the return on the market index on event day t, and,
ε_{it} = the error term for firm i at time t(days), $t = 1,.....,k$ (there are k days in the estimation period).

Using the ordinary least squares (OLS), the excess return (ER_{it}) on event day t is calculated as follows:

$$ER_{it} = R_{it} - (\widehat{\alpha}_i + \widehat{\beta}_i R_{mt})\,, \tag{3}$$

The mean excess return (MER_t) on event day t is obtained by dividing the aggregate excess returns for all assets on day t by the number of assets (N):

$$MER_t = \sum_{i=1}^{N} ER_{it} / N \tag{4}$$

The (MER_t) is cumulated for event days t_1 through t_2 using the formula:

$$CMER_d = \sum_{t=t_1}^{t_2} MER_t \tag{5}$$

Mean excess return is tested for significance using the *t*-statistics,

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[6] The market model is estimated using close-to-close return data and an equally weighted market index. Abnormal returns are defined by subtracting the expected return implied by the estimated market model from the daily return for that firm.

[7] See for instance Dhatt *et al*. (1994); Henderson (1990); and Glascock *et al*. (1987).

$$t = \frac{MER_t - 0}{\sigma / \sqrt{N}} \tag{6}$$

where, t is the standard t-ratio; σ is the standard deviation of the estimate; and N is the total number of observations.

The ARMA-GARCH Lag Specification of the Market Model

The OLS market model discussed earlier is founded on a number of assumptions the satisfaction of which is a pre-condition in order to have efficient parameter estimates and consistent test statistics. The bivariate ARMA-GARCH lag specification was developed by Solibakke (2002) to enhance the performance of the market model, by means of controlling for the above OLS assumptions. We follow this model to examine the impact of bond rating changes on common stock returns. These returns are assumed to follow a stationary stochastic process in the absence of influential events. However, when an event of that sort occurs, the market participants revise their value of the stock, causing a shift in the return generating process.

With ARMA model applied for the conditional mean, and the GARCH model for the conditional volatility, the diagonal bivariate ARMA (p, q) – GARCH (m, n) market model is defined by controlling for non-synchronous trading (θ_i, θ_M), asymmetric volatility (γ_i, γ_M), and conditional heteroscedasticity. These models are shown below:

$$R_{i,t} = \alpha_i + \sum_{j=1}^{pi} \phi_{i,j} R_{i,t-j} + \beta_{i,1}\varepsilon_{M,t} + \gamma_{i,j} D_{i,j,t} + \varepsilon_{i,t} - \sum_{j=1}^{qi} \theta_{i,j}\varepsilon_{i,t-j}\,, \tag{10}$$

where

$$E(\varepsilon_{i,t}^2 \mid \Phi_{i,t-1}) = h_{i,t} = m_i + \sum_{j=1}^{m} \alpha_{i,t-j}\varepsilon_{i,t-j}^2 + \sum_{j=1}^{n} b_{i,t-j} h_{i,t-j} + \lambda_{i,1} D_{i,t}\varepsilon_{i,t-1}^2\,; \tag{11}$$

and

$$R_{M,t} = \alpha_M + \sum_{j=1}^{pM} \phi_{M,j} R_{M,t-j} + \varepsilon_{M,t} - \sum_{j=1}^{qM} \theta_{M,j}\varepsilon_{M,t-k}\,, \tag{12}$$

where

$$E(\varepsilon_{M,t}^2 \mid \phi_{M,t-1}) = h_{M,t} = m_M + \sum_{j=1}^{n_m} \alpha_{M,t-j}\varepsilon_{M,t-j}^2 + \sum_{j=1}^{n_M} b_{M,t-j} h_{M,t-j} + \lambda_{m,1} D_{M,t}\varepsilon_{M,t-1}^2\,; \tag{13}$$

for $i = 1,.....,N,$ where $R_{i,t}$ is the asset and $R_{M,t}$ the index return in period *t*; $\varepsilon_{i,t}$ and $\varepsilon_{M,t}$ are the error terms for the two mean Equations (10) and (12) in period *t*; $\theta_{i,j}$ and $\theta_{M,j}$ are the non-synchronous trading parameters at lag *j* and $\gamma_{i,j}$ is the event day *j*'s abnormal return for firm *i*. $D_{i,j,t}$ is a dummy variable taking the value of one during event periods, zero otherwise. for asset (*i*) and index (*M*), respectively, the conditional variances $h_{i,t}$ and $h_{M,t}$ (conditional on the information set at time $t-1$, ϕ_{t-1}) depend themselves upon the following parameters: m_i and m_M are the constant terms; $\alpha_{i,j}$ and $\alpha_{M,j}$ are the parameters for the lagged squared error (shock) at lag *j*; $b_{i,j}$ and $b_{M,j}$ are the parameters for the lagged conditional variance at lag *j*; $\lambda_{i,1}$ and $\lambda_{M,1}$ are the parameters for asymmetric volatility where $D_{i,t}(D_{M,t})$ is a dummy variable taking the value of one when $\varepsilon_{i,t-1}(\varepsilon_{M,t-1})$ is less than or equal to zero. ARMA-GARCH models are estimated using the Maximum Likelihood (ML). The optimal lag lengths for these models are chosen based on the Akaike's (1969) Final Prediction Error (FPE) criteria.

The following *t*-ratio is computed to test for significance of the mean event effect:

$$t = \frac{\gamma_i - 0}{\sigma_i / \sqrt{N}}, \tag{14}$$

where γ_i is the event effect for asset *i,* and σ_i is the estimate of the standard deviation of γ_i around the true event-effect for asset *i*, and *N* is the number of observation.

Sample selection

The following criteria must be met before a firm could be included in the study:

i. the firm must be listed in the KLSE (now known as Bursa Malaysia) when the rating change takes place;
ii. rating would be eliminated from the sample if and when other significant news is announced by or about the same firm at the time of the rating change;
iii. Provided that the stock market is closed the day RAM or MARC announces the rating change, that rating would not be included in the sample;
iv. in the case of simultaneous rating changes of different bond issues for the same issuing firm, we would retain the rating change for the most senior issue available, so that each rating change for a firm would result in one sample observation regardless of the number of bonds affected.

Data

The study uses daily continuously compounded returns of individual Bursa Malaysia stocks for the period Jan 1993 to Dec2003. Both the index and individual stocks were obtained from Bursa Malaysia. From the records of RAM and MARC, we managed to identify a total of 295[8] long term debt ratings whose respective issuers were listed in Bursa Malaysia during the designated sample period. Out of these 295 firms, we excluded a total of 29 firms due to lack of sufficient data on stock returns. For instance, when a firm is rated shortly after being listed in Bursa Malaysia or being de-listed shortly after a rating was assigned. To be included in the sample, a firm must have daily returns for up to 431 consecutive days (250 days for the estimation period, and 181 days for the event period).

Figure 1
Derivation of the Sample of Bond Ratings Changes for the Period 1993 – 2003

295 Total debt ratings of listed firms from 1993 to 2003

29 Observations excluded due to lack of enough returns

13 Observations excluded due to contaminations

47 Observations lost due to other reasons

206 Total observations satisfying the selection criteria

71 Upgrades | 135 Downgrades

Table 1

[8] See Figure 1 for other details about this.

Percentage of Firms Passed the Selection Criteria

Particulars		Upgrades	Downgrades	Total
Total number of observations[a]		105	190	295
Lost due to lack of data[b]		(15)	(14)	(29)
Lost due to contamination[c]		(5)	(8)	(13)
Lost due to other reasons		(14)	(33)	(47)
Total satisfied criteria	Number	71	135	206
	%	68%	71%	70%

Notes:

[a] Total no. of observations represents the total number of firms passed the selection criterion of exchange listing.

