CORPORATE CREDIT RATING ANNOUNCEMENTS: INFORMATION CONTENT OF RATING ANNOUNCEMENTS AND RATING ANNOUNCEMENTS MODELS: EVIDENCE FROM THE AUSTRALIAN FINANCIAL MARKETS

by

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ABSTRACT

Rating agencies have claimed that their rating announcements incorporate both publicly available information and information provided directly by rated issuers. Thus the announcements of rating have the potential to provide information that will impact on the equity and bond markets. The dissertation examines the impact that the release of ratings announcements had on equity and bond returns and also the factors that play a major role in determining the ratings assigned.

The first part of the thesis examines the role of information asymmetry in determining the price effects of announcements of both rating changes and the placing of issuers on CreditWatch. Results from the event studies indicate that firms whose ratings were re-rated downgrades and/or placed on negative CreditWatch record statistically significant negative excess equity returns. However, no such evidence is found in the bond market during the rating downgrades. The results support the presumption that rating downgrades and negative CreditWatch announcements provide new information to the market. Furthermore, we find some evidences of bond market positively reacting to issuers whose ratings were upgraded and/or placed on positive CreditWatch but no such evidence is found in the equity market. Interestingly, we find that equity and bond markets respond more vigorously to information preceding rating announcements, which suggests that rating announcements provided by the rating agencies are anticipated by market participants. Further, we document that markets tend to react more significantly when the rating announcement is unexpected, contaminated, a cross-classes rating changes and/or due to the firm changing its financial structure.

The second part of the thesis examines the impact of various accounting; financial and economic variables in the determination of the ratings. A multiple logistic regression model, which incorporates accounting; finance and economic variables, suggests that debt coverage and earning stability have the most pronounced effect on rating change announcements. When conducting both in-sample and out-of-sample forecast, the model is consistently forecast towards rating no changes. Also, we document that the success rate of out-of-sample forecasts using a moving window procedure is higher than normal out-of-sample forecast procedure.

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1 INTRODUCTION

1.1 Introduction

Rating agencies assign ratings to firms and structured finance products as a measure of their credit quality and ability to meet their financial commitments. Ratings change in response to changes in a firm's financial and economic conditions. Rating changes have significant economic implications as rating upgrades (downgrades) imply that issuers can access additional capital at lower (higher) cost. At the extreme, rating downgrades could lead to the potential termination of an issuer's access to credit markets. Ratings also have the potential to enhance credit market efficiency by reducing information asymmetry between borrowers and lenders by providing the market with an independent measurement of an issuer's relative credit risk. Furthermore, market participants use ratings for various purposes. Issuers use ratings to signal their own creditworthiness, thus helping to improve their credibility and the value of their debt instruments. Investment banks and fund managers use ratings to measure and limit the riskiness of their portfolios. Regulators and other agencies also use ratings to monitor risks taken by financial institutions and to ensure the stability of their financial system. Thus rating agencies can serve an important credit-monitoring role in the financial markets. The financial scandals involving Enron, and more recently, the market turbulence, which erupted in mid-2008 question the role-played by rating agencies. The main issue being whether the rating agencies failed to monitor the rating issuers closely and so be able to provide timely information to the capital market relating to both issuers and also specific financial products.

1.2 Institutional Background

1.2.1 Industry Background

Standard & Poor's Ratings Services, Moody's Investors Services and Fitch Ratings are the three major rating agencies, each being recognized by the Securities and Exchanges Commission (SEC) in 1975 as a Nationally Recognized Statistical Rating Organization (NRSRO). Standard & Poor's was founded in 1860 as a publicly owned corporation and remained so until McGraw-Hill Inc., a major publishing company, acquired all of its common stocks in 1966.

Standard & Poor's operates as a financial services company whose products and services include ratings, indices, equity research, risk solutions, investment advisory services and data services. Standard & Poor's provide ratings on approximately USD32 trillion of debt issued in more than 100 countries.

Moody's began its bond rating services in 1909 when John Moody first provided rating services to railroad bonds. Moody's is a global leader in credit ratings research and credit risk analysis, serving more than 9,300 customer accounts in some 2,400 institutions around the globe.

Fitch was founded as the Fitch Publishing Company in 1913 by John Knowles Fitch and experienced significant growth in the ratings industry when it was capitalized by a new management team since 1989. Moreover, in response to the evolving credit market, Fitch merged with IBCA Limited in 1997 and acquired Duff & Phelps Credit Rating Co., in 2000. As a result of rigorous growth strategies, Fitch today is the third largest rating company following Standard & Poor's and Moody's.[1]

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[1] Standard & Poor's, Moody's and Fitch corporate information obtained from their corporate website: www.moodys.com, www.standardandpoors.com and www.fitchratings.com

Currently, there are ten rating agencies designated by NRSRO. Among them, Standard & Poor's, Moody's and Fitch account for approximately 98 percent of the market for debt ratings in the U.S. The rating industry is highly concentrated and have very limited competition, thus rating agencies have long been able to benefit from monopoly status and regulatory protection.[2] Moreover, rating agencies have also benefited from rapid developments of structured financial instruments including residential mortgage-backed securities (RMBS) and collateralized debt obligations (CDO). However, the poor performance of subprime-loans commencing in 2007 caused a number of RMBSs and CDOs to be re-priced and re-rated. The Committee on the Global Financial System reported in 2007 that the magnitude and frequency of more than one notch downgrades for such products far exceeded those on corporate securities.[3] One consequence being that market participants and regulators had their confidence undermined in the ratings provided by these rating agencies. In particular, this raised questions as to how rating agencies form their rating opinions.

1.2.2 Rating Process

Standard & Poor's, Moody's and Fitch issue short-term and long-term issuer and issuer-specific credit ratings to reflect a company's capacity to meet its financial obligations and also establish rating scales for short-term and long-term instruments. These ratings have become easy tools for investors to interpret in order to be able to differentiate the credit quality of issuers and specific credit products. In addition, Standard & Poor's introduced its CreditWatch service in 1981 and Moody's its Watchlist service in 1985 to

[2] Rating agencies are explicitly exempted from liability under Section 11 of the Securities Act of 1933 and from Regulation FD – for "faire disclosure" proposed by U.S. Securities and Exchange commission in 1999. Moreover, Credit Rating Agency Reform Act of 2006 limits on private rights of taking action against rating agencies.

[3] Bank for International Settlements, 2008, 'Ratings in Structured Finance: What Went Wrong and What Can Be Done to Address Shortcomings', *Committee on the Global Financial System*, Working Paper.

provide the market with information as to which issuers were under review for potential upgrade or downgrade.[4] Keenan et al., (1998) studied the historical analysis of Moody's Watchlist and found that the average amount of time for an issuer to be placed on the Watchlist is 108 days.

Rating agencies typically assign corporate credit ratings based on a thorough evaluation of the available qualitative data supplemented by use of quantitative models, as appropriate to form rating opinions. Qualitative analysis incorporates evaluating a firms' operational and financial performance within its industry and assessing firms' management strategies, capital structure, and corporate governance and risk profile. Quantitative analysis involves building financial model inputs from evaluated qualitative information. In addition, Standard & Poor's, Moody's and Fitch claim that during the rating process, they have access to, and use, confidential non-public information such as budget forecasts, contingent risk analyses and potential new financing, acquisition and restructure information.[5] In 2000 SEC adopted the Regulation FD allowing the rating issuers to share certain material non-public information with rating agencies during the rating process.[6] A general description of the Standard & Poor's, Moody's and Fitch process for arriving at corporate credit ratings is provided below.

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[4] Standard & Poor's. 2008, 'Ratings Definition', Moody's, 2003, 'Rating Symbols and Definition' and Fitch, 2009, 'Definition of Ratings and Other Scales' define issuer credit ratings are those issued on corporate bond, municipal note, preferred stock, commercial paper and certificate of deposit and issuer-specific credit ratings are those issued on corporate credit ratings, counterparty ratings and sovereign credit ratings. In addition, Standard & Poor's and Fitch classify rating scale for their short-term instrument from 'A-1' down to 'D' and from 'F-1' down to 'D' respectively and for their long-term instrument from 'AAA' down to 'D' and additional plus (+) or minus (-) sign between categories 'AA' and 'CCC'. On the other hand, Moody's classify its ratings scale from 'P-1' down to 'P-3' for short-term instrument and from 'Aaa' down to 'C' for long-term instrument.

[5] Standard & Poor's, 2008, 'Standard & Poor's Corporate Rating Criteria', *The McGraw-Hill Companies*, Moody's, 2002, 'Understanding Moody's Corporate Bond Ratings and Rating Process', *Moody's Investors Service Global Credit Research* and Fitch, 2006, 'The Rating Process', *Fitch Ratings*.

[6] U.S. Securities and Exchange Commission.1999, 'Selective Disclosure and Inside Trading',*U.S. Securities and Exchange Commission.*

At the start of the rating process, rating agencies assign a team of analysts to gather information that is pertinent to the rating and review all the information provided by the rating issuers. Such information includes financial reports, operational environments, management strategies, capital structure, economic conditions, industry and regulatory environments. Moreover, as part of the information gathering, the analytical teams meet with management of the issuers to discuss some key issues that may come to the rating agencies' attention. Standard & Poor's in the corporate rating criteria report states that:

> *"Several of the members of the analytical team meet with management of the organization to review, in detail, key factors that have an impact on the rating, including operating and financial plans and management policies. The meetings also help analysts develop the qualitative assessment of management itself, an important factor in the rating decision".*[7]

After all the information has been reviewed, the rating agencies decide as to whether there is sufficient information for them to form a rating opinion on the issuer's creditworthiness. [8] Following the credit analyst's qualitative and quantitative assessment, the leading analyst will put forward a rating recommendation to the rating committee. At the committee meeting, the committee members will discuss the rating recommendations and supporting information. The committee will then vote on the recommendation and the issuer will be notified the outcome of the committee's decision. Once the rating is assigned, it will be under continuous surveillance and review. The process of rating review is quite similar to the process of forming an initial

[7] Standard&Poor's.2008, 'Standard&Poor's Corporate Rating Criteria', *The McGraw-Hill Companies*.
[8] If the issuer declines to participate in the rating process, the issuer will be designated as non-participating.

rating: when new financial or economic information arises that is believed to have the potential to impact on an issuer's credit quality but which is considered insufficient to cause an immediate rating change, the rating agencies will generally place issuers under CreditWatch listing. Rating agencies will continue to monitor the situation and assess the potential impact on the firm's current rating. If a rating change is required, the issuer is then notified.[9]

1.2.3 Conflict of Interest

Rating agencies have been described as financial gatekeepers in the capital markets and also as information intermediaries providing independent and objective assessments on the default probability of issuers with respect to their general financial obligations or particular debt instruments. However, the shift from an 'investor-pays' to a 'issuer-pays' business model in the early 1970s caused a massive corporate accounting scandal between 2001 and 2002 and was a contributing factor in recent global credit crisis.[10] Rating agencies were accused of having a conflict of interest leading them to making inaccurate assessments on their rated instruments. As a result, the performance of rating agencies has been the subject of intense criticism (Bolton et al., 2009).

The ratings market generally functions differently from the financial markets in which the investors incur the cost of acquiring information. In the ratings market, issuers incur

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[9] Standard & Poor's 2008, 'Standard & Poor's Corporate Rating Criteria', *The McGraw-Hill Companies*, Moody's. 2002, 'Understanding Moody's Corporate Bond Ratings and Rating Process', *Moody's Investors Service Global Credit Research* and Fitch. 2006, 'The Rating Process', *Fitch Ratings*.

[10] U.S. Securities and Exchange Commission introduces the NRSRO concept in the mid-1970 further more encourage regulator to increase their reliance on rating. During the same period, the NRSROs stopped selling ratings to investor and began charging the companies that issue the debt they rated. Enron Corporation carried investment grade rating just few months before its bankruptcy in late 2001, AIG holding double-A rating when the United States Federal Reserve Bank announced the US$85 billion bailout to prevent the company's collapse, and Lehman Brothers was rated a single-A rating just a few months before its collapsed. Rating agencies involved more than just rate the CDO and RMBS for risk; they play integral role in the market such as investigate the quality of the mortgage and offering guidance and expertise to investment banks.

all the cost while investors have free access to the ratings. Moreover, rating issuers have an incentive to pay for ratings issued as a good rating helps to improve the marketability or pricing of their securities issued whereas investors have no incentive to pay for ratings because once the ratings are identified they are released to the market. Also rating issuers have all the knowledge regarding the risk of their firms while investors do not possess such information, thus investors require higher risk premiums on the securities issued to compensate for the unknown risk. However, rating agencies can minimize this information asymmetry and risk premium by providing rating information, which reflect the risk of the firms. Unfortunately, it remains questionable as to whether rating agencies will provide a fair rating to the market under the present structure since they are conflicted. Investors would like rating agencies to issue an accurate rating so that they can make good investment decisions while issuers desire higher rating from rating agencies to signal their strong financial commitment to the market so they can sell their securities at higher prices. Since the rating issuers are the party paying the rating agencies, this suggests the possibility that the rating agencies are under pressure to provide the favorable ratings desired by the issuer.

