PREDICTABILITY OF CREDIT WATCH PLACEMENTS AND THE DISTRIBUTION OF WEALTH EFFECTS ACROSS THE TRIGGER EVENT, PLACEMENT AND REMOVAL DATES

DISSERTATION

Presented to the Graduate Council of the
University of North Texas in Partial
Fulfillment of the Requirements

For the Degree of

DOCTOR OF PHILOSOPHY

By

William C. Hudson, B.A., M.B.A.

Denton, Texas

May 1996

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Standard and Poor's began publication of *Credit Watch* in November of 1981 as an early warning list for firms whose debt is under review for a possible rating change. This dissertation is composed of three essays which address various aspects of *Credit Watch* and the impact on shareholder wealth.

The first essay uses a discriminant analysis model to classify the *Credit Watch* status of firms which engaged in mergers and acquisitions activity in 1991. The model correctly classifies 69.85% of the in-sample firms and 65.83% of the out of sample firms.

The second essay examines whether the stock market reacts more strongly to trigger events which cause *Credit Watch* placements than to the actual placement. Significantly larger negative abnormal return are found around the trigger event than the placement. No evidence is found for the differential reaction evolving over time.

The third essay examines firm specific and economy-wide factors which may be related to the strength of the abnormal

stock return around the *Credit Watch* removal date. The removal return is found to be positively related to the number of trading days a firm remains on *Credit Watch*, negatively related to the number of updates regarding the firm released by Standard and Poor's while on the list, and positively related to the cumulative abnormal return measured between the placement and removal. This evidence suggests that the number of trading days a firm remains on *Credit Watch* is a proxy for information leakage to the market. The negative relationship between the removal return and the number of updates implies that the market reacts to a string of negative news of which the removal announcement is the final announcement. Finally, the positive relationship with the cumulative abnormal return between placement and removal suggests that much of the information content of the removal has been impounded into the stock price at the time of the removal.

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CHAPTER I

INTRODUCTION

The topic of debt rating has been explored extensively in the finance, accounting and economics literature. The rating assigned to a firm for a particular class of debt greatly influences the cost of future debt financing for the firm. Furthermore, a debt rating change often times affects the wealth of current debt holders as debt is repriced in the market to reflect the new risk class implied by the rating. The three major debt rating agencies, Standard and Poor's, Fitch, and Moody's, claim to have superior or inside information about firms whose debt they rate. While the rating agencies do not divulge such inside information to the public, a rating action signals the implication of the information on the quality of a firm's debt to the market. Numerous studies have documented common stock and bond price reaction to bond and preferred stock rating changes. These results suggest that rating changes do in fact provide the market with additional unexpected information.

The chain of events which culminate in Standard and Poor's assigning a bond rating change or affirmation varies across firms.

A firm may be initially examined by Standard Poor's as a result of a firm specific event which is observed by Standard and Poor's. Such an event is deemed to have a high probability of changing the default risk of the firm's outstanding debt. A firm may also come under the scrutiny of Standard and Poor's as a result of a periodic review process. In this case, the rating review event is solely a function of time and the instance at which a firm comes under review may or may not be reported. Standard and Poor's publishes *Credit Week* every Friday in which a *Credit Watch* list is maintained listing firms for which Standard and Poor's has initiated a rating review in that given week. Firms are listed with a positive, negative or developing rating implication. Sometimes the specific reason (trigger event) for the *Credit Watch* placement is listed along with the particular debt issue(s) under review. It is important to note that not all firms for which a rating review is initiated are listed on *Credit Watch*. Finally, Standard and Poor's announces a rating decision which is reported in *Credit Week* at which time the firm is removed from the *Credit Watch* list.

The collection of three essays which comprise this dissertation examine various aspects of the Standard and Poor's bond rating process and their various implications.

Essay one develops a method to predict the probability of a firm being placed on *Credit Watch* given the announcement of a firm bidding on or initiating a takeover of a target firm. A discriminant analysis model is used to classify *Credit Watch* placements versus non-placements.

Using a set of nine financial measures which have been proven useful in predicting bond rating changes, the discriminant model is able to correctly classify 69.85% of the in-sample firms and 65.83% of the out of sample firms.

Essay two examines stock price reaction to trigger events and *Credit Watch* placement. *Credit Watch* was introduced in 1981. Studies using early 1980's data find significant abnormal returns for firms placed on *Credit Watch* even when the placement was preceded by an identifiable trigger event. This essay seeks to determine the extent to which the market has learned to recognize and respond to those trigger events which appear to cause a *Credit Watch* placement. Since Standard and Poor's has access to inside information about firms, a *Credit Watch* placement may signal the implications of this inside information given the occurrence of a trigger event. The market may have an incentive to learn which types of trigger events cause a *Credit Watch* placement resulting in an increase in market efficiency. Essay two seeks to determine if the stock price response to *Credit Watch* placements has changed relative to the preceding trigger events as the market is allowed to observe which events appear to cause a *Credit Watch* placement for the twelve years subsequent to the inception of Credit Watch. Abnormal common stock returns are calculated around *Credit Watch* placement dates and the preceding trigger events as they are indicated in the *Credit Watch* write-up.

The abnormal returns are computed from the beginning of *Credit Watch's* existence (November 1981) through the end of 1993 providing a twelve year period over which the market may have an opportunity to "learn". If the market has "learned" to recognize the significance of particular types of trigger events which result in *Credit Watch* placements over the last twelve years, then the abnormal returns should be increasing through time around the trigger events and decreasing through time around the *Credit Watch* placement dates.

The results indicate that the market reacts more strongly to trigger events than to subsequent *Credit Watch* placements for both positive and negative implication placements. Specifically, the difference in reaction is much more pronounced for the negative implication placements. There is weak evidence of the relative market reaction changing over time.

The third essay examines the information content of the signalling provided by Standard and Poor's to the market when they place a firm on *Credit Watch* and when the subsequent bond rating decision is announced. The relative strength of the market reaction to this sequence of signals is examined to determine to which signal the market responds more strongly. The pattern of market reaction to the two signals may be a function of market attributes, firm specific attributes, and the time between *Credit Watch* placement and the rating change announcement.

The results show that the abnormal stock return measured around the *Credit Watch* removal announcement date is positively related to the number of trading days for which the firm has remained on the *Credit Watch* list, negatively related to the number of updates listed by Standard & Poor's, and, positively related to the cumulative abnormal return measured between the placement and removal date.

CHAPTER II

LITERATURE REVIEW

Literature Review for Essay One

The literature review for essay one is organized by topics which are motivations for this study. The sections consist of papers discussing: the stock price and bond effect of *Credit Watch* placements, the determinants of bond rating and rating changes, and, conditional probability failure models and their applications.

Credit Watch Placement Effects Papers

Since the inception of Credit Week, several papers have examined the stock and bond price effects of *Credit Watch* placements.

Wansley and Clauretie (1985) examine equity returns and bond returns around *Credit Watch* placement dates. The equity and bond returns for firms placed on *Credit Watch* are compared to those for firms whose debt was re-rated during the same period but which never appeared on *Credit Watch*. They find that in examining common stock returns, significant negative abnormal returns are found on the placement date for firms placed on *Credit Watch* which were subsequently downgraded. No significant abnormal returns are found for firms whose debt was placed on *Credit Watch* which were later confirmed. Firms which were not placed on *Credit Watch*, experience significant abnormal returns around the actual rating change date. No abnormal returns are found on the actual rating change date for firms listed on *Credit Watch* prior to either rating upgrades or downgrades. Their results did not change significantly when firms placed on *Credit Watch* because an identifiable trigger event were excluded from the sample. To examine the effect on bond prices, bonds which were placed on *Credit Watch* are compared to a portfolio of matched bonds which were not placed on *Credit Watch*. For bonds not placed on *Credit Watch*, bond prices declined by more than the matched portfolio in the 12 months prior to the rating change. No such reaction is observed for bond upgrades. No bond price reaction is observed before or after the *Credit Watch* placement for industrial and utility firms which experienced a subsequent rating confirmation. A similar result is found for *Credit Watch* additions with positive implications which were subsequently upgraded. However, for firms placed on *Credit Watch* with a positive implication which were subsequently upgraded, a significant price increase was observed by the fourth month following the addition.

Holthausen and Leftwich (1986) expand on the Wansley and Clauretie (1985) study by using daily returns, *Credit Watch* addition press release dates and by filtering the sample for contaminating firm specific announcements around the *Credit Watch* placement date. The study found that additions to *Credit Watch* with negative implications are associated with significant negative abnormal returns for both the contaminated and non-contaminated sample. For *Credit Watch* placements with positive implications, there is little evidence of stock price reaction although the effect was stronger for the non-contaminated sample. Finally, rating changes preceded by a *Credit Watch* placement have lower abnormal returns suggesting that a rating change supplies less information to the market when it is preceded by a *Credit Watch* placement.

Elayan, Maris and Maris (1990) examine common stock price reaction to "false" signals from *Credit Watch* placements. A false signal is denoted as a rating decision which is not in the direction of the implication listed with the prior *Credit Watch* placement. The authors find no significant abnormal returns for firms placed on *Credit Watch* with a negative implication which are later downgraded on either the *Credit Watch* placement date or the *Credit Watch* removal date. For firms placed on *Credit Watch* with a negative implication which were subsequently affirmed, a significant negative abnormal return is observed around the placement date while no significance is found around the removal date. Firms placed on *Credit Watch* with positive implications whose ratings were subsequently upgraded experienced no significant abnormal returns around either

Credit Watch placement or removal date. Firms placed on *Credit Watch* with positive implications whose rating was subsequently affirmed also experienced no significant abnormal returns around either the *Credit Watch* placement or removal date.

Wansley, Elayan and Maris (1990) examine the effect of preferred stock *Credit Watch* placements on preferred stock returns. Using a mean adjusted returns methodology similar to Brown and Warner (1985) they find that *Credit Watch* listings which are eventually downgraded are associated with significant negative abnormal returns around the announcement date. No abnormal returns are found for firms placed on *Credit Watch* with a negative implication that were later affirmed. No abnormal returns are found for firms placed on *Credit Watch* with positive implications which were later downgraded. The authors conclude that abnormal returns experienced ten to three days before the *Credit Watch* placement date are related to announcement effects. Furthermore, abnormal returns are not dependent on whether or not the sample was contaminated. However, abnormal returns for the industrial bond sample are present only for the clean sample.

Chandy, Hsueh and Liu (1993) examine the extent to which *Credit Watch* placements for preferred stock have a common stock price effect taking into account the percent of the capital structure comprised of preferred stock and the extent to which information is available to the market as measured by the number of analysts who follow the firm. Percent of preferred stock financing is measured as the proportion of preferred stock to total assets. They hypothesize that *Credit Watch* placements should have a larger impact for firms which have a higher proportion of their assets financed by preferred stock or have less information available in the marketplace. They find that no abnormal returns are present for preferred stock upgrades and downgrades when the sample is not controlled for information or size. The number of analysts following a stock is not related to abnormal returns while the proportion of preferred stock in the capital structure is found to be related to downgrades but not upgrades. Abnormal returns are not found for preferred stock upgrades but do exist for downgrades for low information firms. For firms with a higher proportion of preferred stock, abnormal returns are found for downgrades but not for upgrades.

Hand, Holthausen and Leftwich (1992) find results which differ from those of the previous papers examining stock price reaction to *Credit Watch* placements. The authors find very little evidence of excess bond or stock returns associated with either a positive or negative *Credit Watch* addition.

Determinants of Bond Rating and Rating Changes Papers

The purpose of this section is to review papers which attempt to predict initial bond ratings and rating changes. This section provides a theoretical foundation for the selection of possible co-variates to be used in essay one.

Fischer (1959) is one of the first papers to examine the determinants of risk premiums for bonds. He reports that the natural log of the average risk premium of a firm's bonds can be estimated by using the natural log of the following variables:

- The coefficient of variation of the firm's net income for the last nine years
- The length of time the firm has operated without defaulting to creditors
- The market value of a firm's equity divided by the par value of its debt

Using a cross-sectional ordinary least squares regression on U.S. industrial firms, the three variables accounted for 75% of the variation in the natural log of the risk premium.

Pogue and Soldofsky (1969) test for the ability of financial and operating statistics to compute the probability that a firm's bonds will receive the higher of two ratings. The authors use the following variables:

- Earnings coverage
- Long term debt to capitalization
- Profitability
- Earnings stability
- Asset size

The model is estimated for industrial firms, railroads and public utilities. The following results are reported: The probability of a bond being rated higher is inversely related to leverage and earnings instability and directly related to firm size and profitability. For corporate bond ratings, leverage and profitability are the most significant variables. The accuracy of the model is greatest when the differences in possible bond ratings is largest.

West (1970) uses the variables proposed by Fisher (1959) to predict bond ratings. West observes that the variables also predict bond risk premiums. Since bond risk premiums are highly correlated with bond ratings, it was thought that the variables would also predict ratings. The model correctly predicts approximately 60% of all bond ratings and slightly less for the out of sample bonds.

Pinches and Mingo (1975) use a multiple discriminant analysis procedure in an attempt to predict industrial bond ratings. The following variables are found to predict 69.7% of Moody's ratings and approximately 60% of the holdout sample:

- Earnings stability
- Size
- Financial leverage
- Debt
- Debt coverage stability
- Return on investment
- The subordination status of the bond

Pinches and Mingo (1975) suggest that the relatively poor predictive ability of their previous study to predict Baa bonds was due to a bias introduced through the use of a (0,1) dummy variable representing subordination. By grouping the bonds on subordination status, the predictive ability of the model increases to 98%.

Melicher and Rush (1974) use data from the electric utility industry to examine to what extent a firms's beta is related to a firm's bond rating. The authors find that Standard and Poor's bond ratings are able to provide some explanation of changes in firm ß's.