[b] Failed the stock return requirement of 431 consecutive days (250 days for the estimation period and 181 days for the event period).

[C] We examined the week surrounding the rating announcement date (3 days before announcement; announcement date; and 3 days after announcement) for possible contaminating elements. Confounding events issued by / or about the rated firms in the sample are regarded as contaminations, and hence eliminated.

In some cases, the negative or positive market response to rating agency announcements could be prompted by a small fraction of the sample observations, in which case, the inferences drawn might not proof to be representative of the population. To test whether or not such cases characterize our results, we employ a *Z*-statistics. When the number of positive parameter estimates equals the number of negative parameter estimates, this statistic takes the value of zero. But if the number of negative parameter estimates exceeds the positive ones, the *Z*-statistics would be positive, and vice versa. Thus, as long as the *Z*-statistics is statistically significant, our results are said to be free from the above noted inference problem. The *Z* - statistics is shown in line 5 of Tables 3 and 4 and is defined as $\frac{G-Mp}{\sqrt{Mp(1-p)}}$ [9], where *G*, is the number of negative parameter estimates; *M*, is the total number of parameter estimates; and *p*, is the probability of a negative parameter estimate. A null hypothesis of zero event effect sets the probability *p* equal to 0.5.

3. Results

This section discusses the results of the impact of corporate bond rating changes (upgrades and downgrades) on stock return using both the OLS market model and the ARMA-GARCH lag specification of the market model. In addition it will also discuss the results of bond rating changes on stock returns pre- and post-South-East Asia financial crisis in 1997/1998.

[9] Reported in Solibakke (2002).

Table 2
OLS Market Model LS_{OLS}

LS_{OLS}	Panel A: Downgrades (Full Sample)								
	Alfa	Beta	E(-90,-61)	E(-60,-31)	E(-30,-1)	E (0, 0)	E(1, 30)	E(31,60)	E(61,90)
Average	-0.001	1.120	-0.047	-0.033	-0.028	0.004	0.019	-0.010	0.015
Standard deviation	0.002	0.430	0.207	0.220	0.201	0.043	0.210	0.232	0.199
Negatives %	74.07%	1.48%	57.78%	61.48%	56.30%	47.41%	50.37%	51.85%	48.15%
t-ratio	-5.02* {0.00}	30.25* {0.00}	-2.67* {0.008}	-1.72*** {0.087}	-1.64*** {0.104}	1.07 {0.287}	1.06 {0.291}	-0.48 {0.630}	0.90 {0.367}
Z-statistics	5.59* {0.00)	-11.27* {0.00}	1.81*** {0.070}	2.67* {0.007}	1.46 {0.144}	-0.60 {0.548}	0.09 {0.928}	0.43 {0.667}	-0.43 {0.667}
CAR			-0.047	-0.080	-0.108	-0.104	-0.085	-0.095	-0.079
LS_{OLS}	Panel B: Upgrades (Full Sample)								
	Alfa	Beta	E(-90,-61)	E(-60,-31)	E(-30,-1)	E(0, 0)	E(1, 30)	E(31,60)	E(61,90)
Average	0.000	1.026	-0.046	0.013	-0.031	-0.004	-0.039	0.004	-0.093
Standard deviation	0.002	0.359	0.151	0.112	0.148	0.043	0.245	0.258	0.227
Negatives %	60.56%	0.00	61.97%	45.07%	56.34%	52.11%	57.75%	52.11%	71.83%
t-ratio	-1.75*** {0.083}	24.04* 0.00	-2.56* {0.012}	0.95 {0.347}	-1.76*** {0.082}	-0.72 {0.475}	-1.34 {0.185}	0.12 {0.903}	-3.44* {0.001}
Z-statistics	1.78*** {0.075}	-8.43* {0.00}	2.02** {0.043}	-0.83 {0.406}	1.07 {0.284}	0.36 {0.718}	1.31 {0.190}	0.36 {0.718}	3.68* {0.00}
CAR			-0.046	-0.033	-0.064	-0.068	-0.107	-0.103	-0.196

Notes:

*, **, and *** denote statistical significance at the 1, 5 and 10% levels, respectively. Numbers in {.} are *p*-values. All samples are cleaned from confounding events that had occurred during the period 1993 to 2003. Event windows are specified as follows:

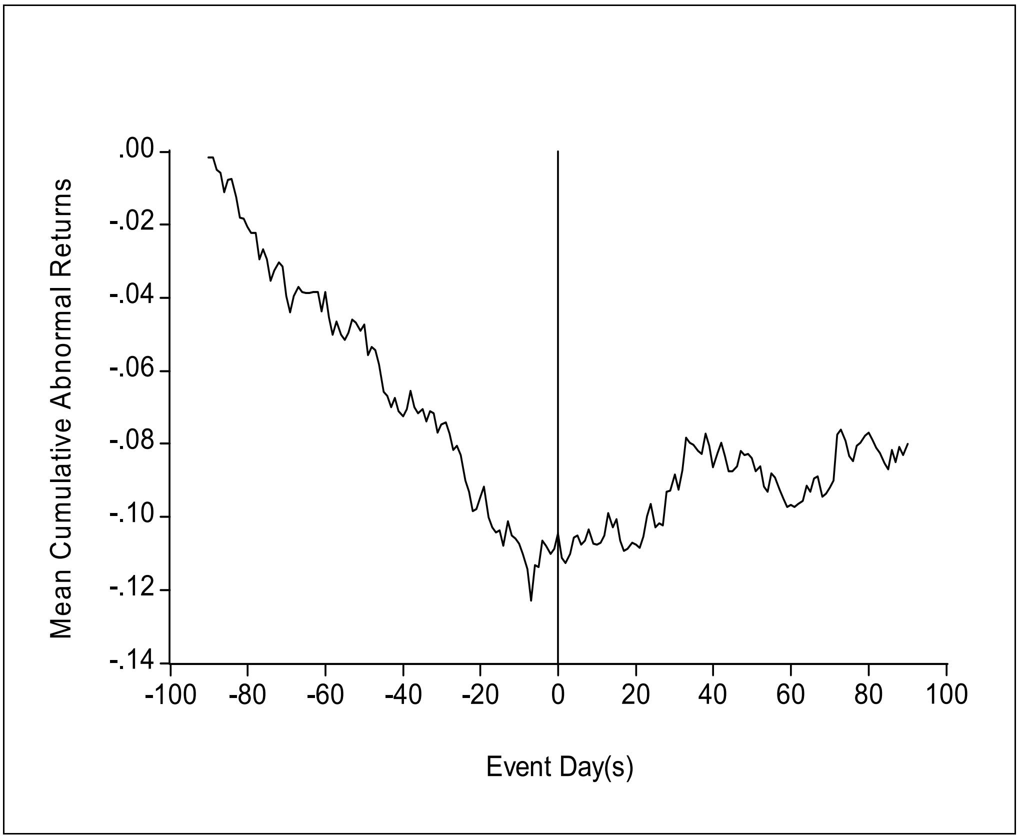
E(-90, -61)	Event window from day -90 to day -61 relative to announcement date
E(-60, -31)	Event window from day -60 to day -31 relative to announcement date
E(-30, -1)	Event window from day -30 to day -1 relative to announcement date
E(0 , 0)	Event announcement date
E(1, 30)	Event window from day 1 to day 30 relative to announcement date
E(31, 60)	Event window from day 31 to day 60 relative to announcement date
E(61, 90)	Event window from day 61 to day 90 relative to announcement date.

