Do Credit Ratings Reflect Underlying Firm Characteristics?

Evidence from the Utility Industry

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This Version: December 2010

ABSTRACT

The recent financial crisis has raised questions regarding the role credit rating agencies play in monitoring the quality of corporate debt. Utility industry deregulation serves as a natural testing ground for evaluating the prudence of rating agencies and their monitoring process. Following deregulation and the Enron scandal, the general opinion among industry professionals is that utilities are being punished by credit rating agencies. Contrary to this popular belief, we find that the utility credit ratings are significantly higher compared to those of other firms, and this significance is more pronounced in the post-deregulation period. We also do not find any evidence that the credit ratings of utilities are more likely to be downgraded (upgraded) following deregulation. Although rating agencies often cite regulatory reasons for placing utilities on negative credit watches, these firms' ratings are rarely downgraded after being placed on negative watches. We also find that while firms in other industries adjust their capital structures following rating changes, rating changes have insignificant impact on utilities. Thus, despite the statements often seen in popular press, credit ratings of utilities seem more of a product of interactions between utilities and rating agencies than of firm characteristics. In general, our evidence indicates that credit ratings might not always be reflective of the underlying firm characteristics.

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1 INTRODUCTION

Credit ratings impact a firm's cost of debt and, subsequently, its overall cost of capital. Firms with a higher credit rating can issue lower-yield debt and vice versa. Graham and Harvey (2001) find that maintaining financial flexibility and good credit ratings are the two most important factors firms consider when deciding to issue additional debt. Consideration of credit rating becomes especially important for firms at risk of seeing their ratings fall into non-investment grade category. For instance, Grinblatt and Titman (2002) point out that many bond portfolio managers are restricted from owning speculative-grade bonds. Therefore, receiving a speculative-grade rating carries additional stigma for firms. Although credit ratings are vital to firms' financial health, little research has been done in this area, especially with regard to credit ratings of a particular industry.

Moody's and *Standard and Poor's (S & P)*, two major rating agencies, each use nine major grades for credit ratings, often assigning additional positive and negative signs to these grades. The ordered nature of credit ratings renders *Ordinary Least Squares* (*OLS*) regression practically inapplicable. In addition, credit ratings are based not only on measurable quantitative data, but also on qualitative measures such as the nature of a firm's management team, corporate strategy, and industry position. Although Kaplan and Urwitz (1979) are the first authors to employ ordered probit models to measure credit ratings in a cross-sectional setting, it was not until 1998 that ordered probit models in a panel setting are employed by Blume, Lim and Mackinlay (1998). Since then, a number of authors have used credit ratings models in panel settings. Blume et al. find that the credit quality of U.S. corporate debt has declined in recent years. Their analysis shows that rating standards have indeed become more stringent over the 1978 to 1995 period. This is especially applicable to credit ratings of firms that are facing the risk of falling into speculative grade ratings. Their findings are echoed by Gray, Mirkovic, and Ragunathan (2005) who find that the declining credit qualities are not only a U.S. phenomenon but are also applicable to Australian firms.

Most of the previous research either excludes regulated utilities from their samples or use dummies to capture the utility effect. Our view is that regulated utilities themselves are of special interest. Utilities have undergone significant transformations since the passing of the *Public Utility Regulatory Policies Act* (*PURPA*) in 1978 and *Energy Policy Act* (*EPAct*) in 1992. Although the effects of deregulation on utilities are still unfolding, the general opinion is that deregulation has presumably negative effect on utilities' credit ratings. Before deregulation, utilities enjoyed rate protection and monopoly status within specified geographic areas. Increased competition and uncertainty associated with deregulation could be expected to drive down credit ratings. Moreover, although regulators still are concerned with credit ratings, *S & P*'s (2006) rating manual states that "…there is little basis to believe regulators would insist that a utility maintain an 'A' profile" (see *S & P*, 2006, pp.88). Since regulators are presumably becoming more concerned with service quality than with credit quality, decreased incentives to maintain the highest level ratings- combined with growing uncertainty- could have negative impacts on utilities' credit ratings.

The recent financial crisis has directed attention towards the role credit rating agencies play in monitoring the risk and credit quality of complex instruments such as the mortgage-backed securities. Although the general opinion is that the rating agencies either have the tendency to over-rate the financial instruments or to be negligent, the quantitative support for these claims has remained elusive.[1] The central purpose of this paper is to determine whether credit ratings reflect underlying firm characteristics or not. By doing so, we expect to shed some lights on the prudence of rating agencies and their monitoring process. Since credit rating process is not fully transparent and it often involves use of 'qualitative' information, the task at hand is not easy. Thus, we use the utility deregulation as a natural testing ground to determine whether utilities are being strictly monitored- as often claimed by industry professionals and rating agencies themselves- in the post-*EPAct* period.

While previous research has focused on the forecasting of out of sample credit ratings, our approach in this paper is to understand the changing ratings in a particular industry and their implications. Our first goal is to investigate whether utilities experience significantly lower credit ratings following deregulation. The traditional view has been that firms operating in regulated industries enjoy higher credit ratings due to lower default risk. This lower default risk arises from lessened competition enabled by regulatory protection and, in the case of utilities, guaranteed rates of returns over prudent investment outlays. Since the passing of *PURPA* and *EPAct*, utilities have been exposed to increased competition. Numerous articles in the popular press have presumed that the credit quality of utilities has been declining following deregulation.[2]The utility industry supposedly underwent another downward reassessment in 2001 following the Enron scandal. Although not often cited in academic literature, consensus among industry

[1] Following the sub-prime crisis, several lawsuits have been filed against the rating agencies for negligence. At the time of this paper, the outcomes of lawsuits involving rating agencies remain pending.

[2] Please refer to Table 1 for industry-related news excerpts.

professionals has been that credit issuers have been extremely cautious with the utility ratings following deregulation and the Enron scandal (see Table 1). Therefore, utility industry and deregulation serve as a natural ground for testing whether credit rating agencies have been prudent in their rating processes.

[Insert Table 1 about Here]

Our results indicate that, over the full sample period of 1985-2006, the utility industry enjoys credit ratings that are higher than those of other industries. When we divide our sample to pre- and post-*EPAct* periods, our results run counter to the popular belief that the utility credit ratings have suffered following deregulation. Following deregulation, the utility credit ratings remain high compared to firms in other industries. In fact, significance (and marginal effects) is even higher compared to that of pre-*EPAct* period. When we run similar regressions with binary probit specifications, results remain robust: utilities are more likely to receive investment-grade ratings compared to other firms, and this likelihood is higher for the post-*EPAct* period. We also do not find evidence that, regardless of the sample period selected, utilities are facing higher likelihood of being downgraded or upgraded following deregulation. All in all, we do not find evidence that rating agencies either favor or punish utilities in comparison with other firms.

Our second goal is to investigate the effect of credit rating changes on utilities' leverage ratios. Conventional wisdom suggests that credit downgrades would cause the cost of debt to rise as firms become riskier, and credit upgrades would imply an opposite effect. If utilities are conscious of the cost of debt and subsequent financial distress, they should downwardly adjust leverage ratios following credit downgrades, and upwardly adjust leverage ratios following upgrades. We do not find evidence that utilities adjust their leverage ratios following rating changes. This is in sharp contrast to firms in other industries. Thus, rating changes do not seem to be as important for utilities as they are for other firms.

The remainder of the paper is organized as follows. Section 2 provides an overview of the utility regulation and deregulation, credit ratings, and the utility capital structure. Section 3 provides data, methodology, and summary statistics. Section 4 presents the main results, and Section 5 concludes.

2 BACKGROUND

2.1 Utility Industry Regulation and Deregulation

There exists an extensive literature on the nature of utility regulation and deregulation. [3] Utility regulation can be traced back to late 19th century when a U.S. Supreme Court's decision validated the right of federal and state governments to regulate firms that provide electricity and related services. The *Federal Power Commission* (*FPC*), the predecessor of the *Federal Energy Regulatory Commission* (*FERC*), was founded in 1920 to coordinate federal hydropower development. Though originally intended to oversee the development of hydroelectric projects, it also came to regulate interstate natural gas and electric utilities in the following years. The *Public Utility Holding Company Act* of 1935 (*PUHCA*) limited each utility's operations to a single geographic area. Under *PUHCA*, each utility retained control over the generation, transmission, and distribution facilities in its region. Thus, the electric utility industry undertook the form of vertically

[3] Refer to Moyer (1993), and Bulan and Sanyal (2005) for more detailed accounts of utility regulation and deregulation.

integrated regulated firms within a specified geographical area.

Under *PUHCA*, utility holding companies that are engaged in regulated businesses are prevented from engaging in unregulated businesses. The *Securities and Exchange Commission* (*SEC*) was responsible for approving holding companies that wish to undertake non-utility businesses. Prices were set based on costs and a 'fair' return on investments ensuring a stable revenue stream for utilities and allowing them to pass through many costs to customers. In 1977, *FERC* was created, replacing the *FPC*. The *FERC* and state regulators (*Public Utility Commission* or *PUC*) oversee *Investor Owned Utilities* (*IOUs*) which are the primary focus of this paper.

Utility deregulation was initiated with the passing of the *Public Utility Regulatory Policies Act* (*PURPA*) in 1978. Deregulation was aimed to promote competition by enabling customers to choose their energy services providers, a process known as 'retail wheeling.' Ideally, retail wheeling should enable consumers to choose their own energy supplier by allowing suppliers to sell energy, through the transmission grids owned by local the utility firms, to consumers not within their geographic area. Regulation requires that local utilities do not charge excessive rates for access to their transmission grids. *PURPA* intended to improve, among other things, the wholesale distribution of energy and promote 'equitable' retail rates for consumers. This act allowed 'qualifying facilities'- i.e., non-utility power generators that meet certain ownership and generation criteria- to compete with established utilities by mandating that utilities buy power from these non-utility electric power producers at the 'avoided cost" rate, the cost utilities have to incur if they were to produce extra power. Qualifying facilities consist of cogeneration facilities and small power producers. Cogeneration facilities produce electricity and thermal energy (such as heat or steam), byproduct of electricity generation, which is put to 'good' use. Small producers generally use renewable resources such as hydro, wind, solar, and geothermal. In 1992, the passing of the *Energy Policy Act* (*EPAct*) gave rise to open-access transmission grids for wholesale transactions, thereby increasing the level of competition in the generation segment. Although *EPAct* was focused primarily on wholesale competition, it also promoted increased retail competition by requiring utilities that own transmission networks to provide their transmission services to other independent power generators at cost-based non-discriminatory prices. Under *EPAct*, large holding companies are allowed to operate in multiple states more freely.[4] The regulated utilities we consider in this paper are those with SIC codes 4911 (Electric services), 4922 (Natural gas transmission), 4923 (Gas transmission and distribution), 4924 (Natural gas distribution), 4931 (Electric and other services combined), and 4932 (Gas and other services combined).[5] We exclude SIC codes 4941 (Water supply).

2.2 Credit Rating Overview

Commercial rating agencies such as *Standard and Poor's* (*S & P*), and *Moody's* use publicly available and confidentially provided quantitative and qualitative information to assign ratings to firms. Credit ratings simply indicate the current opinion of the agency regarding the credit worthiness of an obligor. Ratings can be assigned as per requests by firms, or in the case of U.S. firms for public debt issuances, *S & P* assigns and publishes its ratings irrespective of issuer request. In most markets outside the U.S., ratings are assigned only upon requests. A credit rating may be assigned to a particular debt issue,

[4] At the time of this paper, approximately half of the U.S. states have undergone some form of deregulation. Our results are similar when we control for the state and regulated state dummies.
[5] Our results are robust when we separate gas and electric utilities. Gas utility deregulation began a few years earlier than the electric utility deregulation.

or it may indicate the general ability of the firm to meet its obligations.

As stated in *S & P Corporate Rating Criteria* (*S & P*, 2006), a credit rating is "Standard & Poor's opinion of the general creditworthiness of an obligor, or the creditworthiness of an obligor with respect to a particular debt security or other financial obligation, based on relevant risk factors" (pp. 8). Thus, credit ratings fall under two broad categories; ratings that are applicable to specific debt issues, i.e. issue credit ratings, and ratings that are applicable to overall creditworthiness of the issuer, i.e., issuer credit ratings. Each category of rating can be subdivided into long-term and short-term. In this paper, we look at the overall long-term creditworthiness of the issuer, i.e., issuer credit rating with regard to long-term debt securities. Long-term credit ratings range from 'AAA', the highest quality, to 'D', the lowest. Long-term ratings from 'AA' to 'CCC' could be further given a plus or minus sign. Issuer credit ratings are provided "in response to a need for rating evaluations on a company when no public debt is outstanding" (pp.9).