Ang and Patell (1975) make a comparison of four statistical bond rating methods on their ability to replicate Moody's bond ratings. The accuracy of models from highest to lowest were those used by Horrigan, West, Pogue and Soldofsky and Pinches and Mingo.

Reilly and Joehnk (1976) derive a market driven ß for bonds. They hypothesize that there should be an inverse relationship between bond ß's and bond ratings. The authors find that the ß of a bond is not necessarily related to it's risk rating.

Bhandari, Soldofsky and Boe (1979) examine the electric utilities industry to determine if a multivariate discriminant model which incorporates recent levels, past trends, and instability of financial ratios can predict and explain bond rating changes. They find that 90% of bond rating changes can be predicted by the most recent levels and past trends of three ratios:

- Fixed charges earned
- Debt to capitalization
- Return on assets and a measure of earnings stability

Their model is better able to predict a higher proportion of bond ratings in the holdout sample than previous models.

Kaplan and Urwitz (1979) point out that previous bond rating prediction studies had accuracy problems. This study uses the following independent variables:

- (cash flow before interest and taxes)/(total debt)
- (long term debt)/(total assets)
- (long term debt)/(net worth)
- (net income)/(total assets)
- (total assets)/(size of bond issue)
- Coefficient of variation of total assets
- Coefficient of variation of net income
- A (0,1) dummy variable to represent subordination

The authors find that a simple model which uses a subordination dummy variable, total assets, one financial ratio and the ß of the firm's common stock is able to correctly classify about two-thirds of a hold out sample of newly issued bond. The authors conclude that ordinary least squares regression when compared with an N-Probit model appears robust and does not bias the equations.

Baran, Lakonishok and Ofer (1980) use multiple discriminant analysis to test the ability of two types of accounting data sets to explain Standard and Poor's bond ratings. A historical cost data accounting system is compared with price level adjusted data. The authors show that the use of price level adjusted data improves the bond classification accuracy for the multi-discriminant analysis model.

Wingler and Watts (1982) contrast a multivariate discriminant analysis model with a multivariate probit model in predicting rating change decisions based on a set of financial ratios. The advantage of the probit model is that it takes into account the ordinal nature of the dependent variable, in this case the bond rating. The ratios include:

- A leverage measure using the trend of debt to total capital for the five years preceding the rating change
- Return on assets
- The five year trend in construction expenditures relative to total assets
- The three year trend in (operating income + non cash charges)/(total interest payments)
- Allowance for funds used during construction

After approximately two decades of ardent research exploring the determinant of bond ratings, Altman (1982) points out four reasons why it is difficult to replicate bond ratings of the rating agencies. He first concludes that until recently, there has been a lack of sound methodology. Second, bond ratings may not be evenly distributed across industries. The rating agencies may be implicitly treating certain industries as more risky than other industries for which the independent variables are not sensitive to a systematic ordinal ranking. Third, assignment of a bond rating is a very subjective process and thus statistical studies cannot completely replicate the process based solely on reported data. Finally, bond rating agencies often list mixed ratings at a particular point in time. Altman observes that the average time by which one rating agency led or lagged another with regard to a given bond rating was 12 months.

Fabozzi (1982) uses an ANOVA model to test for the association between the market ß for the common stock of a firm and the firm's bond rating. The author finds a significant relationship between a firm's ß and the risk classification assigned for bonds and common stock.

Monahan and Barenbaum (1983) estimate a bond rating prediction model using financial attributes calculated from historical cost data. The predictive power of the model increases when the data is adjusted to constant dollar amounts. The model correctly classifies 97% of the bonds in the original sample and 96% of the out of sample firms. The model uses the following historical cost related variables:

- Coverage = (EBIT+depreciation)/(current portion of L.T. debt)
- Earnings quality = (allowance for funds used during construction)/(net income)
- Return on equity = (net income)/(owners equity)
- Trend for coverage

- Trend for earnings quality
- Trend for return on equity
- Coefficient of variation of coverage
- Coefficient of variation of earnings quality
- Coefficient of variation of return on equity

Bhandari, Soldofsky and Boe (1983), similar to the work of Mohanan and Barebaum (1983), use a multivariate discriminant model and the most recent levels, past trends, and instability of key financial ratios. They find that the most recent level of the past five year trend for three financial ratios were sufficient to successfully duplicate over 75% of industrial bond rating changes. The ratios used are:

- Times interest earned
- Debt to capitalization
- A measure of earnings instability

Singleton, Gronewoller and Hennessey (1983) suggest that because of the business cycle, bond ratings may tend to lag behind the true risk of the bond. The authors design a test to determine whether bond ratings are relative or absolute. They test to determine if quality of a given bond rating class changes over time. The authors report that most research agrees on the following determinants of bond ratings:

- Coverage = (net income+interest)/(interest)
- Leverage = (long term debt)/(total assets)

- Profitability = (net income)/(sales)

Using a MANOVA model, the authors find that bond rating standards change over time. Furthermore, they find no ratings lag implying that the same standards appear to apply uniformly to new bonds as well as to seasoned bonds.

Perry (1985) tests for the similarity of the rating systems used by Moody's and Standard and Poor's. The authors use multiple discriminant analysis to estimate a rating prediction model for each agency. The models are then used to classify the ratings of the other agency. The authors find that the two agencies' rating systems are very similar.

Peavy and Scott (1986) examine bond rating assignments made by Moody's and Standard and Poor's for 21 bond issues of the new firms formed after the AT&T breakup. The two rating agencies disagree on all rating assignments. The following variables are used:

- Pre-tax fixed charge coverage
- Log of total assets
- Return on equity
- Coefficient of variation of return on equity
- Internal cash flow as a percent of construction expenditures.
- Debt-to-total capital ratio.
- (intrastate)/(interstate toll revenues).

The fixed charge coverage and return on equity variables are found to best explain the rating assignments of Standard and

Poor's while none of the variables contain any explanatory power for Moody's bond ratings.

Boyd and Jackson (1988) test for stationarity in the significance of bond rating explanatory variables over time. They examine the following explanatory variables:

- Subordination status
- Natural log of total assets
- (Long term debt)/(total long term debt)
- Estimated coverage ratio = based on 5 year trend of

  (Net Income + Interest + Rents) + (Taxes)/(Interest) + Rents +
  (preferred Dividends)/(1 - Tax Rate)
- Variability of the coverage ratio = standard error of the above ratio
- Estimate of expected profitability based on a five year trend equal to (Cash Flow)/(Total Assets)
- (Cash Flow)/(Total Assets) variability = standard error of the above prediction

The authors find that bond rating categories did not change between adjacent years, however, categories were found to change with 2 to 3 intervening years. They also find weak evidence that the independent variable coefficients change between adjacent years with strong evidence that coefficients change with intervening years. Finally, the authors find weak evidence that the bonds and characteristics of issuing firms change over time.

Cornell, Landsman and Shapiro (1989) examine the results of the Holthausen and Leftwich (1986) paper testing whether common stock price reaction to bond rating changes is related to the nature of a firm's assets. More specifically, they hypothesize that a rating change may provide additional information to the market because rating agencies have access to inside information which allows them to make a superior valuation of the firm's net intangible assets. The authors regress common stock returns on the following variables:

- Net intangible assets
- The number of grades which the bond changed
- A dummy variable to denote a firm moving across investment grade status

The regression coefficients are insignificant when historical accounting measures are used, however, the coefficients become significant when current cost data is used.

Iskandar (1992) tests to determine whether bond rating agencies apply the same rating standards to new issues over time. They examine the stability of the coefficients of the explanatory variables in addition to the accuracy of the bond rating model over time. They hypothesize that there may be two possible sources of non-stationarity: The coefficients of the explanatory variables could vary over time or the variables themselves could also vary over time. The author uses the following independent variables:

- Natural log of the book value of the assets
- (long term debt)/(total assets)
- (net income)/(total assets)

- A dummy subordination variable
- A dummy sale or lease back covenant variable
- A dummy variable indicating the presence of an embedded call option such as warrant or conversion feature

The author finds that for both Moody's and Standard and Poor's, the explanatory coefficients on the variables are not stationary over time. Finally, they find that rating agencies apply stricter standards to lower grade issues than higher grade issues when the economy is in a state of recession.

Schweitzer, Szewczyk and Varma (1992) examine the stock price reaction of bank holding companies to bond rating changes. They find significant negative abnormal returns for downgrades only. They then perform a cross sectional regression of abnormal returns using the following independent variables:

- Number of grades the rating is downgraded
- A dummy variable equal to one if the Wall Street Journal reported a *Credit Watch* placement prior to the rating change and zero otherwise
- A dummy variable equal to one if a Standard and Poor's rating change preceded the Moody's rating change

The authors find no significance for the independent variables and no explanatory power for the regression.

Ho and Rao (1993) also test for stationarity of explanatory variables for a bond rating change model. They test to determine if the variables vary with the economic environment. The authors apply a logistical regression to examine differences in the bond rating process for industrial bonds issued during 1967-1968 (a relatively stable period) and 1980-1981 (a relatively less stable period). The logit model computes the conditional probability that a bond is more likely to belong to one particular bond rating class than another, given a set of underlying variables. The paper uses the following independent variables:

- A dummy variable representing subordination status
- (Long term debt)/(total long term capital)
- (EBIT+depreciation)/(total interest obligation)
- Total assets for the year preceding the issue date
- (Net income)/(total assets)
- Coefficient of variation of (net income)/(total assets)

The authors report the following results: For the years 1967-68, all variables are significant with the exception of (EBIT+depreciation)/(total interest obligation) and the coefficient of variation of (net income)/(total assets). For the years 1980-81, all variables are significant except for (net income)/(total assets). It appears that in the later sample, which incorporates a period of relative economic instability, additional variables are incorporated by the rating agencies in making the determination of a rating change. Furthermore, the subordination status variable and the coefficient variation of (net income)/(total assets) have different significance for assigning bond ratings between the two time periods. Finally, the rating model estimated for 1967-68 misclassifies bonds in the 1980-81 sample and vice versa.

The set of variables proposed in this section will be used in a step-wise regression to select a group of co-variates for discriminant analysis regression to predict the placement of a firm on *Credit Watch* given that the firm has made or announced the possibility of a bid for another company.

Papers Utilizing Prediction Models

Papers attempting to predict a certain event based on a given set of independent variables have been pervasive in the natural and physical sciences for many years. One of their main uses in the field of finance to this point has been in the area of bank failures. Numerous papers have used several statistical techniques to predict the probability of bank failure and bank distress based on bank specific as well as exogenous independent variables. Martin (1977) uses a logit model with current balance sheet and income statement information to predict the conditional probability of future bank failure. West (1985) uses factor analysis to compile a set of financial ratios and other information taken from bank examinations. The selected variables are then used in a logit model to compute the conditional probability of a bank experiencing financial distress. Whalen and Thomson (1988) utilize a logit model and bank call report data to predict the CAMEL (capital adequacy, asset quality, management, earnings and liquidity) rating of a given bank. Thomson (1991) uses a logit model to further refine the computation of the probability of a bank failure controlling for regulatory, budgetary and political influences.

Sinkey (1977) uses discriminant analysis to construct an early warning model using data from the failed Franklin National Bank of New York.

Bovenzi, Marino and McFadden (1993) use a probit model to compute the probability of a bank failing using call report data.

Although the probit, logit and discriminant analysis models have proven useful in determining the probability of a particular event occurring, the Cox Proportional Hazard Model (CPHM) is superior in certain applications. The CPHM is better suited to bank failure prediction because while logit and probit yield the probability of bank failure, the CPHM gives the probability of a bank failing within a specified period of time. The ability to establish a probable time to failure is helpful for bank regulators as they can better allocate their efforts to those banks with impending failure. The ability to compute the probable time to the occurrence of a given event is also critical to establishing the trading rule for essay one because an estimation of the time over which a portfolio position must stay open is critical.

Several studies have used the CPHM. Jain and Vilcassim (1991) use the CPHM to compute the probable time until the next major household purchase given: marketing variables, household characteristics and heterogeneity across households. Lynch (1991) used the CPHM to compute the probability of an individual leaving invalidity benefits given personal characteristic and economic factors. Lane, Looney and Wansley (1986) model bank failure using the CPHM. Using a sample of failed banks from 1979 through 1983, failed banks are matched with non-failing banks on geographic location, charter status, size, holding company affiliation and age. Utilizing a step-wise regression, the authors determine the 21 financial ratios which best fit the CPHM. Whalen (1991) also uses the CPHM to estimate a survival function for banks.

Literature Review for Essay Two

The literature review for essay two is a subset of the articles reviewed for essay one. Essay one refers to papers covering stock price reaction to *Credit Watch* placement, determinants of bond rating changes as well as articles discussing previous applications failure time models. Essay two investigates the possibility of changes in inter-temporal common stock price reaction to *Credit Watch* placements and trigger events. The portion of the essay one literature review which is also relevant for the second essay is the section containing articles covering common stock price reaction to *Credit Watch* placements. This body of knowledge supports the hypothesis that *Credit Watch* placements do provide additional unexpected information to the market resulting in a significant stock price reaction. This is the beginning basic premise for essay two.

Literature Review for Essay Three

The literature review for essay three contains a summary of the papers which examine the information content of bond rating changes, the information content of preferred stock rating changes and trading volume as a measure of market reaction. Currently, the majority of papers have examined bond rating upgrades and downgrades. Very few articles have looked at the information effect of bond rating confirmations. This literature review is composed of the following three sections: The information effect of bond rating changes, preferred stock rating changes and corporate paper rating changes.

Information Content of Bond Rating Changes Papers:

Katz (1974) was one of the first papers to test for bond market efficiency with respect to bond rating changes. He constructs a model to forecast the yield to maturity for each rating class. The yield to maturity for a bond which experiences a rating change is compared to the predicted yield to maturity of the bond if there had been no rating change. Katz finds that the yield to maturity of a bond does not change prior to a rating change. A six to ten week adjustment lag is found after a rating change during which a bond's yield to maturity adjusts to that of the new ratings class. He concludes that there exist inefficiencies in the bond markets as evidenced by the yield to maturity adjustment lag.