Mathis et al., (2009), Bolton et al., (2009), Skerta and Veldkamp (2009), Becker and Milbourn (2009), and Stolper (2009) examine the conflict of interest between issuers and rating agencies. They indicate that rating agencies have an incentive to assign inflated ratings when rating agencies' revenue stream comes from the issuers. The finding is consistent with the U.S. Securities Exchange Commission's (SEC) examination of the three major rating agencies. SEC finds that issuers' payments may influence ratings because rating agencies allow key participants such as senior analytical managers and analysts' immediate supervisors to participate directly in fee discussions with the issuers. Moreover, when making decisions as to possible changes in rating methodology, the analytical staff appears too concerned about the firm's market share and the potential loss of transactions (SEC, 2008). A number of papers including Mathis et al., (2009), Bolton et al., (2009), Becker and Milbourn (2009) use reputation models to examine whether reputation concerns are sufficient to discipline rating agencies to give honest credit assessments. They find that when there is a high reputational cost, the quality of credit ratings assessment is unbiased and based on due diligence. Moreover, in well functioning capital markets, rating agencies will not risk their reputation by inflating ratings for short-term gain. Reputation plays a major role in aligning the interest of rating agencies with that of the market. Standard &Poor's reported to SEC in 2002 that:

> "*Most importantly, the ongoing value of Standard and Poor's credit rating business is wholly dependent on continued market confidence in the credibility and reliability of its credit ratings. No single issuer fee or group of fees is important enough to risk jeopardizing the agency's reputation and its future*".[11]

Bolton et al., (2009), Skreta and Veldkamp(2009) and Becker and Milbourn(2009) extend the study to further investigate the effects of issuers shopping for the best ratings, competition levels, and their ability to mitigate the conflict of interest problem. They document that an increase in issuers shopping for the best ratings and competition amongst rating agencies result in decreasing the quality of rating issues because rating agencies will issue friendly-ratings to avoid the loss of business transactions. SEC states

[11] Standard and Poor's Rating Services, 2002, 'Role and Function of Credit Rating Agencies in the U.S. Securities Market', *U.S. Securities and Exchange Commission Public Hearing* – November 15, 2002.

that:

> *"Typically, the rating agency is paid only if the credit rating is issued, though sometimes it receives a breakup fee for the analytic work undertaken even if the credit rating is not issued".*[12]

Since the cost of not taking up of the rating decision is significantly small, the issuers may approach a number of rating agencies to obtain a rating and then accept the best one to make public. As a consequence, issuers shopping for ratings may influence rating agencies' decisions to inflate ratings to secure transactions. Therefore, having more rating agencies would exacerbate the quality problem of ratings because there are increased choices in ratings. In contrast, according to SEC's report and comments from Association for Financial Professionals (AFP) to SEC, regulation should increase competition and avoid unnecessary regulatory barriers to entry in the rating market.[13]

Skreta and Veldkamp (2009) who examine whether the increase in rated assets complexity may cause rating agencies to issue inflated ratings, find that an increase in the rated assets complexity will increase the ability of rating issuers to shop for the best ratings. They claim that when the rated assets are simple rating agencies issue nearly identical ratings and rating issuers will disclose all relevant information to reduce

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[12] U.S. Securities and Exchange Commission. 2008, 'Summary Report of Issues Identified in the Commission Staff's Examinations of Select Credit Rating Agencies', *U.S Securities and Exchange Commission,* Washington.

[13] U.S. Securities and Exchange Commission in the report on the role and function of credit rating agencies in the operation of the securities market in 2003 stated that: *"Hearing participants recognized that limited competition exists today in the credit rating industry and, in general, were of the view that additional competition would have a beneficial effect on the marketplace".* In 2005, Kate, J.G. president and CEO of the Association for Financial Professionals commented to U.S Securities and Exchange Commission *"The commission should establish stringent criteria and clear procedures that will eliminate unnecessary regulatory barriers to entry into the rating market. The appropriate criteria should be based on whether an agency can consistently produce credible and reliable rating... ".*

investors' uncertainty and increase the value of issued assets. When the rated assets are complex, rating agencies issue different ratings for the same product, which provides the incentive for rating issuers to shop for the best ratings. Similar results are found in Mathis et al., (2009) who conclude that when a large fraction of rating agencies' incomes is derived from structured complex financial product MBS and CDO, there is a greater incentive for issuers to shop around which will cause rating agencies to compromise their standards.

2 LITERATURE REVIEW

Studies in the finance literature on ratings have largely concentrated on two areas. The first area of research examines the impact that rating announcements have on markets in order to assess whether the ratings contain information beyond what is publicly available. The second area of research seeks to identify the types of information that rating agencies use when arriving at their ratings. We provide a synopsis of the first type of research in Section 2.1 and we report on previous work in the second area in Section 2.2.

2.1 Information Content of Rating Announcements

2.1.1 Rating Changes and CreditWatch

Rating agencies assign ratings to the issuers and continuously review the implications of any new information for these ratings. The provision of the ratings is widely believed to promote greater efficiency in capital markets and reduce information asymmetry. Rating downgrades (upgrades) for a company can mean a higher (lower) cost of capital, limited (ready) access to the capital markets and a fall (increase) in the price of its securities (Ederington et al., 1987 and Hickman 1985). As a consequence, the information content of the rating announcements has long drawn the attention of academic literature to evaluate whether they contain valuable private information about future prospects of the firms and what insights they provide as to the efficiency of equity and bond markets. An early study by Katz (1974) uses regression models and monthly bond yields data to examine the efficiency of the bond market, particularly, the bond price adjustment process to rating reclassifications. The empirical results of this study show that there is no change in bond yields prior to the rating changes, a slight price adjustment during the month of the rating changes, which is maintained in the subsequent month. Similar results are found in Grier and Katz (1976) who study the industrial and public utility bond market and find that rating announcements are clearly not anticipated by the bond market but that bond prices adjust gradually over a significant period of time after the rating changes. These results imply that the bond market is inefficient as it is slow in assimilating new price-relevant information. Weinstein (1977) concentrates on monthly holding period returns of straight debt issues over the period from July 1962 through to July 1974 and provides contradictory evidence to Katz (1974) and Grier and Katz (1976). Weinstein finds that the bond market has fully adjusted to the information content in rating changes several months before the rating changes occur and there is no prices reaction to rating changes during the announcement and the post-announcement periods. This result is consistent with the view that rating agencies only process publicly available information with any ratings changes only reflecting information, which is already reflected in the price of the security.

The impact of rating changes on the equity market were first examined by Pinches and Singleton (1978) who studied the adjustment of stock prices to bond rating changes over the period from 1950 to 1972. They document that the accumulated abnormal returns increase (decrease) in a systematic manner over the two years prior to the announcement of rating upgrades (downgrades) followed by a slight reversal over the subsequent year. When company specific information is incorporated, the lag is only about a half year for rating downgrades. Like Weinstein (1977) this suggests rating changes have long been anticipated by the market.

On the other hand, Griffin and Sanvicente (1982) employing three different techniques to measure abnormal returns find evidence that is in conflict with previous studies.

When using either a two-factor model or control portfolios to calculate abnormal returns, they find a significant negative price reaction during the month of rating downgrades. However, there is no significant evidence of prices adjusting to rating upgrades, although some upgraded firms' experience positive abnormal returns in the month subsequent to the announcements. Similar results are found in Zaima and McCarthy (1988) and Wansley et al., (1992) who use weekly excess returns of common stocks and bonds to study the impact of rating changes on equity and bond market. They document that the stock prices do not react to rating upgrades but significant reaction is found over an 18-week period prior to and during the week of rating downgrade announcements. Moreover, they find no bond market reaction to rating announcements except around the announcement of rating downgrades.

Boot et al., (2006) examines whether credit ratings serve as a coordinating mechanism in situations where multiple equilibria occur. They find that rating act as "information equalizer" and serve as "focal point" that in the end all investors may rationally base their investment and pricing decisions on the raring. Moreover, the empirical result show that stock prices react negatively to rating downgrades and no such results are found in rating upgrades. The study also present the important of credit watch, any subsequent credit rating changes occurring after the credit watch procedure not lead to a further change in stock prices because the rating agency is not at any informational advantage. Chan et al., (2011) conduct empirical study on Boot et al., (2006) examine rating confirmation and downgrades following watch negative. They find a zero (negative) stock price reaction following watch procedure that result in confirmations (downgrades). Their result is inconsistent with Boot et al., (2006) due to the lack of effect for confirmation. Moreover, they find downgrades that do not follow credit watch procedure are neither more nor less information than those that do.

Holthausen and Leftwich (1986), Glascock et al., (1987), Hand et al., (1992) and Goh and Ederington (1993) were the first to use daily stock and bond price data to examine the effect of rating agencies' announcements. The use of daily data provides them with an opportunity to precisely examine the announcement process by narrowing the event window and eliminating instances of concurrent disclosures release surrounding the rating announcements date. Findings common to these papers are that bond and stock market react negatively to rating downgrades during the announcement window with there being an even greater adjustment during the pre-announcement window. Both studies find that bond and stock excess returns are positively associated with rating upgrades but only Glalcock et al., (1987) find this relationship to be statistically significant.

It is ambiguous as to why downgrade changes contain price relevant information but the same does not apply for upgrade changes. Goh and Ederington (1998) explain that management has an incentive to hide the unfavorable information and voluntarily releases positive information to the market with the intention of inflating stock prices, hence resulting in the market being more sensitive to rating downgrades. Alternatively, because of the higher reputation costs of the failure to detect rating problems, rating agencies tend to allocate more resources in detecting firms that experience deteriorating financial and operating positions, thus making information on downgrades more valuable to market participants. However, it should be noted that in more recent studies Dichev and Piotroski (2001) and Micu et al., (2006) report significant market reactions to rating upgrades and they attribute their different findings to the use of a larger data set.

Empirical literature on the impact of rating changes on the financial market has been critical of the role of rating agencies suggesting that they lag the market in processing publicly available information. As a response to this criticism, Standard & Poor's introduced their CreditWatch whilst Moody's introduced Watchlist to indicate the rating is under review for possible changes. Much of the early research that has examined the impact of rating reviews claimed that there is little information in CreditWatch. Cook (1983) uses Standard & Poor's CreditWatch data from 1981 to 1982 to analyze equity abnormal returns to CreditWatch. He finds that there are significantly small excess equity returns and bond prices differential for firms whose ratings were placed on CreditWatch. Similar findings are reported in Wansley and Clauretie (1985) who use a sample of 164 firms whose ratings were placed on CreditWatch from November 1981 to December 1983 to analyze the effect of CreditWatch on equity and bond market. They document that firms whose ratings were placed on positive (negative) CreditWatch appear to have significantly higher positive (negative) abnormal stock returns during the pre-announcement window than the actual announcement window.

Wansley and Clauretie (1985) extend the study to further examine whether rating agencies actually lag the market in processing information and whether the presence of CreditWatch can reduce the ratings lag. Their results indicate that firms that were re-rated without previously being placed on CreditWatch experience significant higher equity abnormal returns around the announcement window than firms who were placed on CreditWatch prior to the re-rating. Consistent results are found for bonds which all suggest that the presence of CreditWatch appear to reduce the ratings lag.

Matolcsy and Lianto (1995) are the first study to examine the information content of rating revisions in the Australian market using weekly data from 1982 to 1991. They use a total sample of 34 rating upgrades and 38 rating downgrades after excluding any changes due to major corporate announcements such as takeovers, mergers, corporate restructuring or suspension from listing. The results show that cumulative abnormal returns are statistically significant for all announcement windows of -17 to +17, -17 to 0, and from 0 to +17 for both rating upgrades and downgrades. However, after controlling for earning announcements and using cross-sectional regression to analyze rating upgrades and downgrades separately, the results indicate that only the coefficient variables associated with downgrades are significant. Consistent results are found in Choy et al, (2006) who also find no evidence of equity market responses to rating upgrades whilst finding there is significant market responses to rating downgrades particularly in the pre-announcement and announcement windows.

Walter et al., (2009) extend the study on the information content of rating revisions in the Australia market by including subscription-based ratings. Subscription-based ratings are distinct from non-subscribing ratings since investors are required to subscribe for the credit rating reports from rating agencies. In the study, they use non-subscribing ratings data from Moody's Investor Services and subscription-based ratings from the Corporate Scorecard Group between 1991 and 1997 to examine the information content of rating announcements. The results of the study find that there are statistically significant abnormal equity returns for both rating downgrades and rating upgrades prior to rating announcements for non-subscribing ratings data but no such evidence are found for the after announcement window. On the other hand, the results for subscription-based ratings show that there is no market reaction to rating upgrades during the pre-announcement period but significant market reaction during the post-announcement period. For the rating downgrades, they find significant market reaction during the pre-announcement period but no market reaction during the post-announcement period. From the results, they conclude that the investors who subscribe to credit reports from subscription-based rating agencies benefit by allowing them to develop trading strategies based on these credit reports.

2.1.2 Expected and Unexpected Rating Changes

Hand et al., (1992) develop an expectation model to distinguish the rating changes between those that are expected and those that are unexpected.[14] They find no excess equity and bond returns for both downgrades and upgrades that are expected, whereas unexpected rating downgrades (upgrades) have a significant negative (positive) impact on bond and equity returns. Wansley et al., (1992) use CreditWatch as the basis for determining whether a rating changes was expected or not. They report that rating downgrades, whether preceded or not by CreditWatch, are associated with significant negative abnormal returns. In contrast Choy et al., (2006) using a different method for determining expectation to both Hand et al., (1992) or Wansley et al., (1992) find that the abnormal returns during the announcement window are much greater for expected rating downgrades than they are for unexpected rating downgrades.[15] Purda (2007)

[14] Hand et al., (1992) "We develop an expectations model of bond rating changes based on yield-to-maturity, and use that model to increase the likelihood of detecting announcement effects associated with Credit Watch additions and bond rating changes. We measure the expectation of a bond rating change by comparing the yield-to-maturity on a bond of interest (Credit Watch or actual rating changes), estimated from the price available just prior to the rating agency announcement, with the yield-to-maturity of a benchmark, namely the median yield to maturity of other bonds with the same bond rating". If the interested bond yield-to-maturity is greater than the benchmark, downgraded bonds classify as expected and upgraded bonds classify as unexpected and vice versa for interested bond yield-to-maturity are lower than the benchmark.

[15] Choy et al., (2006) develop their expectation model by dividing those samples have cumulative abnormal returns for window (-10, -1) positive or insignificantly negative as unexpected rating changes and those samples have cumulative abnormal returns for window (0, +1) significantly negative as expected.

constructs a measure of rating changes model anticipated by investors and examine the stock price reaction surrounding rating change announcements made by Moody's. The result shows that stock market reacts negatively to downgrades that are largely predictable and to those that are a surprise. The market does not react at all to upgrades, even those that were anticipated.