Previous research has utilized either issue or issuer credit ratings but not both. As both issuer and issue ratings measure the ability of an entity to meet its obligations, either rating is acceptable for our study. Both issuer and issue ratings are assigned identical definitions. Since we are not only interested in firms that have outstanding debt but are also interested in firms that do not, we prefer to use issuer credit rating. However, for junior debt issues, issue credit rating is usually lower than issuer credit rating. We control for this by including a subordinated debt dummy in all our regressions. From Figure 1, we could see that the percentage of firms that are rated investment-grade has been declining over the past two decades for both non-utility and utility firms. In addition, we see from Figure 2 that percentage of firms that received rating downgrades dramatically increased in the late 1990s and sharply declined after 2001-2002. This finding is applicable to both utility and non-utility firms. For non-utility firms, the percentage of firms that received rating upgrades also declined in the above-mentioned period. However, we could see that percentage of firms that receive credit upgrades does not exhibit any particular trend for utilities.

[Insert Figures 1 & 2 about Here]

2.3 Utility Capital Structure Overview

Bradley, Jarell, and Kim (1984) document that regulated firms such as telephone, electric and gas utilities, and airlines are consistently among the most highly levered firms. Our Figure 3 shows that leverage ratios of regulated utilities have been steadily declining since the late 1970s. Authors such as Bulan and Sanyal (2005) attribute this decline to deregulation. To calculate the leverage ratios, we simply aggregate the total book debt (Compustat data 9 + Compustat data 34) over all firms for each year and divide these yearly aggregates by yearly aggregated total assets (Compustat data 6). Several studies have shown that regulated utilities choose high debt levels to induce rate or price increases. Authors such as Taggart (1985), Spiegel and Spulber (1994), and Rao and Moyer (1994) argue that assuming debt would cause regulators set rates at a higher level to mitigate the potential costs of financial distress. The predominant argument in the literature is that a stricter regulatory environment increases the leverage ratios. If regulation causes firms to hold high leverage ratios, deregulation could be expected to cause downward readjustments of leverage ratios as uncertainties associated with a market environment and the absence of regulation may have forced firms to be more conservative in their capital structure decision.

[Insert Figure 3 about Here]

3 DATA & METHODOLOGY

Issuer credit rating (Compustat data 280), which measures the senior long-term debt obligations, is readily available in Compustat database starting from 1985. Compustat long-term issuer credit rating assigns numerical values to S&P ratings. The values range from 2, S&P equivalent of AAA, to 90, suspended debt. As these values are too numerous to develop any meaningful credit rating model, previous authors re-group numerical ratings into certain classes. To be consistent with previous research, the multiple ratings are classified into seven categories as provided in Table 2.

[Insert Table 2 about Here]

Previous research has used both issue and issuer credit ratings. For instance, Bhojraj and Sengupta (2003) use a sample of 1,005 industrial bond issues (issue-specific) over 1991–1996 period to show that better corporate governance mechanisms lead to higher bond ratings and lower bond yields. On the other hand, Ashbaugh-Skaif, Collins, and LaFond (2006) use issuer credit rating to show that firms with stronger corporate governance benefit from higher credit ratings relative to firms with weaker governance. While some authors use investment-grade ratings only, others use all available ratings. For instance, Blume et al. and Gray et al. use samples of investment-grade ratings for the U.S. and Australian firms while Ashbaugh-Skaife et al. use all firms. In this paper, we include all available firms and ratings.

Explanatory variables included in our models are the ones previously found to be significant in explaining credit ratings. These variables are also comprised of accounting variables applied by *S & P*. We closely follow Blume et al. and Ashbaugh-Skaif et al. for these variables. To be consistent with agencies' rating process known as "rating through the cycle", we use three-year averages of the financial ratios– except in cases of dummy variables- in our models using data from 1983-2006. In cases where three years of data are not available (e.g., newly listed companies), we use averages of two years or just single year depending on data availability. *LEVERAGE*, or leverage, is the total debt (Compustat data 9 + Compustat data 34) divided by total assets (Compustat data 6). Higher leverage is associated with higher risk and, therefore, high-leveraged firms are expected to have lower ratings. Return on assets (*ROA*) is the net income before extraordinary items (Compustat data 18) divided by total assets. *LOSS* is a dummy variable assigned one if the net income before extraordinary items is negative in the current fiscal year, zero otherwise. While *ROA* might be able to capture the upside of credit ratings, the *LOSS* dummy could further capture the downside potential of firms that are currently facing losses. *INTCOV* is the interest coverage, or operating income before depreciation (Compustat data 13) divided by interest expense (Compustat data 15). As pointed out by Blume et al, interest coverages that exceed a certain level and negative coverages are not meaningful. Thus, three-year average of the interest rate coverage that exceeds 100 is set to 100 and negative coverages are set to zero.

The coefficient of *SIZE*, natural log of total assets, is expected to be positive as larger firms are also older firms with more established product lines and more diversified sources of revenues. We remove firms that have total assets values lower than $500,000. *SUBORD* is a dummy variable that takes on the value of one if a firm has subordinated debt (Compustat data 80), zero otherwise. *CAPINT* is the capital intensity measured by gross property, plant and equipment (PPE, Compustat data 7) divided by total assets. The hypothesis is that firms with high capital intensity pose lower risk as tangible assets make better collateral.[6] Some authors have suggested other measures of capital intensity such as PPE-capital expenditure (Compustat data 30) divided by sales. PPE-capital expenditure excludes spending on acquisitions on existing operations. Since utilities are increasingly engaging in mergers and acquisitions, this measure fails to capture the current trends in regulated utilities, which is our primary interest. Thus, we decide to use gross PPE as our primary measure of capital intensity. Firms with PPE to total assets ratios of one or greater are removed. The S&P credit rating manual suggests that 'moderate' capital intensity is regarded favorably by the agency. Therefore, we could not assume a monotonic relationship between capital intensity and credit ratings. As capital intensity increases, firms also lose their operational flexibility. To capture this effect, we include the squared term of capital intensity measure.

Following Blume et al., we also use beta coefficients (*FIRMβ*) and (*FIRMσ*) - or idiosyncratic risk- from the market model. Firm betas are estimated from

$$r_{j,t} = \alpha_j + \beta_j r_{m,t} + \varepsilon_{j,t} \tag{1}$$

where firm j's monthly returns are regressed on value-weighted market returns for each month t. From 1983 to 2006, monthly returns are collected for each Compustat firm and the market. Firms that do not have twelve observations within each year are removed. For each year i, idiosyncratic risk for firm j is

$$FIRM\sigma_{j,i} = \sum_{t=1}^{12} (\varepsilon_{j,t})^2 \tag{2}$$

[6] When we replace gross PPE with net PPE (Compustat data 8), results are almost identical.

where $FIRM\sigma_{j,i}$ is the idiosyncratic risk of firm j at year i.[7] We do not average the firm betas and volatilities. Therefore, we have a panel data of betas and idiosyncratic risks and firm characteristics from 1983 to 2006. As equity risk increases, a firm's ability to meet its debt obligations will deteriorate. Firm-specific volatility could provide information on firm-specific factors such as competency of management while systematic risk could provide information on a firm's position vis-à-vis the market. The expected signs of coefficients for both measures of risk are negative. Figure 4 exhibits the time trend of idiosyncratic risk for utility and non-utility firms as measured by Equation 2.2. As expected utility firms exhibit significantly lower idiosyncratic risk compared to non-utilities. While idiosyncratic risk has been steadily rising for non-utilities over the past four decades, we could see that the rise is more abrupt for utilities in the 1990s, coinciding with the ongoing deregulation in that decade.

[Insert Figure 4 about Here]

Next, we consider leverage as another proxy of risk. During times of high volatility, leverage exacerbates firm's performance. Some might argue that effect of leverage might already be incorporated in stock return volatility. However, our opinion is that managers are also inclined to consider the level of leverage in addition to firm-specific volatility. We also consider other measures such as Research and Development (R & D) intensity. However, R & D data are very limited and we also do not wish to over-stress our credit rating models. *FIN* and *UTIL* are dummies that take on values of one if firm is a financial institution (one-digit SIC code 6) or a utility (as defined in Section 2.1), zero otherwise. Though regulatory environment and higher capital intensity distinguish

[7] Our results are similar when we use the standard deviation and variance of regression residuals.

utilities from other industrials, they are nonetheless similar to other industrials in many aspects. However, financials are different in many aspects. While variables such as profitability, size, and volatility are applicable to all firms, variables such as capital intensity and assumption of subordinated debt are not applicable to financials. On the other hand, variables such as non-performing loans and capital adequacy become more important in determining their credit risk. Furthermore, financial institutions are more sensitive to macroeconomic factors such as interest rates. As a result, prior research usually excludes financials, in addition to utilities, from their datasets. Our results are virtually the same whether we exclude financials or not. For ordered probit results, we estimate

$$y_i^* = x_i \beta + e_i,\ e_i \sim N(0,1),\ \forall i = 1, \ldots, N \tag{3}$$

where y_i, the observed credit ratings, takes on values of 0 through 6 according to $y_i = j \Leftrightarrow \mu_{j-1} < y_i^* \leq \mu_j$, where $j=0,\ldots,6$, and x_i's are a set of aforementioned characteristics.

[Insert Table 3 about Here]

Table 3 presents the correlation matrices of our variables. As expected, ratings are significantly positively correlated with capital intensity, interest coverage, profitability, and size. On the other hand, they are negatively correlated with leverage, and both measures of risk. Although many correlations appear significant, none is excessively large enough to raise concerns about the possibility of inflated standard errors of the regression estimates.[8] As *S & P* states in its rating manual, it also considers "industry prospects for growth and vulnerability to technological change, labor unrest, or regulatory actions" (pp.9). Therefore, industry-specific factors, in addition to firm-

[8] This is confirmed by low *Variance Inflation Factors* (*VIF*). *VIFs* are not tabulated here to conserve space. *VIF* greater than 10 is considered as indicative of multicollinearity in this paper.

specific factors, are also important in determining firms' credit ratings. To control for industry effects, we also run our regressions including Fama-French 48 industries.[9]

In the absence of industry-specific effects, firms with similar characteristics should receive similar ratings. An obvious approach to would be to predict the ratings by using coefficients from ordered probit models in a base period and to compare predicted ratings in each category with actual ratings for the forecast period. In addition to this approach, Blume et al. also use intercept coefficients from yearly probit regressions to show that rating standards have become more stringent (as indicated by lower intercept coefficients) over time. The intuition is that year dummies should measure the changes in propensities to receive higher or lower ratings after controlling for all other characteristics. Probit predictions have varying accuracies depending on the variables included and the base period on which the forecast is built upon. In addition, our independent variables also could have time-varying explanatory powers. Therefore, we follow the latter approach to determine whether the rating standards have become more stringent over time for utilities and for all other firms.

4 FINDINGS

The full sample consists of over 3,000 firms and 19,000 firm years. We run our regressions with and without financial, utility, and other industry dummies. Although we follow Fama and French's 48 industry classification, we add an additional dummy variable for regulated utilities as defined in Section 2.1. The original Fama and French utilities (SIC 4000-4999) are divided into regulated utilities -as defined earlier- and other

[9] See Fama and French (1997).

utilities. Therefore, there are altogether 49 industry dummies in our regressions. While including all individual industry dummies enables us to determine each industry's position vis-à-vis the base industry, we are mainly interested in the coefficients of utilities. Thus, we only include *FIN* and *UTIL* dummies in most of our other regressions. To be consistent with prior research, we also examine our models with financials and utilities removed from the sample. Where applicable, we use standard errors that are robust to clustering.[10]

4.1 Ordered Probit Regression Results

[Insert Table 4 about Here]

To be consistent with prior research, we first estimate our models by initially excluding financials and utilities. From Table 4 (A), all variables are highly significant and have expected signs. Leverage, market and firm risks, and presence of subordinated debt significantly lower credit ratings while interest coverage, capital intensity, profitability, and size raise credit ratings significantly. Different from Ashbaugh-Skaife et al. who find capital intensity negative and insignificant, we find that capital intensity is positive and significant. The squared term of capital intensity is negative and significant, confirming our prediction of the non-linear effect of capital intensity. Thus, while moderate levels of capital intensity are viewed favorably by rating agencies, excessive reliance on capital intensity is considered risky by rating agencies. Including financials and utilities does little to change the significance of our variables. While the utility dummy is highly significant at 1% level, our financial dummy is not significant at conventional levels.