Hettenhouse and Sartoris (1976) test to determine if the yield to maturity of bonds which experience rating changes adjust to the yield to maturity of the bonds in the rating class into which they are moved. Using a control group of bonds in the new and old rating class, they find that for downgrades, bond yields adjust into the new rating class prior to the rating change announcement. Bond prices do not necessarily increase for rating upgrades. The authors conclude that bond markets appear to be sufficiently efficient to set prices independent of the major rating agencies.

Weinstein (1977) examines the behavior of corporate bond prices during the period surrounding a bond rating change. He uses one month holding period returns rather than bond yields. Bond ratings are used as a proxy for a bond's systematic risk. The author finds no abnormal bond returns after the rating change announcement. No abnormal returns are found during the six months prior to the rating change. A small abnormal return is found approximately .5

to 1.5 years prior to the rating change. The authors conclude that this is a reaction to events which eventually cause the rating change.

Pinches and Singleton (1978) find that abnormal stock returns precede a bond rating change with larger abnormal returns being associated with downgrades. Abnormal returns are found to be larger during the two years prior to a rating change than during time periods which follow.

Griffin and Sanvicente (1982) use three models to measure abnormal returns around bond rating changes. The models include: the one factor market model, the two factor cross-sectional model proposed by Black (1972) and Fama and McBeth (1973), and a method of matched control firms in a portfolio to which they compare the (event) experimental portfolio. Using all three models, the authors find negative abnormal returns for downgrades but no abnormal returns for upgrades.

Glascock, Davidson and Henderson (1987) examine the effect of Moody's bond rating changes on common stock returns. They find abnormal stock price reaction around bond rating changes for both upgrades and downgrades. The market appears to anticipate the rating change prior to the re-rating (i.e. negative returns are found prior to a rating downgrade). However, the sign of the return reverses after the rating change announcement.

Zaima and McCarthy (1988) find significant abnormal returns due to bond rating changes only for downgrades. No abnormal returns are found for upgrades. The authors attribute their results to the conflict between the information content hypothesis and the wealth redistribution hypothesis. The former predicts that a downgrade should result in negative abnormal returns with the reverse being true for upgrades. The latter hypothesis predicts that a bond rating downgrade should result in a positive stock price reaction with a negative bond price reaction as wealth is expropriated from bond holders to shareholders because a downgrade signals an increase in firm risk. The reverse is hypothesized for upgrades. The authors conclude that the information content effect dominates the wealth redistribution effect for downgrades. However, the information content reaction is canceled out by the wealth redistribution effect for upgrades.

McCarthy and Melicher (1988) examine the information content of bond rating changes in a portfolio context. Using matched firms whose bonds were not downgraded, they construct minimum variance portfolios of bonds. The optimal weights for each of the bonds in the portfolio were computed before and after the rating change. The authors hypothesize that a bond upgrade should cause an increase in demand for a bond thereby increasing the weight in which the bond is held in the portfolio. The reverse should be true of downgrades. The authors find that changes in the optimal weights for bonds which were re-rated preceded the rating change for both upgrades and downgrades. The market reaction also reflects the fact that weights change earlier for downgrades than for upgrades. Although this is a unique framework in which to evaluate the impact of a bond rating change, the results correspond to those of other studies.

Hsueh and Liu (1992) hypothesize that the stock price reaction from a bond rating change is a function of the amount of information available about the firm and the certainty of market conditions. They find abnormal returns for upgrades and downgrades in firms for which there is a relatively small amount of information available. Furthermore, the stock price reaction to rating changes is more pronounced in periods of market uncertainty when the information content of a bond rating change has a greater impact on reducing market uncertainty.

Schweitzer, Szewczyk and Varma (1992) investigate the effect of bond rating changes on the common stock returns of bank holding companies. They find significant negative abnormal returns for downgrades and insignificant positive abnormal returns for upgrades. The results were not dependent upon whether or not the sample was contaminated by confounding events. Finally the authors compare the stock price reaction of the bank holding companies to a bond rating change to that of a group of industrial firms which experienced a rating change. No difference was found between the two groups.

Goh and Ederington (1993) examine the reaction of common stock returns to bond rating changes. The authors found no abnormal returns for upgrades and significant negative abnormal returns for downgrades. Furthermore, they find significant negative abnormal returns for downgrades due to deteriorating conditions resulting in a loss in firm value. No abnormal returns were found for downgrades due to an increase in leverage.

Information Content of Preferred Stock Rating Changes

Davidson and Glascock (1985) examine the stock return behavior of firms which undergo a preferred stock rating change by Standard and Poor's. For the complete sample of firms, both industrial and utilities, positive abnormal returns precede upgrades while negative returns precede downgrades. However, reversals in the abnormal returns follow the rating change date. For the sample of just utilities, negative abnormal returns do not precede the downgrade.

Stickel (1986) examines the effect of preferred stock rating changes on preferred and common stock prices. The author computes daily returns with a clean sample of firms that are free of confounding events around the rating change announcement date. Using the non-contaminated sample, abnormal returns are found on the day after the rating change for preferred stock while no abnormal returns are found on this day for common stock. Large abnormal returns are found when using the contaminated sample. The authors conclude that much of the abnormal returns can be attributed to confounding events.

Chandy, Hsueh and Liu (1993) test the common stock price reaction to preferred stock rating changes. They focus on the amount of information available in the market for a given firm and the proportion of preferred stock financing in a given firm. The authors hypothesize that a preferred stock rating change should have a larger effect on stock price the less information is available for the firm and the larger the proportion of preferred stock in the firm's capital structure. Information available for a firm is measured as the number of financial analysts following the firm. Relative size of the preferred stock is measured as the ratio of preferred stock to total assets. Without controlling for information or size, the authors find no abnormal common stock returns for either upgrades or downgrades. The number of analysts is not related to abnormal returns for upgrades or downgrades. However, the relative size of preferred stock in the firm's capital structure is significantly related to downgrades but not to upgrades. Abnormal returns are associated with low information firms for downgrades but not for upgrades. Abnormal returns are associated with firms for which preferred stock financing is a relatively larger proportion.

The authors attribute the weak results of previous preferred stock rating change papers to the relatively low proportion of preferred stock in the firm's capital structure.

CHAPTER III

ESSAY ONE

Theoretical Motivation

One of the fundamental finance theories upon which papers that examine stock price reaction to bond rating changes are based is the *Efficient Markets Hypothesis* formalized by Fama (1970). The three forms of this hypothesis describe stock market efficiency in terms of stock prices reflecting an increasing set of information. The weak form hypothesizes that markets are efficient with respect to all past price information. The semi-strong form hypothesis states that markets are efficient with respect to all publicly available information. Finally, the strong form hypothesis states that markets are efficient with respect to all information both public and private. The overall consensus of the finance literature is that the stock market is at least semi-strong form efficient and in certain instances is strong form efficient with respect to certain private types of information.

If there is a stock price reaction to a bond rating change, then this implies that the rating change announcement supplied unexpected information to the market. The rating agencies supply the market with information regarding a change in the probability of default of a firm's debt through a debt rating change announcement. Rating agencies claim that they are privileged to inside information supplied by the firms which they review. Although the rating agencies are obligated not to reveal the "inside" information, they signal the implications of the inside information combined with relevant publicly available information through a bond rating change or *Credit Watch* placement. If the rating agency truly uses "inside" information in their determination of a bond rating change, then a stock price reaction to such an announcement would represent a violation of strong form market efficiency. However, several studies have been able to replicate Moody's and Standard and Poor's rating change decisions using publicly available firm specific financial information as well as aggregate economic factors. If the rating agencies are formulating estimates of changes in default risk based on publicly available information, then a stock price reaction to a bond rating change would imply a violation of semi-strong form market efficiency.

The *Efficient Markets Hypothesis* assumes that information is available without cost to all market participants. In practice, however, the gathering and interpretation of publicly available information is costly when such actions are undertaken by individuals. Since bond rating agencies specialize in gathering and interpreting information regarding the default risk of firms, economies of scale may be realized. In such a case, one may expect a stock price reaction to a bond rating change which was formulated based on publicly available information. Investors who earn abnormal returns from such a prediction may simply be earning the additional return resulting from their additional factor inputs in the form of the time and resources consumed in formulating the prediction. Therefore, the capacity of the rating agency may not be one of signalling the implication of firm specific privileged information but rather one of being the low cost gatherer of information.

Essay one uses discriminant analysis to classify which firms are likely to be placed on *Credit Watch* given an announcement of a firm bidding on or agreeing to acquire another firm. The nature of the trigger event is similar to those mentioned in *Credit Watch* as the reason for a firm being added to the list. Wansley and Clauretie (1985), using a sample of firms placed on *Credit Watch* from November 1981 - December 1983 find that of the 164 *Credit Watch* placements in the sample, 51 (31%) are caused by a firm specific trigger event. Numerous papers have established a relationship between *Credit Watch* placements and negative abnormal returns. The majority of articles published since the inception of *Credit Watch* have found abnormal returns around the *Credit Watch* placement date. Wansley and Clauretie (1985) find significant negative abnormal returns on the *Credit Watch* placement date for firms whose debt was subsequently downgraded. Holthausen and Leftwich (1986) further refine the work done by Wansley and Clauretie (1985) by using daily returns and a sample filtered for contaminating events around the *Credit Watch* placement date. They find significant negative abnormal returns for firms placed on *Credit Watch* with a negative implication. The result was found for the contaminated as well as the non-contaminated sample. However, the announcement effect was more pronounced for the non-contaminated sample. Hand, Holthausen and Leftwich (1992) use an expectations model to classify a *Credit Watch* placement as being either "expected" or "unexpected". The expectations model compares the yield to maturity of a given bond at the time of the *Credit Watch* placement to the median yield to maturity of other bonds with the same rating. Negative *Credit Watch* additions classified as "unexpected" are found to be associated with significant negative abnormal returns. It is interesting to note that negative *Credit Watch* additions classified as "expected" experienced no negative abnormal returns.

Hypothesis 1: The type of trigger event and condition of the firm cannot be used to determine the likelihood of a firm being placed on *Credit Watch*.

Methodology

A discriminant analysis model is used in essay one is to classify the *Credit Watch* status firms which experienced merger and acquisition activity. A firm is initially included in the sample if it was announced that a firm was discussing the possibility of bidding on another firm, had actually made a bid, or already agreed to acquire another firm.

The discriminant analysis model is similar to the ANOVA model which is discussed later in this chapter. The purpose of discriminant analysis is to estimate a relationship between a single categorical dependent variable and a set of independent variables in the general form:

$Y_1 = X_1 + X_2 + X_3 + \ldots + X_n$

where Y_1 represents a categorical designation such as *Credit Watch* placement or no *Credit Watch* placement and the X's represent a set of independent variables deemed to influence the classification of a firm.

Discriminant analysis derives the linear combination of the independent variables which best discriminate between a priori classified groups. This is accomplished by the statistical decision rule of maximizing the between-group variance relative to the within-group variance which is expressed as the between-group variance divided by the within-group variance. A discrimination function for each group is then derived which takes the following form:

$Z = W_1X_1 + W_2X_2 + W_3X_3 + \ldots + W_nX_n$

where

Z = the discrimination score for a given firm.

W = discriminant weights

X = independent variables

Plugging in the value of the independent variables into the discrimination functions for placements and no placements, two discrimination scores are obtained for each firm. A firm is then classified as being in the group associated with the discrimination function yielding the higher discrimination score.

A classification matrix is constructed detailing the number of firms in each group that the model correctly and incorrectly classified. Additionally, the percentage of firms correctly classified for each group as well as the total percentage correctly classified for all groups combined is computed.

Sample Description

Essay one uses a sample of firms which experienced merger and acquisition activity. Specifically, the sample includes firms for which there was either an announcement of a possible bid, a letter of intent to bid or a definitive agreement which was announced in 1991. Within the realm of mergers and acquisition activity, any one of these similarly related events has proven sufficient to land a firm on Credit Watch.

The *Newspaper Abstract CD ROM* data base was searched for the year 1991 looking under various search words relating to mergers and acquisitions. From this initial sample, a sub-sample of firms were obtained which comprised firms which were deemed eligible to be placed on Credit Watch. A firm was eligible if they had a listing for either a Standard & Poor's commercial paper rating or a Standard & Poor's long term debt rating as reported by *Compu-Stat.*

Initially, the number of *Credit Watch* placements relative to the number of firms not placed on Credit Watch in 1991 was extremely small such that the discriminant analysis model was able to maximize the F-Statistic and percent of cases correctly classified by predicting that a firm would not be placed on *Credit Watch.* To help correct this problem, additional firms placed on *Credit Watch* for mergers and acquisitions activity were obtained from the years 1989 and 1990. This increased the percentage of firms placed on Credit Watch as a percentage of the total sample. Furthermore, this drastically improved the performance of the discriminant analysis model.

The following independent variables which have been used in the literature to predict corporate bond rating changes were used in the discriminant analysis model:

A. (Net Income + Interest)/(Interest) i.e. one plus the coverage ratio as used by Singleton, Gronewoller and Hennessey (1983)

B. (Long Term Debt)/(Total Assets) i.e. the debt to total assets ratio as used by Kaplan and Urwitz (1979) and Singleton, Gronewoller and Hennessey (1983)

C. (Net Income)/(Sales) i.e. return on sales as used by Singleton, Gronewoller and Hennessey (1983)

D. Total Assets i.e. a size measurement as used by Pogue and Soldofsky (1969), Pinches and Mingo (1975), and Ho and Rao (1993)

E. (Net Income)/(Total Assets) i.e. return on assets as used by Kaplan and Urwitz (1979), Wingler and Watts (1982) and Ho and Rao (1993)

F. The natural log of total assets as used by Peavy and Scott (1986), Boyd and Jackson (1988) and Iskandar (1992).

G. (Long Term Debt)/(Equity) i.e. the debt to equity ratio as used by Pogue and Soldofsky (1969) and Kaplan and Urwitz (1979)

H. (Net Income)/(Equity) i.e. return on equity as used by Monahan and Barenbaum (1983) and Peavy and Scott (1986)

I. (EBIT + Depreciation)/(Current Portion of Long Term Debt) i.e. a coverage ratio as used by Monahan and Barenbaum (1983)

J. Net intangible assets i.e. good will as used by Cornell, Landsman and Shapiro (1989)

The sample description for 1991 is contained in table 1.