OLS Market Model

OLS results of full sample downgrades and upgrades are reported in Table 2, Panels A and B, respectively. Panel A shows a negative and statistically significant abnormal return for all three windows preceding the downgrade announcement date. This is visually demonstrated in Figure 2 by the steep decline of the curve up to around eight days prior to the downgrade announcement date (T_0). From there, the curve slopes upward, forming a V- shape with E(-90, -61), and E(61, 90) on its top left and top right, respectively. The highest negative abnormal return is -4.7% which, is associated with E(-90, -61) with a *t*-value of -2.67. The negative drift diminishes to -2.83% in E(-30, -1). However, for E (0, 0); and E(1, 30), there are positive average abnormal returns of 0.39% and 1.91%, respectively. Even though, these positive returns are statistically insignificant, but they signal an end to persistent pre-announcement negative abnormal returns. The *Z*-statistic of E(-60, -31), and E(-90, -61) are statistically significant at the 1% and 10% levels, respectively. This is an indication that these pre-announcement windows contain the highest numbers of negative parameter estimates in the overall event period. This fact lends further support to the inference that downgrades are preceded by a negative run in abnormal returns.

A large number of similar studies reported negative and statistically significant average abnormal returns following bond rating downgrades, (Zaima and McCarthy 1988; Dicheiv and Piotroski 2001). However, in this study, the negative impact occurred well before the downgrade announcement, signalling the presence of information leakage. This finding is consistent with Bacha and Meera (1997), and Shamser and Annuar (1993) who documented the finding that Malaysian bonus stock issuance (BSI) announcement are anticipated by about three weeks.

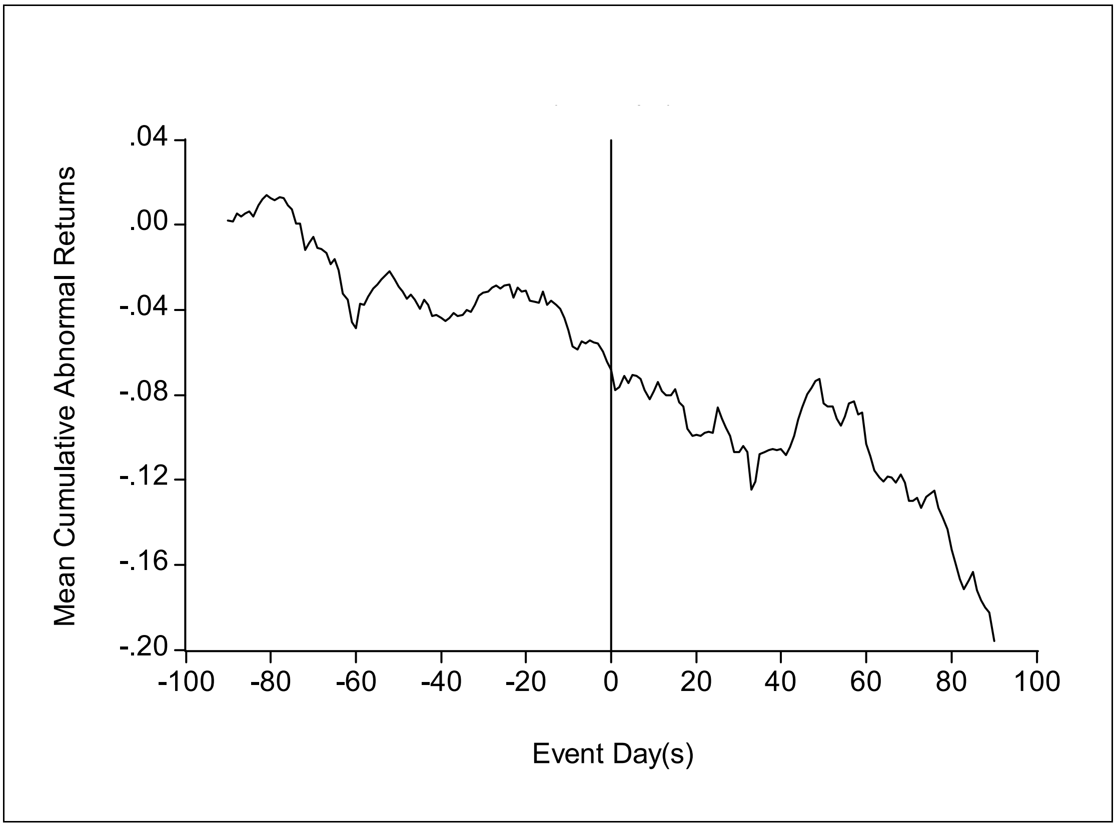
Figure 2
Impact of Bond Downgrades on Common Stock Returns (Full Sample)



Panel B of Table 2 reports the OLS results for upgrades. Defying expectations, the market seem to have responded negatively to the announcement of upgrades. It sounds odd, but this is what has been indicated by the statistics of event windows

E(-90, -61); E(-30, -1); and E(61, 90). Applying the standard *t*-ratio, all three windows reported statistically significant average abnormal returns at the levels of 1%, 10%, and 1%, respectively. The *Z*-statistics implies that the number of negative parameter estimates for each of the windows E(-90, -61); and E(61, 90) are statistically significant at the 1% level. The daily mean abnormal returns for upgrades are depicted in Figure 3.

Figure 3
Impact of Bond Upgrades on Common Stock Returns (Full Sample)



The curve steadily slopes downwards from the top left to the bottom right of the graph, indicating an overall decline in returns throughout the 180 days surrounding the event day. On statistical grounds, the evidence presented for upgrades so far indicates that market agents foresee no difference between upgrades and downgrades. However, common sense and observation tell a different story. To reconcile statistics with common sense and observation, we further analyzed upgrades by excluding all the observations that occurred during the South East Asian financial crisis in 1997/98. Then we applied the same analytical techniques to both, the pre-crisis and post-crisis upgrade samples. Interestingly, the results, which would be covered in detail in another part of this study, indicate that neither the pre-crisis, nor the post-crisis sub-samples reported any significant negative abnormal returns whatsoever. Nevertheless, a positive and statistically significant abnormal return is observed in only a single window of the pre-crisis upgrade sample. Therefore, unlike the case for downgrades, the announcement of upgrades imposes no significant pressure on the market. The results of both upgrades and downgrades lend support to the view that rating agencies are information specialists who obtain private information not available to many other market agents. The phrase 'not available to many' is used here to impose a caveat as the results have also shown some signs of information leakage.

The significant abnormal returns around the announcement date of bond downgrades serves as an indication of the market response. This is to say that, the market has presumably received new information, though, well before the rating announcement date. At this point, one would ask – if bond downgrades raise negative expectations, and bond upgrades signal the opposite, then why would the market react with asymmetry to the announcement of both? It is argued that the management of rated-firms often acts swiftly when providing good news to the rating agency as they are expected to always seek favorable rating. However, they are usually reluctant to release negative information. Hence, the market agents form their expectations accordingly. These expectations could be the cause for the asymmetric behavior. To have more insights on the impact of upgrades and downgrades, we have conducted some forensic analyses to see whether these findings will hold.

Forensic Analysis for Downgrades and Upgrades

Additional analyses are conducted in this subsection with the aim of testing whether the findings on the market response to corporate bond upgrades and downgrades are robust to other alternative specifications. First, we contend that the negative market reaction to downgrades without a corresponding positive response following upgrades could be due to some mismatching in the sizes of upgrades and downgrades.