[10] These are White standard errors adjusted to account for possible correlation within a cluster (also known as Rogers standard errors). Our results are similar when we use standard errors that are robust to heteroscedasticity.

Table 4 (C) reports regression results that include 49 industry dummies as defined earlier. Joint test shows that industry dummies are significant at 1% level. Including all industry dummies does little to change the significance of our other coefficients. We separately report them in Table 2.5 for readers who might be interested in them.

[Insert Table 5 about Here]

We next divide the sample period into pre- and post-deregulation periods. The pre-deregulation period consists of 1983 to 1992 inclusive. Excluding 1992 from our regressions does not change our results. As with our previous regressions, the coefficient on the utility dummy is our primary interest. Contrary to popular belief, we find that the coefficient on the utility dummy is more significant in the pre-*EPAct* period (1% level) compared to the post-*EPAct* period (5% level). Table 4 (A) regression also provides us with the year dummy coefficients from 1986 to 2006 for all firms excluding financials and utilities. In order to understand the declining credit qualities with regard to the utilities, we repeat the ordered probit regression for utilities only (results are reported in Table 7, Panel A). We plot the time dummy coefficients of the utility credit rating models alongside those of the full sample (excluding financials and utilities) credit rating models.

[Insert Figure 5 about Here]

Figure 5 reports the plot of year dummy coefficients for utilities and all firms (from Table 4 (A) and Table 7 (A) probit estimations). Plots of year dummy coefficients confirm findings from previous research that the credit ratings have declined even after controlling for firm characteristics. From a visual inspection of Figure 5, it is apparent that while utilities also experience a significant drop in their credit ratings, this decline is much less pronounced compared to other firms in the sample. This is especially true of post-1990s. Therefore, at the very least, we could say that utilities, when compared to other firms, do not seem to be suffering undue hardship and lower credit ratings following deregulation.

4.2 Binary Probit Regression Results

When we replace the dependent variable with investment-grade dummies, results are similar. Investment-grade is coded one if the firm's credit rating is BBB or better, zero otherwise. Table 6 reports the standard binary probit regression results. Firms with higher capital intensity, interest coverage, profitability, and bigger size are more likely to be rated investment-grade while firms with higher leverage, firm volatility and systematic risk are more likely to be rated speculative-grade. The presence of subordinated debt and loss also significantly reduces the likelihood of being rated investment-grade. Our financial and utility dummies are significantly positive, indicating that, after controlling for firm characteristics, being a financial or the utility firm increases the probability of being rated investment-grade. From calculations of marginal effects (not reported here to conserve space), being a utility increases the probability of receiving an investment-grade rating by almost 20%. All in all, results are similar to those of the ordered probit model reported in Table 4. When we divide our sample to pre- and post-*EPAct* periods, results remain robust: utilities are more likely to receive investment-grade rating compared to other firms. In the pre-*EPAct* period, being a utility increases the probability of receiving an investment-grade rating by 12%. On the other hand, the effect is 15% for the post-*EPAct* period.

[Insert Table 6 about Here]

Since the propensity to receive an investment-grade rating for utilities is higher in the post-*EPAct* period, utilities with speculative-grade ratings seem to have improved their ratings after this period. One possible explanation is that, after deregulation, utilities- especially those with credit ratings in speculative grades- are becoming more concerned with cost of capital and are striving harder to maintain their ratings. It should be stressed that this improvement does not mean that utility ratings are improving *per se*. This is the result of a less pronounced decline in utility ratings compared to other firms. In addition, while systematic risk is insignificant for the pre-*EPAct* period, it becomes highly significant in the post-*EPAct* period. This is applicable to all firms and not only to utilities since we are using the full sample firms. If utility ratings are improving vis-à-vis other firms in the post-*EPAct* period, we would expect that, after deregulation has been initiated, utilities would experience fewer downgrades compared to other firms. In the next section, we formally test this intuition. In summary, both the overall credit rating and the propensity to receive investment-grade ratings do not show deterioration after deregulation. In fact, after controlling for firm characteristics and risks, utilities historically enjoy much higher credit ratings than other firms in any sample period.

[Insert Table 7 about Here]

Although our main interest lies in comparing the credit ratings of utility firms vis-à-vis firms in other industries, it is useful to track changes within the industry itself. Table 7 (A-C) reports the results with utility firms only. Panel A reports the estimates with year dummies, and Panels B-C report estimates without year dummies but with the post-*EPAct* dummy. For ordered credit ratings, the post-*EPAct* dummy is significantly negative (Panel B). However, the significance is weak at 10% level. On the other hand, the coefficient of the post-*EPAct* dummy is neither statistically nor economically significant when the dependent variable is the investment-grade dummy (Panel C).[11] Thus, although utilities are receiving lower ratings compared to pre-deregulation period, the effect is limited. When we include all firms and interact the utility dummy with the post-*EPAct* dummy (Table 7, Panels D-E), the interaction term (*POST-EPACT* * *UTIL*) is insignificant, and its marginal effect is -4.5%.[12] Thus, being a utility in the post-deregulations effect does not seem to have significant impact on credit ratings. We do, however, see that all firms in general are receiving significantly lower credit ratings. For the sample including all firms, coefficients of *POST-EPACT* are significantly negative whether we are considering general or investment-grade ratings. For binary probit regressions, the calculated marginal effect of *POST-EPACT* for all firms (Panel E) is -16%.

4.3 Utility Downgrades and Upgrades

We consider two potential definitions for credit downgrades and upgrades. Credit ratings rarely change from one full letter grade to another (e.g., from BBB to AAA). Rather, they usually change in smaller notches (e.g., from BBB to BBB+). For ordered probit models, several ratings are classified into one group for model estimation. For instance, Compustat data 280 of rating 9 represents letter-grade A- (or rating of 4 in our model) while Compustat data 280 of rating 10 represents letter-grade BBB+ (or rating of 3 in our model). Thus, changes from BBB+ to A are accounted for in our ordered probit models

[11] The marginal effect of *POST-EPACT* is -2%.

[12] This setup is essentially the difference-in-difference estimate where utilities belong to the treatment group. However, we could not infer causality here as the treatment group is not randomly selected.

as rating changes from 3 to 4. On the other hand, suppose a firm's rating is upgraded from BBB to BBB+. However, according to our classification, both BBB and BBB+ represent coding of 3 in our ordered probit models. For our binary probit model, we consider partial rating changes.

[Insert Table 8 about Here]

DOWNGRADE is a dependent variable that takes on the value of one if a firm's rating has been downgraded over two consecutive years. We define *UPGRADE* similarly. A limitation of binary probit model is that it ignores the level of credit changes. There are several instances where a firm's rating was downgraded or upgraded by more than one notch. In addition, rating changes are not binary in nature. A firm could either retain its current rating, could be downgraded, or be upgraded. Thus we remove firms that have been upgraded from our downgrade regressions, and vice versa. We exclude firms with single-year observations or with no two consecutive years of available data. We also lose the first year of our sample (year 1985) when we calculate changes in ratings. Similar to our previous regressions, our interest lies in the utility dummy coefficients. Since upgrades and downgrades measure the changes in credit ratings, we also compute the changes in firm characteristics. We remove the dummy variables for loss and subordinated debt from our regressions. For downgrades, we expect the coefficients to have opposite signs when compared to those of our ordered probit or binary probit regression models. For upgrades, we expect the signs to be of same direction.

From Table 8, we see that all coefficients have the expected signs. Increases in capital intensity, profitability, interest coverage, and size are negatively associated with propensities to be downgraded while increases in leverage, firm volatility, and beta are positively associated with higher propensities to be downgraded. While all other coefficients are significant at a 5% level or lower, our *FIN* and *UTIL* dummies are insignificant. Therefore, being a utility does not result in higher likelihood to be downgraded. Our regression results with upgrade dummy also confirm our intuition. Increases in capital intensity, profitability, interest coverage, and size are positively associated with higher propensities to be upgraded while increases in leverage and firm volatility are negatively associated with lower propensities to be upgraded. Capital intensity, while positive, is insignificant. Once again, *FIN* and *UTIL* dummies are not significant. Evidence seems to suggest credit rating agencies neither favor not punish utilities when deciding to alter their credit ratings.

[Insert Table 9 about Here]

While an increase in capital intensity reduces the likelihood of being downgraded, it has no effect on credit upgrades. This is consistent with our findings from ordered probit regressions: while capital intensity is viewed favorably up to a certain level, excessive levels of capital intensity negatively affect credit ratings. Firm betas also play a similar role. While increases in firm betas are associated with higher propensities to be downgraded, reductions in firm betas do not result in credit upgrades. On the other hand, the reverse seems true for firm-specific volatility. As with the previous regressions, we divide the sample into pre- and post-deregulation periods. After controlling for the usual explanatory variables, utilities are neither more likely to be downgraded nor upgraded for any period. These results are not upgrades and downgrades *per se* but are relative to other firms in the sample.

Table 9 (A-B) reports results from our ordered and binary probit regressions for utility firms only. From 9 (A), the post-deregulation dummy (*POST-EPACT*) is insignificant for credit downgrades. The marginal effect of *POST-EPACT* is 5.7%. However, we do find that utilities are becoming less likely to receive credit upgrades following deregulation (Panel B). While this effect is statistically significant (10% level), its economic significance is weak. In particular, being in the post-deregulation period decreases the probability of receiving a credit upgrade by merely 2%. When we include all firms and interact the utility dummy with the post-*EPAct* dummy (Table 9, C-D), the interaction term (*POST-EPACT* * *UTIL*) is insignificant for both credit downgrades and upgrades. Thus, being a utility in the post-deregulations effect does not seem to have significant impact on credit downgrades and upgrades. The marginal effects are also small (1% and -0.5% respectively). For the sample including all firms, coefficient of *POST-EPACT* is insignificant for credit downgrades but significantly negative for credit upgrades.

As mentioned before, rating changes are not binary in nature. A firm could maintain its current credit rating, receive a downgrade, or receive an upgrade. To address this concern, we recode the credit downgrades and upgrades and estimate them in a single regression. Table 10 reports the regression results. The dependent variable, change in credit rating (*RATING CHANGE*), is an ordered variable that takes on value of 0-2. Firms that have received credit downgrades over two consecutive years are assigned ratings of zero. Firms that have not experienced any changes in their credit ratings are assigned values of one, and firms that have received credit upgrades are assigned ratings of two. Once again, we see that the coefficient of utility dummy is insignificant, implying that utilities are neither more nor less likely to receive rating changes compared to other firms, and this is true for any sample period.

[Insert Table 10 about Here]

4.4 Additional Evidence from Credit Watch Placements and Downgrades

Firms are often placed on Credit Watch if they are likely to face rating changes in foreseeable future pending outcomes of certain actions such as “mergers, recapitalizations, regulatory actions, or unanticipated operating developments” (see *S & P*, 2006, pp. 14). *S & P* and *Moody’s* use *Credit Watch* negative, positive, and *Credit Watch* developing to describe potential rating changes while Fitch uses Rating Watch negative, positive, or evolving. Credit or rating watch data are not readily available in programmable format, and rating agency websites only contain information on credit watch placement data for the most recent year. Thus, we searched for news excerpts of credit watch placements using *FACTIVA*. We use ‘rating watch’ and ‘credit watch’ to search for news covering the energy industry in the entire post-deregulation period. Though firms could be placed on different types of credit watches, we are mainly interested in firms that have been placed on non-positive (negative and developing) watches. Our purpose is to identify ratings that have been placed on non-positive watches due to regulatory reasons.