Table 1. Sample Description of 1991 *Credit Watch* Placements for Bidding Firms

	Positive Implication Placements	Negative Implication Placements	No *Credit Watch* Placements	Total
Initial Sample	13	19	550	582
No CUSIP Number	6	10	151	167
No S&P Bond or CP Rating	2	1	245	248
Final 1991 Sample	5	8	154	167

As previously mentioned, discriminant analysis performed poorly on this sample. Although the model was able to correctly classify a large portion of the "*No CW*" firms, the number of correctly classified that were placed on *Credit Watch* with a positive or negative implication was small. Therefore, firms placed on *Credit Watch* in 1989 and 1990 due to mergers and acquisitions activity were introduced to the sample in order to bring the proportion of firms placed on *Credit Watch* vs. firms not placed on *Credit Watch* to a more equitable level. Finally, firms placed on *Credit Watch* with a positive implication were deleted from the sample for the following reasons: First, firms placed on *Credit Watch* with a positive implication are smaller in number for a given year than the negative placement firms making it difficult to create a sample with a substantial proportion of positive placements relative to the full sample of firms. Secondly, and perhaps most importantly, as is shown in essay three, the market appears to react significantly to negative *Credit Watch* placements which reacting insignificantly to positive placements. Therefore, there appears to be more value in the ability to predict negative placements as their announcement directly affects shareholder wealth whereas positive placements do not.

The final sample of companies contained a total of 199 firms which includes 45 firms placed on *Credit Watch* with negative implications and 154 firms not placed on *Credit Watch*. The ratio of placements to non-placements is 29.22% and the ratio of placements to the total sample is 22.61%.

The financial measures used to compute the ten independent variables were obtained from the *Compu-Stat* data base. They are listed as follows:

Variable	Compu-Stat Description	Data Code
Assets	Total liabilities and shareholder equity	006
Debt	Long term debt	083
Interest	Interest expense	015
Income	Net Income (loss)	172
Sales	Sales (net)	012
Equity	Common equity - Total	060
EBIT	Operating income after Depreciation	178

Net Intangible Assets	Good Will	204
Depreciation	Depreciation and Amortization	014
Current Portion of Long Term Debt	Debt in Current Liabilities	034

Results

The assumptions of the discriminant analysis model are as follows:

1. The independent variables are normally distributed.
2. The variance/covariance matrices of variables are homogeneous across groups.

In testing the first assumption, the normality of each variable used in the final model is tested for those firms placed on *Credit Watch*, those not placed on *Credit Watch* and for the total number of observations on the variable. The test results for normality for the variables of the firms placed on *Credit Watch* with a negative implication are reported in table 2.

Table 2. Normality of the Independent Variables for Firms Placed on *Credit Watch* with a Negative Implication

Variable	Chi-Square	P-value
A: Coverage 1	114.28	0.0000
B: Debt/Assets	13.219	0.0013
C: Return on Sales	35.814	0.0000
D: Total Assets	99.984	0.0000
F: ln(Total Assets)	5.3809	0.6136
G: Debt/Equity	14.060	0.0009
H: Return on Assets	77.562	0.0000
I: Coverage 2	107.45	0.0000
J: Good Will	160.96	0.0000

The test results for normality for the variables of the firms not placed on *Credit Watch* are reported in table 3.

Table 3. Normality of the Independent Variables for Firms not Placed on *Credit Watch*

Variable	Chi-Square	P-value
A: Coverage 1	76.012	0.0000
B: Debt/Assets	31.290	0.0000
C: Return on Sales	38.611	0.0000
D: Total Assets	222.14	0.0000
F: ln(Total Assets)	23.238	0.0099
G: Debt/Equity	60.333	0.0000
H: Return on Assets	80.589	0.0000
I: Coverage 2	295.98	0.0000
J: Good Will	150.6	0.0000

The test results for normality for the variables for all firms in the sample are reported in table 4.

Table 4. Normality of the Independent Variables for all Firms; Placements and Non-placements

Variable	Chi-square	P-value
A: Coverage 1	188.29	0.0000
B: Debt/Assets	48.028	0.0000
C: Return on Sales	73.376	0.0000
D: Total Assets	1400.6	0.0000
F: ln(Total Assets)	28.247	0.0017
G: Debt/Equity	67.576	0.0000
H: Return on Assets	106.02	0.0000
I: Coverage 2	526.65	0.0000
J: Good Will	217.26	0.0000

Although the majority of the chi-square tests reject the hypothesis that the data is normally distributed, a visual inspection of a histogram for each data set with a superimposed normal curve suggests that the variables are not bi-modal and in fact have reasonably normal distributions.(See graphs in appendix) Although normality is one of the assumptions of the discriminant analysis model, deviation from this assumption is not fatal. Furthermore, the classification matrix for the specified discriminant model using the nine variables does a reasonably good job of classifying firms.

In testing the second assumption, a Bartlett Chi-square test is used because the sample sizes of the firms placed on *Credit Watch* and those not placed are unequal. The results of this test are reported in table 5.

Table 5. Homogeneity of the Variance and Covariance Matrices Across Independent Variables

Variable	Bartlett Chi-square	P-value
A: Coverage 1	244.1789	0.000000
B: Debt/Assets	16.3036	0.000054
C: Return on Sales	15.5885	0.000079
D: Total Assets	7.0603	0.007885
F: ln(Total Assets)	.0260	.871987
G: Debt/Equity	33.7945	0.000000
H: Return on Assets	236.2817	0.000000
I: Coverage 2	103.5223	0.000000
J: Good Will	152.6807	0.000000

Note that the test rejects the homogeneity of variance assumption in the majority of groups. However, unless the means and variances are correlated, this problem is diminished.

Using the ten independent variables previously outlined, a discriminant analysis regression was estimated on the final sample of 199 firms. A forward step-wise regression was estimated using the *Statistica* software package. Using the step-wise method, the first variable received into the model was noted and removed from the model. The remaining variables were then again run using the step-wise method. The process of removing the first (i.e. strongest) variable and then re-estimating the model was repeated until no additional variables were included in the model. This resulted in the model described in table 6.

Table 6. Final Discriminant Model

Variable	Wilk's Lambda	Partial Lambda	p-level
A: Coverage 1	.914333	.990566	.181321
B: Debt/Assets	.906231	.999422	.741314
C: Return on Sales	.918865	.985681	.099182
D: Total Assets	.905932	.999753	.829009
F: ln(Total Assets)	.907060	.998509	.595934
G: Debt/Equity	.909181	.996179	.395612
H: Return on Assets	.936947	.966658	.011463
I: Coverage 2	.909505	.995825	.374507
J: Good Will	.909284	.996067	.388745

Note that variable *E* was not included in the model that resulted in the best classification matrix.

The Wilk's *lambda* denotes the statistical significance of the discriminatory power of the model as each variable is entered into the model. It's value ranges from 1.0 (no discriminatory power) to 0.0 (perfect discriminatory power). The second column denotes the *Wilks' lambda* after the respective variable has been entered into the model.

The Partial *Wilks' lambda* measures the contribution of each variable to the total discriminatory power of the model.

The overall *Wilk's lambda* for the model is .9057076 with an F value of 2.1863 and a corresponding p-value of .0247.

The discrimination functions for the within sample discriminant analysis model are reported in table 7.

Table 7. Discrimination Functions

Variable	Negative *Credit Watch* Placement Function Coefficients	Positive *Credit Watch* Placement Function Coefficients
A: Coverage 1	.07912	.04746
B: Debt/Assets	7.41739	8.09618
C: Return on Sales	9.70503	6.06175
D: Total Assets	.00003	.00003
F: ln(Total Assets)	3.79248	2.13853
G: Debt/Equity	-.19147	-.00551
H: Return on Assets	1.45827	.69257
I: Coverage 2	.00101	.00228
J: Good Will	-.00034	-.00019
Constant	-1.96441	-1.45827

The classification matrix for the within sample model is described in table 8.

Table 8. In-Sample Classification Matrix

Group	Percent Correct	Predicted as a Negative Placement	Predicted as No Placement
Negative *Credit Watch* Placements (45)	62.22222%	28*	17
No *Credit Watch* Placement (154)	72.07792%	43	111*
Total	69.84924%	71	128

Note: * = correctly classified firms.

In order to test for the ability of the model to classify out-of-sample observations, the "jack-knife" or "remove and replace" method was used. In employing this method, a firm is removed from the sample and a discriminant analysis model is estimated on the remaining 198 firms. This procedure was repeated for all 199 firms resulting in 199 firm specific discrimination functions. Finally, a discrimination score is computed for each firm using the firm specific independent variables. The higher of the two scores indicates into which group the model classifies a firm. The results of the out of sample test are reported in table 9.

Table 9. Out-of-sample Classification Matrix

Group	Percent Correct	Predicted as a Negative Placement	Predicted as No Placement
Negative *Credit Watch* Placements	42.22222%	19*	26
No *Credit Watch* Placement	72.72772%	42	112*
Total	65.829146%	61	138

Note: * = correctly predicted firms

Note that although the number of firms correctly classified as *Credit Watch* placements declines by twenty percentage points, the overall classification rate only declines by approximately four percentage points.

When analyzing the classification matrix the percentage of firms correctly classified, the percentage of firms that could be correctly predicted by chance must be derived. The *Proportional Chance Criterion* yields a percentage of firms which one would expect to be correctly classified by chance alone. The formula is as follows:

$C_{PRO} = p^2 + (1-p)^2$

where

p = the proportion of firms in group 1

1-p = the proportion of firms in group 2

In computing the proportional chance criterion there were 45 firms placed on *Credit Watch* with a negative implication and

154 firms that were not placed. Therefore, the proportion of firms placed on *Credit Watch* is 45/199 = .22613065 and the proportion of firms not placed on *Credit Watch* is 154/199 = .77386935. Thus computing C_{PRO}

$$C_{PRO} = (.22613065)^2 + (1-.22613065)^2 = 65.00\%$$

That is, one would expect approximately 65% of the firms to be correctly classified by chance alone. The discriminant analysis model does slightly better than this criterion as the in-sample model correctly classifies 69.84924% while the out-of-sample model correctly classifies 65.83% of the firms.

Discussion of Results

In examining the classification matrices of the in-sample versus out of sample classifications, it is apparent that the overall predictive ability has diminished slightly with the out of sample firms. Overall, the predictive ability of both models is slightly above the rate at which firms would be expected to be correctly classified purely by chance alone.

Although the model performs reasonably well, these types of variables tend to do a better job at predicting bond rating changes. The question then arises as to why these variables do more of an inferior job in predicting *Credit Watch* placements than in predicting bond rating changes. A possible reason for this discrepancy is that Standard and Poor's uses criteria for instigating a bond rating change that are different from those used to place a firm on *Credit Watch*. That is, the financial ratios for the pool of firms whose bonds are downgraded may be substantially different from those of the firms which were simply placed on *Credit Watch*. A bond rating downgrade indicates that the default risk of the firms' bonds has changed where as a *Credit Watch* placement may only imply the possibility of a future downgrade. A fraction of firms placed on *Credit Watch* with a negative implication may eventually be upgraded or simply have their debt rating affirmed. Therefore, it is not unreasonable to assume that the financial measures for firms receiving debt rating downgrades may be significantly different (weaker) than those of firms only receiving a *Credit Watch* placement. Furthermore, the difference in quality of financial measures for firms receiving a debt rating downgrade versus firms not downgraded may be substantially higher than the difference in financial measures for firms placed on *Credit Watch* versus firms not placed on *Credit Watch*. That is, the means of the independent variables (financial measures) may be more different for firms receiving bond rating changes versus firms not receiving bond rating changes than for firms placed on *Credit Watch* versus firms not placed on *Credit Watch*.

Alternatively, variables other than those used to predict bond rating changes may not in themselves be useful in predicting *Credit Watch* placements. The variables that are useful in predicting bond rating changes are obtained from published sources. The firm specific information or variables used by Standard and Poor's in placing a firm on *Credit Watch* may not be publicly available.

In summary, discrimination models may have more difficulty classifying *Credit Watch* placements than bond rating changes due to the aforementioned reasons.

CHAPTER IV

ESSAY TWO

Theoretical Motivation

The underlying theory for essay two is developed from previous works which illustrate how the market may become sensitive to *Credit Watch* placements with negative implications which have historically been followed by bond rating downgrades. Before the inception of *Credit Watch* there existed no uniform system for alerting the market that a firm's debt was in question before the occurrence of the actual bond rating change. Studies prior to the inception of *Credit Watch* report significant negative abnormal stock returns upon announcement of a bond rating downgrade. Studies conducted since the inception of *Credit Watch* have shown that for firms which are placed on *Credit Watch* with a negative implication and subsequently downgraded, negative abnormal returns are observed on the *Credit Watch* placement date while no abnormal returns are observed on the date of the bond rating change announcement. It would appear that the market has become more responsive to the *Credit Watch* placement which the market may interpret as a signal of a high probability of an eventual bond rating change. When Standard and Poor's places a firm on *Credit Watch*, an explanation for the placement is included in a brief one to two paragraph write-up where sometimes a mention of a firm specific event is given as the reason for the *Credit Watch* placement. Before the inception of *Credit Watch*, the market reacted negatively to bond rating downgrades. In the early 1980's *Credit Week* began to issue what was in effect a warning that a possible rating change was imminent. Evidence seems to suggest that after observing numerous negative *Credit Watch* additions and noticing that frequently a negative placement eventually resulted in a bond rating downgrade, the market began to respond to the *Credit Watch* placement rather than to the eventual bond rating downgrade. Wansley and Clauretie (1985) report no abnormal returns for a firm on the date which their bond rating change is reported when such a rating change is preceded by a *Credit Watch* placement. The study used a sample of firms taken from 1981-1983. It may be possible that over the course of some thirteen years since the inception of *Credit Watch* in November of 1981 the stock market has become more sensitive to trigger events that have historically been associated with *Credit Watch* placements and less sensitive to the *Credit Watch* placements themselves.