In other words, the majority of downgrades might be big downgrades while the majority of upgrades are small upgrades. 'A small downgrade is an only one notch downgrade' while a big downgrade involves more than one notch. For example, a downgrade from A_1 to A_2 or from A_3 to BBB_1 is defined as a small downgrade. However, a downgrade from A_1 to A_3 or from A_3 to BBB_2 or lower is regarded as a big downgrade, (the same definition applies to upgrades).

We hypothesize that the disproportionate market response to upgrades and downgrades is mainly caused by the mismatch in the sizes of upgrades and downgrades. This hypothesis is strongly rejected as we find that the majority of upgrades (65%) are big upgrades and the majority of downgrades (71%) are also big downgrades. The detailed lists of upgrades and downgrades sorted by their size are shown in Appendices 1, 2, 3, and 4. This finding provides further support to the earlier claim that the market response to upgrades and downgrades is basically due to the bias of company management in providing information to rating agencies as we asserted earlier.

Second, it could be argued that the profound negative response by the market following downgrades might have been triggered by only a handful of two or three badly-performing firms. If this is true, then the generalization of these results to the whole spectrum of firms in Bursa Malaysia would be misleading. Taking these concerns into consideration, we ranked all downgrades by the size of market reaction, that is, after calculating the CAR% for the two weeks surrounding the announcement date T_0, E(-7, +7). For both downgrades and upgrades, we ranked the firms in a way that the firm with the highest negative CAR% is placed on top of the list, while the firm with the biggest positive CAR% is placed right at the bottom of the list. Then, we tested all CAR_s, individually for significance using the standard *t*-test. The lists of ranked upgrades and downgrades are shown in Appendices 5 and 6. We find that 64% of the downgraded firms experienced negative CAR_s, 22% out of which are statistically significant. This finding then, rejects the above arguments that the negative market response to downgrades might have been caused by only two or three firms.

Third, using the same rankings for upgrades and downgrades in 'second' above, we made a comparison between the mean cumulative abnormal return (MCAR%) of the top and bottom quartiles for downgrades with the MCAR% of the top and bottom quartiles of upgrades. All quartiles presented statistically significant $MCAR_s$. However, the absolute MCAR is the highest for the top quartile downgrades (-1.42%) and bottom quartile upgrades (1.06%) as compared to that of the top quartile upgrades (-0.71%) and bottom quartile downgrades (0.94%). The results of this quartile analysis are reported in Appendix 7.

The relatively high absolute MCAR% for the top quartile downgrade and bottom quartile upgrade motivated us to examine some of the distinguishing features characterizing the firms in these quartiles. Specifically, we wanted to see if the ratio of total face value of bonds to market capitalization of the firms concerned is different. Also we are interested to know whether the board of listing has any role in determining the extent of the market reaction.

Corresponding to the above finding relating the highest absolute MCAR to top quartile downgrades and bottom quartile upgrades, we also find these two quartiles to have the highest percentage of average leverage and the largest number of firms listed in the main board compared to the other quartiles. Hence, we could conclude this part by reiterating the finding that, relative to the top quartile upgrades and bottom quartile downgrades, the majority of firms identified with the top quartile downgrades and bottom quartile upgrades are listed in the main board. Separately, these quartiles report a relatively high absolute amount of MCAR%, and a relatively high percentage of average leverage. Details of board listing and percentages of leverage are shown in Appendix 8.

Last, we attempt to examine the implications of the corporate bond downgrade announcements to the efficiency of the market. It is obvious that if the market is efficient, it should react differently to small downgrades and big downgrades. Reaction to big downgrades must be more profound compared to its reaction to small downgrades. Therefore, our objective in this part is to test the null hypothesis that there is no difference in the market response to small downgrades as compared to big downgrades. Results are reported in Panels A and B of Appendix 9. The results seem to indicate that the market reacts more sharply to big downgrades and less so following a small downgrade. In addition, the results have shown that big downgrades are anticipated for up to three months preceding their announcement. This result lends some support to market efficiency because in general terms, if there is no difference in the market response to small downgrades as compared to big ones, then the efficiency of the market would be questionable. Thus, we conclude that our findings regarding the market reaction to the announcement of corporate bond rating changes have passed all the executed robustness checks. Therefore, we reiterate that, while downgrades elicit strong negative reaction by the market, upgrades do not.

The ARMA – GARCH Lag Specification (ML_{GARCH})

At the earlier part of this paper, data were analyzed using the OLS market model. However, this model is extensively criticized for producing biased results. For instance, this method 'frequently causes the null hypothesis of zero average abnormal returns to be rejected when it is, in fact, true' (Boehmer *et al*., 1991, p. 254). The basic version of the market model is developed under a number of statistical assumptions. For example, the error term is normally distributed with a mean of zero and constant variance (homoscedasticity), no correlation between residuals for the different firms, and the coefficients are constant and symmetric over the event and non-event periods. The violation of these assumptions leads to inefficient parameter estimates and inconsistent test statistics, (Solibakke, 2002). In reality however, security returns are not normally distributed, especially in the case of daily returns.

Henderson (1990) documented that serial correlation is present in security returns traded in thin markets, a phenomenon known in the literature as "non-synchronous" trading. Henderson also documented variance shifts associated with financial events. While the non-normality is believed to be a serious problem for studies using daily data, (Berry *et al*., 1990), claim that serial correlation induces bias in the betas of individual securities. Hence, Henderson pointed that the betas of infrequently traded securities are downward biased, while shares trading with more than average frequency have upward biased betas. However, in measuring the abnormal performance, it is highly important to get a correct estimate of the standard error for the purpose of statistical inferences. Thus, previous researchers attempted to account for the weaknesses of the market model by either adjusting the test statistics in the case of Boehmer *et al*. (1991), or by using a cross-sectional estimate of the variance as in Penman (1982). Nevertheless, all these attempts are not free from loopholes themselves. That is why we apply the ARMA-GARCH specification of the market model, which is developed in Solibakke (2002). Instead of adjusting the test statistics, the ARMA-GARCH specification considers the above assumptions as parts of the model itself. Thus this new specification is expected to produce more efficient parameter estimates and consistent test statistics compared to the basic market model. Table 4 below reports the results of some selected specification tests for the ML_{GARCH} and LS_{OLS}. The results suggest the presence of fewer violations of model assumptions by ARMA-GARCH compared to OLS.

Table 4
Selected Model Specification Tests

ML_{GARCH}	$Q_{(8)}$	$Q^2_{(8)}$	$ARCH_{(8)}$
Downgrades (Full Sample)	4.732 (0.449)	6 .549 (0.256)	7.003 (0.536)
Upgrades (Full Sample)	7.746 (0.257)	7.216 (0.301)	7.745 (0.458)
LS_{OLS}	$Q_{(8)}$	$Q^2_{(8)}$	$ARCH_{(8)}$
Downgrades (Full Sample)	22.979 (0.003)*	12.397 (0.134)	11.8001 (0.160)
Upgrades (Full Sample)	5.601 (0.692)	16.205 (0.040)**	15.201 (0.055)*

Notes:

*, ** stand for statistical significance at the 1 and 5% levels, respectively. Numbers in parentheses are the *p*-values for the Q_k,, Q_k^2, and ARCH statistics. $Q_{(8)}$ is the Ljung and Box (1976) statistic for serial correlation up to lag *8*. The null hypothesis is that there is no autocorrelation up to lag *8*. if the p-value associated with the cumulative *Q*-statistic is significant, it indicates the rejection of the null hypothesis and hence, the presence of auto correlation. Q_k^2, displays the auto correlation (AC) and partial auto correlation (PACF) of the squared residuals from an estimated equation. If there is no ARCH in the residuals, the AC and PACF should be zero at all lags and the *Q*- stat should not be significant. Archest carries out Lagrange Multiplier (LM) tests for Arch in the residuals. Arch in itself does not invalidate standard LS inference but, ignoring its effects may result in a loss of efficiency. The null hypothesis is that there is no Arch up to lag q in the residuals.