From Table 1, we see that cases of rate hearing and other regulatory actions play a very significant role in determining whether or not firms are placed on credit watch. In almost all credit watch cases we identified using *FACTIVA*, pending rate hearing cases and other regulatory actions, utilities are placed on negative watch rather than on watch evolving or watch developing. Thus, uncertainties associated with regulation seem to have a negative impact on credit rating outlooks. Several non-positive credit watch placements are also attributed to tightening credit standards and more contentious regulatory environment.

Apart from earnings reasons and the reasons explored above, the most common reasons for credit watch placements in our sample period are acquisitions and restructuring. Almost all cases of restructuring and acquisitions result in negative watch placements. We do not report these instances here to conserve space.

In principle, firms that have been placed on negative credit watches are either subsequently downgraded or are removed from the watch. To assess the claim of the negative impacts of regulatory actions on rating changes, we look for instances where firms' ratings that were placed on non-positive credit watches are actually downgraded. Rather than searching in *FACTIVA* for instances of removals from negative watches, we simply assume that firms that are not subsequently downgraded are removed from the watches. From *FACTIVA* searches, we find 24 instances of *S & P* negative watch placements in the post-deregulation period. When we expand our search to include all credit watch placements by all rating agencies, we find approximately 110 instances, with most placements clustering in post-2000 period. We limit our analysis to S&P watch placements since we are able to combine these placements with Compustat rating data. We match these negative watches to S&P credit data on Compustat for years t and t+1. Since the S&P manual (2006) states that credit watch issues are normally resolved within 90 days upon placement, the two-year windows we impose should be more than sufficient to capture the subsequent developments.

Out of 24 instances, we find just one instance of a credit downgrade in the same year as placement on negative watch. For year t+1, we find additional 4 downgrades. Therefore, all other ratings that were placed on negative watches were either removed from the watches or were downgraded at a much later time. We are not concerned with rating changes that might occur beyond year t+2 since other factors rather than those cited for original placements are most likely to be the contributing factors. Though the sample is relatively small and a formal analysis could not be conducted, comparisons of credit watch placements to actual credit downgrades give us useful insight into the severity of credit downgrades often attributed to deregulation: despite numerous citations of credit watch placements pending rate hearings and regulatory actions, the actual downgrades are much less frequent.

4.5 Credit Ratings and Endogeneity of Leverage

So far, we have assumed that leverage is exogenous. In this section, we allow for the possibility that leverage is endogenously determined. While we are also interested in the robustness of our previous estimates when leverage is endogenously determined, our primary interest is in the effect of credit rating changes on leverage. Credit downgrades increase the cost of borrowing while credit upgrades decrease the borrowing cost. Thus, all else equal, we could hypothesize that rating changes could lead to capital structure changes. Although leverage affects credit ratings contemporaneously, subsequent readjustments in leverage due to rating changes could occur with a lagged effect. We consider the lagged effect since capital structures are highly persistent and it would require reasonable time for firms to adjust their leverage ratios. To the best of our knowledge, no prior research has considered the simultaneous nature of credit ratings and capital structure.

Changes in credit ratings are credit upgrades and downgrades as defined earlier. In order to track changes in leverage ratios following credit changes, we include lagged dummies for 3 years following downgrades and upgrades. Nothing prevents us from using lagged dummies for more than three years. However, our intuition is that rating changes would prompt firms to readjust their leverage ratios within a reasonable period of time. As has been well-documented, leverage itself is determined by a number of variables such as asset tangibility, growth, profitability, size, and risk. Asset tangibility reduces the risk for lenders, and thus firms with more tangible assets could assume more debt. Our measure of asset tangibility is simply the capital intensity ratio (PPE/A) measured earlier. Rajan and Zingales (1995) find a positive relationship between tangibility and leverage for all the G-7 countries in their sample. Our results indicate a positive, though insignificant, relationship between capital intensity and leverage.

We use market- to- book as measure of growth opportunities. Growth companies are usually smaller, less profitable, and riskier companies. Therefore, one side of argument is that these companies should borrow less as high levels of debt may hinder their ability to undertake positive net present value projects. This is in line with debt overhang argument. On the other hand, since these companies have high investment requirements and low cash flows, internal financing is not likely to be sufficient to meet the cash flow needs. Since internal financing is not sufficient, these companies will borrow at a higher level. This is in line with pecking order argument: firms would issue debt before they issue equity. Therefore, these companies are likely to hold more debt. While Titman and Wessels (1988) do not find any connection, Rajan and Zingales (1995) report a negative relationship between growth and leverage. We find positive and significant results for growth and leverage.

After controlling for growth opportunities and other financial constraints, firms with low profitability have less retained earnings, and these firms would have higher need to issue more debt. In contrast, profitable firms would have fewer needs to issue debt. The counter argument to the above proposition is that since profitable firms face higher marginal tax rates and have more ability to service debt payments, they could assume higher levels of debts. Agency-based theories also predict that more profitable firms should hold more debt to prevent managers from investing free cash flows in negative net present value projects. Rajan and Zingales (1995) and Titman and Wessels (1988) find a negative relationship between profitability and leverage. Our results also report negative effect of profitability on leverage. Our measure of profitability, as denoted by E/A, follows that of Fama and French (2001). We find that profitability has significantly negative impact on leverage ratios. Bigger firms are more stable and less risky. Therefore, they could assume higher level of debt. Rajan and Zingales (1995) find a positive relationship between size and leverage for the US, UK, Japan and Canada. Other authors like Titman and Wessels (1988) find no relationship for the U.S. Our results indicate significantly positive effect of size on leverage. The expected cost of financial distress increases with risk. Firms that have high variability in cash flows should hold lower leverage. Titman and Wessels (1988) report a negative but non-significant relationship. Our measure of systematic risk, betas from market model regressions is negatively significant while unsystematic risk, sums of squared residuals, is insignificant.

We develop the following two simultaneous models of rating changes and leverage:

$$DOWNGRADE_{it} = B_0 + B_1 \Delta LEVERAGE_{it} + B_2 \Delta CAPINT_{it} + B_3 \Delta INTCOV_{it} + B_4 \Delta ROA_{it} + B_5 \Delta SIZE_{it} + B_6 \Delta FIRM\sigma_{it} + B_7 \Delta FIRM\beta_{it} + \varepsilon_{it} \qquad (4)$$

where

$$\Delta LEVERAGE_{it} = B_0 + B_1 DOWNGRADE_{it} + B_2 \Delta CAPINT_{it} + B_3 \Delta M/B_{it} + B_4 \Delta CASH_{it} + B_5 \Delta E/A_{it} + B_6 \Delta SIZE_{it} + B_7 \Delta FIRM\sigma_{it} + B_8 \Delta FIRM\beta_{it} + B_9 DOWNGRADE_{it-1} +$$

$B_{10}DOWNGRADE_{it\text{-}2} + B_{11}DOWNGRADE_{it\text{-}3} + \varepsilon_{it}$

and

$$UPGRADE_{it} = B_0 + B_1 \Delta LEVERAGE_{it} + B_2 \Delta CAPINT_{it} + B_3 \Delta INTCOV_{it} + B_4 \Delta ROA_{it} + B_5 \Delta SIZE_{it} + B_6 \Delta FIRM\sigma_{it} + B_7 \Delta FIRM\beta_{it} + \varepsilon_{it} \quad (5)$$

where

$$\Delta LEVERAGE = B_0 + B_1 UPGRADE_{it} + B_2 \Delta CAPINT_{it} + B_3 \Delta M/B_{it} + B_4 \Delta CASH_{it} + B_5 \Delta E/A_{it} + B_6 \Delta SIZE_{it} + B_7 \Delta FIRM\sigma_{it} + B_8 \Delta FIRM\beta_{it} + B_9 UPGRADE_{it\text{-}1} + B_{10} UPGRADE_{it\text{-}2} + B_{11} UPGRADE_{it\text{-}3} + \varepsilon_{it}$$

where *DOWN*- and *UP-GRADE* $_{t\text{-}1 \text{ to } t\text{-}3}$ are lagged dummies of credit downgrades and upgrades for years t-1 to t-3. *CASH* is defined as cash and short-term investments (Compustat data 1) scaled by total assets. Profitability (*E/A*) and market-to-book ratios (*M/B*) are defined as in Fama and French's (2001). All other variables are measured as in our previous credit rating models. We also include year dummies in our simultaneous models. Similar to previous models, all our variables are measured in changes to correspond to changes in credit ratings. Thus, it would not be practical to directly compare our results with those of leverage models from previous research. One challenge with our simultaneous models is the nature of dependent variables. While leverage is continuous in nature, our dummies- *DOWNGRADE* and *UPGRADE*- are binary. Fortunately, *STATA* provides simultaneous models where one endogenous variable is continuous and the other is binary.[13] Another difficulty is that we cannot estimate both *DOWNGRADE* and *UPGRADE* in the same simultaneous model. Thus, when we develop simultaneous models of credit downgrades (upgrades) and leverage changes, we need to exclude observations that have undergone credit upgrades (downgrades).

[13] Please refer to *STATA* manual for '*CDSIMEQ*' command.

[Insert Tables 11 & 12 about Here]

We initially run regressions covering all firms in our sample period. Table 11 reports the regression results for simultaneous models of downgrades and upgrades for all firms and for utilities. Just as in the case of exogenous leverage models, our results from simultaneous models remain the same whether leverage is considered endogenously determined or not. The instrumented downgrade dummy variable is significantly positive, indicating that firms increase their leverage ratios in the year of downgrades. When we track the leverage ratios in years following downgrades, the signs of coefficients reverse. In years following downgrades, firms decrease their leverage ratios. The coefficient is significant for t+1, t+2, and t+3. We also see consistent results for credit upgrades. Following upgrades, firms increase their leverage ratios, and the effect is highly significant for all three years following upgrades.

For robustness, we also estimate the coefficients by removing the instrumented upgrade and downgrade dummies. The advantage of this approach is we are able to estimate the lagged upgrade and downgrade dummies concurrently in a single *OLS* model. Table 12 reports the results from the *OLS* model. Although the effects of leverage adjustments are not as pronounced as in the simultaneous models, we still see that firms adjust their leverage ratios following rating changes. For utilities, the coefficients of lagged variables are not significant. In addition, we also see that, regardless of rating changes, the leverage ratios continue to decline, though the decline is insignificant. We offer a few potential explanations for this finding. The utility sample is limited with just over 1,000 firm years. Thus, it is possible that our regression models could not estimate their coefficients with precision. The second possibility is that utility capital structure is actually independent of credit ratings: i.e., credit ratings do not matter to utilities as they do to other firms.

5 CONCLUDING REMARKS

Our research confirms the previous finding that, after controlling for firm characteristics, credit quality of U.S. corporate debt has declined in recent years. Although we do not predict propensities from ordered probit regressions, plots of our year dummy coefficients from all firms and utilities confirm the previous finding that credit ratings have declined for all firms and for utilities. Although utilities have experienced a significant drop in their credit ratings, this decline is much less pronounced compared to those of all other firms in the sample. This finding is important given that most popular press and industry professionals have promoted the view that utilities, after deregulation, have undergone a series of downgrades and are facing 'lower-than-deserved' ratings (see Conrad, 2007).

Our results from the ordered probit models indicate that the utility industry enjoys credit ratings that are higher than those of other industries, and the significance of positive utility coefficient is more pronounced in the post-*EPAct* period. We also find from binary probit regressions that utilities are more likely to be rated investment-grade compared to other firms, and this likelihood is higher in the post-*EPAct* period. One interesting finding is that some of the variables, such as systematic risk, become more significant in determining the utility credit rating after deregulation. For instance, while systematic risk is insignificant in explaining the propensity to receive investment-grade rating for pre-*EPAct* period, it becomes highly significant in post-*EPAct* period.

Probit regressions from downgrades and upgrades further confirm our findings indirectly. Following deregulation, utilities are neither more likely nor less likely to be downgraded. This is also true of credit upgrades. We also find that although rating agencies often cite regulatory reasons for placing utilities on negative credit watches, these firms' ratings are rarely downgraded after being placed on negative watches. This finding, combined with the finding that utilities' debt ratios do not respond to rating changes, seem to suggest that utilities' credit ratings might not convey as meaningful information as those of other firms. Rather, credit ratings of utilities seem more of a product of interactions between utilities and rating agencies than of firm characteristics. Thus, our findings suggest that credit ratings might not always be reflective of the underlying firm characteristics.

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Table 1: Selected Articles from *FACTIVA* Search (1992 through 2006).