2.1.3 Contaminated and Non-Contaminated Rating Changes and CreditWatch

There are a number of studies including Holthausen and Leftwich (1986), Wansley et al., (1992) and Hand et al., (1992) who have questioned whether the impact of rating changes and being placed on CreditWatch are overstated in cases where there are concurrent disclosures in the period surrounding the rating announcements date. To control for concurrent disclosures, they classify the rating change and CreditWatch observations into contaminated and non-contaminated sub-samples. Hanthausen and Leftwich (1986) use Moody's and Standard & Poor's rating changes over the 1977 to 1982 find that the impact of across-classes rating downgrades is much larger in the contaminated sample than it is in the non-contaminated sample.

The cumulated abnormal return for the contaminated sample is -4.77% over the 2-day event window, while it is only -0.96% for the non-contaminated sample. On the other hand, the announcement effect on equity returns after classifying the CreditWatch sample into contaminated and non-contaminated are approximately equal with neither being significant. A consistent result is found in Hand et al., (1992) when they examine the market reaction to the non-contaminated rating announcements, who report weaker abnormal returns for both stock and bond returns in the case of non-contaminated rating downgrades but not in the case of non-contaminated rating upgrades. Wansley et al.,

(1992) focus on the impact of CreditWatch report excluding cases where there are concurrent disclosures and report that the results are weaker than for the total sample of CreditWatch reports.

Choy et al., (2006) control for other contemporaneous announcements surrounding the release of information relating to ratings and find that only the results relating to the downgrade sample are statistically significant. For the contaminated rating downgrades, most of the negative reaction occurs prior to the rating changes date with a small and insignificant negative reaction at the time of the announcement. In contrast, the non-contaminated rating downgrades show no market reaction during the pre-announcement window but significant market reaction on the day leading up to, and on the day of, the announcement itself.[16]

2.1.4 Cross-Class and Within-Class Rating Changes

Holthausen and Leftwich (1986) were the first study to classify the rating changes sample into cross-class and within-class rating changes.[17] They find that only cross-class rating downgrades are associated with statistically significant negative abnormal stock returns, and most of the reaction is limited to the 2-days announcement window. No negative market reaction was detected for within-class rating downgrades and upgrades and across-class rating upgrades. Wansley et al., (1992) use rating changes

[16] Hanthausen and Leftwich (1986) identify concurrent information by searching the Wall Street Journal Index for the information around the announcement date basically [-1, 2] window where 0 is the announcement date. Hand et al., (1992) and Wansley et al., (1992) use the same approach but they shorter window [-1, 1] and [-1, 0] respectively. Within window if there is any announcements from a source other than the rating agency then they are classified as contaminated; otherwise, they are classified as non-contaminated. On the other hand, Choy et al., (1996) they search The Australian Financial Review 2 days before and after the announcement date and the identification approach is the same as the study in U.S but they also classify the samples as contaminated if there is any earnings announcement 10days before the rating change announcement date.

[17] Hanthusen and Leftwich (1986) indicate that cross-classes rating changes if the rating changes are from e.g. AA- to A+ and within-classes rating changes if the rating changes are from e.g. AA+ to AA-.

either preceded or not by CreditWatch to examine cross-class and within-class rating downgrades. They document that market reacts negatively to across-class rating downgrades that are not preceded by CreditWatch but there was no such market reaction where the downgrades are within-class. Moreover, they find no market reaction to rating downgrades preceded by a CreditWatch either within-class or across-class. Choy et al., (2006) when studying the impact of single-step and multiple-step rating changes find some significant positive abnormal returns for single-step rating upgrades. Also, they find the abnormal returns for multiple-steps rating downgrades are larger than the single-step rating downgrades.[18]

Hite et al., (1997) examine the impact of bond-rating changes on bond price performance using monthly bond trading data and S&P's and Moody's bond rating changes. They classify rating changes into three different categories: Remaining Investment Grade, Drop below Investment Grade and Remaining below Investment Grade. The results from the event study show that six months prior to a rating downgrades, the bond prices performance are negatively and statistically significant for all three categories. However, the event-month only the rating downgrades remaining below investment grades are highly significant. Post-announcement window has very small negative effect. Similarly, they find no evidence to support all three categories of rating upgrades.

2.1.5 Rating Changes and CreditWatch by Reasons

Rating changes are made for many different reasons. Goh and Ederington (1993) classify rating changes made by Moody's into three distinct categories: rating changes

[18] Choy et at., (2006) they classify multiple steps rating changes if the rating changes is from e.g. AAA to AA- and single step rating changes if the rating changes is from e.g. BBB to BB-.

made as a consequence of a deterioration or improvement in the firm's "financial prospects" or "performances"; rating changes made as a consequence of an increase or decrease in leverage caused by a leveraged buyout, share repurchase, or debt-finance expansion; rating changes made for other reasons or where no reason is given. They document negative cumulative abnormal returns for all three categories at the time of the announcement of a downgrade but only rating changes made as a consequence of deterioration in the firm's financial prospects is statistically significant.

This highlights that market participants tend to react strongly to any information related to the firms' financial prospects. However, they find no market reaction to rating upgrades made as a consequence of changing firm's financial prospect and where no reason is given. Similar results are found in Goh and Ederington (1999) who report significant abnormal returns for rating downgrades due to firm's changing financial prospects but no such evidence is found for rating upgrades.

Historically, numerous statistical models have been developed in attempting to classify and predict ratings and rating changes but many of these models exhibited a relatively high level of classification errors and a low level of predicting power. The following section discusses related researches on rating changes models:

2.2 Rating Changes Statistical Modeling

2.2.1 Multiple Regression Model

Horrigan (1966) is the first paper that estimates and predicts bond ratings and bond rating changes based on the financial ratios of the firms and the characteristics of the bonds using multiple regression analysis. He focuses on bond issues rated by Moody's and Standard & Poor's during the period 1959 - 64. He uses the model estimated on the sample to predict firms who received either a new bond rating or a change in rating over the period 1961 - 64. Numerous financial ratio variables and a 0-1 dummy variable, which represent the subordination status, are tried as independent variables in his study. However, only the independent variables that yield the highest correlation with the bond ratings and are significant at 5 per cent level are included in the model. The variables included in his model were: total asset, working capital to sales, net worth to total debt, sales to net worth, and net operating profit to sales plus the subordination status variable. The estimated regression coefficients of the final model predicts correctly 58 per cent of the Moody's and 52 per cent of the Standard & Poor's new ratings and 54 per cent of the Moody's and 57 per cent of the Standard & Poor's changed ratings.

West (1970) criticizes Horrigan (1996) 's methodology and goes on to suggest that applying the Fisher approach (1959) to predict bond ratings and bond rating changes could provides a better prediction. The rationale behind the use of Fisher's model is that it has performed very well in estimating risk premiums and risk premiums are highly correlated with ratings. The four independent variables from Fisher's study are earning variability, period of solvency, equity to debt ratio and bonds outstanding. When applying the estimated regression coefficients from the 1949 equation to predict the bond ratings in 1953 samples, the model predicts the ratings correctly in about 62 per cent of cases (48 out of 77). Moreover, when applying this equation to predict the 50 outstanding bonds issued in 1961, the model predicts the ratings correctly in 60 per cent of the cases.

Pogue and Soldofsky (1969) examine the variables that are believed to explain industrial, railroad, and public utility bond ratings. In this study they limit bond rating to four rating scales (Aaa, Aa, A and Baa) and five independent variables are included in this study: earning coverage, long-term debt to capitalization, profitability, earning instability and asset size. Pairwise comparisons are used in the analysis: 1, Aaa and Aa bonds, 2, Aa and A bonds, 3, A and Baa bonds, 4, Aaa and Baa bonds. In analyzing the first pair wise, they find the sign of the estimated coefficients of the independent variables to be consistent with their hypotheses with all being statistically significant except the coefficient of the profitability variable. The estimated linear probability function is then used to assign each bond to the higher rating (e.g., Aaa) or the lower rating (e.g., Aa). The classification results indicate that the function discriminates ratings very effectively between the high rating and low rating; particularly when discriminating Aaa - Baa rating samples. Moreover, they also use the estimated function to predict 10 industrial bond ratings selected randomly from the
New York Stock Exchange Bond List and found that 8 out of 10 bonds are correctly predicted.

Kaplan and Urwitz (1979) criticize Horrigan (1966), West (1970) and Pogue and Soldofsky (1969) for assuming that bond ratings represent equal interval on a bond rating scale and do not incorporate the underlying structure in the bond rating process. In their study, they incorporate the structure of the bond rating process by measuring default risk of the bond issues in ordinal ranking. That is, higher rated bonds are less risky than lower rated bonds. As a result, by using ordinal ranking they can avoid measuring bond ratings as equal interval, which is the main assumption under the ordinary less squares (OLS). In this study, Kaplan and Urwitz (1979) use the following independent variables: interest coverage ratio, capitalization (leverage) ratio, profitability ratio, size variable, stability variable, subordination status, systematic accounting risk measure (β^A), unsystematic accounting risk measure (σ^A), market beta (β^M), and the estimated standard error of residuals in the market model used to estimate market beta (σ^M). Moreover, they divide bond ratings into two distinct groups (the outstanding bonds and the new-issue bonds) and examine them separately. The results of the analysis are consistent across the two groups. The subordination variable, size variable, and leverage ratio are highly significant for both groups while the profitability variable is insignificant. For the new-issue bonds, the market beta and the residual standard error are insignificant, whilst for the outstanding bonds, the residual standard error is significant and market beta is insignificant. The systematic and unsystematic accounting risk measure does not provide any information to bond ratings. The estimated model on the new issue bonds sample is used to predict the holdout sample of new issues. The prediction result shows that 69 per cent of the ratings are correctly classified. Moreover, for further model validation, they also use the estimated equation on the total new issue bonds to predict the rating of the outstanding bonds and use the model estimated on the outstanding bonds to predict the holdout sample of the new issue bonds. The model only predicted correctly 43 per cent of the outstanding bonds and 55 per cent of the new issue bonds.

2.2.2 Multiple Discriminant Model

Pinches and Mingo (1973 and 1975) apply a number of different approaches when developing a model for predicting bond ratings. Initially, they conduct factor analysis to account for variations in the data. A total of thirty-five different financial variables are included and the analysis grouped the variables into seven different patterns which appear to represent: size, financial leverage, long term capital intensiveness, return on investment, short term capital intensive, earning stability and debt coverage stability. The results from the multiple discriminant analysis indicate that the provisions of the bond issues and the stability of the firms are the most important variables in determining bond ratings with the financial performance being of less importance. They use the estimated model to classify bond ratings data, which is the same as the data used to develop the model. The model classifies 70 per cent of the bond ratings correctly. When they apply the estimated model to the holdout sample, the model correctly classifies ratings in 64 per cent of the cases examined.

Belkaoui (1980) uses stepwise multiple discriminant analysis similar to Pinches and Mingo (1973 and 1975) to predict Standard & Poor's industrial bond ratings during 1978 but employed different approaches for selecting the explanatory variables. In this study, the author relies on economic rational to identify the factors and corresponding variables to be included in the multiple discriminant analysis model. Firm related, market related and indenture-related factors are used to capture the investment quality of the bond. Firm related variables demonstrate the ability of the firms in providing bondholders protection, market related variables measure the ability of the firms' performance, and indenture related variables are the relevant covenants imposed on the issued bonds. Eight variables are included in the stepwise discriminant analysis and six discriminant functions are identified with only the first three functions being statistically significant. Moreover, the first discriminant function is the most important function, which account for 89 per cent of the total variance explained by model. The model correctly classifies bond ratings in the case of 63 per cent for the experiment group and

66 per cent for the control group. In addition, Belkaoui conducts univariate analysis and stepwise regression to determine the rating order of the eight explanatory variables and finds that subordination status, long-term capital intensiveness, total size of the firm to be the most important variables.

Perry (1985) examines whether there are differences in bond rating models by using bonds that are rated by Moody's and Standard & Poor's in March 1982 and May 1982. He models the two bond rating periods by using multiple discriminant analysis similar to Pinches and Mingo (1973 and 1975) but applies different approaches in selecting the variables. A total of 33 variables which measure liquidity, leverage, activity, profitability and some variability of these measures are used in the multiple discriminant analysis; only the best multiple discriminant analysis models are used to cross-classify agency's ratings.[19] The final model classifies correctly 77 per cent of March 1982 bond ratings and almost 42 per cent of May 1982 bond ratings.

Bhandari et al., (1979) is the only study to model Moody's 1971-1976 utility bond rating revisions. They developed a bond quality rating changes model using multiple discriminant analysis identical to that of Pinches and Mingo (1973, 1975) which included six explanatory variables: interest coverage ratio, slope of the interest coverage ratio, leverage ratio, slope of the leverage ratio, return on asset and slope of the return on asset. They divide the study into two parts: the two-group discriminant analysis (rating upgrades and rating downgrades) and the three-group discriminant analysis (rating upgrades, no-changes and rating downgrades). Also, they divide the total sample

[19] The best models are those that result in the highest Jackknife (Lachenbruch) classification rate.

into two samples: one sub-sample used to estimate the coefficient of the discriminant model and the other sub-sample used to test the model. The results of the two-group discriminant analysis show that the estimated model correctly classifies rating changes in the case of 87 per cent for the original

sample and almost 93 per cent for the test sample. The higher percentage for correct classification for the test sample indicates that the estimated model perform very well in predicting rating changes. The results for the three-group discriminant analysis show the estimated model is less satisfactory than is the case with the two-group analysis. By including the rating no-changes group, the estimated model correctly classifies rating changes: 70 per cent for original sample and 75 per cent for the test sample.