Hypothesis 2: There is no statistical difference over the four time periods for the absolute value of the market reaction to trigger events and *Credit Watch* placements.

To test this hypothesis, each trigger event and subsequent *Credit Watch* placement is classified by the implication of the *Credit Watch* placement; positive, negative. There is an insufficient number of *Credit Watch* placements with a developing implication to construct a third group. For both groups, positive and negative implication *Credit Watch* placements, a one factor, four level ANOVA procedure is performed. The single factor is the absolute value of the abnormal return computed around the *Credit Watch* placement announcement date minus the absolute value of abnormal return computed around the trigger event listed by Standard & Poor's as having caused the placement. The measure of the differential market reaction between placement and trigger event is denoted as $|AR_{p,i}|-|AR_{t,i}|$ where $AR_{p,i}$ is the abnormal return for firm *i* measured around the *Credit Watch* placement announcement date and $AR_{p,i}$ is the abnormal return measured around the trigger event announcement date.

The reason for using the difference of the absolute values of the abnormal returns around the trigger event and placement is due to the sign of the difference providing an inconsistent measure of the relative strengths of the two abnormal returns. When subtracting the two abnormal returns without taking their absolute values, four outcomes are possible. Let "P" denote the abnormal return around the placement date and "T" denote the abnormal return around the trigger date.

Case	Placement - Trigger	Result
1	(-) - (-)	If P>T, then P-T is positive.

		If T>P, then P-T is negative.
2	(+) - (-)	P>T, and P-T is positive.
3	(+) - (+)	If P>T, then P-T is positive. If T>P, then P-T is negative.
4	(-) - (+)	T>P and P-T is negative.

In case 1, where the sign of both the placement and trigger event abnormal returns is negative, if P>T there is a stronger negative market reaction to the trigger event and a less negative reaction to the placement and the sign of the difference is positive.

Also, in case 1, if T>P there is a stronger negative market reaction to the placement and a less negative market reaction to the trigger event and the sign of their difference is negative.

In case 3, where the sign of both the placement and trigger event abnormal returns is positive, if P>T there is a stronger positive market reaction to the placement and a lesser positive reaction to the trigger event and their difference is positive.

Also in case 3, if T>P there is a stronger positive market reaction to the trigger event and a lesser positive market reaction to the placement and the sign of their difference is negative.

The problem is as follows: In case 1 when P>T the market has reacted more negatively (strongly) to the trigger event than the placement and the sign of the measure of their difference is positive. In case 3 when T>P the market has reacted more positively (strongly) to the trigger than the placement and the sign of the measure of their difference is negative.

In each of these cases, the market has reacted more strongly to the trigger event than the placement. However, due to the signs of the abnormal return, while the relative strengths of market reaction to the trigger event and placement are identical, the measure of their relative strengths yields opposite signs.

The reverse is also true between cases 1 and 3. In case 1 when T>P the market has reacted more negatively (strongly) to the placement than to the trigger event and the sign of the measure of their difference is negative. In case 3 when P>T the market has reacted more positively (strongly) to the placement than to the trigger event and the sign of the measure of their difference is positive.

In each of these cases, the market has reacted more strongly to the placement than the trigger event. However, due to the signs of the abnormal return, while the relative strengths of the market reaction to the trigger event and placement are identical, the signs of the measure of their relative strengths yield opposite signs.

Furthermore, measures of relative market reaction computed in cases 2 and 4 also provide an incorrect measure. For example, in case 2, if the placement return was +3% and the trigger event return was -7% the sign of the measure of their difference would be positive regardless of the relative strengths of the market reaction in absolute value terms as the sign of the difference for case 2 will always be positive.

For case 4 the same problem holds in that the sign of the measure of difference in abnormal returns is always negative regardless of the relative strengths of the market reaction in absolute value terms.

A solution to this problem is to take the absolute value of the abnormal return for the trigger event and placement and then take their difference as the measure of the relative strength of the market reaction. Such a method indicates to which event there was a larger market reaction and consistently evaluates their relative strengths.

The observations are grouped into four levels based on the year in which the trigger event and placement occurred. The four levels are as follows:

Level 1: 1981-1984

Level 2: 1985-1987

Level 3: 1988-1990

Level 4: 1991-1993

The levels are segmented to maximize the likelihood that there will be approximately an equal number of observations in each level in addition to providing equal temporal segmentation. The years 1987 and 1988 are among the years containing the largest number of placements and are thus assigned to different levels. November and December of 1981 are included in the first level as there are relatively fewer placements in the early years of *Credit Watch*.

The null hypothesis states that there is no difference in the means of the four levels. If the market has learned to recognize and react to firm specific trigger events which ultimately result in a firm being placed on *Credit Watch*, then one would expect the mean of $|AR_{P,i}|-|AR_{T,i}|$ to be highest for the first level and decreasing in levels two, three and four. That is, for the first level, the market reaction around the first level is larger than the reaction to the trigger event and thus a positive measure of their difference. If the market has learned to recognize and react to trigger events which cause placements, one would expect the reaction to trigger events relative to placements to increase and thus the measure of their differences to decrease and possibly become negative.

Methodology

Computation of Abnormal Returns Using the SIMM

The EVENTUS SAS macro computes abnormal returns over a specified time period using the Single Index Market Model (SIMM) to calculate the bench mark return. EVENTUS will be utilized in essays two, and three.

In essay three, the "TWIN" function is used to compute the cumulative abnormal returns between two event dates for a given firm. The cumulative abnormal return for each firm placed on *Credit Watch* with a negative implication will be computed from the day after the trigger event until 2 days after the *Credit Watch* placement. This will represent the cumulative abnormal return from taking a short position in the common stock of the firm beginning the day after the trigger event and ending 2 days after the *Credit Watch* placement date. Essay two and three, will use standard event study methodology to compute abnormal returns over an event window centered around the trigger event and the subsequent *Credit Watch* placement date. A comparison will be made of relative abnormal returns between those associated with the trigger event and those associated with the subsequent *Credit Watch* placement beginning with the inception of *Credit Watch* and ending with December 1993. The market may have learned to perceive the information content of trigger events relative to *Credit Watch* placements differently as the market has had an opportunity to observe the types of trigger events that appear to result in a *Credit Watch* placement with negative implications. If the abnormal returns around the *Credit Watch* placement are monotonically decreasing through time and the returns around the prior trigger event are increasing through time, this may be an indication of the market learning to identify which types of trigger events are significant.

Essay three will use standard event study methodology to compute abnormal returns over an event window centered around *Credit Watch* placement dates and the subsequent rating change announcements. Tests will be conducted to determine if the relative stock price reaction between the two event dates is a function of the trigger event which caused the *Credit Watch* placement, the amount of firm specific information available to the market, the level of market uncertainty, the industry in which a firm operates and the elapsed time between the *Credit Watch* placement and the subsequent rating change.

The EVENTUS manual for version 6.0 is used in describing the technical aspects of the methodology for this section.

The single index market model assumes that the return of any security can be described by a single factor, the return of the market, which is defined as:

$$R_{jt}=\alpha_j+\beta_j R_{mt}+\epsilon_{jt},$$

where R_{jt} is defined as the rate of return on the common stock of the j^{th} firm measured on day t. R_{mt} is defined as the market return on day t and ϵ_{jt} is defined as a random variable with an expected value of zero and is assumed to be un-correlated with the market return. No autocorrelation with past or future returns along with a condition of homoskedasticity is assumed. β is defined as a parameter which measures the sensitivity or R_{jt} to the market index. α_j is defined as the constant of the regression equation. α_j and β are estimated over a pre-event estimation period by regressing the return of stock j on the market return. The abnormal return or prediction error for the j^{th} firm on day t is defined as:

$$PE_{jt}=R_{jt}-(\hat{\alpha}_j+\hat{\beta}_j R_{mt})$$

$\hat{\alpha}_j$ and $\hat{\beta}_j$ are the ordinary least squares regression estimates of α_j and β_j respectively.

The average abnormal return, or average prediction error denoted by APE_t is the sample mean defined as:

$$APE_t=\frac{\sum_{j=1}^{N} PE_{jt}}{N}.$$

The subscript t refers to the trading day relative to the event date. The average abnormal return on a given day t is the average of the sum of firm specific abnormal returns for a given trading day t. The average abnormal return for all firms in a sample on a given trading day can be computed and compared to other days around the event to determine on which day(s) they experience a price adjustment due to the information content of a firm specific announcement. For example, the average prediction error for all firms in the sample four trading days prior to the event date is denoted as APE_{t-4}.

Essay three will use the cumulative average abnormal return of firms in the sample over a period beginning with day T_1 and ending with day T_2 which is defined as:

$$CAPE_{T_1,T_2}=\frac{1}{N}\sum_{j=1}^{N}\sum_{t=T_1}^{T_2}PE_{jt}$$

EVENTUS computes abnormal return test statistics for abnormal returns computed using the SIMM model using the standardized abnormal return model.

Essays two and three will estimate abnormal returns around specific event dates. For standard single day event studies, EVENTUS computes a test statistic using standardized abnormal returns following the work of Patell (1976). The null hypothesis states that each PE_{jt} has mean zero and a variance of $\sigma^2_{PE_{jt}}$. The maximum likelihood estimate for the variance of prediction errors is defined as:

$$S^2_{PE_{jt}}=S^2_{PE_j}\left[1+\frac{1}{D_j}+\frac{(R_{mt}-\overline{R}_m)^2}{\sum_{k=1}^{D_j}(R_{mk}-\overline{R}_m)^2}\right].$$

Define $S^2_{PE_j}$ as:

$$S^2_{PE_j}=\frac{\sum_{k=1}^{D_j}PE^2_{jk}}{D_j-2},$$

where R_{mt} is defined as the market return observed on day t, $\overline{R}_m$ denotes the mean market return over the estimation period and D_j is the number of trading day returns that are not missing which are used to estimate parameters for firm j. The standardized abnormal return is defined as:

$$SPE_{jt}=\frac{PE_{jt}}{S_{PE_{jt}}}.$$

Assuming the null hypothesis is true, each PE_{jt} follows a student's t distribution with D_j-2 degrees of freedom. The t statistic of the standard prediction errors of all firms is found by summing across all firms in the sample:

$$TSPE_t=\sum_{j=1}^{N} SPE_{jt}.$$

The expected value of the t statistic of the total standard prediction errors is zero while the variance of $TSPE_{jt}$ is defined as:

$$Q_t=\sum_{j=1}^{N} \frac{D_j-2}{D_j-4}.$$

The test statistic for cumulative abnormal returns over an event window is defined as:

$$Z_{T_1,T_2}=\frac{1}{\sqrt{N}}\sum_{j=1}^{N} Z_{T_1,T_2}^{j},$$

Where:

$$Z_{T_1,T_2}^{j}=\frac{1}{\sqrt{Q_{T_1,T_2}^{j}}}\sum_{t=T_1}^{T_2} SPE_{jt}$$

and

$$Q_{T_1,T_2}^{j}=(T_2-T_1+1)\,\frac{D_j-2}{D_j-4}$$

assuming $Z^{j}_{T_1,T_2}$ is cross-sectionally independent then $Z^{j}_{T_1,T_2}$ under the null hypothesis follows the standard normal distribution.

Essays two and three compare the relative level of abnormal returns between two event dates for a given firm. A further statistical test to calculate the significance of the difference in these two abnormal returns will be performed.

Essay three uses the "TWIN" EVENTUS function to compute cumulative abnormal returns between two event dates where the number of trading days varies across firms. The cumulative abnormal return for firm j is defined as:

$$CPE_{T_{1j},T_{2j}}=\sum_{t=T_{1j}}^{T_{2j}} PE_{jt}$$

The Z statistic used for testing the significance of the $CPE_{T_{1j},T_{2j}}$ is defined as:

$$Z_j=\frac{\sum_{t=T_{1j}}^{T_{2j}} SPE_{jt}}{\sqrt{(T_{2j}-T_{1j}+1)\frac{D_j-2}{D_j-4}}}.$$

Assuming time-series and cross-sectional independence, the test statistic for the cumulative average prediction error for the cumulative prediction errors between event dates T_1 and T_2 defined as:

$$CAPE=\sum_{j=1}^{N} CPE_{T_{1j},T_{2j}}$$

is:

$$Z_{CAPE}=\sqrt{N}\sum_{j=1}^{N} Z_j .$$

One Way ANOVA Model

A one way ANOVA model for comparing more than two means is used in the second essay. The model is used to test whether the level of the factor (the specific years in which a *Credit Watch* occurred) affects the measured observations (the absolute value of the abnormal returns measured around the *Credit Watch* placement minus the absolute value of the abnormal returns measured around the trigger events).

Specifically, the ANOVA will test the null hypothesis:

H_o: $\mu_1 = \mu_2 = \ldots = \mu_k$

H_a: not all the μ's are equal.

The ANOVA model has the following assumptions:

1. Observations are obtained randomly and independently from each of the populations. The value of one observation in a given group does not affect the value of other observations within the same group or within other groups.
2. The observations from each population approximately

follow a normal distribution.