For this table, we use 'rating watch' and 'credit watch' to search for news covering the energy industry in the entire post-deregulation period.

Article Date	Source	Quotation
Apr 09, 2008	Electric Power Daily	Fitch put [the company] on Rating Watch Negative on February 1 after the state's political and regulatory environment became more contentious.
Apr 07, 2006	The Washington Times	Moody's Investors Service yesterday cut the ratings of Baltimore Gas & Electric Co. (BGE) and warned that it will further downgrade the utility and its parent Constellation Energy Group if Maryland legislators follow through on threats to prevent them from recouping soaring fuel costs.
Jun 07, 2006	Platts Commodity News	Standard & Poor's Wednesday said ratings on Constellation Energy Group and its subsidiaries will remain on CreditWatch with developing implications, pending resolution of significant regulatory and legislative uncertainties ...
Sep 28, 1998	Associate Press Newswires	Standard & Poor's said Monday it had placed GMP on a "credit watch with negative implications," due to the company's high power costs and …Vermont's "increasingly contentious regulatory environment."
May 27, 2005	Platts Commodity News	Fitch Ratings Friday removed the ratings of Entergy New Orleans Inc from Rating Watch Negative...[S]table outlook reflect "the substantial improvement in the credit quality over the past 18 months" attributable in large part to... increase in the utility's rates.
Sep 05, 2005	Natural Gas Week	Some utilities have already had to face intense opposition from state regulators and officials when seeking rate increases …Standard & Poor's (S&P) put Entergy on credit watch with negative implications last week.
Nov 18,2004	Platts Commodity News	MichCon was placed on rating watch negative due to uncertainty surrounding the final outcome of its rate case.
Aug 24,1992	Reuters News	Duff & Phelps Credit Rating Co said it downgraded Commonwealth Edison Co's debt securities because recent regulatory and judicial decisions have increased the company's financial risks.
Dec 20, 2001	The Wall Street Journal	The credit rating of Mirant Corp. was downgraded… making the power generator the latest in a growing list of energy companies to suffer from tightening credit standard.
Jan 08, 2003	Gas Daily	S&P said it is re-evaluating the relationship between Coral and the owners due to Coral's higher level of merchant gas and power trading activity ``at a time of much greater sector volatility."
Nov 17, 2006	Business Wire	Fitch Ratings has placed the ratings of Commonwealth Edison Co. (ComEd) on Ratings Watch Negative following the latest legislative actions supporting rate freeze legislation in Illinois.
Aug 16, 2000	Capital Markets Report	Fitch said it downgraded the credit ratings of Consolidated Edison Co. of New York (Con Ed)... following the recent passage of state legislation prohibiting Con Ed's collection of replacement power costs...

Table 2: Credit Rating Classifications.
In this table, Compustat and S&P debt ratings are converted to rating scores of 0-6.

All Ratings				Investment-grades Only			
S&P Debt Rating	Compustat Data 280	Assigned RATING Score	Grade	S&P Debt Rating	Compustat Data 280	Assigned RATING Score	Grade
AAA	2	6	Investment	AAA	2	3	Investment
AA+	4	5	Investment	AA+	4	2	Investment
AA	5	5	Investment	AA	5	2	Investment
AA-	6	5	Investment	AA-	6	2	Investment
A+	7	4	Investment	A+	7	1	Investment
A	8	4	Investment	A	8	1	Investment
A-	9	4	Investment	A-	9	1	Investment
BBB+	10	3	Investment	BBB+	10	0	Investment
BBB	11	3	Investment	BBB	11	0	Investment
BBB-	12	3	Investment	BBB-	12	0	Investment
BB+, BB, BB-	13,14,15	2	Speculative				
B+,B,B-	16,17,18	1	Speculative				
CCC+	19	0	Speculative				
CCC or CC	20,23	0	Speculative				
C	21,24	0	Speculative				
D or SD	27,29,90	0	Speculative				

Table 3: Correlation Matrix.

The table presents the correlation matrices involving the dependent and selected independent variables. The dependent variable, credit rating (*RATING*), is an ordered variable that takes on values of 0-6. The independent variables include: capital intensity (*CAPINT*), measured by the ratio of property, plant, and equipment to total assets; leverage (*LEVERAGE*), measured by the ratio of total debt to total assets; interest coverage (*INTCOV*), measured by the ratio of operating income before depreciation to interest expense; return on assets (*ROA*), measured by the ratio of net income before extraordinary items to total assets; firm size (*SIZE*), measured by log of total assets; firm-specific risk (*FIRMσ*), proxied by the sum of squared residuals from the market model regression; systematic risk (*FIRMβ*), calculated from the market model regression. The significance of the correlation coefficients is based on two-tail P-value. ***, ** and * indicate the significance of coefficient at the 1%, 5%, and 10% level, respectively.

	RATING	CAPINT	LEVERAGE	INTCOV	ROA	SIZE	FIRMσ	FIRMβ
RATING	1	.085(***)	-.462(***)	.314(***)	.436(***)	.520(***)	-.446(***)	-.266(***)
CAPINT	.085(***)	1	.091(***)	-.078(**)	-.014(**)	-0.013(*)	-.062(***)	-.154(***)
LEVERAGE	-.462(***)	.091(***)	1	-.434(***)	-.350(***)	-.233(***)	.278(***)	.048(***)
INTCOV	.314(***)	-.078(***)	-.434(***)	1	.302(***)	.150(***)	-.119(***)	.022(***)
ROA	.436(***)	-.014(**)	-.350(***)	.302(***)	1	.166(***)	-.403(***)	-.208(***)
SIZE	.520(***)	-0.013(*)	-.233(***)	.150(***)	.166(***)	1	-.226(**)	0.009
FIRMσ	-.446(***)	-.062(***)	.278(***)	-.119(***)	-.403(***)	-.226(***)	1	.339(***)
FIRMβ	-.266(***)	-.154(***)	.048(***)	.022(***)	-.208(***)	0.009	.339(***)	1

Table 4: Estimates from Panel Ordered Probit Regressions of the Effects of Firm Characteristics on Credit Rating.

The dependent variable, credit rating (*RATING*), is an ordered variable that takes on values of 0-6. The independent variables include: capital intensity (*CAPINT*), measured by the ratio of property, plant, and equipment to total assets; ($CAPINT^2$), the squared term of capital intensity; leverage (*LEVERAGE*), measured by the ratio of total debt to total assets; interest coverage (*INTCOV*), measured by the ratio of operating income before depreciation to interest expense; return on assets (*ROA*), measured by the ratio of net income before extraordinary items to total assets; firm size (*SIZE*), measured by log of total assets; firm-specific risk (*FIRMσ*), proxied by the sum of squared residuals from the market model regression; systematic risk (*FIRMβ*), calculated from the market model regression; (*LOSS*), a dummy variable assigned one if the net income before extraordinary items is negative in the current fiscal year, zero otherwise; presence of subordinated debt (*SUBORD*), a dummy variable that takes on the value of one if a firm has subordinated debt, zero otherwise; (*FIN*), a dummy variable that takes on the value of one if a firm is a financial firm, zero otherwise; (*UTIL*), a dummy variable that takes on the value of one if a firm is a utility, zero otherwise. All standard errors are clustered by firm. We include year dummies for all regressions but are not reported here. The z-statistics are given in the parentheses: ***, ** and * imply the significance of coefficient at the 1%, 5% and 10%, respectively.

(see next page)

Variable	Panel A: Financials and Utilities Excluded Dependent= Credit Rating Coefficient	Panel B: All Firms Dependent= Credit Rating Coefficient	Panel C: All Firms with 49 Industry Dummies Dependent= Credit Rating Coefficient	Panel D: Pre-*EPAct* Period Dependent= Credit Rating Coefficient	Panel E: Post-*EPAct* Period Dependent= Credit Rating Coefficient
CAPINT	0.44	0.41	0.79	0.45	0.36
	(4.06)***	(4.22)***	(7.06)***	(3.00)***	(2.89)***
$CAPINT^2$	-0.20	-0.16	-0.22	-0.17	-0.13
	(-4.36)***	(-3.95)***	(-5.20)***	(-4.00)***	(-2.12)**
LEVERAGE	-1.62	-1.54	-2.03	-2.10	-1.38
	(-11.05)***	(-11.66)***	(-13.88)***	(-8.41)***	(-9.77)***
INTCOV	0.01	0.01	0.01	0.02	0.02
	(6.14)***	(6.92)***	(6.87)***	(3.20)***	(7.43)***
ROA	3.47	3.41	4.48	8.28	2.91
	(5.3)***	(5.68)***	(6.39)***	(5.61)***	(5.06)***
SIZE	0.52	0.46	0.48	0.42	0.49
	(22.43)***	(22.65)***	(22.96)***	(13.27)***	(22.06)***
FIRMσ	-17.42	-19.26	-20.20	-50.16	-16.13
	(-5.61)***	(-5.87)***	(-5.81)***	(-7.51)***	(-5.15)***
FIRMβ	-0.18	-0.16	-0.12	-0.17	-0.24
	(-6.67)***	(-6.23)***	(-4.21)***	(-2.92)***	(-8.76)***
LOSS	-0.64	-0.67	0.79	-0.34	-0.69
	(-12.71)***	(-14.41)***	(7.06)***	(-4.00)***	(-14.04)***
SUBORD	-0.45	-0.43	-0.22	-0.48	-0.37
	(-10.94)***	(-11.17)***	(-5.20)***	(-7.46)***	(-8.3)***
FIN	-	0.16	-	0.45	0.18
	-	(1.77)*	-	(2.66)***	(1.8)*
UTIL	-	0.33	-	0.26	0.34
	-	(3.37)***	-	(2.04)**	(3.2)***
Firm Years	15,878	19,125	19,125	5,248	13,877
Firms	2,698	3,141	3,141	1,223	2,682
Log Pseudo-likelihood	-18058	-22316	-21659	-6075	-15420
Pseudo R^2	0.2884	0.3027	0.3065	0.3408	0.3123

Table 5: Estimates from Panel Ordered Probit Regressions of the Effects of Industry Characteristics on Credit Rating.

Other regression estimates are separately reported Table 2.4, Panel C. The reported results are the coefficients of the industry dummies and their corresponding test statistics. The base industry is the regulated utility industry as defined in Section 2.1 and the base year is 1985. The z-statistics are given in the parentheses: ***, ** and * imply the significance of coefficient at the 1%, 5% and 10%, respectively.

Industry	Coefficient	t-stat	Industry	Coefficient	t-stat
AERO	-0.30	(-2.05)**	HSHLD	-0.16	(-0.98)
AGRIC	-1.02	(-2.92)***	INSUR	-0.18	(-1.16)
AUTO	-0.72	(-4.50)***	LABEQ	-0.30	(-2.10)**
AUTOS	0.12	(0.39)	MACH	-0.19	(-1.21)
BANKS	-0.16	(-0.82)	MEALS	-0.62	(-3.14) ***
BEER	-0.45	(-2.34)**	HLTH	-0.82	(-5.39)***
BLDMT	0.32	(2.09)**	MEDEQ	-0.07	(-0.44)
BOOKS	-0.36	(-1.62)	MINES	-0.64	(-3.07)***
BOXES	-0.28	(-2.07)**	MISC	-0.11	(-0.31)
BUSSV	-0.43	(-3.50)***	PAPER	-0.35	(-2.40)**
CHEMS	-0.67	(-4.07)***	PERSV	-0.88	(-3.55)***
CHIPS	-0.45	(-2.40)**	RLEST	-0.72	(-1.93)*
CLTHS	-0.47	(-2.41)**	RTAIL	-0.57	(-4.67) ***
CNSTR	-1.29	(-5.85)***	RUBBR	-0.36	(-1.90)*
COAL	-0.77	(-3.30)***	SHIPS	-0.78	(-4.01)***
COMPS	0.42	(2.40)**	SMOKE	-0.54	(-1.74)*
DRUGS	0.18	(0.99)	SODA	0.56	(2.33)**
ELCEQ	-0.70	(-5.29)***	STEEL	-0.91	(-4.51)***
ENRGY	-0.45	(-2.25)**	TELCM	-0.39	(-3.05)***
FIN	-0.10	(-0.49)	TOYS	-0.56	(-2.93)***
FOOD	-0.02	(-0.12)	TRANS	-0.80	(-5.74)***
FUN	-0.91	(-6.98)***	TXTLS	-0.70	(-3.63)***
GOLD	-0.76	(-3.21)***	UTIL (OTHERS)	0.42	(1.60)
GUNS	-0.98	(-5.11)***	WHLSL	-0.33	(-1.92)*

Table 6: Estimates from Panel Probit Regressions of the Effects of Firm Characteristics on Investment-grade Credit Ratings.