2.2.3 Probit Model

Gentry et al., (1988) use an n-chotomous multivariate probit model with the six financial ratios identified in Pinches and Mingo (1978) and fund flow components to predict industrial bond ratings. They classify bond ratings with three sets of financial information: one based on financial ratios, another based on cash flow information and the third based on combining financial ratios and cash flow information. They use parameters estimated from the 2003 sample to predict the 2004 bond ratings. The results of this study show that, including the cash flow information in the model increases its predictive ability.

Blume et al., (1998) employ an order probit model to analyze how the rating agencies use public information when setting quality rating. In setting up the model, they assign a value of 4 if bond is rated AAA, 3 if AA, 2 if A, and 1 if BBB. Then the standard maximum likelihood technique is used to estimate the parameters in the probit model to determine the most probable rating category. In this study, they use ten financial ratios to analyze the bond creditworthiness. Five ratios measure interest coverage, two ratios measure profitability, and three ratios measure leverage. The model predicts 57 per cent of the four rating categories correctly. Gray et al., (2005) also applied an ordered probit model to examine the relationship between the credit ratings of Australian companies using industry variables and industry concentration variables as the explanatory variables.

Similar to Blume et at., (1998), they only focus on investment grade ratings which are classified into three categories: value 1 if company is rated AAA or AA, 2 if A, and 3 if BBB. The result of the full model correctly assigns credit rating for in excess of 61 per cent of the total sample with the model predicting correctly more than two-third of the A and BBB ratings when using parameters estimated from 1997-2002 to predict ratings for 1995 and using parameters estimated from 1995 and from 1997-2002 to predict rating 1996 and so on. In all cases, they find that the predictive ability exceeds 50 per cent.

3 HYPOTHESES AND CONTRIBUTION OF THE CURRENT STUDY

3.1 Hypotheses

If the Australian market is strong-form efficient, then we would expect no market responses to rating announcements. However if the Australian market is only semi-strong form efficient and the rating agencies have access to private information when assessing ratings, then it is possible that market participants would consider ratings announcements to contain price-relevant information. Therefore, we propose the first part of this thesis to consider the following hypotheses:

1. Stock and bond returns should react negatively (positively) to rating downgrades (upgrades).
2. Stock and bond returns should react negatively (positively) to negative (positive) CreditWatch.
3. Stock returns should have a stronger reaction to unexpected rating changes than expected rating changes.
4. Stock returns should have a greater reaction to the contaminated than non-contaminated rating changes.
5. Stock returns should have a greater reaction to the contaminated than non-contaminated CreditWatch.
6. Stock returns should have a greater reaction when rating changes and CreditWatch are attributable to a perceived change in the firms' financial prospects.

Rating agencies use financial and non-financial information obtained from public and private sources to determine the rating of an issuer. However, statistical bond rating only utilize the historical financial data of the firm to determine the rating, thus in this study we examine several variables that are hypothesized to influence rating agencies decision.

3.2 Contribution of the Current Study

This study refines and enhances previous literatures on the Australian market in several ways. First, we examine a substantially larger sample of Australian domiciled firms whose ratings were re-rated and/or placed on CreditWatch. Second, using daily listed and over-the-counter traded corporate bond yields from the Australian Financial Markets Association (AFMA) allow us to more precisely examine the Australian bond market efficiency. Third, we differentiate between the rating announcement samples that were released concurrently with and without other announcements from sources other than rating agencies. Fourthly, we also examine equity market reactions to rating changes that were previously foreshadowed by CreditWatch, versus rating changes that were not foreshadowed by CreditWatch. We also document the market reactions to those ratings that were re-rated and placed on CreditWatch due to firms' changing (i) financial prospects; (ii) financial structures; (iii) miscellaneous reasons. Previous studies have analyzed and predicted ratings in different rating categories, in his paper we extends the analysis in a number of directions. First, we apply the multiple logistic regression models to Australia data. Second, we are able model the direction of rating announcements based on the Standard & Poor's rating announcements.

4 DATA DESCRIPTION AND METHODOLOGY

4.1 Data Description

The focus in the first study is on tracing the impact on changes in ratings on equity and bond prices. The data used in this study is drawn from five sources: (1) Rating changes and CreditWatch for all Australian domiciled firms are collected from Bloomberg. (2) Historical daily stock return index and All Ordinaries return index data are extracted from DataStream. (3) Daily government and corporate bond yields that are traded in the centralized exchange and over-the-counter are obtained from Australian Financial Markets Association (AFMA). (4) Financial accounting data are collected from ASPECTHUNTLEY. (5) Corporate announcement information is obtained from Dow Jones Factiva.

The collected rating changes and CreditWatch announcements are eliminated if there is insufficient equity return index data. Rating histories announced by Standard & Poor's and Moody's between January 1995 and December 2008 are investigated. Table 4.1 presents the rating announcements on a yearly basis. During our sample period, there were 191 re-ratings with 126 rating downgrades and 65 rating upgrades. In addition, there were 184 ratings being placed on CreditWatch, with 144 being placed on negative CreditWatch and 40 being placed on positive CreditWatch. The majority of the rating downgrades and negative CreditWatch are clustered between 2000 and 2003. Also, instances of rating downgrades issuers being placed on negative CreditWatch occur more frequently than rating upgrades and issuers being placed on positive CreditWatch. Lastly, for those firms whose used both rating agencies to rate their corporate rating, if their ratings were re-rated and/or placed on CreditWatch by one of the rating agencies and subsequently (within two weeks) were re-rated and/or placed on CreditWatch by the other rating agency, we consider as one rating change or one CreditWatch placement and we use the former one as the official announcement date.

Table 4.1: Summary Statistics of Rating Changes and CreditWatch on a Yearly Basis

The table presents the distribution of Standard Poor's and Moody's Rating Changes and CreditWatch between January 1995 and December 2008. This table reports total number of rating changes and CreditWatch and theirs direction by calendar year. Rating upgrades (downgrades) refer to actual rating changes. Positive (Negative) CreditWatch indicate ratings are placed on review for possible downgrades (upgrades).

	Rating Changes			CreditWatch		
Year	Downgrades	Upgrades	Total Rating Changes	Negative	Positive	Total CreditWatch
1995	1	3	4	2	0	2
1996	3	5	8	0	1	1
1997	8	2	10	5	0	5
1998	10	1	11	5	1	6
1999	7	1	8	14	2	16
2000	14	3	17	10	4	14
2001	20	5	25	18	4	22
2002	8	2	10	10	2	12
2003	22	6	28	23	3	26
2004	2	8	10	11	7	18
2005	10	6	16	10	3	13
2006	3	7	10	12	7	19
2007	9	12	21	14	4	18
2008	9	4	13	10	2	12
Total	126	65	191	144	40	184

For the purposes of this analysis, we divided our rating changes and CreditWatch sample into different sub-samples as described in Table 4.2:

- We define rating changes as expected rating changes if they were previously placed on CreditWatch and subsequently changed in the same direction as was indicated when they were placed on CreditWatch; otherwise, they are classified as unexpected rating changes.
- We use the same method as in Hanthausen and Leftwich (1986) to determine contaminated rating changes and CreditWatch. For each observation of the rating changes and CreditWatch, we identify the official announcement date then we use Dow Jones Factiva online newspaper database search for the concurrent disclosures 2-days before

and after the announcement date, where day 0 is the announcement date. If there are any concurrent disclosures during this 5-day window that is believed to contain price sensitive information, the relevance of the information is checked with the information release by the rating agencies. If this information is cross-referenced by sources other than rating agencies, the observations are classified as contaminated rating changes and CreditWatch; otherwise, they are classified as non-contaminated rating changes and CreditWatch.

- Standard & Poor's rates issuers on a scale from AAA to D and may modify them with an additional plus (+) and minus (-), while Moody's rates issuers on a scale from Aaa to C and may modify them by giving additional 1, 2 and 3. Any rating changes modified by plus (+), minus (-), 1, 2 and 3 are classified as within-class rating changes; otherwise, they are classified as cross-class rating changes.
- When rating agencies announce rating changes and issuers being placed on CreditWatch, they usually provide the reasons for the actions. Thus we classified rating changes and CreditWatch placements into three different categories: ratings were changed and/or placed on CreditWatch as the result of firm's changing (i) financial prospects; (ii) financial structure, or; (iii) miscellaneous reasons.[20]

The transition matrix for rating changes by both Standard &Poor's and Moody's is presented in Table 4.3. There are 191 ratings were re-rated between January 1995 and December 2008. The main diagonal reports within-class rating changes (e.g. B to B- or

[20] (i) Changing firm's financial prospects: deterioration or improvement firm's financial performance, (ii) changing firm's financial structures: merger and acquisition, takeover, leverage buyout, debt expansion and share repurchase, (iii) miscellaneous: no reason and other reason.

A to A+) while off diagonal reports cross-class rating changes (e.g. A to BBB or BBB+ to A). Above the main diagonal represents cross-class rating downgrades and below the main diagonal represents cross-class rating upgrades. There are 104 within-class rating changes (54%), 30 cross-class upgrades (16%) and 57 cross-grade downgrades (30%). We observe that the majority of within-class rating changes are in the BBB rating, indicating the reluctance of the rating agencies to move a rating outside of investment grade.

Table 4.2: Summary Statistics of Rating Changes and CreditWatch across Sub-Samples

The table presents the distribution of Standard & Poor's and Moody's Rating Changes and CreditWatch between January 1995 and December 2008. This table reports total number of rating changes and CreditWatch across sub-samples. Rating changes are classified as expected upgrades (downgrades) when the rating changes follow the same direction as they were previously placed on CreditWatch. Rating changes and CreditWatch are classified as contaminated when there is concurrent announcement made by sources other than rating agencies 2-days before and after the announcement date. Rating changes are classified as cross-class rating changes when the ratings move across the rating classes (e.g. A to BBB or BBB+ to A) and within-class rating changes when the ratings changes move within the rating classes (e.g. A- to A+ or B+ to B-). Rating changes and CreditWatch are classified into three different categories: firm's changing (i) financial prospects; (ii) financial structures; (iii) miscellaneous reasons.

Rating Changes			
Sub-Samples	Downgrades	Upgrades	Total Rating Change
Rating Changes	126	65	191
Expected	52	14	66
Unexpected	74	51	125
Contaminated	36	16	52
Non-Contaminated	90	49	139
Cross-Class	57	30	87
Within-Class	63	41	104
Financial Prospects	55	31	86
Financial Structures	45	21	66
Miscellaneous	26	13	39

CreditWatch			
Sub-Samples	Negative	Positive	Total CreditWatch
CreditWatch	144	40	184
Contaminated	49	10	59
Non-Contaminated	95	30	125
Financial Prospects	35	5	40
Financial Structures	87	25	112
Miscellaneous	22	10	32

Table 4.3: Transition Matrix of Rating Changes

The table presents transition matrix of Standard & Poor's and Moody's cross-class and within-class rating changes between January 1995 and December 2008. The main diagonal reports within-class rating changes and the off diagonal reports cross-class rating changes. Above the main diagonal represents cross-class rating downgrades and below the main diagonal represents cross-class rating upgrades.

	Revised Rating										
Previous Rating	AAA	AA	A	BBB	BB	B	CCC	CC	C	D	Total
AAA		2									2
AA		9	8								17
A		8	29	23							60
BBB			8	50	11	1					70
BB				9	10	4					23
B					3	6	3				12
CCC						2		3			5
CC										2	2
C											
D											
Total	0	19	45	82	24	13	3	3	0	2	191

Previous studies on the impact of rating changes on bond markets are subject to a number of data constraints. First, not many listed firms issue bonds. Second, the corporate bond market is not as liquid as the equity market so it is very difficult to get accurate daily bond data. Third, most of the bonds are traded over-the-counter. Fourth, Australian bond market quotes bonds in yield. However, we are able to overcome these problems by having access to daily government and corporate bond yields that are traded in the centralized exchange and over-the-counter provided by the Australian Financial Markets Association (AFMA) covering the period between January 2005 and December 2008. A number of the sample firms have multiple bond issues but for simplicity and to avoid data elimination, we treat each bond as a separate observation.[21] Our sample consists of firms who were re-rated and/or placed on CreditWatch by Standard & Poor's and Moody's, regardless of whether they are listed on the ASX, as their bond yields can be obtained from AFMA. Our final sample consisted of 17 rating

[21] Bessembinder et al., (2009) when measuring abnormal bond performance, they use three approaches to deal with firms with multiple bonds issue: (i) bond level approach treats each bond as a separate observation; (ii) representative bond approach selects a representative bond; (iii) firm level approach treat the firms as a portfolio.

downgrades, 92 rating upgrades, 49 being placed on positive CreditWatch and 53 on negative CreditWatch. Since the number of observations in our bond sample is relatively small and almost half of the sample firms are not listed on ASX, we do not divide the sample into sub-samples as previously described for the sample we use to examine the equity market.

4.2 Methodology

We conduct our first study by using classical event study methodology (Brown and Warner 1985). We define t = 0 as the announcement date and selected three event windows as follows: $[t_1, t_2]$ = [-20, -2], [-1, +1] and [2, 10] where [-20, -2] is the pre-announcement window, [-1, +1] is the announcement window and [2, 10] is the post-announcement window. We then estimate the equity excess returns using both match-counterpart-adjusted return and market-adjusted return[22] to analyze the effect of rating announcements on the equity market and estimate the bond abnormal returns using mean-adjusted model[23] to analyze the effect of rating announcements on the bond market.

Match-counterpart-adjusted return model

We match each firm that was re-rated and/or placed on CreditWatch with the firm in the same industry of closest size that was not re-rated and/or on CreditWatch. We first match sample firms with all firms in the same industry using DataStream level6 industry reclassification and then we select the one with the closest market capitalization. Daily excess returns using the match-counterpart-adjusted return model is defined as

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[22] See Brown and Warner (1985) for a detail and discussion of the market-adjusted return model.
[23] See Bessembinder (2009) for a detail and discussion of the mean-adjusted return model.

$$CER_{i,t} = R_{i,t} - R_{c,t} \tag{4.1}$$

Where $CER_{i,t}$ is the daily excess returns for firm i at day t using match-counterpart-adjusted return model, $R_{i,t}$ is the daily returns for firm i at day t and $R_{c,t}$ is the daily returns for the match firm c at day t.