ML_{GARCH} results shown in Table 5 indicate that downgrades do contain negative information to the market. Moreover, the results reinforce our earlier LS_{OLS} finding that there exist some signs of information leakage in the Malaysian stock market.

Panel A of Table 5 shows that the average event effect in each of E(-90, -61), E(-60, -31), and E(-30, -1) is negative and statistically significant at the 5%, 10%, and 5%, respectively. The average percentage of negative observations is 55% for the event period preceding T_0 .

For the period post t_0 however, that percentage is 47%. This implies that even in terms of the number of negative parameter estimates, the pre-announcement period gets the lion's share. With percentages of 58% and 50% pre-and-post T_0 , LS_{OLS} results also reported the same 8% difference in negative parameter estimates. In general, ML_{GARCH} and LS_{OLS} report similar results with regard to the information contents of bond downgrades. Although the coefficient γ reports higher abnormal returns for ML_{GARCH} than LS_{OLS}, this rise in abnormal returns is compensated by higher standard deviations across all event windows using ML_{GARCH}.

The analysis of upgrades (full sample) using ML_{GARCH} provided extra evidence that the negative market response to bond upgrade announcement was motivated by the financial crisis of 1997/98. ML_{GARCH} results for upgrades (full sample) are reported in Panel B of Table 5. With *t*-ratios of -2.05 and -2.43, event windows E(-30, -1) and E(61, 90) produced negative and statistically significant abnormal returns. Recalling the LS_{OLS}, results, event windows E(-30, -1) and E(61, 90) also report negative abnormal returns, but with T-ratios of -1.76 and -3.44, respectively. This comparison provides a demonstration that negative abnormal returns are more significant after t_0. The average percentage of negative parameter estimates for the periods post-and-pre t_0 are 61% and 55% for $ML_{GARCH;}$ and 57% and 53% for LS_{OLS}, respectively.

Table 5
ARMA–GARCH Lag Specification, ML_{GARCH}

ML_{GARCH}	**Panel A: Corporate Bond Downgrades (Full Sample)**								
	Alfa	Beta	E(-90,-61)	E(-60,-31)	E(-30,-1)	E (0, 0)	E(1, 30)	E(31,60)	E(61,90)
Average	-0.003	1.090	-0.053	-0.038	-0.041	0.003	0.009	-0.035	0.038
Standard deviation	0.004	0.409	0.268	0.255	0.231	0.055	0.224	0.272	0.226
Negatives %	86.67%	0.00	56.30%	52.59%	55.56%	49.63%	48.89%	49.63%	42.96%
t-ratio	-8.75* {0.00}	30.94* {0.00}	-2.30** {0.023}	-1.71*** {0.089}	-2.06 {0.041}	0.56 {0.570}	0.45 {0.657}	-1.47 {0.143}	1.97** {0.050}
Z-statistics	8.52* {0.00}	-11.62* {0.00}	1.46 {0.144}	0.60 {0.549}	1.29 {0.197}	-0.09 {0.928}	-0.26 {0.795}	-0.09 {0.928}	-1.64*** {0.101}
CAR			-0.053	-0.091	-0.132	-0.129	-0.120	-0.155	-0.116
ML_{GARCH}	**Panel B: Corporate Bond Upgrades (Full Sample)**								
	Alfa	Beta	E(-90,-61)	E(-60,-31)	E(-30,-1)	E (0, 0)	E(1, 30)	E(31,60)	E(61,90)
Average	-0.001	0.964	-0.037	-0.021	-0.063	-0.007	-0.029	0.082	-0.084
Standard deviation	0.002	0.340	0.287	0.131	0.258	0.054	0.285	0.426	0.290
Negatives %	56.34%	0.00	53.52%	49.30%	54.93%	59.15%	63.38%	45.07%	63.38%
t-ratio	-2.32** {0.023}	23.87* {0.00}	-1.10 {0.277}	1.37 {0.174}	-2.05** {0.045}	-1.11 {0.269}	-0.87 {0.387}	1.63*** {0.107}	-2.43* {0.017}
Z-statistics	1.07 {0.284}	-8.43* {0.00}	0.59 {0.555}	-0.12 {0.904}	0.83 {0.407}	1.54 {0.124}	2.26** {0.023}	-0.83 {0.407}	2.26** {0.023}
CAR			-0.037	-0.016	-0.079	-0.086	-0.115	-0.033	-0.116

ML_{GARCH} results for downgrades and upgrades provided the following points:

First, bond downgrade announcements negatively affect the stock market in Malaysia. Second, bond downgrades produce negative wealth effect. Third, there are signs of information leakage as the market appeared to have responded well before the announcement date of bond downgrades. Fourth, bond upgrades seem to have negative impact on the market. However, by excluding the observations of the years 1997 and 1998, upgrades produced no more negative impact on the market. This is an indication that upgrades do not provide any new information to the market. Fifth, bond upgrades do not have any impact on the wealth of shareholders. Sixth, even though average abnormal returns have increased across all the event windows in the ML_{GARCH} specification compared to LS_{OLS}, the corresponding standard deviations have also increased so that in many occasions, the *t*-ratio becomes less significant for the ML_{GARCH} specification.

4. Summary and Conclusion

This study aims at examining the market response to various announcements by the Rating Agency Malaysia (RAM) and the Malaysian Rating Corporation (MARC) for the period spanning 1993 through to 2003 inclusive. Four inter-linked parts form the main theme of the study. The central focus of the study is to investigate the market response to bond upgrades and downgrades.

For any firm to be included in the sample, it must pass some pre-defined selection criteria. These are: the firm must be listed on the Bursa Malaysia at the time of rating announcement; a firm would be eliminated from the sample if and when other significant news is announced by or about the same firm at the time of the rating change; provided that the stock market is closed the day RAM or MARC announces the rating change, the rated firm would not be included in the sample; and finally, in the case of simultaneous rating changes of different bond issues for the same firm, we would retain the rating change for the most senior issue available so that each rating change for a firm would result in one sample observation regardless of the number of bonds affected.

Two variations of the market model are used in estimating the expected returns to stocks, namely, the standard OLS market model and the ARMA-GARCH lag specification of the market model.

Serious violations of assumptions may occur as a result of using the OLS model to analyze financial data. These violations do not necessarily invalidate the OLS estimates which, may also not be biased but to a great extent, inefficient. Some attempts were made to account for the weaknesses of the market model. These are either done by adjusting the test statistics (Boehmer et al, 1991), or by using a cross-sectional estimate of the variance (Penman, 1982). However, to have more efficient estimates and relatively consistent test statistics, we use the ARMA-GARCH lag specification of the market model in which, the OLS assumptions are considered as parts of the model itself rather than being imposed on it.