The dependent variable is a dummy variable that takes on the value of one for investment-grade ratings, zero otherwise. The independent variables include: capital intensity (*CAPINT*), measured by the ratio of property, plant, and equipment to total assets; ($CAPINT^2$), the squared term of capital intensity; leverage (*LEVERAGE*), measured by the ratio of total debt to total assets; interest coverage (*INTCOV*), measured by the ratio of operating income before depreciation to interest expense; return on assets (*ROA*), measured by the ratio of net income before extraordinary items to total assets; firm size (*SIZE*), measured by log of total assets; firm-specific risk (*FIRMσ*), proxied by the sum of squared residuals from the market model regression; systematic risk (*FIRMβ*), calculated from the market model regression; (*LOSS*), a dummy variable assigned one if the net income before extraordinary items is negative in the current fiscal year, zero otherwise; presence of subordinated debt (*SUBORD*), a dummy variable that takes on the value of one if a firm has subordinated debt, zero otherwise; (*FIN*), a dummy variable that takes on the value of one if a firm is a financial firm, zero otherwise; (*UTIL*), a dummy variable that takes on the value of one if a firm is a utility, zero otherwise. All standard errors are clustered by firm. We include year dummies for all regressions but are not reported here. The z-statistics are given in the parentheses: ***, ** and * imply the significance of coefficient at the 1%, 5% and 10%, respectively.

(see next page)

	Panel A: All Period	Panel B: Pre-*EPAct*	Panel C: Post- *EPAct*
	Dependent= Investment-grade Rating	Dependent= Investment-grade Rating	Dependent= Investment-grade Rating
Variable	Coefficient	Coefficient	Coefficient
INTERCEPT	-2.15	-2.27	-1.99
	(-8.26)***	(-5.63)***	(-6.63)***
CAPINT	0.62	1.86	0.41
	(2.86)***	(3.87)***	(1.78)*
$CAPINT^2$	-0.23	-0.80	-0.15
	(-1.84)*	(-2.64)***	(-1.19)
LEVERAGE	-2.41	-2.87	-2.23
	(-9.21)***	(-6.97)***	(-7.64)***
INTCOV	0.01	0.01	0.01
	(1.88)*	(1.26)	(2.09)**
ROA	6.60	10.50	5.43
	(3.90)***	(7.18)***	(3.26)***
SIZE	0.54	0.53	0.53
	(19.04)***	(10.82)***	(16.48)***
FIRMσ	-70.33	-114.20	-73.50
	(-12.75)***	(-13.78)***	(-9.69)***
FIRMβ	-0.18	-0.12	-0.19
	(-4.16)***	(-1.24)	(-3.96)***
LOSS	-0.42	-0.25	-0.44
	(-5.09)***	(-2.51)**	(-4.97)***
SUBORD	-0.71	-0.68	-0.73
	(-10.87)***	(-5.85)***	(-9.43)***
FIN	0.45	1.11	0.39
	(3.09)***	(4.02)***	(2.49)**
UTIL	0.44	0.40	0.44
	(3.28)***	(1.96)**	(2.92)***
Firm Years	19,125	5,248	13,877
Firms	3,141	1,223	2,682
Log Pseudo-likelihood	-5182	-1105	-4013
Pseudo R^2	0.5926	0.6701	0.5727

Table 7: Estimates from Panel Probit Regressions of the Effects of Firm Characteristics on Ordered Credit Ratings and Investment-grade Ratings.

The dependent variables are ordered credit ratings and investment-grade ratings. The ordered credit rating is an ordered variable that takes on values of 0-6. Investment-grade is a dummy variable that takes on the value of one for investment-grade ratings, zero otherwise. The independent variables include: capital intensity (*CAPINT*), measured by the ratio of property, plant, and equipment to total assets; ($CAPINT^2$), the squared term of capital intensity; leverage (*LEVERAGE*), measured by the ratio of total debt to total assets; interest coverage (*INTCOV*), measured by the ratio of operating income before depreciation to interest expense; return on assets (*ROA*), measured by the ratio of net income before extraordinary items to total assets; firm size (*SIZE*), measured by log of total assets; firm-specific risk (*FIRMσ*), proxied by the sum of squared residuals from the market model regression; systematic risk (*FIRMβ*), calculated from the market model regression; (*LOSS*), a dummy variable assigned one if the net income before extraordinary items is negative in the current fiscal year, zero otherwise; presence of subordinated debt (*SUBORD*), a dummy variable that takes on the value of one if a firm has subordinated debt, zero otherwise; post- Energy Policy Act period (*POST-EPACT*), a dummy variable that takes on the value of one if the corresponding period is from 1992-2006, zero otherwise; post-*EPACT* utility dummy (*POST-EPACT* * *UTIL*), the interaction term between the post-*EPACT* and utility dummies; (*FIN*), a dummy variable that takes on the value of one if a firm is a financial firm, zero otherwise; (*UTIL*), a dummy variable that takes on the value of one if a firm is a utility, zero otherwise. All standard errors are clustered by firm. Except Panel A, we exclude year dummies from all other regressions. The z-statistics are given in the parentheses: ***, ** and * imply the significance of coefficient at the 1%, 5% and 10%, respectively.

(see next page)

	Panel A: Utilities Only	Panel B: Utilities Only	Panel C: Utilities Only	Panel D: All Firms	Panel E: All Firms
	Dependent= Ordered Credit Rating	Dependent= Ordered Credit Rating	Dependent= Investment-grade Rating	Dependent= Ordered Credit Rating	Dependent= Investment-grade Rating
Variable	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
INTERCEPT	-	-	2.49	-	-2.14
	-	-	(2.49)**	-	(-10.06)***
CAPINT	-1.09	0.84	-1.27	0.50	0.77
	(-1.25)	(0.18)	(-1.28)	(5.17)***	(3.67)***
$CAPINT^2$	0.91	0.96	0.92	-0.18	-0.29
	(1.99)**	(2.24)**	(2.16)**	(-4.63)***	(-2.37)**
LEVERAGE	-2.08	-1.68	-1.77	-1.54	-2.32
	(-2.53)**	(-2.17)**	(-1.62)	(-11.99)***	(-10.06)***
INTCOV	0.14	0.13	0.01	0.01	0.001
	(1.29)	(1.32)	(0.21)	(5.98)***	(0.60)
ROA	17.38	17.83	12.6	3.22	6.55
	(3.05)***	(3.35)***	(2.47)**	(5.53)***	(6.55)***
SIZE	-0.02	-0.03	0.03	0.43	0.51
	(-0.34)	(-0.48)	(0.38)	(23.06)***	(21.62)***
FIRMσ	-72.00	-56.68	-71.69	-16.73	-49.68
	(-8.79)***	(-7.87)***	(-5.85)***	(-6.12)***	(-13.28)***
FIRMβ	-0.26	-0.30	-0.36	-0.25	-0.34
	(-1.63)	(-2.59)***	(-2.3)**	(-11.34)***	(-9.94)***
LOSS	-0.07	-0.08	-0.39	-0.62	-0.37
	(-0.42)	(-0.54)	(-2.3)**	(-13.67)***	(-6.23)***
SUBORD	-0.94	-0.91	-1.33	-0.41	-0.68
	(-3.25)***	(-3.80)***	(-3.52)***	(-10.91)***	(-10.94)***
POST-EPACT	-	-0.23	-0.28	-0.49	-0.44
	-	(-1.77)*	(-1.39)	(-12.61)***	(-8.27)***
POST-EPACT* UTIL	-	-	-	-0.13	-0.13
	-	-	-	(-1.30)	(-0.68)
FIN	-	-	-	0.15	0.47
	-	-	-	(1.66)*	(3.45)***
UTIL	-	-	-	0.37	0.50
	-	-	-	(3.05)***	(2.87)***
Year Dummies	YES	NO	NO	NO	NO
Firm Years	2,055	2,055	2,055	19,125	19,125
Firms	179	179	179	3,141	3,141
Log Pseudo-likelihood	-2013	-2069	-377	-23031	-5710
Pseudo R^2	0.2587	0.2349	0.3984	0.28	0.5514

Table 8: Estimates from Panel Probit Regressions of the Effects of Firm Characteristics on Credit Downgrades and Upgrades.

The dependent variable is a dummy variable that takes on the value of one for credit downgrades (upgrades), zero otherwise. The independent variables include: capital intensity (*CAPINT*), measured by the ratio of property, plant, and equipment to total assets; leverage (*LEVERAGE*), measured by the ratio of total debt to total assets; interest coverage (*INTCOV*), measured by the ratio of operating income before depreciation to interest expense; return on assets (*ROA*), measured by the ratio of net income before extraordinary items to total assets; firm size (*SIZE*), measured by log of total assets; firm-specific risk (*FIRMσ*), proxied by the sum of squared residuals from the market model regression; systematic risk (*FIRMβ*), calculated from the market model regression; (*FIN*), a dummy variable that takes on the value of one if a firm is a financial firm, zero otherwise; (*UTIL*), a dummy variable that takes on the value of one if a firm is a utility, zero otherwise. Except for *FIN* and *UTIL* dummies, all other independent variables are measured as changes. All standard errors are clustered by firm. We include year dummies for all regressions but are not reported here. The z-statistics are given in the parentheses: ***, ** and * imply the significance of coefficient at the 1%, 5% and 10%, respectively.

(see next page)

Variable	Panel A: All Period Dependent= Downgrade Coefficient	Panel B: Pre-*EPAct* Dependent= Downgrade Coefficient	Panel C: Post- *EPAct* Dependent= Downgrade Coefficient	Panel D: All Period Dependent= Upgrade Coefficient	Panel E: Pre-*EPAct* Dependent= Upgrade Coefficient	Panel F: Post- *EPAct* Dependent= Upgrade Coefficient
INTERCEPT	-1.15	-1.07	-1.60	-1.67	-1.73	-1.71
	(-15.53)***	(-13.34)***	(-17.06)***	(-17.05)***	(-15.70)***	(-18.49)***
Δ CAPINT	-0.40	0.59	-0.75	0.35	-0.53	0.62
	(-1.28)	(1.02)	(-2.17)**	(0.85)	(-0.57)	(1.3)
Δ LEVERAGE	2.93	2.99	2.84	-4.43	-5.73	-4.18
	(6.15)***	(4.19)***	(4.14)***	(-9.27)***	(-6.08)***	(-7.53)***
Δ INTCOV	-0.02	-0.02	-0.02	0.01	0.00	0.01
	(-6.16)***	(-2.11)**	(-5.67)***	(2.87)***	(0.31)	(2.94)***
Δ ROA	-4.90	-2.68	-6.34	4.17	7.21	3.86
	(-4.18)***	(-1.73)*	(-7.23)***	(6.25)***	(4.30)***	(5.58)***
Δ SIZE	-0.63	-0.70	-0.65	0.71	0.81	0.73
	(-4.67)***	(-2.74)***	(-4.09)***	(4.62)***	(2.41)**	(4.25)***
Δ FIRMσ	4.16	1.61	6.11	-10.08	-20.89	-9.14
	(2.30)**	(1.20)	(1.84)*	(-4.79)***	(-3.20)***	(-4.13)***
Δ FIRMβ	0.10	-0.19	0.16	0.05	0.04	0.05
	(2.18)**	(-2.02)**	(3.16)***	(0.82)	(0.31)	(0.74)
FIN	-0.10	0.15	-0.14	0.05	0.13	0.02
	(-1.28)	(0.95)	(-1.72)*	(0.63)	(0.71)	(0.19)
UTIL	0.02	-0.06	0.06	0.02	0.10	-0.02
	(0.34)	(-0.60)	(1.15)	(0.33)	(1.01)	(-0.18)
Firm Years	14,960	3,794	11,166	14,465	3,666	10,799
Firms	2,098	890	1,859	2,071	878	1,842
Log Pseudo-likelihood	-3635	-1008	-2601	-2394	-690	-1698
Pseudo R^2	.0832	0.0685	0.0964	.0632	0.0619	0.0653

Table 9: Estimates from Panel Probit Regressions of the Effects of Firm Characteristics on Credit Downgrades and Credit Upgrades.