Market-adjusted return model

We use the All Ordinaries return index as a proxy of market return. The daily excess returns using the market-adjusted return model is defined as

$$MER_{i,t} = R_{i,t} - R_{m,t} \tag{4.2}$$

Where $MER_{i,t}$ is the daily excess returns for firm i at day t using market-adjusted return model, $R_{i,t}$ is the daily returns for firm i at day t and $R_{m,t}$ is the daily market returns at day t.

Mean-adjusted return model

Since bonds in the Australian market are quoted in terms of their yield, we use the Reserve Bank bond-pricing formula to convert daily bond yields into daily bond prices and adjust for accrued interest to obtain daily bond returns. We match corporate bonds with government bonds with similar maturities and then determine the excess bond returns by subtracting the government bond returns from the corporate bond returns. The daily excess bond returns using mean-adjusted return model is defined as

$$BER_{i,t} = BR_{i,t} - BR_{g,t} \tag{4.3}$$

Where $BER_{i,t}$ is the daily bond excess returns for corporate i at day t using mean-adjusted return model and $BR_{i,t}$ is the daily bond returns for corporate i at day t and

$BR_{g,t}$ is the daily government bond returns at day t.

The procedure to determine cumulative excess returns, cumulative average excess returns and t-statistic is the same for the match-counterpart-adjusted return, market-adjusted return and mean-adjusted return procedures, thus only the procedure for the match-counterpart-adjusted return procedure is presented. Cumulative excess returns over day t_1 to day t_2 is defined as

$$CCER_i[t_1,t_2] = \sum_{t=t_1}^{t_2} CER_{i,t} \tag{4.4}$$

Cumulative average excess returns is fined as

$$CACER[t_1,t_2] = \frac{1}{N}\sum_{i=1}^{N} CCER_i[t_1,t_2] \tag{4.5}$$

Under the null hypothesis that the cumulative average excess returns are equal to zero and are assumed to be normally distributed with zero mean. The conventional t-statistic is defined as

$$t_{CACER}[t_1,t_2] = \frac{CACER[t_1,t_2]}{\sigma_{CCER_i[t_1,t_2]} / \sqrt{N}} \tag{4.6}$$

Where $\sigma_{CCER_i[t_1,t_2]}$ is the cross-sectional sample standard deviation of cumulative average excess returns and N is the number of observations in the sample.

5 EMPIRICAL RESULTS

5.1 Information Content of Rating Changes

The empirical results of the information content of rating announcements are now presented. First, we provide a summary of the overall results on the rating announcements. Second, we provide a detailed discussion on the equity returns surrounding the rating announcements and various sub-samples. Then we provide evidences on equity market reaction to rating announcements instigated for differing reasons. Third, we provide results on the bond returns surrounding the rating announcements. In doing so, this allows us to compare our results with that of previous studies on market reaction to rating announcements in the U.S. Last, we provide results of cross-sectional variation on equity excess returns.

5.1.1 Summary of the Results

(i) The announcement of rating downgrades and being placed on negative CreditWatch are associated with significant negative equity excess returns over the announcement window. In addition, the impact of both of these announcements is greater during the pre-announcement window than it is during the announcement window.

(ii) Announcements of rating upgrades do not have any impact on equity excess returns over the event window.

(iii) The announcement of being placed on positive CreditWatch is associated with significant positive equity excess returns during the announcement window.

(iv) The announcement of being placed on negative CreditWatch is associated with significant negative bond excess returns, but the announcement of rating downgrades has no impact on bond excess returns. Unlike the equity market, we document some bond market reaction to rating upgrades.

5.1.2 Equity Market

5.1.2.1 Rating Changes

In Table 5.1 we report the cumulative average excess returns using match-counterpart-adjusted return model (CACER) and cumulative average excess returns using market-adjusted return model (CAMER) and their t-statistics for the three event windows where the analysis is conducted separately for rating upgrades and downgrades.

The main finding of Table 5.1 is that there are statistically significant excess returns for rating downgrades during the announcement window. The CACER and CAMER during the announcement window are -1.31% and -1.60% respectively. Also, we find that excess returns during the pre-announcement window to rating downgrades are greater than those found during the announcement window reporting CACER and CAMER of -4.11% and -4.45% respectively. The values for CACER (0.13%) and CAMER (0.09%) during the post-announcement window are basically flat. The result indicates that all of the negative market reaction to rating downgrades occurred either prior to, or at the time of, the announcement. In contrast to this finding for rating downgrades, we find no evidence of any market reaction to rating upgrades over the entire event windows.

The results for the entire sample of rating changes indicate that there is significant information contained in rating downgrades although something like 75 per cent of the information is anticipated by the market, whereas the market effectively finds no information in the rating upgrade announcements. Our results are consistent with Goh and Ederington (1999) and Boot et al., (2006). Goh and Ederington (1999) find statistically significant abnormal returns associated with rating downgrades during the 2-days announcement period (reporting a CAR of -1.21%) and an absence of significant excess returns associated with rating upgrades. They also find that abnormal returns during the pre-announcement period are significantly higher than those found during the announcement period. On the other hand, Boot et al, (2006) show that stock price react negatively to rating downgrades and no such result are found in rating upgrades. A possible explanation for the finding that markets only respond to the rating downgrades and ignore the rating upgrades is that the management teams have an incentive to release good news to, and hide bad news from, market participants that relates to firms' financial prospects and financial structures. Thus, rating downgrades are likely to reflect more in the way of new information than is the case with rating upgrades and so have a larger impact on excess returns.

The effect of rating changes on the market may vary depending on whether the firm has previously being placed on CreditWatch as this will affect the extent to which the subsequent rating change might be expected. As shown in Table 5.1 the results of expected rating downgrades are similar to our previous finding for the total sample of rating downgrades. We find statistically significant excess returns to expected rating downgrades during the announcement window and the market reacting to expected rating downgrades during the pre-announcement window is greater than during the announcement window. No such evidence is found during the announcement window for unexpected rating downgrades but there is some evidence of an adjustment in equity markets during the pre-announcement window. Moreover, we find no market reaction to rating upgrades despite splitting our entire sample into expected and unexpected rating upgrades. Our findings are somewhat surprising but consistent with those of Choy et al., (2006), Boot et al., (2006), Pruda (2007) and Chan et al., (2011). However, they contrast with those of Hand et al., (1992) and Purda (2007) who find that excess stock returns are negatively associated with unexpected rating downgrades and statistically significant but not with expected rating downgrades.

In order to investigate the impact of our findings for the market response to rating change announcements being contaminated by other price sensitive information becoming public around the same time, we control our rating changes sample by classifying them as being contaminated if there is any related price sensitive announcements released within 2-days before and after the day of the ratings change announcement. Table 5.1 presents results that provide insights into the markets response to the contaminated and non-contaminated rating changes. As expected, contaminated rating downgrades are associated with higher negative excess returns than non-contaminated rating downgrades. The CACER and CAMER associated with contaminated rating downgrades are -2.86% and -3.05% respectively during the announcement window and both are statistically significant. For non-contaminated rating downgrades the results show CACER (-0.70%) and CAMER (-1.00%) as being much smaller and less significant than is the case for the contaminated sub-sample. We find no market reaction to rating downgrades during the post-announcement window but significant market reaction in the pre-announcement window for both contaminated and non-contaminated sample. There is no evidence of market reaction to rating upgrades for either the contaminated or non-contaminated sample, other than a small positive but still significant market reaction to the contaminated rating upgrades when using the market-adjusted return model. This significant result may be due to the market reaction to information stemming from sources other than the rating agencies' rating upgrades. Our results are consistent with Holthausen and Leftwich (1986) but contrast with those of Choy et al., (2000) who find no evidence of a market reaction to both contaminated and non-contaminated rating upgrades while in the case of contaminated ratings downgrades they find that most of the reaction occurs during the pre-announcement window. Table 5.1 contrasts the excess returns associated with rating changes across classes as compared to within-class rating changes. We find no evidence of excess returns for either sub-samples during the announcement window in the case of rating upgrades but some significant positive excess returns in the case of cross-class rating upgrades during the pre-announcement window. Turning to rating downgrades, both sub-samples experience significant negative excess returns during the announcement window. Cross-class rating downgrades report CACER and CAMER of –1.55% and -2.31% respectively (both significant) with the equivalent figures for within-class rating downgrades being -1.01% and -1.07% (with only the latter being significant). As expected, firms who experience cross-class rating downgrades show stronger market reaction than those that experience within-class rating downgrades. Our results for cross-class and within-class rating changes are consistent with Holthausen and Leftwich (1986) and Hite et al., (1997) who found higher negative abnormal performance associated with cross-class rating downgrades compare to those associated with within-class rating downgrades.

5.1.2.2 CreditWatch

Table 5.2 presents the excess returns of firms' experience with CreditWatch for various sub-periods and sub-samples. Table 5.2 reports that the excess returns at the time of announcements of negative CreditWatch are -0.95% with CAMER which is significant at the 10% level while the excess returns are slightly smaller and not significant with CACER. Similar to the results from rating changes, we find that market reaction to negative CreditWatch is higher during the pre-announcement window than over the announcement window. In the case of positive CreditWatch announcements we find significant positive excess returns with CACER and CAMER of 2.02% and 1.33% respectively during the announcement window.

Table 5.2 reports the result for CreditWatch when it is divided into contaminated and non-contaminated sub-samples. The evidence indicates that the market reacts significantly to negative CreditWatch for both contaminated and non-contaminated sub-samples during the pre-announcement window, reporting CACER (-3.53%) and CAMER (-3.04%) for contaminated sample and CACER (-3.39%) and CAMER (-2.23%) for non-contaminated samples. Consistent with our previous findings for credit rating changes, the market has a stronger reaction to the contaminated negative CreditWatch than non-contaminated negative CreditWatch. The results are insignificant for both contaminated and non-contaminated which is at variance with that of Holthausen and Leftwich (1986) who find that contaminated and non-contaminated negative CreditWatch have a significant negative impact that is of similar magnitude.

Table 5.1: Excess Equity Returns for Rating Changes

The table presents cumulative average excess returns using match-counterpart-adjusted return model (CACER) and market-adjusted return model (CAMER) and their t-statistics (t-stat.) of all sample and sub-samples rating changes over the three event widows [-20, -2], [-1, 1] and [2, 10] where day 0 is the announcement date. Table reports the results of various sub-samples rating changes including all rating changes, expected vs. unexpected rating changes, contaminated vs. non-contaminated rating changes, cross-class vs. within class rating changes. t-statistics are presented to test of whether the CACER and CAMER for the three event windows [-20, -2], [-1, 1] and [2, 10] is different from zero. *, **, and *** indicates significance at the 5%, 1%, and 0.1%.

		Match-Counterparts Adjusted Returns				Market-adjusted Returns			
		Upgrades		Downgrades		Upgrades		Downgrades	
Sample	Window	CACER	t-stat.	CACER	t-stat.	CAMER	t-stat.	CAMER	t-stat.
All	[-20,-2]	-0.27%	-0.28	-4.11%	-3.45 ***	0.51%	0.60	-4.45%	-4.25 ***
	[-1,+1]	0.08%	0.18	-1.31%	-2.71 **	0.27%	0.72	-1.60%	-4.06 ***
	[+2,+10]	0.21%	0.35	0.13%	0.15	0.03%	0.08	0.09%	0.14
Expected	[-20,-2]	-1.03%	-0.54	-6.98%	-2.90 **	0.66%	0.64	-5.95%	-3.50 ***
	[-1,+1]	0.10%	0.18	-2.14%	-2.29 *	-0.07%	-0.14	-2.64%	-3.55 ***
	[+2,+10]	0.54%	0.67	0.00%	0.00	0.30%	0.65	-0.04%	-0.03
Unexpected	[-20,-2]	-0.18%	-0.14	-2.52%	-1.94 *	0.15%	0.16	-2.98%	-2.42 **
	[-1,+1]	0.00%	0.00	-0.64%	-1.19	0.33%	0.78	-0.83%	-2.24
	[+2,+10]	-0.16%	-0.21	0.00%	0.00	-0.08%	-0.18	0.25%	0.34
Contaminated	[-20,-2]	-1.25%	-1.31	-4.97%	-2.22 *	1.06%	1.00	-4.65%	-2.63 **
	[-1,+1]	0.53%	0.89	-2.86%	-2.62 **	1.20%	2.00 *	-3.05%	-2.99 **
	[+2,+10]	0.66%	0.87	2.24%	1.44	-0.73%	-0.98	2.07%	1.68
Non-Contaminated	[-20,-2]	0.05%	0.04	-3.84%	-2.70 **	0.32%	0.30	-4.37%	-3.38 ***
	[-1,+1]	-0.07%	-0.14	-0.70%	-1.39	-0.03%	-0.07	-1.00%	-2.84 **
	[+2,+10]	0.06%	0.08	-0.68%	-0.65	0.28%	0.62	-0.73%	-0.89
Cross-Class	[-20,-2]	0.10%	0.09	-6.43%	-3.46 ***	1.36%	1.79 *	-6.08%	-3.52 ***
	[-1,+1]	-0.37%	-0.59	-1.55%	-2.10 *	-0.14%	-0.23	-2.31%	-3.64 ***
	[+2,+10]	0.89%	0.95	1.68%	1.07	0.62%	1.02	2.00%	1.65

Within-Class	[-20,-2]	-0.73%	-0.55	-2.05%	-1.39	-0.65%	-0.56	-2.64%	-2.09 *
	[-1,+1]	0.33%	0.72	-1.01%	-1.61	0.46%	1.21	-1.07%	-2.23 *
	[+2,+10]	-0.85%	-1.31	-1.22%	-1.46	-0.25%	-0.59	-1.30%	-1.87 *

Table 5.2: Excess Equity Returns for CreditWatch

The table presents cumulative average excess equity returns of match-counterparts adjusted returns (CACER) and market-adjusted returns (CAMER) and their t-statistic (t-stat.) of all sample and sub-samples CreditWatch over the three event widows [-20, -2], [-1, 1] and [2, 10] where day 0 is the announcement date. Table reports the results of various sub-samples CreditWatch including all CreditWatch and contaminated vs. non-contaminated CreditWatch. t-statistics are presented to test of whether the CACER and CAMER for the three event windows [-20, -2], [-1, 1] and [2, 10] is different from zero. *, **, and *** indicates significance at the 5%, 1%, and 0.1%.