The findings of this study are noted below:

First, though with some signs of information leakage, the market has reacted negatively to the announcements of both upgrades and downgrades. In addition, only corporate bond downgrades seem to generate a negative abnormal return. This result sounds familiar only with respect to downgrades, as many researchers ended up with the same conclusion. Examples include the work of Dicheiv and Piotroski (2001), Goh and Ederington (1998), Matolcsy and Liano (1995), and Glascock *et al*. (1987). However, the finding that upgrades trigger negative market reaction is indeed a very special one that has never been documented internationally. Instead, the common finding in the international literature is that upgrades do not have any impact on the market. To improve our understanding on this issue, we have excluded observations of the years 1997 and 1998, named here as the crisis period. Using the adjusted sample, we find that upgrades do not signal the arrival of new information to the market. This finding serves as a testimony that our earlier conclusion regarding the existence of negative market response following bond upgrades was entirely driven by the spectacular impact of the financial crisis of 1997/98 that struck the whole region of South East Asia. Possible justification of this finding is that, while they are reluctant to provide negative information to rating agencies, a company management acts swiftly when providing these agencies with positive information. Therefore, positive information reaches the market almost instantaneously while negative news usually comes as a surprise to the market. It is worth noting that even though average abnormal returns have increased across all event windows in the ML_{GARCH} specification compared to LS_{OLS}, the corresponding standard deviations have also increased so that in many occasions, the T-ratio becomes less significant for the ML_{GARCH} specification.

To confirm and check the robustness of these results, we have conducted the following forensic analyses:

1. It could be argued that the disproportionate response to upgrades and downgrades could be due to some mismatching in the sizes of upgrades and downgrades. That is, the majority of upgrades might be ‘small upgrades’ while the majority of downgrades are ‘big downgrades’. Our additional analyses rejected this contention as we find that the majority of upgrades (65%) are big upgrades. Similarly, the majority of downgrades are also ‘big downgrades’ (71%).

2. It could also be pointed that the profound negative reaction by the market following downgrades might have been prompted by a number of two or three badly performing firms only. Taking these concerns into consideration, we ranked all downgrades by the size of reaction (CAR%) for the two weeks E(-7, +7) surrounding the announcement date t_0, then we tested all CARs% individually for significance. We find that 64% of the downgraded firms experienced negative CARs, 22% out of which are statistically significant. This finding then rejects the above argument that the negative market response to downgrades might have been caused by two or three firms.

3. Using the same rankings for upgrades and downgrades in 2 above, we made a comparison between the MCAR% of the top and bottom quartiles for downgrades with the MCAR% of the top and bottom quartiles for upgrades. All quartiles presented statistically significant MCARs. However, the absolute MCAR is the highest for top quartile downgrades (-1.42%) and bottom quartile upgrades (1.06%) compared to that of the top quartile upgrades (-0.71%) and bottom quartile downgrades (0.94%).

   These results motivated us to perform even further scrutiny on the characteristics of firms identified with each quartile. Our interest is focus on whether the ratio of total face value of corporate bonds to market capitalization is different. In addition, we wanted to know whether the board of listing has any role in determining the extent of the market reaction. Our finding is that, of all the quartiles identifying upgrades and downgrades, the majority of firms in the top quartile downgrade and bottom quartile upgrade are listed in the main board. Separately, these quartiles report a relatively high absolute MCAR%, and a relatively high percentage of average leverage.

4. We also attempted to examine the implications of corporate bond downgrade announcements to the efficiency of the market. It is obvious that if the market is efficient, it should react differently to small downgrades when compared to big downgrades. Market reaction to big downgrades must be more profound compared to its reaction to small downgrades. The results seem to indicate that the market reacts more sharply to big downgrades and less so following a small downgrade. Thus, the efficiency of the market is implied.

Based on the above findings, we could conclude that rating agency announcements seem to signal the arrival of new information to the Malaysian capital market, albeit, with some signs of information leakage. Furthermore, downgrade announcements trigger negative wealth effect, while upgrades generate no effects whatsoever.

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Appendix 1
List of Small Upgrades: 35% of Total Upgrades

Stock Code	From	To
1. ACPI	A_3	A_2
2. AKN	A_3	A_2
3. AKN	A_3	A_2
4. CMSB	BBB_3	BBB_2
5. GAMUDA	A_2	A_1
6. HICOM	BBB_2	$BBB_{1(s)}$
7. HLCRED	BBB_3	BBB_2
8. IPMUDA	$A_{3(bg)}$	$A_{2(bg)}$
9. IREKA	$BBB_{2(bg)}$	$BBB_{1(bg)}$
10. KIMHIN	$A_{2(bg)}$	$A_{1(bg)}$
11. MRCB	BBB_3	BBB_2
12. MTD	BBB_2	BBB_1
13. RPB	$A_{3(bg)}$	$A_{2(bg)}$
14. TENAGA	AA_2	AA_1
15. UMW	A_3	A_2
16. V.S	A_3	A_2
17. YTL	AA_2	AA_1

Appendix 2
List of Big Upgrades: 65% of Total Upgrades

Stock Code	From	To
1. AMMB	BBB_2	$AA_{3(bg)}$
2. ANTAH	BBB_3	$A_{2(bg)}$
3. AOKAM	A_1	AA_3
4. APEX	BBB_3	BBB_1
5. BOLTON	BBB_2	A_3
6. CIMA	$BBB_{3(s)}$	BBB_1
7. CHG	BBB_1	$A_{2(bg)}$
8. CHHB	B_1	BB_2
9. EG	A_2	AA_1
10. F&N	BB_3	A_2
11. GAMUDA	BBB_2	A_3
12. HLCRED	BBB_1	A_3
13. IGB	BBB_3	$A_{1(bg)}$
14. ILB	BB_1	BBB_3
15. ILB	BBB_3	$A_{3(bg)}$
16. IOICOR	A_3	A_1
17. MCSB	$A_{1(bg)}$	$AA_{3(bg)}$
18. MTD	BB_1	BBB_2
19. PARKMAY	BB_3	BBB_3
20. PERNAS	$A_{3(s)}$	$A_{1(s)}$
21. PPHB	$A_{3(bg)}$	$AA_{1(bg)}$
22. RHB	B_2	$BB_{2(s)}$
23. RHBCAP	BBB_3	$A_{2(s)}$
24. SMI	D	B_2
25. SAB	BB_1	BBB_3
26. SAB	BBB_3	BBB_1
27. TENAGA	AA_3	$AA_{1(s)}$
28. TNTT	$A_{1(bg)}$	$AA_{3(bg)}$
29. TNTT	BBB_2	$A_{2(bg)}$
30. UNIPHON	BBB_2	$AA_{1(bg)}$
31. WINGTIEK	D	$A_{3(bg)}$

Appendix 3
List of Small Downgrades: 29% of Total Downgrades

Stock Code	From	To
1. ACTACOR	C_2	C_3
2. ASIAPAC	BB_3	B_1
3. COMMERZ	$AA_{3(bg)}$	$A_{1(bg)}$
4. EG	$AA_{2(bg)}$	$AA_{3(bg)}$
5. FABER	BB_2	BB_3
6. FACBRES	$BB_{2(s)}$	$BB_{3(s)}$
7. GADK	$AA_{3(bg)}$	$A_{1(bg)}$
8. GAMUDA	$A_{1(bg)}$	A_2
9. GOPENG	$A_{1(s)}$	$A_{2(s)}$
10. GPERAK	$A_{2(bg)}$	$A_{3(bg)}$
11. IREKA	$A_{2(bg)}$	$A_{3(bg)}$
12. LIENHOE	A_3	BBB_1
13. METPLEX	BBB_2	BBB_3
14. METPLEX	$BBB_{1(bg)}$	$BBB_{2(bg)}$
15. PJDEV	$A_{2(bg)}$	$A_{3(bg)}$
16. PROMTO	$A_{3(bg)}$	$BBB_{1(bg)}$
17. SCIENTX	$A_{3(bg)}$	$BBB_{1(bg)}$
18. SCIENTX	$BBB_{1(bg)}$	$BBB_{2(bg)}$
19. WINGTIEK	$AA_{3(bg)}$	$A_{1(bg)}$
20. YECHIU	A_2	A_3