The dependent variables are credit downgrades and upgrades. Downgrade (*upgrade*) is a dummy variable that takes on the value of one for credit downgrades (upgrades), zero otherwise. The independent variables include: capital intensity (*CAPINT*), measured by the ratio of property, plant, and equipment to total assets; leverage (*LEVERAGE*), measured by the ratio of total debt to total assets; interest coverage (*INTCOV*), measured by the ratio of operating income before depreciation to interest expense; return on assets (*ROA*), measured by the ratio of net income before extraordinary items to total assets; firm size (*SIZE*), measured by log of total assets; firm-specific risk (*FIRMσ*), proxied by the sum of squared residuals from the market model regression; systematic risk (*FIRMβ*), calculated from the market model regressions; post- Energy Policy Act period (*POST-EPACT*), a dummy variable that takes on the value of one if the corresponding period is from 1992-2006, zero otherwise; post-*EPACT* utility dummy (*POST-EPACT* * *UTIL*), the interaction term between the post-*EPACT* and utility dummies; (*FIN*), a dummy variable that takes on the value of one if a firm is a financial firm, zero otherwise; (*UTIL*), a dummy variable that takes on the value of one if a firm is a utility, zero otherwise. All independent variables except *POST-EPACT*, *POST-EPACT* * *UTIL*, *FIN*, and *UTIL* dummies are measured as changes. All standard errors are clustered by firm. We exclude year dummies for all regressions. The z-statistics are given in the parentheses: ***, ** and * imply the significance of coefficient at the 1%, 5% and 10%, respectively.

(see next page)

	Panel A: Utilities Only	Panel B: Utilities Only	Panel C: All Firms	Panel D: All Firms
	Dependent= Downgrade	Dependent= Upgrade	Dependent= Downgrade	Dependent= Upgrade
Variable	Coefficient	Coefficient	Coefficient	Coefficient
INTERCEPT	-1.73	-1.54	-2.56	-3.11
	(-14.81)***	(-16.62)***	(-36.65)	(-35.99)***
Δ CAPINT	-0.44	-2.47	-1.13	0.84
	(-0.41)	(-1.49)	(-1.76)*	(0.88)
Δ LEVERAGE	3.60	-3.58	5.90	-8.54
	(1.93)*	(-1.15)	(6.71)***	(-9.41)***
Δ INTCOV	0.00	-0.09	-0.04	0.02
	(0.02)	(-1.10)	(-5.65)***	(3.01)***
Δ ROA	-20.65	1.04	-12.35	7.23
	(-3.62)***	(0.18)	(-6.48)***	(4.98)***
Δ SIZE	1.03	-2.11	-1.25	1.53
	(1.91)*	(-2.07)**	(-4.66)***	(4.74)***
Δ FIRMσ	25.94	-32.35	9.69	-16.32
	(2.04)**	(-2.19)**	(1.14)	(-4.47)***
Δ FIRMβ	0.47	0.07	0.26	0.05
	(3.42)***	(0.38)	(3.11)***	(0.5)
POST-EPACT	0.04	-0.24	-0.06	-0.45
	(0.37)	(-2.07)**	(-0.84)	(-4.62)***
POST-EPACT* UTIL	-	-	0.20	-0.13
	-	-	(0.82)	(-0.47)
FIN	-	-	-0.14	0.10
	-	-	(-0.84)	(0.540)
UTIL	-	-	-0.11	0.12
	-	-	(-0.5)	(0.6)
Firm Years	1,788	1,733	14,960	14,465
Firms	153	153	2,098	2,071
Log Pseudo-likelihood	-404	-275	-3668	-2427
Pseudo R^2	0.0976	0.0405	0.0748	0.0503

Table 10: Estimates from Panel Ordered Probit Regressions of the Effects of Firm Characteristics on Credit Rating Changes.

The dependent variable, change in credit rating (*RATING CHANGE*), is an ordered variable that takes on value of 0-2. Firms that have received credit downgrades over two consecutive years are assigned ratings of zero. Firms that have not experienced any changes in their credit ratings are assigned ratings of one, and firms that have received credit upgrades are assigned ratings of two. The independent variables include: capital intensity (*CAPINT*), measured by the ratio of property, plant, and equipment to total assets; leverage (*LEVERAGE*), measured by the ratio of total debt to total assets; interest coverage (*INTCOV*), measured by the ratio of operating income before depreciation to interest expense; return on assets (*ROA*), measured by the ratio of net income before extraordinary items to total assets; firm size (*SIZE*), measured by log of total assets; firm-specific risk (*FIRMσ*), proxied by the sum of squared residuals from the market model regression; systematic risk (*FIRMβ*), calculated from the market model regression; (*FIN*), a dummy variable that takes on the value of one if a firm is a financial firm, zero otherwise; (*UTIL*), a dummy variable that takes on the value of one if a firm is a utility, zero otherwise. Except for *FIN* and *UTIL* dummies, all other independent variables are measured as changes. All standard errors are clustered by firm. We include year dummies for all regressions but are not reported here. The z-statistics are given in the parentheses: ***, ** and * imply the significance of coefficient at the 1%, 5% and 10%, respectively.

(see next page)

	Panel A: All Period	Panel B: Pre-*EPAct*	Panel C: Post- *EPAct*
	Dependent= Rating Change	Dependent= Rating Change	Dependent= Rating Change
Variable	Coefficient	Coefficient	Coefficient
Δ CAPINT	0.41	-0.59	0.75
	(1.490)	(-1.15)	(2.50)**
Δ LEVERAGE	-3.51	-3.54	-3.45
	(-8.38)***	(-5.40)***	(-6.53)***
Δ INTCOV	0.02	0.02	0.02
	(6.93)***	(2.14)**	(6.85)***
Δ ROA	4.63	3.32	5.15
	(6.20)***	(2.04)**	(8.07)***
Δ SIZE	0.66	0.63	0.72
	(6.16)***	(3.01)***	(6.26)***
Δ FIRMσ	-5.05	-2.50	-7.10
	(-2.71)***	(-1.65)*	(-2.53)**
Δ FIRMβ	-0.04	0.12	-0.08
	(-1.15)	(1.59)	(-1.83)*
FIN	0.08	-0.02	0.09
	(1.70)*	(-0.14)	(1.73)*
UTIL	0.00	0.06	-0.04
	(0.00)	(1.09)	(-0.79)
Firm Years	15,579	3,980	11,599
Firms	2,103	894	1,864
Log Pseudo-likelihood	6097	-1730	-4341
Pseudo R^2	0.0716	0.0565	0.0818

Table 11: Estimates from Simultaneous Models of Leverage and Credit Downgrades (Upgrades) for All Firms Excluding Financials and Utilities.

The dependent variables are change in leverage (*ΔLEVERAGE*) and credit downgrades (*upgrades*). The independent variables include: instrumented downgrade (*upgrade*) dummy (*I_DOWN(UP)GRADE*); instrumented leverage (*I_LEVERAGE*); capital intensity (*CAPINT*), measured by the ratio of property, plant, and equipment to total assets; firm size (*SIZE*), measured by log of total assets; firm-specific risk (*FIRMσ*), proxied by the sum of squared residuals from the market model regression; systematic risk (*FIRMβ*), calculated from the market model regression; market-to-book ratios (*M/B*); profitability (*E/A*); cash holdings (*CASH*), measured by the ratio of cash and short-term investments to total asset; return on assets (*ROA*), measured by the ratio of net income before extraordinary items to total assets; interest coverage (*INTCOV*), measured by the ratio of operating income before depreciation to interest expense. Lags 1-3 indicate credit downgrades (*upgrades*) at times t-1, t-2, and t-3 respectively. Except for the instrumented and lagged variables, all other independent variables are measured as changes. All standard errors are clustered by firm. We include year dummies for all regressions but are not reported here. The z-statistics are given in the parentheses: ***, ** and * imply the significance of coefficient at the 1%, 5% and 10%, respectively.

(see next page)

	Panel A: Simultaneous Downgrade and Leverage		Panel B: Simultaneous Upgrade and Leverage	
	Dependent = *Downgrade*	Dependent = Δ *Leverage*	Dependent = *Upgrade*	Dependent = Δ *Leverage*
Variable	Coefficient	Coefficient	Coefficient	Coefficient
INTERCEPT	-6.98	0.70	-7.43	-0.83
	(-81.42)***	(8.4)***	(-76.75)***	(-6.77)***
I_DOWN(UP)GRADE	-	0.1	-	-0.12
	-	(8.36)***	-	(-6.85)***
I_LEVERAGE	4.22	-	1.61	-
	(2.84)***	-	(1.01)	-
Δ CAPINT	-0.87	0.07	-0.15	0.01
	(-2.84)***	(3.79)***	(-0.84)	(0.38)
Δ SIZE	-0.94	0.11	0.76	0.15
	(-8.93)***	(10.87)***	(6.80)***	(8.81)***
Δ FIRMσ	3.14	-0.29	-2.53	-0.29
	(5.53)***	(-4.07)***	(-3.69)***	(-3.17)***
Δ FIRMβ	0.04	-0.01	0.005	-0.0015
	(3.61)***	(-3.78)***	(0.31)	(-0.88)
Δ M/B	-	0.002	-	0.0033
	-	(4.32)***	-	(6.11)***
Δ E/A	-	-0.05	-	-0.15
	-	(-1.73)*	-	(-4.68)***
Δ CASH	-	-0.09	-	0.07
	-	(-3.18)***	-	(1.81)*
Δ ROA	-0.56	-	1.53	-
	(-1.32)	-	(3.00)***	-
Δ INTCOV	-0.01	-	0.01	-
	(-3.04)***	-	(4.15)***	-
LAG1	-	-0.05	-	0.03
	-	(-6.54)***	-	(3.52)***
LAG2	-	0.03	-	0.05
	-	(-4.48)***	-	(5.48)***
LAG3	-	-0.01	-	0.02
	-	(-1.71)*	-	(2.35)**
Firm Years	13,222	13,222	12,702	12,702
Firms	2,025	2,025	2,011	2,011
Pseudo/ Adjusted R^2	0.0553	0.1627	0.0440	0.1542

Table 12: Estimates from Ordinary Least Squares Models.

The dependent variable is the change in leverage (*ΔLEVERAGE*). The independent variables include: capital intensity (*CAPINT*), measured by the ratio of property, plant, and equipment to total assets; firm size (*SIZE*), measured by log of total assets; firm-specific risk (*FIRMσ*), proxied by the sum of squared residuals from the market model regression; systematic risk (*FIRMβ*), calculated from the market model regression; market-to-book ratios (*M/B*); profitability (*E/A*); cash holdings (*CASH*), measured by the ratio of cash and short-term investments to total asset. *DOWN*- and *UP-GRADES* $_{t\text{-}1\ to\ t\text{-}3}$ are lagged dummies of credit downgrades and upgrades for years t-1 to t-3 respectively. Except for the lagged variables, all other independent variables are measured as changes. All standard errors are clustered by firm. We include year dummies for all regressions but are not reported here. The z-statistics are given in the parentheses: ***, ** and * imply the significance of coefficient at the 1%, 5% and 10%, respectively.

(see next page)

	Panel A: Utilities Only	Panel B: All Other Firms
	Dependent= Δ Leverage	Dependent= Δ Leverage
Variable	Coefficient	Coefficient
INTERCEPT	0.0015	0.0084
	(0.33)	(2.3)**
Δ CAPINT	0.1127	0.0014
	(4.61)***	(0.12)
Δ SIZE	0.0492	0.0528
	(2.97)***	(8.18) ***
Δ FIRMσ	0.1669	0.0199
	(0.42)	(0.43)
Δ FIRMβ	0.0004	-0.0016
	(0.16)	(-2.67)***
Δ M/B	0.0043	0.0027
	(1.26)	(6.28)***
Δ E/A	-0.1415	-0.2497
	(-2.17)**	(-16.19)***
Δ CASH	-0.0622	-0.0402
	(-0.56)	(-2.23)**
$DOWNGRADE_{t-1}$	-0.0047	0.0027
	(-1.36)	(0.83)
$DOWNGRADE_{t-2}$	0.0017	0.0010
	(0.46)	(0.34)
$DOWNGRADE_{t-3}$	-0.0048	-0.0093
	(-1.22)	(-3.24)***
$UPGRADE_{t-1}$	-0.0068	-0.0041
	(-1.01)	(-1.17)
$UPGRADE_{t-2}$	-0.01	(0.01)
	(-1.52)	(2.33**)
$UPGRADE_{t-3}$	-0.004	(0.000)
	(-0.92)	(0.09)
Firm Years	1,648	14,375
Firms	146	2,712
Pseudo/ Adjusted R^2	0.1360	0.1285
Fixed Effects	Yes	Yes

Figure 1: Percent of Firms with Investment-grade Credit Ratings.
Investment-grade rating is coded one if the firm's credit rating is BBB or better, zero otherwise.