		Match-Counterparts Adjusted Returns				Market-adjusted Returns			
		Positive		Negative		Positive		Negative	
Sample	Window	CACER	t-stat.	CACER	t-stat.	CAMER	t-stat.	CAMER	t-stat.
All	[-20,-2]	1.70%	1.73	-3.37%	-3.59 ***	2.29%	3.32 **	-2.51%	-3.06 **
	[-1,+1]	2.02%	2.44 **	-0.85%	-1.41	1.33%	1.87 *	-0.95%	-1.98 *
	[+2,+10]	0.34%	0.44	-1.71%	-2.58 **	-0.40%	-0.77	-0.91%	-1.56
Contaminated	[-20,-2]	1.27%	0.69	-3.53%	-2.11 *	1.66%	0.76	-3.04%	-2.18 *
	[-1,+1]	0.78%	0.73	-1.35%	-1.36	0.86%	1.08	-1.14%	-1.41
	[+2,+10]	2.02%	1.16	-1.21%	-1.20	1.10%	0.96	0.17%	0.17
Non-Contaminated	[-20,-2]	1.82%	1.55	-3.39%	-2.96 **	2.46%	3.79 ***	-2.23%	-2.19 *
	[-1,+1]	2.35%	2.29 *	-0.79%	-1.05	1.46%	1.62	-0.85%	-1.42
	[+2,+10]	-0.11%	-0.13	-1.95%	-2.24 *	-0.80%	-1.39	-1.48%	-2.06 *

5.1.2.3 Rating Changes and CreditWatch by Reasons

Table 5.3 Panel A and Panel B presents excess returns where the rating changes and CreditWatch samples are broken up into sub-samples on the basis of the reason for the credit rating changes or the placement on CreditWatch. In all three sub-samples based on the reason given: (i) changes in the firm's financial prospects, (ii) changes in the firm's financial structures, and (iii) miscellaneous reasons. The result in the miscellaneous group may not be reliable due to the small number of observations as is also the case for some of the rating upgrades and positive CreditWatch group that face the same constraint.[24] We find that there is a significant negative market reaction over each of the three announcement windows to rating downgrades where they are due to the firms' changing financial structures. For example, we report CACER and CAMER of -2.45% and -1.83% respectively during the announcement window. Using the market-adjusted return model we find some evidences of a market reaction to rating downgrades as a result of a firms' changing financial prospects but no such evidence is found when using the match-counterpart-adjusted return model. Consistent with previous results, there is no evidence of any market reactions to rating upgrades during the announcement window under any of the three different reasons for undertaking the rating change.

For the CreditWatch, we find that the market only reacts to negative CreditWatch during the announcement window when it is attributed to deterioration in the firms' financial structure. There is no evidence of the market reacting to being placed on negative CreditWatch in the changing financial prospects and miscellaneous reasons sub-samples. Somewhat unexpectedly we find some market reactions to positive

[24] The miscellaneous sub-sample for rating downgrades and upgrades are 26 and 13 observations, and for negative and positive CreditWatch are 22 and 10 observations. The financial prospects sub-sample for positive CreditWatch are 5 observations and for financial structures are 25 observations.

CreditWatch motivated by a perceived improvement in the firm's financial prospects with a reported CACER and CAMER of 2.81% and 1.98% respectively.

Table 5.3: Excess Equity Returns for Rating Changes and CreditWatch by Reasons

The table presents cumulative average excess equity returns of match-counterpart-adjusted return model (CACER) and market-adjusted return model (CAMER) and their t-statistic (t-stat.) of rating changes and CreditWatch classified by reasons over the three event widows [-20, -2], [-1, 1] and [2, 10] where day 0 is the announcement date. Table 5.3 Panel A. reports the results of rating changes due to firm's changing (i) financial prospects, (ii) financial structures; and (iii) miscellaneous reasons. Table 5.3 Panel B. reports the results of CreditWatch due to firm's changing (i) financial prospects, (ii) financial structures, and (iii) miscellaneous reasons. t-statistics are presented to test of whether the CACER and CAMER for the three event windows [-20, -2], [-1, 1] and [2, 10] is different from zero. *, **, and *** indicates significance at the 5%, 1%, and 0.1%

Panel A: Rating Changes

	Match-Counterparts Adjusted Returns											
	Upgrades						Downgrades					
	Financial prospects		Financial Structures		Miscellaneous		Financial prospects		Financial Structures		Miscellaneous	
Window	CACER	t-stat.	CACER	t-stat.	CACER	t-stat.	CACER	t-stat.	CACER	t-stat.	CACER	t-stat.
[-20,-2]	-1.38%	-1.39	0.60%	0.32	-0.54%	-0.97	-1.71%	-1.09	-4.62%	-2.36 *	-7.32%	-2.48 **
[-1,+1]	-0.20%	-0.16	-1.36%	-1.75	-1.43%	-1.00	0.36%	0.67	-2.45%	-3.61 ***	-1.34%	-1.05
[+2,+10]	1.63%	1.69	-0.82%	-0.82	0.35%	0.50	1.54%	1.25	-1.89%	-1.85 *	2.21%	0.76

	Market-adjusted Returns											
	Upgrades						Downgrades					
	Financial prospects		Financial Structures		Miscellaneous		Financial prospects		Financial Structures		Miscellaneous	
Window	CAMER	t-stat.	CAMER	t-stat.	CAMER	t-stat.	CAMER	t-stat.	CAMER	t-stat.	CAMER	t-stat.
[-20,-2]	-0.59%	-0.66	1.07%	0.66	0.91%	0.91	-2.50%	-1.77	-4.31%	-2.6 **	-8.00%	-2.93 **
[-1,+1]	-0.19%	-0.26	0.62%	1.09	0.18%	0.32	-1.33%	-2.03 *	-1.83%	-3.25 ***	-1.57%	-1.57
[+2,+10]	0.17%	0.26	0.03%	0.05	-0.19%	-0.32	1.95%	1.90 *	-1.57%	-2.05 *	0.48%	0.21

Table 4.3–*Continued*

Panel B: CreditWatch

	Match-Counterparts Adjusted Returns																	
	Positive									Negative								
	Financial prospects			Financial Structures			Miscellaneous			Financial prospects			Financial Structures			Miscellaneous		
Window	CACER	t-stat.		CACER	t-stat.		CACER	t-stat.		CACER	t-stat.		CACER	t-stat.		CACER	t-stat.	
[-20,-2]	0.57%	0.48		3.74%	1.13		3.27%	1.64		-1.00%	-1.22		-6.46%	-2.49	**	-7.93%	-2.78	**
[-1,+1]	2.81%	2.21	*	2.34%	1.56		0.05%	0.08		-0.34%	-0.61		-4.15%	-3.22	**	-1.31%	-0.80	
[+2,+10]	-0.02%	-0.02		-0.86%	-0.48		1.76%	1.70		-1.05%	-1.70		-1.82%	-1.38		-4.00%	-1.35	

	Market-adjusted Returns																	
	Positive									Negative								
	Financial prospects			Financial Structures			Miscellaneous			Financial prospects			Financial Structures			Miscellaneous		
Window	CAMER	t-stat.		CAMER	t-stat.		CAMER	t-stat.		CAMER	t-stat.		CAMER	t-stat.		CAMER	t-stat.	
[-20,-2]	1.76%	1.86	*	4.80%	2.65	**	2.25%	2.06	*	-0.80%	-1.17		-4.11%	-2.00	*	-6.31%	-2.06	*
[-1,+1]	1.98%	1.89	*	1.28%	0.78		-0.14%	-0.18		0.51%	0.93		-3.89%	-3.64	***	-1.72%	-1.42	
[+2,+10]	-1.32%	-1.98	*	1.55%	1.37		0.75%	0.82		-0.64%	-1.27		-1.13%	-0.99		-1.55%	-0.57	

5.1.3 Bond Market

Table 5.4 Panel A and B presents excess bond returns associated with firms whose rating were re-rated and/or placed on CreditWatch.[25] Table 5.4 Panel A. reports the bond market reaction to rating changes. In contrast to the equity results, we find that the bond market reacts significantly to rating upgrades, reporting CABER of 0.04%, and that this upward adjustment continues for at least two weeks after the announcement. There is no significant market reaction to rating downgrades at the time of the announcement. However, there is evidence of the anticipation of downgrades as significant negative returns are realised during the pre-announcement window. Our results for bond market are inconsistent with Holthausen and Leftwicht (1986) and Hand et al., (1992) who find significant negative bond market reaction to rating downgrades at the time of the announcement. Table 5.4 Panel B. reports the bond market reaction to firms being placed on CreditWatch. Consistent with the equity market, we find bond markets react to both positive and negative CreditWatch, reporting CABER of 0.02% for positive CreditWatch and CABER of -0.02% for negative CreditWatch during the announcement period. Similar to the situation identified for bond rating upgrades, there is evidence that the bond market continues to positively react to a company being placed on positive CreditWatch for several days after the announcement.

[25] The small availability of data meant that we could not examine the various sub-samples as we did when investigating the equity market's response to the same events.

Table 5.4: Excess Bond Returns for Rating Changes and CreditWatch

The table presents cumulative average excess bond returns using mean-adjusted return model (CABER) and the t-statistics (t-stat.) of rating changes and CreditWatch over the three event widows [-20, -2], [-1, 1] and [2, 10] where day 0 is the announcement date. Table 5.4 Panel A. reports the results of rating changes sample. Table 5.4 Panel B. reports the results of CreditWatch sample. t-statistics are presented to test of whether CABER for the three event windows [-20, -2], [-1, 1] and [2, 10] is different from zero. *, **, and *** indicates significance at the 5%, 1%, and 0.1%

Panel A: Rating Changes

	Mean-Adjusted Returns - Bond Prices					
	Upgrades			Downgrades		
Window	CABER	t-stat.		CABER	t-stat.	
[-20,-2]	0.04%	1.01		-0.10%	-2.39	**
[-1,+1]	0.04%	4.97	***	-0.02%	-1.38	
[+2,+10]	0.05%	3.92	***	-0.08%	-0.99	

Panel B: CreditWatch

	Mean-Adjusted Returns - Bond Prices					
	Positive			Negative		
Window	CABER	t-stat.		CABER	t-stat.	
[-20,-2]	0.02%	0.57		0.06%	1.12	
[-1,+1]	0.02%	1.92	*	-0.02%	-2.13	*
[+2,+10]	0.11%	4.26	***	-0.07%	-1.42	

5.1.4 Cross-Sectional Variation on Equity Excess Returns

Cross-sectional regressions are conducted to analyze market reaction to rating changes using several firms' characteristic and rating changes variables. The following regression is estimated separately for rating downgrades and upgrades:

$CAMER_i = \beta_0 + \beta_1 \#GRADES_i + \beta_2 INVGRADE_i + \beta_3 SIZE_i + \beta_4 REG_i + \beta_5 MTB_i + \beta_6 D/E_i + \varepsilon_i$

where:

$CAMER_i$	=	dependent variable measured as equity excess returns for observation i over the period of day -1 to day +1;
$\#GRADES_i$	=	number of grades of the rating changes equal to previous rating less current rating, where ratings are measured from 1(D) to 28(AAA).
$INVGRADE_i$	=	dummy variable: takes value of one if the rating moves out of (move into) investment grade status for rating downgrades (upgrades), zero otherwise;
$SIZE_i$	=	log book value of total asset;
REG_i	=	dummy variable: takes value of one if firms whose ratings were re-rated are operated in the highly regulated industry (utilities and financial), zero otherwise;
MTB_i	=	market to book value ratio;
D/E_i	=	debt to equity ratio;

The dependent variable CAMER is the 3-days announcement period cumulative average excess returns. The variable #GRADES is negative (positive) for downgrades (upgrades). Since rating downgrades (upgrades) are associated with negative (positive) excess returns, the predicted sign for #GRADES's coefficient should be negative (positive) for downgrades (upgrades). Ratings upgrades (downgrades) into (out of) investment grades are associated with higher excess returns, thus we expect the coefficient of INVGRADE to be negative (positive) for rating downgrades (upgrades). Large and highly regulated firms generally make additional information available to the market as part of their regulation process. Hence, rating changes for these firms provide relatively less information implying a lower magnitude of excess returns. Given that the coefficients of the variable SIZE and REG are expected to be positive (negative) for rating downgrades (upgrades). Chen and Zhao (2006) examine the relationship between market-to-book ratios and leverage ratios find that firms with higher market-to-book value ratios issue more debt than equity therefore they are more likely to have higher leverage ratios. Given this hypothesis, we expect the coefficients of the variable MTB and D/E to be negatively (positively) associated with rating downgrades (upgrades).

The results of the regression for rating downgrades and upgrades are reported separately in Table 5.5 Panel A and B. Table 5.5 Panel A. reports the Adjusted R-Squared= 20.11% and F-Statistic = 4.6499 (statistically significant at 5% level) which implies that the rating downgrades regression has good explanatory power.[26] As predicted, the coefficients of rating changes variable INVGRADE and firms' characteristic variable MTB and D/E are negative and statistically significant. The results indicate a higher negative magnitude of excess returns when the firms' experience a rating downgrade out of investment grade, a higher market-to-book value and leverage ratio. The coefficients of the variable #GRADES, SIZE and REG are not statistically significant but the sign of coefficients SIZE and REG are consistent with the predicted sign.

[26] For rating downgrades the critical value of F-Statistic significant at 5% and 10% is 2.09 and 1.77.