3. There is a common variance for each population.

The four groups of differential abnormal returns are configured as follows:

<u>Group 1</u>	<u>Group 2</u>	<u>Group 3</u>	<u>Group 4</u>	
.	.	.	.	
.	.	.	.	
.	.	.	.	
n_1 obs.	n_2 obs.	n_3 obs.	n_4 obs.	
.	.	.	.	
.	.	.	.	
.	.	.	.	
T_1	T_2	T_3	T_4	Totals

Let T equal the sum of T_1 through T_4.

Note that in essay two, the number of observations varies across groups.

The sum of squares (SS) factor which measures between-sample variation is calculated as:

$$SS(factor) = \left[\frac{T_2^1}{n_1} + \frac{T_2^2}{n_2} + \frac{T_3^3}{n_3} + \frac{T_4^4}{n_4}\right] - \frac{T^2}{n}$$

The sum of squares (SS) total measures the within sample variation and is defined as:

SS(total) = SS(factor) + SS(error)

Or more formally defined:

$$SS(total) = \Sigma x^2 - \frac{T^2}{n},$$

where $T = \Sigma x = T_1 + T_2 + T_3 \;\; T_4$ = sum of all observations and Σx^2 is found by squaring each observation then summing them.

The sum of squares (SS) error measures the within sample variation and is defined as SS(total) - SS(factor). More formally:

$$SS(err) = \Sigma x^2 - \left[\frac{T_1^2}{n_1} + \frac{T_2^2}{n_2} + \frac{T_3^2}{n_3} + \frac{T_4^2}{n_4}\right].$$

The mean square (MS) factor is defined as:

$$MS(factor) = \frac{SS(factor)}{df\ for\ factor},$$

where the degrees of freedom equal k-1 with k being the number of levels (4).

The mean square (MS) error is defined as:

$$MS(error) = \frac{SS(error)}{df\ for\ error},$$

where the degrees of freedom equal n-k with n being the number of observations in all levels (305).

The test statistic for testing the null is:

$$F = \frac{MS(factor)}{MS(error)}$$

which has an F distribution with k-1 and n-k degrees of freedom.

Bartlett Chi-square Test for Unequal Variances

The Bartlett test is a test for unequal variances across groups. The null hypothesis for essay two is that variances of the difference in the absolute value of abnormal returns are equal, stated as follows:

H_o: $\sigma^2{}_1 = \sigma^2{}_2 = \sigma^2{}_3 = \sigma^2{}_4$

H_A: H_o is not true.

The test statistics are as follows:

$$\frac{-4.60517 \log M}{1+N} \sim \chi^2_{m-1}$$

where

$$\log M = \frac{\sum (n_i - 1)}{2} \log S_i^2 - \frac{n-m}{2} \log \frac{\sum (n_1 - 1) s_i^2}{n-m};$$

$$N = \frac{\sum (1/n_i) - (1/n)}{3(m-1)};$$

and

$$S_i^2 = \frac{\sum (y_{ij} - \overline{Y}_i)^2}{n_i - 1} \qquad (i=1,2,\ldots,m; j=1,2,\ldots,n_i).$$

In this case n_i would denote the number of observations in each of the four groups and m would denote the number of groups (4). s_i^2 denotes the sample variance across groups.

Tukey Honest Squares Difference Test for Unequal Sample Sizes

The Tukey HSD test for unequal sample sizes is an extension of the Tukey test for equal sample sizes. This test is used to test for significant differences in the means across the four groups. The test statistic for this method is computed as follows:

$$Q = \frac{\overline{X}_i - \overline{X}_k}{\sqrt{MS_w\left(\frac{1/n_i + 1/n_k}{2}\right)}},$$

where the numerator is the difference in the two means that are being compared, MS_W is the means square error of the ANOVA and terms n_i and n_k are the number of observations in groups i and k respectively.

The null hypothesis for the test is:

H_o: $\mu_i = \mu_k$ for $i \neq k$

The test statistic uses the studentized range (Q) distributions rather than the t distribution for the sampling distribution. The test statistic will give a significance test for the null hypothesis that the means of two given groups are different.

Kruskal-Wallis ANOVA by Ranks

The Kruskal-Wallis test is the nonparametric counterpart to the one-way ANOVA model. The test may be used if the assumptions of normality and/or equal variance of the ANOVA model are violated. For the Kruskal-Wallis test, the assumption of normality is not necessary and is less sensitive to violations of the equal variance assumption. The assumptions of the test are as follows:

1. Random samples are obtained from each of the k populations.
2. Each sample is obtained independently.
3. Observations in each sample can be ranked.

The null hypothesis is:

H_o: the k populations have identical probability distributions.

H_a: at least two of the populations differ in location.

The test is conducted using essay two by denoting the sample size of each group as n_1, n_2, n_3, and n_4 where $n = n_1 + n_2 + n_3 + n_4$. The samples are then pooled and arranged in order with a ranking assigned to each observation with an average rank assigned to tied positions. Define T_i as the total of the ranks from the i'th sample. The Kruskal-Wallis test statistic is then defined as:

$$KW = \frac{12}{n(n+1)}\sum_{i=1}^{k}\frac{T_i^2}{n_i}-3(n+1)$$

The KW statistic approximately follows a chi-square distribution with k-1 (4-1) degrees of freedom.

Sample Description

Essay two uses all non-municipal *Credit Watch* placements obtained from the inception of *Credit Watch* through the end of 1993.

The event dates for *Credit Watch* placements are taken to be the earlier of the following three possible dates: The publication date of the *Credit Watch* issue in which the placement was announced, *Wall Street Journal* publication date in which the placement was announced or the date of the news service wire report as found in the *NEXIS* database.

The event dates for the trigger events are taken to be the earlier of the following two possible dates: The *Wall Street Journal* publication date in which the placement was announced or the date of the news service wire report announcing the trigger event as found in the *NEXIS* database.

A clean event window of (-2,+1) around both the *Credit Watch* placement and trigger event dates was obtained using the *Wall Street Journal Index*. A firm was eliminated from the sample if a substantive announcement regarding the firm was found within two days prior through one day after either the placement or trigger date.

Firms in the sample must be listed on either the NYSE/AMEX or NASDAQ CRSP tapes during the event windows and estimation period. For wholly owned subsidiaries placed on *Credit Watch*, the returns of the parent company are used.

Credit Watch placements with a developing implication were deleted from the sample as it is unclear whether or not there should be a market reaction to these announcements. Furthermore, the number of *Credit Watch* placements with developing placements is substantially smaller than the number of positive or negative placements. The number of developing placements for each year are listed in table 10.

Table 10. *Credit Watch* Placements with Developing Implications Preceded by a Trigger Event

Year	*Credit Watch* Placements with Developing Implications
1981-1982	5
1983	10
1984	6
1985	11
1986	12
1987	14
1988	14
1989	14
1990	11
1991	2
1992	7
1993	4

A description of sample deletions for both positive and negative implication *Credit Watch* placements are summarized in tables 11, 12 and 13.

Table 11. *Credit Watch* Placements with Positive Implications Preceded by a Trigger Event

Year	Initial Sample	Contaminated Event Dates	Final Sample
1981-82	8	6	2
1983	19	9	10
1984	14	8	6
Group 1	41	23	18
1985	24	8	16
1986	19	10	9
1987	35	14	21
Group 2	78	32	46
1988	37	25	12
1989	35	26	9
1990	18	15	3
Group 3	90	66	24
1991	25	19	6
1992	32	17	15
1993	48	34	14
Group 4	105	70	35
Total All Years	314	191	123

Table 12. *Credit Watch* Placements with Negative Implications Preceded by a Trigger Event

Year	Initial Sample	Contaminated Event Dates	Final Sample
1981-82	71	38	33
1983	58	22	36
1984	69	45	24
Group 1	198	105	93
1985	120	73	47
1986	124	89	35
1987	93	56	37
Group 2	337	218	119
1988	116	90	26
1989	90	74	16
1990	62	48	14
Group 3	268	212	56
1991	45	35	10
1992	44	130	14
1993	57	41	16
Group 4	146	106	40
Total All Years	949	641	308

Table 13. *Credit Watch* Placements with Positive and Negative Implications Preceded by a Trigger Event

Year	Initial Sample	Contaminated Event Dates	Final Sample
1981-82	79	44	35
1983	77	31	46
1984	83	53	30
Group 1	239	128	111
1985	144	81	63
1986	143	99	44
1987	128	70	58
Group 2	415	250	165
1988	153	115	38
1989	125	100	25
1990	80	63	17
Group 3	358	278	80
1991	70	54	16
1992	76	47	29
1993	105	75	30
Group 4	251	176	75
Total All Years	1,263	832	431

Note: Columns denoting groups one through four contain the sum total of the items in a column for the years of *Credit Watch* placements in that group.

Results

Abnormal returns using the market model, standardized residual method with a value weighted index are reported in table 14.

Table 14. Abnormal Returns for Positive and Negative Implication Credit Watch Placements and Trigger Events; 1981-1993

Group	Trigger Event Implication	Median Cumulative Abnormal Return Trigger Events	Z Score	Placement Implication	Median Cumulative Abnormal Return Placements	Z Score
All Groups	Negative	-.01%	-18.99***	Negative	-.49%	-3.06**
All Groups	Positive	2.08%	18.91***	Positive	-.05%	-1.53$

Note: $ = .10 significance, * = .05 significance, ** = .01 significance, *** = .001 significance

The results summarized in table 14 suggest that overall the market does react more strongly to trigger events than to the subsequent *Credit Watch* placement. Table 15 reports the market reaction to trigger events and *Credit Watch* placements across time.

Table 15. Abnormal Returns for Positive and Negative Implication Credit Watch Placements and Trigger Events Categorized by Year Groupings

Group	Trigger Event Implication	Median Cumulative Abnormal Return Trigger Events	Z Score	Placement Implication	Median Cumulative Abnormal Return Placements	Z Score
1	Negative	-.62%	-7.85***	Negative	-.33%	-1.73*
1	Positive	2.95%	4.29***	Positive	.2%	.11
2	Negative	.47%	18.67***	Negative	-.41%	-.66
2	Positive	2.2%	13.57***	Positive	-.17%	-.49
3	Negative	.55%	11.73***	Negative	-.67%	-1.2
3	Positive	6.88%	15.71***	Positive	.14%	.87
4	Negative	-.28%	-3.52***	Negative	-1.28%	-6.29***
4	Positive	.78%	3.7***	Positive	-.52%	-2.64**

Note: $ = .10 significance, * = .05 significance, ** = .01 significance, *** = .001 significance

The positive *Credit Watch* placement firms are dropped from the study at this point for three reasons. First, the size of the positive placements sample is relatively small compared to that of the negative placements. Second, whereas the overall significance of the abnormal returns calculated around the trigger events preceding the positive implication placements is significant, the overall significance for the placement date is significant only at the 10% level. Finally, previous studies have indicated that although the market reacts significantly to negative placements, there is no or very little reaction to positive placements.

Continuing with the analysis of the negative placements and trigger events, the test statistics for the normality of the distribution of the difference in the absolute value of the placement abnormal returns and the trigger event abnormal returns are reported as follows: Examining the normality of all groups combined using a Kolmogorov-Smirnov test, d=.12171 with p<.01.

Table 16 reports the normality of each group.

Table 16. Normality of Groups One through Four

Group	Chi-Square	Degrees of Freedom	P-Value
Group 1 (1981-1984)	33.479	3	.0000
Group 2 (1985-1987)	20.784	3	.0001
Group 3 (1988-1990)	18.107	3	.0004
Group 4 (1990-1993)	26.194	3	.0000

There is evidence that the assumption of normality is violated in the data. Histograms of the data distribution for each group and the total are included in the appendix. However, Lindman (1974) shows that the F statistic is quite robust against violations of the normality assumption. Furthermore, if the sample size for each group is relatively large, then deviations from the normal distribution are less important as the *central limit theorem* applies.

An additional assumption of the ANOVA model is that of equal variances across groups. Because the sample sizes of the groups are unequal, a Bartlett chi-square test is used yielding a value of 26.90536 with a p-value of .000006. Thus the null hypothesis of equal variances across groups is rejected violating one of the assumptions for the ANOVA model. Lindman (1974) shows that the F statistic for the ANOVA model is fairly robust against violations of this assumption. A special case, however, which may serve to bias the F statistic upwards is a situation where the means and standard deviations are correlated across groups. In this case, as the means of the difference in abnormal returns increases so does the standard deviation. The correlation between the two measures is .68527.

Because the means and standard deviations are correlated, the F statistic may be biased upward. As will be discussed later, this violation of the ANOVA assumptions may be sufficient to cast doubt on the significance of the results.

The means and variances of the difference in the absolute values of each group and the total are reported in table 17.

Table 17. Mean and Variance of Groups One through Four

Group	Mean	Variance	Sample Size
Group 1 (1981-1984)	-3.22411%	7.97672%	90
Group 2 (1985-1987)	-3.61765%	10.41971%	119
Group 3 (1988-1990)	-2.72214%	13.57002%	56
Group 4 (1991-1993)	.67450%	14.12604%	40
Total All Groups (1981-1993)	-2.77420%	11.02676%	305

The ANOVA model is a simple one factor, four level design with the factor being the difference in the absolute value of the abnormal returns measured around the *Credit Watch* placement and the trigger event listed as having caused the placement. The four levels are the factors grouped by the years in which the *Credit Watch* placement occurred described previously. The ANOVA regression tests for a difference in means across groups or levels. The computed F statistic is 1.596003 with a p-level of .190384. The null hypothesis that the means of all four groups are equal is rejected at the 20% level. A graphical representation plotting the means of the groups against the group number in included in the appendix.