Appendix 4
List of Big Downgrades: 71% of Total Downgrades

Stock Code	From	To
1. ACTACOR	$AAA_{(bg)}$	BBB_3
2.ANTAH	$A_{3(b)}$	$BBB_{3(bg)}$
3. AOKAM	AA_3	A_2
4. APEX	$AAA_{(bg)}$	BBB_3
5. BRAYA	$AAA_{(bg)}$	BBB_1
6. BOLTON	$AAA_{(bg)}$	BBB_2
7. MSB	A_3	BBB_3
8. CHG	$AA_{3(bg)}$	BBB_1
9. CHHB	$BB_{2(s)}$	B_1
10. CHHB	BB_2	B_2
11. DAIBOCI	$AA_{3(bg)}$	A_2
12. DBHD	$AAA_{(bg)}$	BBB_3
13. FFHB	$A_{2(bg)}$	$BBB_{3(bg)}$
14. F&N	$AAA_{(bg)}$	BB_3
15. GKENT	$AA_{3(bg)}$	A_2
16. GKENT	BBB_3	BB_3
17. GPERAK	$BBB_{2(bg)}$	$BB_{3(s)}$
18. IGB	$AA_{3(bg)}$	BBB_3
19. IOIPROP	AAA(bg)	A_2
20. IPMUDA	$AA_{3(bg)}$	$A_{3(bg)}$
21. JOHAN	$AA_{3(bg)}$	BBB_3
22. JUAN	$A_{2(bg)}$	BBB_1
23. KELMAS	AAA(bg)	BBB_3
24. KIMHIN	AAA(bg)	A_1
25. KULIM	AAA(bg)	BBB_2
26. LHH	AAA(bg)	BBB_2
27. LIENHOE	C_1	D
28. LIONCOR	$A_{3(bg)}$	$BBB_{2(bg)}$
29. MRCB	$AAA_{(bg)}$	BBB_3
30. MPHB	$AAA_{(bg)}$	A_2
31. MWE	AAA(bg)	BBB_3
32. NANYANG	$AA_{3(bg)}$	A_3
33. PERNAS	$A_{1(s)}$	$BBB_{3(s)}$
34. PILECON	AAA(bg)	BBB_2
35. PRIME	A_3	BBB_2
36. RHB	$A_{1(s)}$	B_3
37. RPB	$AA_{3(bg)}$	$A_{3(bg)}$
38. RHBCAP	AA_3	BBB_3
39. SMI	BB_2	D
40. SAB	A_3	BBB_3
41. SRIWANI	A_1	BBB_1
42. SRIWANI	B_1	C_3
43. TENGARA	$AAA_{(bg)}$	BBB_1
44. TENGARA	BBB_1	BB_1
45. TRUTECH	BBB_3	BB_1
46. TSH	$A_{1(bg)}$	$A_{3(bg)}$
47. UCB	BBB_3	BB_2
48. YTL	$AAA_{(bg)}$	AA_2
49. SUNINC	$AAA_{(bg)}$	$A_{1(bg)}$
50. SUNINC	$AA_{3(bg)}$	$A_{3(bg)}$

Appendix 5
Impact of Bond Upgrades on Stock Returns

Stock Code	CAR%	*t*	Stock Code	CAR%	*t*
ILB	-0.0199	-2.16**	BOLTON	0.001	0.19
AOKAM	-0.0158	-2.27**	PERNAS	0.001	0.46
MTD	-0.0076	-0.64	V.S	0.002	0.65
ACPI	-0.0072	-1.32	HLCRED	0.002	0.77
TNTT	-0.0071	-1.49	KIMHIN	0.003	0.74
IREKA	-0.0061	-1.11	AKN	0.003	0.29
EG	-0.0046	-0.58	RPB	0.003	0.32
AKN	-0.004	-1.29	TNTT	0.004	0.6
IPMUDA	-0.0039	-0.53	HICOM	0.006	0.32
UMW	-0.0032	-0.92	WINGTIEK	0.006	1.42
IGB	-0.0031	-1.54	ILB	0.007	0.55
YTL	-0.0021	-0.74	IOICORP	0.007	1.37
SAB	-0.0017	-0.5	AMMB	0.007	1.41
MTD	-0.0016	-0.19	MCSB	0.008	0.74
CIMA	-0.0009	-0.15	CHG	0.009	1.56
CHHB	-0.0008	-0.34	F&N	0.009	0.78
RHB	-0.0008	-0.24	HLCRED	0.010	1.56
TENAGA	-0.0005	-0.22	APEX	0.010	1.44
SAB	0.0001	0.01	MRCB	0.011	1.88***
TENAGA	0.0001	0.01	SMI	0.011	0.73
GAMUDA	0.0003	0.03	UNIPHON	0.012	1.34
CMSB	0.0004	0.11	ANTAH	0.012	0.86
PPHB	0.0004	0.02	PARKMAY	0.013	0.87
GAMUDA	0.001	0.52	RHBCAP	0.014	1.26

Notes:

[1] At event window E(-7, +7) ranked by size of reaction, with the lowest CARs on top of the list and the highest are at the bottom. Stock code, stands for individual firms whose bonds were rated by RAM or MARC; CAR% is the cumulative abnormal return for each firm; and *t* is the standard *t*-ratio. *, **, *** denote statistical significance at the 1, 5 and 10% levels using a 2-tailed test.

30 firms experienced positive abnormal returns. That is 63% of the sample firms. However, only one observation (3%) is significant at the 10% level. Total number of observations is 48. The occurrence of more than one stock code with the same name does not amount to a repetition because the time span between the announcements of any two of such events is at least one year.

Appendix 6
Impact of Bond Downgrades on Stock Returns

Stock Code	CAR%	t	Stock Code	CAR%	t
GADK	-0.0573	-2.48**	JUAN	-0.0009	-0.13
EG	-0.0255	-2.60**	FFHB	-0.0008	-0.13
SRIWANI	-0.0222	-2.01***	YECHIU	-0.0008	-0.17
SRIWANI	-0.0216	-1.26	GPERAK	-0.0007	-0.20
TENGARA	-0.0188	-1.47	MPHB	-0.0007	-0.16
PJDEV	-0.0142	-1.94***	UCB	-0.0007	-0.18
ACTACOR	-0.0119	-1.94***	GAMUDA	-0.0006	-0.41
ANTAH	-0.0106	-1.10	DAIBOCI	-0.0005	-0.11
RHB	-0.0101	-1.62***	KELMAS	-0.0005	-0.06
GPERAK	-0.0099	-1.40	PRIME	-0.0005	-0.07
COMMERZ	-0.0098	-0.52	GKENT	0.0003	0.03
PERNAS	-0.0084	-1.42	LIENHOE	0.0003	0.06
IOIPROP	-0.0073	-1.65***	TENGARA	0.0003	0.05
BOLTON	-0.0069	-2.11**	CMSB	0.0007	0.08
METPLEX	-0.0060	-1.78***	MRCB	0.0008	0.22
PILECON	-0.0059	-2.55**	RHBCAP	0.0013	0.35
CHHB	-0.0047	-1.16	KULIM	0.0029	0.53
ACTACOR	-0.0044	-0.40	GOPENG	0.0031	0.76
DBHD	-0.0044	-1.15	MWE	0.0034	0.95
GKENT	-0.0044	-1.27	JOHAN	0.0036	1.08
SUNINC	-0.0044	-0.80	NANYANG	0.0041	1.23
IPMUDA	-0.0042	-0.60	BRAYA	0.0050	0.99
CHG	-0.0037	-0.84	SCIENTX	0.0054	0.96
LIENHOE	-0.0036	-0.87	SUNINC	0.0054	0.62
IGB	-0.0034	-0.83	SMI	0.0076	0.40
KIMHIN	-0.0034	-0.35	YTL	0.0080	1.65***
LHH	-0.0031	-0.86	PROMTO	0.0086	1.20
RPB	-0.0028	-0.67	LIONCOR	0.0091	0.41
CHHB	-0.0027	-0.76	IREKA	0.0104	1.48
FACBRES	-0.0026	-0.51	SCIENTX	0.0105	1.47
METPLEX	-0.0025	-0.53	FABER	0.0117	0.86
WINGTEK	-0.0023	-0.35	APEX	0.0131	2.23***
AOKAM	-0.0018	-0.26	TRUTECH	0.0162	0.50
SAB	-0.0017	-0.49	ASIAPAC	0.0195	0.73
TSH	-0.0013	-0.14	F&N	0.0241	2.41***