The explanatory power of the regression for rating upgrades is lower but statistically significant. Table 5.5 Panel B. reports the Adjusted R-Squared is 16.23% and F-Statistic 2.6794 (statistically significant at 5% level).[27] The coefficient of rating changes variable INVGRADE is not significant but the coefficient of #GRADES is positive and statistically significant. For the firms' characteristic variables, the coefficients of the variable REG and D/E are statistically significant and consistent with the predicted sign. This highlights that rating changes have a greater market impact when they relate to highly geared firms in a relatively unregulated industry. Neither the coefficients of the variable SIZE and MTB are significant nor do they have the predicted sign.

[27] For rating upgrades the critical value of F-Statistic significant at 5% and 10% is 2.17 and 1.82.

Table 5.5: Cross-Sectional Regression on Equity Excess Returns

Cross-sectional regression examines the announcements effect of rating downgrades and upgrades. Sample of 126 rating downgrades and 65 rating upgrades are obtained from Standard and Poor's and Moody's corporate credit rating for the period between January 1995 and December 2008. The dependent variable CAMER measures as the 3-days announcement period excess returns. Variable #GRADES, INVGRADES, SIZE, REG, MTB, and D/E are used to explain CAMER. Table 5.5 Panel A and Panel B presents the regression results for rating downgrades and upgrades sample separately with their test statistics.

Panel A: Rating Downgrades

	Independent Variable							F-Statistic	Prob.(F-Statistic)	Adj. R-Squared (%)	Number of Observations
	CONSTANT	#GRADES	INVGRADE	SIZE	REG	MTB	D/E				
Predicted Sign	?	(-)	(-)	(+)	(+)	(-)	(-)				
Coefficient	-0.0180	0.0056	**-0.0372**	0.0006	0.0043	**-0.0009**	**-0.0004**	4.6499	0.0004	20.11%	126
Std. Error	0.0771	0.0044	0.0157	0.0081	0.0119	0.0005	0.0002				
T-Statistic	-0.2334	1.2662	**-2.3687**	0.0728	0.3603	**-2.0448**	**-2.0345**				
Prob.	0.8160	0.2091	0.0202	0.9421	0.7196	0.0441	0.0452				

Panel B: Rating Upgrades

	Independent Variable							F-Statistic	Prob (F-Statistic)	Adj. R-Squared (%)	Number of Observations
	CONSTANT	#GRADES	INVGRADE	SIZE	REG	MTB	D/E				
Predicted Sign	?	(+)	(+)	(-)	(-)	(+)	(+)				
Coefficient	0.0121	**0.0282**	0.0068	0.0033	**-0.0263**	-0.0028	**0.0015**	2.6794	0.0258	16.23%	65
Std. Error	0.0364	0.0094	0.0169	0.0036	0.0104	0.0015	0.0006				
T-Statistic	0.3329	**3.0155**	0.4012	0.9132	**-2.5285**	-1.8810	**2.7318**				
Prob.	0.7407	0.0042	0.6901	0.3659	0.0149	0.0663	0.0089				

6 STATISTICAL MODEL OF RATING CHANGES

6.1 Introduction

Rating agencies generally are influenced when assigning corporate ratings by the firm's financial prospect, economic conditions, and some market variables. Rating assigned by rating agencies plays a very important role in the financing and investment decision; it defines the liquidity position of a firm and the ability of the business to obtain additional funds. Industry participants typically admit that rating is determined by publicly available information of the firm's operation and financial condition such as leverage, interest rate coverage, and profitability of the firms. However, these participants also emphasize the importance of the rater's "judgment" in the assessment of the firm's ability to meet its financial obligation (Pogue and Soldofsky, 1969). The purpose of this study is to develop and test a model for predicting Standard & Poor's rating changes in Australia financial market. The idea is to capture what are the determinants of rating changes. Early statistical models that predicted rating changes often used multiple regression, multiple discriminant model, and/or order probit model in combination with different accounting and financial variables. In this study, we use a multiple logistic regression model with three general types of variables, accounting and finance and economic variables, in attempting to develop and predict rating changes. Moreover, we attempt to gauge the model's prediction by comparing the predicted ratings changes with those made by the rating agencies.

6.2 Organization of the Analysis

Sample

The sample that we use in our analysis is based on Australian domiciled firms who had rated debt securities outstanding during the period 1995 to 2008. From this initial sample we discarded firms that operate in the financial service industry and also firms that are not listed in the stock market. Our final samples consisted of 32 rating upgrades, 85 rating downgrades and 438 rating no changes. Table 6.1 show that rating changes for our sample firms announced by Standard & Poor's in the

period between 1995 and 2008.

Dependent variable

The dependent variable used in the analysis is discrete and takes on a finite number of values that possess a natural order. We examine rating upgrades and rating no changes separately from rating downgrades and rating no changes, thus our setting for the dependent variable is 0 for rating upgrades, 1 for rating no changes and 0 for rating downgrades and 1 for rating no changes.

The independent variables

The accounting, finance and economic variables used in this study were largely based on those found to have explanatory power in previous studies. The accounting variables used include a number of liquidity ratio, leverage ratio, capital turnover ratio, profitability ratio and plus a number of other finance variables such as dividend per share, earning per share and price to book ratio. We chose a number of economic variables such as short and long term interest rate, GDP and inflation on the assumption that the deterioration and/or improvement of these economic variables will have a significant impact on the financial performance of the firms. A total of 40 accounting and finance variables and 11 economic variables were included in the analysis. Appendix A presents accounting, finance and economic variables used in this analysis.

Table 6.1: Summary Statistics of Standard & Poor's Rating Announcements

The table presents the distribution of Standard & Poor's rating announcements between January 1995 and December 2008. This table reports total number of rating theirs direction by calendar year. Rating upgrades (downgrades) refer to actual rating changes.

	Original Sample						Holdout Sample										Total Sample
	1995	1996	1997	1998	1999	Total	2000	2001	2002	2003	2004	2005	2006	2007	2008	Total	
Upgrade	1	0	2	1	3	7	6	3	2	4	5	3	1	1	0	25	32
No Change	5	34	33	34	39	145	32	28	38	27	38	31	34	33	32	293	438
Downgrade	0	8	9	6	10	33	11	5	11	3	5	4	3	9	1	52	85
Total	6	42	44	41	52	185	49	36	51	34	48	38	38	43	33	370	555

The analysis

The first stage of the analysis is to use stepwise multiple logistics regression analysis to select variables that make a contribution to the explanation of rating changes. In stepwise multiple logistic regression model, independent variables are selected either for inclusion or exclusion from the regression in a sequential fashion base solely on some statistical criteria. There are two main versions of the stepwise multiple logistic regressions procedure: (a) forward selection with a test for backward elimination and (b) backward elimination followed by a test for forward selection. We use the procedure (a) for our variables selection. This approach is useful and intuitively appealing in that it builds models in a sequential fashion and it allow for examination of a collection of models which might not otherwise have been examined (Hosmer and Lemesho, 2000).

Based on the stepwise multiple logistic regression, we selected 12 accounting and finance variables and 2 economic variables. Each of these 14 independent variables were examined using univariate analysis and the results are presented in Table 6.2 where we report the means and univariate F-stat. of for these independent variables. Operating Cash Flow to Debt, Return on Equity and Change Debt to Equity prove to be significant at the 0.01 level of significance; Debt to Equity and Dividend per Share is significant at the 5% level, while Change Long Term Debt to Equity prove to be significant at the 10% level. Based on this analysis, Operating Cash Flow to Debt, Return on Equity, and Change Debt to Equity are the most important variables in explaining rating changes.

The second stage of the analysis is the computation of multiple logistic regression of the rating changes on various combinations of the independent variables with the objective of identifying the best multiple logistic regression. The following provides a descriptions as to how the multiple logistic regression model is estimated in this study:

Table 6.2: Summary Statistics of Standard & Poor's Rating Announcements

The table presents descriptive statistics for the independent variables used in the multiple logistic regression model for each rating revision. The statistics are calculated using data sample of 555 observations from 1995 through 2008.

	Rating Change			
Variable	Upgrade	No Change	Downgrade	F-Stat.
Annual Growth Free Cash Flow	0.86	0.32	0.18	0.85
Debt to Equity	1.99	0.91	1.49	3.85**
Dividend per Share	16.63	31.02	30.92	3.31**
Ln Asset	22.05	22.18	22.08	0.53
Operating Cash Flow to Debt	0.24	0.20	0.16	4.96*
Return on Equity	0.30	0.13	0.15	6.88*
Change Asset Turnover	-0.01	3.43	0.07	0.13
Change Debt to Equity	-0.03	0.14	4.42	6.46*
Change Long Term Asset Turnover	0.57	4.13	0.84	0.12
Change Long Term Debt to Equity	0.06	0.60	3.45	2.46***
Change Profit Margin	0.26	1.77	0.00	0.14
Change Working Capital to Revenue	1.10	-0.89	-0.88	0.47
Inflation	3.10	2.65	2.61	1.60
Slope Interest Rate	-0.01	0.00	-0.01	1.33

* $F_{2,\infty}(0.01) = 4.61$
** $F_{2,\infty}(0.05) = 3.00$
*** $F_{2,\infty}(0.10) = 2.31$

In our setting, we assigned rating changes i in time t, Y_{it} take of two values – 0 if rating is upgraded, 1 if rating is no changed and this setting is to analyze rating upgrades and rating no changes. When considering rating downgrades and rating no changes, we assigned rating changes i in time t, Y_{it} take of two values – 0 if rating is downgraded, 1 if rating is no changed. The reason the value assigned for rating upgrades and rating downgrades are the same because we conduct the multiple logistic regression between rating upgrades and no changes separately from rating downgrades and no changes.

$$Y_{i,t} = \begin{cases} 0 \text{ if rating is upgraded} \\ 1 \text{ if rating is no changed} \end{cases}$$

$$Y_{i,t} = \begin{cases} 0 \text{ if rating is downgraded} \\ 1 \text{ if rating is no changed} \end{cases}$$

We relate these rating changes to our explanatory variables, we define:

$$Y_{i,t} = \beta_0 + \beta\ X_{i,t} + \varepsilon_{i,t} \tag{6.1}$$

where $X_{i,t}$ is the vector of independent variables, β is the vector of coefficients to be estimated, and $\varepsilon_{i,t}$ is the standard normal residual.

The estimated logistic probability of a particular set of independent variables being associated with a particular rating announcement is given by:

$$P(x) = \frac{e^{\beta_0 + \beta X_{i,t} + \varepsilon_{i,t}}}{1 + e^{\beta_0 + \beta X_{i,t} + \varepsilon_{i,t}}} \tag{6.2}$$

6.3 Discussion and Results

The multiple logistic regression model developed in the section 6.2 was employed to forecast rating changes both in-sample and out-of-sample. First, we estimate the multiple logistic regression using rating changes announcements from 1995 to 2008 and then the estimated coefficients from this regression were used to predict rating changes during this sample period (within sample forecast). Second, we develop the multiple logistic regression using the first five years of our sample and the estimated coefficient from this regression were used to forecast rating changes over the holdout period (i.e. the remaining years of rating announcements). Third, we estimated the multiple logistic regression using first five years data and the estimated coefficients from this regression were used to forecast the ratings changes in the sixth year. Then the process is moved forward a year with the data from years two to six (i.e. a five-year moving window) being used to estimate a new regression when is then used to predict the ratings changes in the year seventh. This process is then repeated over the remaining sample period.

6.3.1 Original Sample

Table 6.3 presents the results of the estimated multiple logistic regression using 32 rating upgrades, 438 rating no changes and 85 rating downgrades observations over the sample period of January 1995 to December 2008. We estimate rating upgrades and no changes separately from rating downgrades and no changes and the results are presented in Table 6.3 Panel A. Debt to Equity, Dividend per Share, Return on Equity, Change Working Capital to Revenue, Inflation, Operating Cash Flow to Debt, Annual Growth Free Cash Flow, Slope Interest Rate and Ln Asset are selected to include in the regression and their coefficients are used to estimate the probability to classify rating upgrades and rating no changes. Dividend per Share, Return on Equity and Inflation prove statistically significant when explaining rating upgrades and no changes. Operating Cash Flow to Debt, Slope Interest Rate, Change Long Term Asset Turnover, Change Debt to Equity, Change Asset Turnover, Change Profit Margin, Return on Equity and Ln Asset are selected to include in the regression to explain rating downgrades and rating no changes. Only Operating Cash Flow to Debt, Change Long Term Asset Turnover, Change Asset Turnover and Change Profit Margin prove to be statistically significant. Different variables used in analyzing rating upgrades and rating no changes and rating downgrades and no changes due to we allow the stepwise multiple logistic regressions to select the variable to include in the final stage of the analysis. The results of the analysis indicate that debt coverage and earning stability are two major determinants in explaining rating changes. Dividend per Share is positively associated with rating upgrades and Operating Cash Flow to Debt and Change in Profit Margin are negatively associated with rating downgrades. The results imply that firms would need to improve financial earning to maintain their credit rating. The multiple regression presented Pseudo-R squared statistic of 0.19 for rating upgrades and no change and 0.21 for rating downgrades and no changes.