Although there is relatively weak evidence that there exists a difference in means across the four groups, a Tukey Honest Significant Difference (HSD) Test for unequal sample sizes is run. The test is a generalization of the Tukey HSD test listed in table 18 where the p-values for significance of differences between groups are listed in the cells:

Table 18. Tukey Honest Significance Difference Test for Groups One through Four

	Group 1	Group 2	Group 3	Group 4
Group 1		.995136	.995047	.386711
Group 2	.995136		.973171	.299919
Group 3	.995047	.913171		.510893
Group 4	.386711	.299919	.510893	
Group Means	3.22411%	-3.61765%	-2.72214%	.6745000%

Note that the means of groups two and four are different at the 30% level while the means of groups one and four are different at the 40% level.

As noted earlier, the data may violate the ANOVA assumption of homogeneity of variance across groups. An additional non-parametric test is run in an attempt to circumvent this assumption.

The Kruskal-Wallis ANOVA by Ranks test assumes that the dependent variable is continuous and measurable on an ordinal scale. The test assesses the hypothesis that each sample being compared was drawn from either the same distribution or from distributions with the same mean. The interpretation of this test is basically identical to the parametric one-way ANOVA with the exception that the Kruskal-Wallis uses ranks whereas the other uses means. The Chi-square value for the test is 3.934769 with a p-value of .2686 yielding a significance level of approximately 30%.

Discussion of Results

The results for essay two show that for all groups of firms representing *Credit Watch* placements from 1981-1993, the market reacts more strongly to trigger events than to subsequent *Credit Watch* placements. However, the market reaction around the positive implication placement announcement dates is marginally significant, a result consistent with the literature. These results provide additional evidence regarding the market reaction to *Credit Watch* related events. Earlier papers on bond rating changes found a significant stock price reaction to the announcement of bond rating changes. With the inception of *Credit Watch*, later papers such as Wansley and Clauretie (1985) found a stronger reaction to the announcement of the *Credit Watch* than to the bond rating change announcement. Finally, these results suggest that the market reacts even more strongly to the trigger events which cause *Credit Watch* placements than the actual placements.

In testing for the difference in means across the four groups, the ANOVA model yields a significance level of 20% while the non-parametric Kruskal-Wallis test gives a significance level of approximately 30%. The statistical strengths of these results are weak at best. However, an overall interpretation can perhaps be made. Recall that the dependent variable is the absolute value of the abnormal return around the *Credit Watch* placement minus the absolute value of the abnormal return around the trigger event which caused the placement. Therefore, a negative value would suggest a stronger reaction to the trigger event whereas a positive value would suggest a stronger reaction to the *Credit Watch* placement.

In looking at the means of the four groups, the mean of group one is negative -3.22411% followed by the mean of group two which has a value of -3.61765%. This suggests that in the years 1981-1984 the market responded more strongly to the trigger event than to the placement whereas during the years of 1985-1987 the market began to respond less strongly to the trigger event and more strongly to the placement. The means of groups three and four are -2.72214% and .6745% respectively. This suggests that the market continued to react less strongly to the triggers and more strongly to the placements with the passage of time for the years 1988-1993.

In terms of the statistical significance of the differences using the Tukey HSD for unequal sample sizes, groups two and four differ at the 30% level whereas groups one and four differ at the 40% level. This relatively weak evidence suggests that in general over a longer time span, the market tended to react more strongly to *Credit Watch* placements than to trigger events for the period of 1991-1993 than for the period of 1981-1987.

This result is counter-intuitive as, *a priori*, one would expect the dependent variable to become more negative with the passage of time as the market learns to identify trigger events which are associated with *Credit Watch* placements responding more strongly to the trigger events. However, the results show weak evidence to the contrary. These results may be explained in several ways. First, if one dismisses the ANOVA and Kruskal-Wallis results as being insignificant in the first place, then this would suggest that market simply reacts to each event (trigger and placement) evaluating the impact of the news on stock price. The market may react to the news contained in the trigger event independently of the reaction to the placement.

A second explanation could be that in the earlier years of *Credit Watch* the ratio of placements to trigger events was relatively high for firms eligible for a *Credit Watch* placement. In this case, the market could perhaps associate many types of trigger events to a subsequent placement quite easily as a large number of trigger events actually resulted in a placement. Thus, the market may easily infer the additional information regarding the firm in a given trigger event because many similar trigger events landed other firms on *Credit Watch*. If as time progressed, the number of trigger events reported for firms eligible for *Credit Watch* placement grew at a faster rate than actual placements, the market may have begun to respond less to the trigger event as it became less clear to which types of trigger events

Standard & Poor's paid attention. This explanation may account for the relative increase in the market reaction to negative *Credit Watch* placements over time.

CHAPTER V

ESSAY THREE

Theoretical Motivation

Standard & Poor's claim that they have access to privileged information concerning the companies they investigate. If this is the case, Standard & Poor's may have insight into the implications of a particular firm-specific trigger event which occurs for a firm that may allow them to infer a better estimate of the firm's new default risk than can be estimated by the market. One way in which to signal this insight is through a *Credit Watch* placement.

Wansley and Clauretie (1985) find significant negative abnormal returns on the date that Standard & Poor's announced a downgrade of a firm's bonds. However, no such reaction was found for firms whose downgrade was preceded by a *Credit Watch* placement. This may imply that the market considers a *Credit Watch* placement to be a signal of a possible change in the true default risk of the firm. There may be other instances where the market reacts to the *Credit Watch* placement to a lesser extent, instead relying more on the news of the subsequent bond rating decision. This previous study found that over a certain period, November 1981 - December 1983, the market reacted more strongly to

Credit Watch placements relative to the announcement of the bond rating decision. The authors do not attempt to determine the relationship between the relative strength of the market reaction to *Credit Watch* placements and bond rating decisions.

Essay three tests to determine the pattern of market reactions for firms which experience a *Credit Watch* addition and removal along with the factors which may influence the relative strength of the abnormal return around the *Credit Watch* removal announcement date. This essay attempts to answer the question of under what conditions, both economy wide and firm specific, does the market pay more or less attention to the announcement of a *Credit Watch* removal.

A priori I, expect for positive implications a positive abnormal return around the *Credit Watch* placement and removal announcement dates as a positive implication implies there is a higher probability of a eventual ratings upgrade and the majority of *Credit Watch* removals preceded by a positive placement result in ratings upgrades. Conversely, for placements with a negative implication I expect a negative abnormal return around the placement and removal dates as a negative implication implies there is a higher probability of a eventual ratings downgrade and the majority of *Credit Watch* removals preceded by negative placements result in ratings downgrades.

I hypothesize for positive implication placements that there is a negative relationship between the relative strengths of the market reaction to the placement and removal. That is, if a relatively large (small) positive abnormal return is observed around the placement announcement date a relatively small (large) positive abnormal return would expected to be observed around the removal announcement date.

I hypothesize for negative implication placements that there is a positive relationship between the relative strengths of the market reaction to the placement and removal. That is, if a relatively large (small) negative abnormal return is observed around the placement announcement date a relatively small (large) negative abnormal return would be observed around the removal announcement date.

The strength of the abnormal return on the removal announcement date may be a function of market attributes, firm specific attributes and the time between *Credit Watch* placement and the rating decision announcement. Firms are segmented according to the implication assigned to the *Credit Watch* placement by Standard & Poor's; either positive, negative or developing.

Hsueh and Liu (1992) in their study on bond rating changes hypothesize that the market reaction to a bond rating change for a given firm may be a function of the information available to the market for that individual firm. They define high information firms as having a relatively low level of equity dispersion. It is thought that if large blocks of a firm's common stock are held by a small number of shareholders, there will be more information available to the market regarding these firms as shareholders have an incentive to investigate the firm and closely monitor managers. They define low information firms as having a relatively high level of equity dispersion. It is thought that for firms whose stock is held in smaller amounts by a relatively large number of shareholders there will be less information available to the market as it is costly for shareholders to collectively investigate the firm and monitor managers actions.

The level of equity dispersion as measured by the ratio of total number of common shares outstanding to number of shareholders may have an impact on the strength of the removal return. High information firms may experience a relatively small market reaction to *Credit Watch* announcements as shareholders have more closely investigated the implication of the placement and any subsequently released information regarding the default risk of the firm. Thus the implication of the trigger event would already be impounded into the stock price at the time of the *Credit Watch* removal. Low information firms may experience a relatively large market reaction upon the announcement of the removal as the implications of the trigger event, *Credit*

Watch placement, and subsequently released information are more uncertain due to the relatively lesser amount of information available to the market concerning the firm.

I hypothesize that for positive implication placements there is a negative relationship between equity dispersion and the abnormal return measured around the *Credit Watch* removal date. That is, for firms with a relatively high (low) equity dispersion ratio (a high information firm with a relatively large number of shares per shareholder) the removal return will be less (more) positive.

For firms with negative implication placements, I hypothesize a positive relationship between equity dispersion and the abnormal return around the removal announcement date. That is, for firms with a relatively high (low) equity dispersion ratio the removal return is expected to be less (more) negative.

The market reaction to the removal announcement may also be a function of the degree of market uncertainty which exists during the time period spanned between *Credit Watch* placement and removal. Hsueh and Liu (1992) looked at the reaction to bond rating changes taking into account overall market uncertainty proxied by the volatility of market interest rates. The period of 1985-1987 was characterized as a period of relatively low market interest rate volatility therefore the level of market uncertainty during this period is taken to be low. Conversely, the period of

1982-1984 was characterized as a period of relatively high market interest rate volatility therefore the level of market uncertainty during this period is said to be high. I hypothesize that the market reaction to *Credit Watch* removals will be stronger for the period 1982-1984 as the relative importance of the information contained in the *Credit Watch* removal which resolves the uncertainty raised by the *Credit Watch* placement is greater.

For *Credit Watch* placements with positive implications I hypothesize that there is a positive relationship between the level of market uncertainty and the abnormal return measured around the *Credit Watch* removal date. That is, for periods of high (low) market uncertainty there is a greater (lesser) positive abnormal return around the removal announcement date.

For *Credit Watch* placements with negative implications I hypothesize that there is a negative relationship between the level of market uncertainty and the abnormal return measured around the *Credit Watch* removal date. That is, for periods of high (low) market uncertainty there is a greater (lesser) negative abnormal around the removal announcement date.

The strength of the removal return may be dependent upon the length of time between the *Credit Watch* placement and the eventual rating change announcement. The number of trading days which a firm remains on *Credit Watch* may serve as a proxy for information leakage. That is, as the time period over which a firm remains on *Credit Watch* a greater amount of information may be released to the market which further resolves the uncertainty raised by the *Credit Watch* placement. Therefore the strength of the abnormal return around the removal announcement date will be diminished the longer firm remains on *Credit Watch*.

For *Credit Watch* placements with positive implications I hypothesize that there is a negative relationship between the number of trading days a firm remains on *Credit Watch* and the abnormal return around the *Credit Watch* removal. That is, the greater (fewer) number of days a firm remains on *Credit Watch* the less (more) positive the abnormal return around the removal announcement date.

For *Credit Watch* with negative implications I hypothesize that there is a positive relationship between the number of trading days a firm remains on *Credit Watch* and the abnormal return around the *Credit Watch* removal announcement date. That is, the greater (fewer) number of days a firm remains on *Credit Watch* the less (more) negative the abnormal return around the removal announcement date.

A further measure of the market reaction to information regarding the firm is the cumulative abnormal return measured between the *Credit Watch* placement date and removal date. If there is a substantial positive or negative cumulative abnormal return prior to the removal, then there may be little market reaction on the removal announcement date as the market has resolved much of the uncertainty regarding the firm. I hypothesize that if there is an inverse relationship between the cumulative abnormal return measured between the placement to removal dates and the abnormal return measured around the removal date.

For *Credit Watch* placements with positive implications I hypothesize that there is a negative relationship between the cumulative abnormal return placement to removal and the abnormal return around the removal date. That is, the more (less) positive the cumulative return placement to removal the less (more) positive the abnormal return around the removal announcement date.

For *Credit Watch* placements with negative implications I hypothesize that there is a positive relationship between the cumulative abnormal return placement to removal and the abnormal return around the removal date. That is, the more (less) negative the cumulative return placement to removal the less (more) negative the abnormal return around the removal announcement date.

Finally, in some instances, Standard & Poor's will publish updates regarding specific firms during the time period between the placement and removal. Updates may mitigate the market reaction around the removal date as market uncertainty is partially removed by the information contained in the updates.

I hypothesize that the larger the number of updates the lesser the strength of the removal return.

For *Credit Watch* placements with positive implications I hypothesize that there is a negative relationship between the number of updates and the abnormal return around the *Credit Watch* removal date. That is, the larger (fewer) the number of updates the less (more) positive the abnormal return around the *Credit Watch* removal announcement date.

For *Credit Watch* placements with negative implications I hypothesize that there is a positive relationship between the number of updates and the abnormal return around the *Credit Watch*
removal date. That is, the larger (fewer) the number of updates the less (more) negative the abnormal return around the *Credit Watch* removal announcement date.

The measure of market reaction to be used in this paper is abnormal common stock returns. The rationale for using abnormal stock returns is well documented. If the *Credit Watch* placement or bond rating downgrade is unexpected bad news to shareholders, the price of the stock will be bid down resulting in negative abnormal returns.

Hypothesis 3: The level of stock price reaction to *Credit Watch* removals for a specific firm is not dependent on the following factors:

1. The amount of firm specific information available to the market as measured by the degree of equity

ownership dispersion of the firm's common stock.

2. The level of market uncertainty as measured by the relative volatility of market interest rates.
3. The elapsed time between a *Credit Watch* placement and the subsequent rating change.
4. The cumulative abnormal return between the *Credit Watch* placement and the *Credit Watch* removal.
5. The number of updates listed for a firm between placement and removal.
6. The abnormal return measured around the *Credit Watch* placement announcement date.

The OLS regression equation for testing the hypothesis using common stock abnormal returns is specified as follows:

$$R_{cwr,j} = \beta 0 + \beta_1 T_j + \beta_2 D_{1,j} + \beta_3 DISP_j + \beta_4 U_j + \beta_5 R_{cwp,j} + \beta_6 CAR_j + \epsilon_j$$

Where:

$R_{cwr,j}$ = The abnormal return in a (-1,0) event window for the *Credit Watch* removal date measured using standard event study methodology.