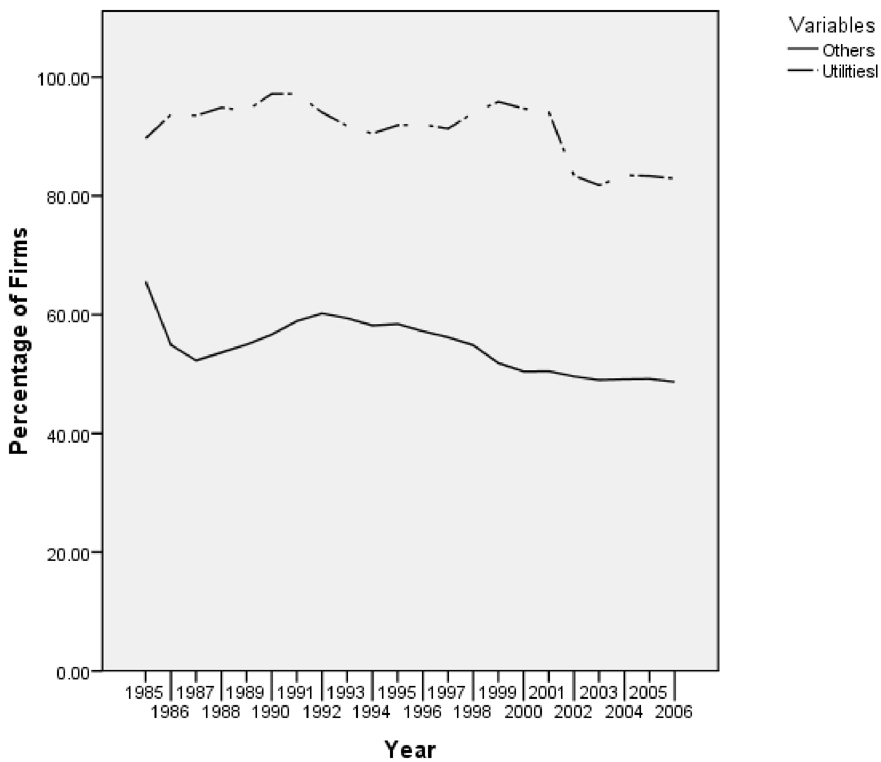
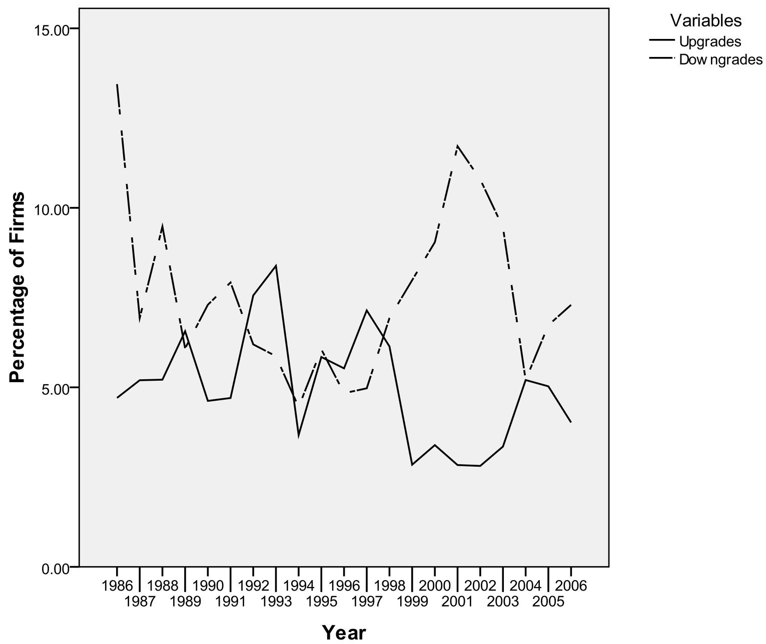


Figure 2: Percent of Firms Upgraded and Downgraded.
Downgrade is a variable that takes on the value of one if a firm's credit rating has been downgraded over the two consecutive years. We define upgrade similarly.

Panel (A): All Firms Excluding Utilities



Panel (B): Utilities Only

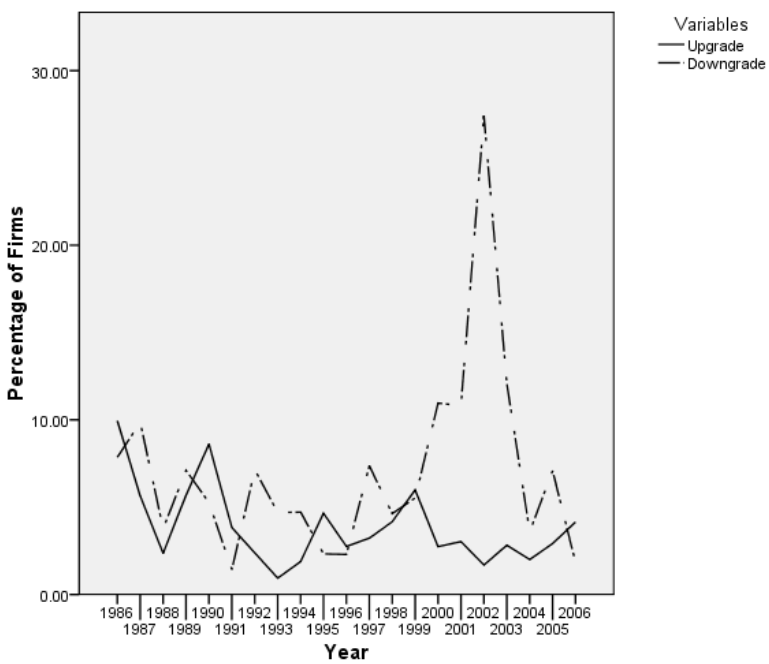


Figure 3: Aggregate Leverage Ratios of Utilities and All Firms.

To calculate leverage ratios, we aggregate total book debts (Compustat data 9 + Compustat data 34) over all utilities (firms) for each year and scale them by yearly aggregates of total asset (Compustat data 6).

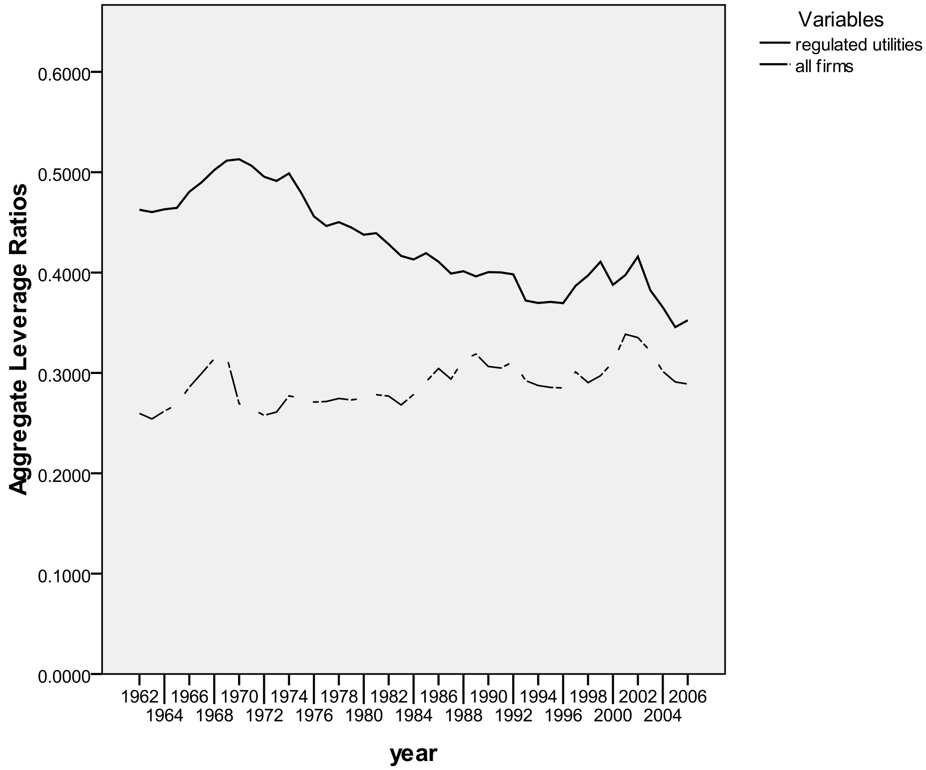


Figure 4: Average Idiosyncratic Risk (1963 through 2006).
For each firm in a given year, idiosyncratic risk is proxied by the sum of squared residuals from the market model regression using monthly data (Equation 2.2). For each year, we average these ratios over all firms.

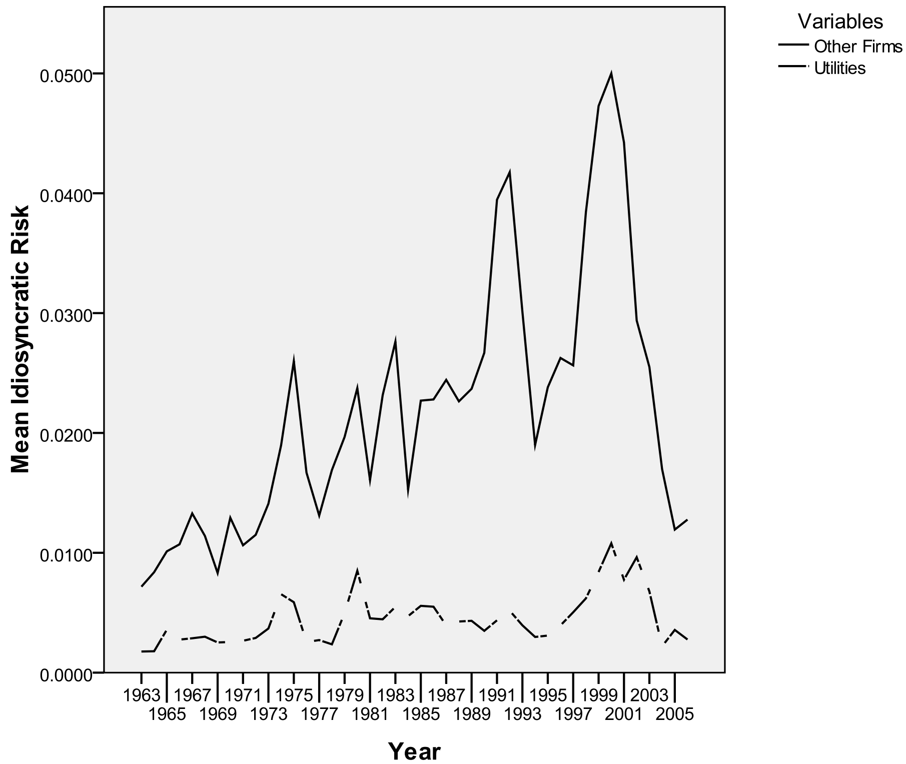


Figure 5: Plot of Time Dummy Coefficients from Ordered Probit Regressions.

Here, rating = $\beta_0 + \beta_1$CAPINT + B_2LEVERAGE + B_3INTCOV + B_4ROA + B_5SIZE + B_6FIRMσ + B_7FIRMβ + B_8LOSS + B_9SUBORD + $\delta_{1\ldots21}$ YEAR INDICATOR $_{it}$ + ε_{it}, where δ's are the year dummy coefficients from 1986 to 2006. We run this regression for all firms and for utilities. The base year is 1985. Time dummies are expected to capture time-specific component not captured by firm characteristics. All standard errors are clustered by firm.