The coefficients obtained from the estimated regression are used to predict rating changes between 1995 and 2008 (within sample forecast). It should be noted that this is not a predictive use of the model since the data set remains the same one from which the model was developed. The classification procedure employed is to use the estimated probability to forecast the group membership between rating upgrades and rating no changes and rating downgrades and rating no changes. To obtain classification we must define a breakpoint, and compare each estimated probability to this breakpoint. If the estimated probability exceeds the breakpoint then we assign that probability equal to 0 (upgrades and/or downgrades); otherwise equal to 1 (no changes). The most commonly used value for the breakpoint is 0.5. However, for our study we do not use a breakpoint to classify the rating changes, we classify them on the basis of the number of observations in the sample forecast. For example, if 10 rating downgrades and 50 rating no changes are included in the forecast, we use the regression to estimate their probability and sort them in the ascending order and then we cut the 10 smallest probabilities observations. If the 10 smallest probabilities observations contain rating downgrades, these observations are treated as being classified correctly or otherwise they are treated as incorrect classifications. The results of applying this classification rules to the multiple logistic regression for the original sample group are presented in Table 6.3 Panel B. The overall rate of correct rating classification of rating upgrades and rating no changes is 90.02 per cent, with 28.13 per cent of rating upgrades group being correctly classified and only 94.70 per cent of rating no changes group. On the other hand, the overall rate of correct rating classification of rating downgrades and rating no changes is 79.73 per cent, with 37.65 per cent of rating downgrades group and only 87.90 per cent of rating no changes group. If we gauge the model on the basis of its ability to identify those cases where there will be a ratings change, the model performs fairy well. When using random selection as the benchmark, the success rate that you would expect when forecasting a ratings upgrade would be 6.80 per cent whereas our in-sample forecasts have achieved a success rate of 28 per cent. For rating downgrades, random selection would suggest a success rate of 16.75 per cent whereas the actual achieved is more than double this at 37.65 per cent. The results of the overall rate of correct rating classifications for both rating upgrades and rating no changes and rating downgrades and rating no changes are relatively higher than in other studies. Pinches and Mingo (1973 and 1975) use the estimated model to classify bond ratings data, which is the same as the data used to develop the model. The model classifies 70 per cent of the bond rating correctly.

Table 6.3: Classification Rating Changes - Original Sample

The table presents result for the multiple logistic regression model that incorporates accounting, finance and economic variables. The model is estimated for the whole sample of 32 rating upgrade, 438 rating no change and 85 rating downgrade observations over the sample period of January 1995 to December 2008. Rating data are sourced directly from Standard & Poor's, accounting and finance data is from ASPECTHUNTLEY and economic data is from Reserve Bank of Australia. Table 6.3 Panel A. presents parameter estimates for rating upgrades and no changes and rating downgrades and no changes. Table 6.3 Panel B. compares the prediction of the rating upgrades and no changes and downgrades and no changes with actual Standard and Poor's rating announcements.

Panel A: Test of significant for logit model

Upgrade / No Change				Downgrade / No Change			
Variable	Coef.	Z		Variable	Coef.	Z	
Constant	7.406	1.740		Constant	-3.856	-1.420	
Debt to Equity	0.039	0.300		Operating Cash Flow to Debt	-2.299	-2.250	*
Dividend per Share	0.051	3.350	***	Slope Interest Rate	-4.692	-1.940	
Return on Equity	-2.685	-2.100	*	Change Long Term Asset Turnover	0.980	3.770	***
Change Working Capital to Revenue	-0.046	-1.050		Change Debt to Equity	0.149	1.680	
Inflation	-0.284	-2.150	*	Change Asset Turnover	-1.032	-3.730	***
Operating Cash Flow to Debt	-2.515	-1.810		Change Profit Margin	-0.940	-2.220	*
Annual Growth Free Cash Flow	-0.108	-1.830		Return on Equity	1.079	1.700	
Slope Interest Rate	2.935	0.890		Ln Asset	0.080	0.670	
Ln Asset	-0.183	-0.960					

*, **, and *** significance at the 5%, 1%, and 0.1% level
Pseudo R-square = 0.1935 (Upgrade / No Change)
Pseudo R-Square = 0.2084 (Downgrade / No Change)

Panel B: Classification of Upgrade/No Change and Downgrade/No Change							
	Upgrade	No Change	Total*		Downgrade	No Change	Total*
Upgrade	9	23	32	Downgrade	32	53	85
No Change	23	415	438	No Change	53	385	438
Total*	32	438	470	Total*	85	438	523
Percentage Correct	28.13%	94.75%		Percentage Correct	37.65%	87.90%	

* Total is the actual number of the observations included in the forecasting

6.3.2 Validation – Holdout Sample Approach

Another approach to evaluate the predictive ability of the model is to develop the model based on a subset of our data and then validates the model on the holdout sample data. In this study the sample data from1995 to 1999 was employed to estimate the multiple logistic regression and their coefficients were used to classify rating changes from 2000 to 2008. We are estimating rating upgrades and rating no changes separately from rating downgrades and rating no changes, thus the two multiple logistic regressions were estimated using sample of 7 rating upgrade, 145 rating no change and 33 rating upgrade observations. The results of the estimated regressions for both rating upgrades and rating no change and rating downgrades and rating no changes are present in Table 6.4 Panel A. The first model shows that the profitability variables such as Return on Equity and Change Profit Margin are significantly explaining rating upgrades and rating no changes. As predicted Change Profit Margin is positively associated with rating upgrades but the negative sign on the Return on Equity variable is contrary to expectations. The coefficients of the second regression show that rating downgrades is negatively associated with short-term liquidity and the leverage ratio. The results imply that rating agencies tend to downgrade firms experiencing financial difficulties. The multiple regression presented Pseudo-R squared statistic of 0.18 for rating upgrades and no change and 0.23 for rating downgrades and no changes. The results of applying the two multiple logistic regressions to the holdout sample from 2000 to 2008 are presented in Table 6.4 Panel B. The results show that the model forecast 3 of 25 rating upgrade and 272 of 294 rating no changes for forecasting rating upgrade and rating no changes. On the other hand, when considering rating downgrades and rating no changes the model forecast 12 of 52 rating downgrade and 254 of 294 of rating no changes. The performance of the model is demonstrably inferior when applied out-of-sample as compared to the in-sample performance discussed above. Still, the success rate in forecasting ratings change is about twice as good as one would expect from random choice for upgrades and 50 per cent better for ratings downgrades. The result of the correct rating classifications of out of sample forecast for both rating upgrades and rating no changes and rating downgrades and no changes are slightly lower than other previous studies. Bhandari et al., (1979) correctly classify ratings almost 93 per cent of the out of sample forecast compare to our study 86 per cent for rating upgrades and rating no changes and 77 per cent for rating downgrades and rating no changes.

Table 6.4: Classification Rating Change - Holdout Sample Approach

The table present result for the multiple logistic regression model that incorporates accounting, finance and economic variables. The model is estimated using sample of 7 rating upgrade, 145 rating no change and 33 rating upgrade observations over the sample period of 1995 to 1999 and the estimated model is used to predict the rating announcement from 2000 to 2008. Rating data are sourced directly from Standard & Poor's, accounting and financial data is from ASPECTHUNTLEY and economic data is from Reserve Bank of Australia. Table 6.3 Panel A, present parameter estimates for rating upgrade and no change and rating downgrade and no change. Table 6.3 Panel B, compares the prediction of the rating upgrade and no change and downgrade and no change with actual Standard and Poor's rating announcements from 2000 to 2008.

Panel A: Test of significant for logit model							
Upgrade / No Change				Downgrade / No Change			
Variable	Coef.	Z		Variable	Coef.	Z	
Constant	4.1949	0.980		Constant	3.2851	2.960	***
Change LT Debt to Equity	-0.2113	-1.190		Change WC Revenue	0.4832	2.020	**
Return on Equity	-1.4229	-1.750	*	Quick Ratio	-6.0408	-1.770	*
Annual Growth FCF	2.3216	1.470		Change LT Debt to Equity	2.4767	1.990	**
Change Profit Margin	2.1569	2.350	*	Current Ratio	5.7583	1.800	*
Ln Asset	-0.1097	-0.560		Debt to Equity	-0.2119	-2.220	**
Change WC Revenue	0.1012	0.940		Change Return on Equity	0.9525	1.800	*

*, **, and *** significance at the 5%, 1%, and 0.1% level
Pseudo R-square = 0.1768 (Upgrade / No Change)
Pseudo R-Square = 0.2273 (Downgrade / No Change)

Panel B: Classification of Upgrade/No Change and Downgrade/No Change							
	Upgrade	No Change	Total*		Downgrade	No Change	Total*
Upgrade	3	22	25	Downgrade	12	40	52
No Change	22	272	294	No Change	40	254	294
Total*	25	294	319	Total*	52	294	346
Percentage Correct	12.00%	92.52%		Percentage Correct	23.08%	86.39%	

* Total is the actual number of the observations included in the forecasting

6.3.3 Validation - Moving Window Approach

The final approach to evaluate the predictive ability of multiple logistic regressions involves using a moving window method. We use the first five years of rating changes data to estimate the multiple logistic regression and the estimated coefficients from the regression were used to predict the rating changes during the next year. The procedure is then repeated using a five –year moving window in order to obtain for the subsequent year. For instance, we predict rating changes for 2000 using the parameters estimated from 1995 to 1999. We predict rating changes for 2001 using the parameters estimated from 1996 to 2001, and so on. We estimate and forecast rating upgrades and rating no changes separately from rating downgrades and rating no changes. The forecasting results are presented in Table 6.5. This approach appears to have a better prediction than the holdout sample approach with respect to rating upgrades and to be almost the equal of the holdout sample method for predicting rating downgrades. The model predicts 28 per cent of rating upgrades and 93.88 per cent of rating no changes when considering upgrades and 23.08 per cent of rating downgrades and 86.39 per cent of rating no changes when considering downgrades. The use of the moving window has lead to an improvement in forecasting for ratings downgrades with the success rate increasing to 28 per cent from the 12 per cent achieved when a single forecasting model was applied across the whole holdout sample.

Table 6.5: Classification Rating Changes – Moving Window Approach

Table 6.4 presents the predictive accuracy the holdout sample using rollover procedure. The first five year rating upgrades, rating no changes and rating downgrades used to estimate the parameters and the estimated parameters were used to predict the next year rating announcements. This procedure is repeated to predict rating announcements up to 2008.

	Upgrade	No Change	Total*		Downgrade	No Change	Total*
Upgrade	7	18	25	Downgrade	12	40	52
No Change	18	276	294	No Change	40	254	294
Total*	25	294	319	Total*	52	294	346
Percentage Correct	28.00%	93.88%		Percentage Correct	23.08%	86.39%	

* Total is the actual number of the observations included in the forecasting

7 CONCLUSION

This paper examines the Australian market efficiency by using Standard and Poor's and Moody's Australian corporate credit rating changes and CreditWatch. The overall empirical results for the equity market is consistent with previous studies that find that the market does not respond to rating upgrades but that it does respond to rating downgrades. The lack of reaction to rating upgrades and the significant reaction to rating downgrades is consistent with the proposition that firms are reluctant to release unfavorable information and once this information is detected by rating agencies, it will quickly be incorporated in stock prices. The study also indicates that rating changes are anticipated by the market well in advance of when they are announced. In addition, we document that equity market reaction is much greater if the rating announcement is either contaminated or relates to a cross-classes rating change. In contrast to previous studies, we find that abnormal equity performance is greater when rating changes are expected rather than unexpected and when the rating changes are the result of firms' changing their financial structures. The result for CreditWatch is consistent with rating changes except that we find that the reaction to a positive CreditWatch announcement is statistically significant over the announcement window.

We used both daily listed and over-the-counter traded corporate bond yields from the Australian Financial Markets Association to test information content of rating announcements in Australian bond market. The results in bond market are not consistent to those in equity market as we find that the bond market does not react to rating downgrades but that there is a significant positive reaction to rating upgrades over the announcement window. For the pre-announcement window, we find consistent results with equity market. Bond market reaction during the pre-announcement window to rating changes is much greater than during the announcement window. When we examine the bond market reaction to CreditWatch, we find that positive (negative) CreditWatch announcements are associated with positive (negative) bond returns during the announcement window and they are statistically significant.

Cross-sectional regression using rating downgrades indicates that excess returns are negatively associated with the investment grades, market to book value ratio and debt to equity ratio. The announcement effect is not associated with the number of grade rating changes, the size of the issuer or the industry in which the issuer operate. Moreover, cross-sectional regression using rating upgrades indicates that excess returns are positively associated with the number of grade rating changes and debt to equity but negatively associated with firms operated in the highly regulated industry.

In the last part of the paper we examine the impact that various accounting, financial and economic variable have on ratings agencies in determining ratings. Our multiple logistic regression model indicates debt coverage and earning stability have the most pronounced effect on the rating.. We conduct both in-sample and out-of-sample forecasts in order to evaluate the predictive ability of our model. The result demonstrates a consistent trend towards rating no changes. Also, we document that the success rates of out of sample prediction using a moving window procedure is higher than normal out of sample forecast procedure.

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APPENDIX

Appendix A Accounting, Finance and Economic variables Used in the Model

ACCOUNTING AND FINANCE VARIABLES	ECONOMIC VARIABLES
Annual Growth Free Cash Flow	GDP Growth
Annual Growth Net Debt	Inflation
Asset Turnover	Consumer Price Index
Cash Flow to Revenue	Change Consumer Price Index
Current Ratio	3 Year Government Bond
Debt to Equity	10 Year Government Bond
Debt to Asset	Change 3 Year Government Bond
Dividend per Share	Change 10 Year Government Bond
Earning Before Interest and Tax Margin	Slope of Change 3 Year Government Bond
Earning per Share	Slope of Change 10 Year Government Bond
Ln Asset	Slope of Interest Rate
Long Term Asset Turnover	
Long Term Debt to Asset	
Long Term Debt to Equity	
Net Interest Coverage	
Operating Cash Flow to Debt	
Price to Book Ratio	
Profit Margin	
Quick Ratio	
Return on Asset	
Return on Invested Capital	
Working Capital to Revenue	
Return on Equity	
Change Asset Turnover	
Change Current Ratio	
Change Debt to Equity	
Change Debt to Asset	
Change Earning Before Interest and Tax Margin	
Change Long Term Asset Turnover	
Change Long Term Debt to Asset	
Change Long Term Debt to Equity	
Change Net Interest Coverage	
Change Operating Cash Flow to Debt	
Change Operating Cash Flow to Revenue	
Change Profit Margin	
Change Quick Ratio	
Change Return on Asset	
Change Return on Equity	
Change Return on Invested Capital	
Change Working Capital to Revenue	