T_j = number of trading days between the *Credit Watch* placement and the subsequent rating change.

$D_{1,j}$ = dummy variable for degree of market uncertainty (volatility of market interest rates). $D_{1,j}$=1 if the event is from period of high interest rate volatility (1982-1984), zero otherwise.

$DISP_j$ = a measure of equity dispersion (# of common shares outstanding / # of common shareholders). A higher ratio would indicate a high information firm while a lower ratio would indicate a low information firm.

U_j = The number of updates listed in *Credit Watch* listed for a firm between the placement and removal dates.

$R_{cwp,j}$ = The abnormal return in a (-1,0) event window for the subsequent *Credit Watch* placement date measured using standard event study methodology.

CAR_j = The cumulative abnormal return for each firm between the *Credit Watch* placement and the *Credit Watch* removal.

The estimation period used for $R_{cwr,j}$ begins 46 days after the *Credit Watch* removal announcement date while the estimation period for $R_{cwp,j}$ and CAR_j begins 46 days before the *Credit Watch* placement announcement date. In this way spurious correlation between the right and left hand sides of the regression equation is avoided.

The regression equations is estimated for three groups of firms, positive, negative and developing implications.

Methodology

Essay three uses a standard ordinary least squares regression which is described in the theoretical motivation section of essay three.

Sample Description

Essay three uses all non-municipal *Credit Watch* placements and removals obtained from the inception of *Credit Week* in November 1981 through 1993. The event date for both placements and removals is taken to be the earlier of the following three possible dates: The publication date of the *Credit Watch* issue in which the placement or removal was announced, *Wall Street Journal* publication date in which the placement or removal was announced or the news service wire report as found in the *NEXIS* database. A clean event window of (-2,+1) around the announcement date was obtained using the *Wall Street Journal Index*. A firm was eliminated from the sample if a substantive announcement regarding the firm was found within two days prior through one day after the announcement date. Firms in the sample must be listed on either the NYSE/AMEX or NASDAQ CRSP tapes during the event windows and estimation period. For wholly owned subsidiaries placed on *Credit Watch*, the returns of the parent company are used.

As previously mentioned, firms were eliminated from the sample for various reasons that in some instances are not mutually exclusive. For example, a firm may have been eliminated from the sample due to contaminating events in addition to lack of *Compu-Stat* data. Therefore, the reasons for elimination from the sample are grouped into two categories. Category I is comprised of the firms which were eliminated because there was either no CUSIP number available or no return available over the period spanning the estimation period prior to the *Credit Watch* placement through the estimation period following the *Credit Watch* removal. Note that numerous firms from the year 1993 were eliminated because they were subsequently removed from *Credit Watch* in 1994 and return data on the CRSP tapes was available only through the end of 1993. Thus the study only included firms which were removed from *Credit Watch* prior to the end of 1993.

Category II is comprised of firms which were eliminated because there was either a contaminating event around the *Credit Watch* placement or removal or a lack of Compu-Stat data for number of common shares outstanding or number of common shareholders.

A description of the sample attrition for each year for positive, developing and negative placements is shown in tables 19, 20 and 21.

Table 19. Positive Implication *Credit Watch* Placements

Year	Total Positive Credit Watch Placements	Category I Deletions	Category II Deletions	Final Sample of Positive Credit Watch Placements
1981-1982	38	16	8	14
1983	31	9	13	9
1984	26	11	9	6
1985	29	10	7	12
1986	30	18	8	4
1987	55	23	20	12
1988	70	28	19	23
1989	67	41	11	15
1990	35	26	5	4
1991	69	46	13	10
1992	81	50	4	27
1993	94	77	5	12
Total	625	355	122	148

Table 20. Developing Implication *Credit Watch* Placements

Year	Total Developing Credit Watch Placements	Category I Deletions	Category II Deletions	Final Sample of Developing Credit Watch Placements
1981-1982	9	7	2	0
1983	14	10	3	1
1984	10	6	4	0
1985	14	7	6	1
1986	17	12	3	2
1987	29	22	5	2
1988	31	22	7	2
1989	26	16	5	5
1990	18	10	7	1
1991	13	13	0	0
1992	12	6	2	4
1993	17	17	0	0
Total	210	148	44	18

Table 21. Negative Implication *Credit Watch* Placements

Year	Total Negative Credit Watch Placements	Category I Deletions	Category II Deletions	Final Sample of Negative Credit Watch Placements
1981-1982	159	74	42	43
1983	102	34	50	18
1984	118	47	41	30
1985	155	73	30	52
1986	186	64	86	36
1987	146	66	52	28
1988	197	103	48	46
1989	166	74	66	26
1990	147	62	41	44
1991	163	82	39	42
1992	194	117	29	49
1993	164	142	8	15
Total	1,897	938	532	427

The final sample includes 427 firms placed on *Credit Watch* with a negative implication, 148 with positive implications and 18 with developing implications.

Results

The final sample included 427 instances of *Credit Watch* placements with negative implications, 148 placements with positive implications and 18 placements with developing implications. The final sample size of firms experiencing a *Credit Watch* placement with developing implications too small to make any statistical inferences from the regression results. Furthermore, it is unclear *a priori* what sign the abnormal placement and removal returns should take. Therefore, this group of firms is deleted from the remainder of the study.

In testing for the overall significance of the abnormal returns around the *Credit Watch* placement and removal dates a one tailed test is used because a priori one would expect a negative abnormal return for both a placement with a negative implication and the subsequent removal where the vast majority of firms experienced a debt rating downgrade. Using the market model, value weighted, standardized residual method, table 22 reports the overall significance levels for abnormal returns calculated around the *Credit Watch* placement announcement dates and the *Credit Watch* removal announcement dates.

Table 22. Abnormal Returns for Positive and Negative Implication *Credit Watch* Placements and Removals

Placement Implication	Median Cumulative Abnormal Return	Z Score
Positive	-.16%	-.83
Negative	-.18%	-5.10**
Removal Implication		
Positive	-.36%	-.11
Negative	-.42%	-1.75*

Note: ** = Significant at the .001 level, * = Significance at the .05 level

For *Credit Watch* placements with positive implications no significant abnormal returns are found around either the placement date or removal date. This finding is consistent with the findings of Holthausen and Leftwich (1986) which find no evidence of abnormal returns for firms placed on *Credit Watch* with positive implications.

For *Credit Watch* placements with negative implications, significant abnormal returns are found around both the placement and removal dates. The significance of the abnormal returns around the placement date is consistent with the findings of Holthausen and Leftwich (1986) and Wansley and Clauretie (1985). However, the significance around the removal date is not consistent with the existing literature. This contrary finding may be attributed to several possible explanations.

First, the sample size of this study encompasses approximately three to four times the number of years of earlier studies. Wansley and Clauretie (1985), Holthausen and Leftwich (1986) along with Elayan, Maris and Maris (1990) use a sample of *Credit Watch* placements for the years 1981-1983. Wansley, Elayan and Maris (1990) use a sample of *Credit Watch* placements for the years 1981-1987. However, the author's sample only includes instances where preferred stock was placed on *Credit Watch*.

Second, event dates were identified and screened for contaminating events using both the NEXIS database and the *Wall Street Journal Index*. This resulted in an accurate and uncontaminated set of event dates in which the market reaction to the *Credit Watch* placement and removal was isolated.

Because both the placement and removal abnormal returns for the *Credit Watch* placements with positive implications are insignificant, these firms will be dropped from the study.

An ordinary least squares regression is estimated for the remaining sample of *Credit Watch* placements with negative implications. The results of this regression are reported in table 23.

Table 23. Ordinary Least Squares Regression Results

Independent Variable	Regression Coefficient	t-statistic	p-level
Intercept	-.63720	-1.41642 (20%)	.157394
T_i Number of Trading Days Between Placement and Removal	.00904	1.64654 (10%)	.100400
$D_{1,i}$ Interest Rate Volatility Dummy Variable	.19810	.28161	.778384
$DISP_i$ Measure of Equity Dispersion	.00143	.26036	.794715
U_i Number of Updates Listed by Credit Watch	-1.59931	-3.67373 (1%)	.000270
$R_{cwp,i}$ Abnormal Return on Placement Date	.05271	1.11226	.266663
CAR_i Cumulative Abnormal Return Between Placement and Removal	.04057	3.91845 (1%)	.000104

Note: Significance of t-score is listed in parentheses.

The overall regression test statistics are as follows:

$F(6,420)$ statistic = 4.637235 significant at 1% level.

Multiple R = .249259538

Multiple R-Square = .062130317

Adjusted R-Square = .048732179

Discussion of Results

The final sample of negative implication *Credit Watch* placements included 427 firms.

The T_j variable coefficient is positive and significant at the 10% level. The T_j coefficient takes on only non-negative values whereas the $CW_{cwr,j}$ dependent variable can take on both positive and (mostly) negative values. The sign of this coefficient implies that the larger (fewer) the number of trading days a firm remains on *Credit Watch* the less (more) negative the abnormal return on the removal date. This result is intuitive as the T_j variable is a proxy for additional information released to the market regarding the status of the firm in that the longer a firm stays on *Credit Watch* the more time additional information regarding the default risk of the firm or the resolution of the circumstances which caused the placement. Therefore the market reaction to the announcement of the *Credit Watch* removal is diminished as a portion of the uncertainty of the new default risk of the company is eliminated.

The regression coefficient of the U_j variable is negative and significant at the 1% level. The U_j variable takes on only non-negative values whereas the $R_{cwr,j}$ variable can take on both positive and (mostly) negative values. The sign of this coefficient implies that as Standard & Poor's increases (decreases) the number of updates the more (less) negative the abnormal return on the removal date. This implies that as Standard & Poor's increases the amount of information to the market regarding a firm, the market responds more negatively or less positively to the announcement of the removal from the *Credit Watch* list.

This result appears to be counter-intuitive because it is hypothesized a priori that the U_j variable is a proxy for information leakage. Therefore, one would expect a result similar to that of the coefficient on the T_j variable being that the more information available about the default risk of the firm, the less the market reacts to the *Credit Watch* removal.

However, there is an alternative explanation which is consistent with the sign of the U_j variable coefficient. Firms which are placed on *Credit Watch* with a negative implication experienced either a single identifiable trigger event which directly led to the placement or were placed as a result of a progressive deterioration in the condition of the firm over a period of time. Updates for firms placed on *Credit Watch* with a negative implication tend to contain additional "bad" news with the *Credit Watch* removal announcement containing the final "bad" news and the rating change announcement. A large number of updates may mean that a particular firm experienced a greater amount of negative information of which the news released in the *Credit Watch* removal is the end of the stream of bad news. If this were the case, then one might expect a larger negative abnormal return for firms which experienced a longer string of "bad" news.

The CAR_j variable coefficient is positive and significant at the 1% level. The sign of the CAR_j and $R_{cwr,j}$ variables can take on both positive and negative signs. The sign of this variable implies that the cumulative abnormal return between the placement and removal dates and the abnormal return on the removal date tend to be in the same direction. The value of the coefficient on the CAR_j variable means that a one percentage point increase (decrease) in the CAR_j variable is associated with a .04% increase (decrease) in $R_{cwr,j}$ variable. This indicates that for a negative abnormal return measured around the removal date, the CAR_j is of greater negative magnitude. Conversely, for a positive return around the removal date, the CAR_j is of greater positive magnitude. Such a phenomenon is consistent with the hypothesis set forth by Cornell and Shapiro (1989) which suggests that information does not in all cases arrive to the market in "discrete 'quanta'" but often times the full value of information regarding a specific event arrives over time in 'dribs and drabs'. It would appear that a substantial portion of the information which resolves the firm specific issues raised in the *Credit Watch* placement is impounded into the stock price prior to the announcement of the removal. This implies that there is either a substantial amount of information leakage to the market or Standard & Poor's is efficiently providing current information to the market on the status of a firm's *Credit Watch* listing. However, the overall significance of the abnormal returns around the *Credit Watch* removal announcement suggests that the removal still contains substantial information regarding the default risk of the firm. In all likelihood, the information contained in the removal announcement is the final piece of information in a stream of information that is received by the market. The stream of information can be though of as either beginning at the time of the *Credit Watch* placement or prior to the placement during the point at which the firm specific trigger event occurred which caused the placement itself.

Regardless, the sign of the CAR_j coefficient lends support to the theory of market efficiency in that information is impounded into stock price as it is received. That is, the market interprets and reacts to information prior to the removal announcement.

$D_{1,j}$, which is a dummy variable that is equal to one during periods of high interest rate volatility and zero otherwise is found to be insignificant. This suggests that for this sample of firms, the strength of the abnormal return around the removal announcement date is not related to the relative volatility of interest rates during the time period in which the *Credit Watch* placements and removals occurred.

The $DISP_j$, which measures the degree of equity dispersion is also found to be insignificant. This suggests that the removal return is independent of the degree of equity dispersion for a given firm. This implies that the shareholders of closely held firms may not have gained an advantage when it comes to inferring the implications of the eventual resolution of the *Credit Watch* placement announcement prior to the removal announcement.

Finally, the $R_{cwp,j}$ variable which measures the abnormal return around the placement date is insignificant. This suggests that the market reaction to the placement return is independent of the market reaction to the removal return. This result makes sense in that the market appears to evaluate and react to the implications of the *Credit Watch* placement and removal independently of one another. This result is intuitive in that one might expect the market to simply react to the information contained in the *Credit Watch* removal announcement irrespective of the reaction to the prior placement announcement.

In summary, it appears that the strength of the *Credit Watch* removal announcement is positively related to the number of trading days between the *Credit Watch* placement and removal (T_j) and positively related to the cumulative abnormal return between the placement and removal (CAR_j). The removal return is negatively related to the number of updates listed by Standard & Poor's.

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