Notes:

[1] At event window E(-7, +7) ranked by size of reaction, with the lowest CARs on top of the list and the highest are at the bottom. Stock code, stands for individual firms whose bonds were rated by RAM or MARC; CAR% is the cumulative abnormal return for each firm; and *t* is the standard *t*-ratio. *, **, *** denote statistical significance at the 1, 5 and 10% levels using a 2-tailed test.

45 firms experienced negative abnormal returns. This represents 64% of the sample firms, out of which 10 observations (22%) are statistically significant. Total number of observations is 70.

Appendix 7
Examination of Top and Bottom Quartiles for Upgrades vs. Downgrades

Quartile	Upgrades			Downgrades		
	MCAR%	***t*-ratio**	***N***	**MCAR%**	***t*-ratio**	***N***
Top quartile	-0.0071*	-4.51 {0.001}	12	-0.0142*	-4.82 {0.000}	18
Bottom quartile	0.0106*	17.12 {0.000}	12	0.0094*	6.81 {0.000}	18

Notes:

MCAR% is the mean cumulative abnormal return; and *N* is the number of stocks within each quartile. * stands for statistical significant at the 1% level. The MCAR is the highest for top quartile downgrades (-1.42%) and bottom quartile upgrades (1.06%) compared to that of the top quartile upgrades (-0.71%) and bottom quartile downgrade (0.94%).

Appendix 8
Upgrades and Downgrades Ranked By Size of Market Reactions

Upgrades Ranked By Size of Market Reactions					
Top Quartile (12 Stocks)			Bottom Quartile (11 Stocks)		
Stock Code	**Board of Listing**	**FV/MC**	**Stock Code**	**Board of Listing**	**FV/MC**
ILB	MAIN	60.52%	AMMB	MAIN	0.57%
AOKAM	MAIN	4.63%	MCSB	2ND	5.72%
MTD	2ND	8.15%	CHG	MAIN	18.02%
ACPI	MAIN	15.29%	F&N	MAIN	7.30%
TNTT	2ND	5.14%	HLCRED	MAIN	4.18%
IREKA	2ND	41.62%	APEX	MAIN	0.81%
EG	2ND	5.16%	SMI	MAIN	328.56%
AKN	2ND	6.33%	UNIPHON	MAIN	24.99%
IPMUDA	MAIN	45.00%	ANTAH	MAIN	13.38%
UMW	MAIN	2.34%	PARKMAY	MAIN	213.34%
IGB	MAIN	6.40%	RHBCAP	MAIN	4.60%
YTL	MAIN	0.48%			
Average		17.00%	Average		56.00%

Downgrades Ranked By Size of Market Reactions					
Top Quartile (18 Stocks)			Bottom Quartile (17 Stocks)		
Stock Code	**Board of Listing**	**FV/MC**	**Stock Code**	**Board of Listing**	**FV/MC**
GADK	MAIN	73.73%	GOPENG	MAIN	22.08%
EG	2ND	7.02%	MWE	MAIN	15.76%
SRIWANI	MAIN	318.54%	JOHAN	MAIN	8.67%
SRIWANI	MAIN	118.39%	NANYANG	MAIN	20.76%
TENGARA	2ND	17.64%	BRAYA	MAIN	5.75%
PJDEV	MAIN	13.05%	SCIENTX	MAIN	32.31%
ACTACOR	MAIN	135.95%	SUNINC	MAIN	15.12%
ANTAH	MAIN	48.50%	SMI	MAIN	260.90%
RHB	MAIN	23.14%	YTL	MAIN	0.41%
GPERAK	MAIN	23.11%	PROMTO	2ND	82.03%
COMMERZ	MAIN	3.63%	LIONCOR	MAIN	92.42%
PERNAS	MAIN	61.56%	IREKA	2ND	5.61%
IOIPROP	MAIN	1.73%	SCIENTX	MAIN	13.33%
BOLTON	MAIN	9.50%	APEX	MAIN	0.85%
METPLEX	MAIN	38.19%	TRUTECH	2ND	41.62%
PILECON	MAIN	13.90%	ASIAPAC	MAIN	245.76%
CHHB	MAIN	34.75%	F&N	MAIN	1.44%
ACTACOR	MAIN	26.29%			
Average		54.00%	Average		51.00%

Notes:

MAIN and 2ND stand for Main Board and Second Board respectively. FV/MC is the ratio of face value of corporate bonds to the market capitalization of rated firms. The ratio of total face value of bonds to market capitalization is the highest for top quartile downgrades (0.70%) and bottom quartile upgrades (0.25%) compared to that of the bottom quartile downgrades (0.50%) and top quartile upgrades (0.20%). 42% of the stocks at the bottom quartile of upgrades are listed in the Second Board while only 8% of the top quartile is listed in this board. On the other hand, these ratios are 17% and 11% for downgrades. This indicates that the majority of the downgraded firms are listed in the main board.

Appendix 9
Market Reaction to Small Downgrades As Compared to Big Downgrades

Average and standard deviation; % negatives; and T-ratio.							
Panel A: Small Downgrades							
	E(-90,-61)	E(-60,-31)	E(-30,-1)	E(0,0)	E(1,30)	E(31,60)	E(61,90)
Average	-0.015	-0.069	-0.037	0.002	-0.004	-0.119	-0.077
Standard Deviation	0.227	0.108	0.182	0.018	0.248	0.390	0.159
Negatives %	55	65	50	40	55	65	65
t-ratio	-0.30	-2.86*	-0.92	0.58	-0.07	-1.37	-2.17**
Panel B: Big Downgrades							
	E(-90,-61)	E(-60,-31)	E(-30,-1)	E(0,0)	E(1,30)	E(31,60)	E(61,90)
Average	-0.043	-0.034	-0.039	0.003	-0.023	0.003	0.005
Standard Deviation	0.160	0.127	0.178	0.032	0.155	0.173	0.182
Negatives %	60	68	52	46	58	50	54
t-ratio	-1.88***	-1.89***	-1.55***	0.55	-1.05	0.12	0.21

Notes:

*, **, *** denote statistical significance at the 1, 5 and 10% levels, respectively. Numbers in {.} are *p*--values A small downgrade is 'an only one notch' downgrade, while a big downgrade involves more than one notch. For example: a downgrade from A_1 to A_2 or from A_3 to BBB_1 is defined as a small downgrade. However, a downgrade from A_1 to A_3 or from A_3 to BBB_2 or lower is regarded as a big downgrade.

It is observed from Appendix 9 that:

- Firms seem to react more sharply to big downgrades and less so following a small downgrade.
- Big downgrades are anticipated for up to three months preceding their announcements.
- This result lends some support to market efficiency because in general terms, if there is no difference in the market response to small downgrades as compared to big downgrades then the efficiency of the market is questionable.