

## **Rating or No Rating? That is the Question: An Empirical Examination of UK Companies**

The aim of this paper is to examine the main determinants of the rating likelihood of UK companies. We use a binary probit specification to model the main drivers of a firm's propensity to be rated. Using a sample of 245 non-financial UK companies over the period 1995 to 2006 representing up to 2,872 firm years, the study establishes important differences in the financial profiles of rated and non-rated firms. The results of the rating likelihood models indicate that the decision to obtain a rating is driven by a company's financial risk, solvency, default risk, public debt issuance, R&D, and institutional ownership, thus identifying a wider range of determinants and extending the current literature. The study also finds that the rating decision can be modelled by means of a contemporaneous or predictive specification without any loss of efficiency or classification accuracy. This offers support to the argument that the rating process is fundamentally forward-looking.

Keywords: credit ratings, rating likelihood, rating determinants, probit

## 1. Introduction

Credit ratings play an important information signalling role in financial markets. They measure the relative creditworthiness of companies (Gonzalez *et al.*, 2004) and are an objective way of distinguishing between relatively risky and safe firms (Amato and Furfine, 2004). They are also measures of long-term corporate credit strength since the focus of the rating process is on ‘the ability of the creditor to repay long-term debt’ (Horrigan 1966, p. 45). Moreover, ratings can be regarded as long-term indicators of possible defaults (Byoun and Shin, 2002). Creighton (2004) and Ong (2002) find that default rates are consistent with lower ratings and show a strong correlation between rating categories and actual defaults respectively.

The majority of earlier studies have focused on the rating process itself; they model the determinants of external credit ratings using financial variables such as profitability, liquidity and financial leverage, largely for companies in developed economies – predominantly the USA (Blume *et al.*, 1998), the UK (Adams *et al.*, 2006), Japan (Poon, 2003) and Australia (Gray *et al.*, 2006) – and from a range of industries, such as insurance (Cantor and Packer, 1997; Pottier and Sommer, 1999), banking (Poon and Firth, 2005) and even local government (Moon and Stotsky, 1993). More recent studies, however, focus to a greater extent on the non-financial determinants of credit ratings (Czarnitzki and Kraft, 2004, 2006; Ashbaugh-Skaife *et al.*, 2006) and examine the effects of new ratings and rating changes on share and bond prices, as well as on other instruments such as financial derivatives (Followill and Martell, 1997; Steiner and Heinke, 2001).

However, to date not much attention has been paid to the decision to obtain a rating itself. The criticism that rating agencies have attracted in relation to their role in the current financial crisis, has given rise to the need for better understanding of the indicators of a company’s creditworthiness, as well as the factors that influence the likelihood of being rated in the first instance. Events suggest that credit rating agencies might not possess unique insights into a company’s true credit quality. Evidently, there is a

need to examine the determinants of the decision of a company to obtain a credit rating in a more systematic and comprehensive fashion. In so doing, we may establish the reasons managers choose ratings as a way of signalling the ‘adequacy of their corporate financial strength’ (Adams *et al.*, 2006, p. 541).

This paper examines UK-based non-financial company data to investigate the determinants of the decision of firms to solicit a credit rating. Managers may employ credit ratings to signal the creditworthiness and efficiency of the internal control mechanisms of their firm as well as their own competence. This study seeks to provide an insight into managerial motives for soliciting credit ratings. In addition, we aim to build upon previous US-based research by examining a large panel of UK companies drawn from across all industrial sectors. Finally, the study aims to contribute to the theoretical debate concerning the differences between rated and non-rated companies.

The remainder of the paper is organised as follows: Section 2 reviews the existing literature, presents the framework for the study and details the hypotheses to be tested, while Section 3 discusses the research methodology and design. Section 4 presents the empirical findings, while Section 5 concludes.

## **2. Literature Review**

Credit ratings are voluntary by nature and thus managers need to have a strong incentive to solicit a rating. Anecdotal evidence suggests that firms which issue bonds are in general rated; this possibly reflects the mandatory requirement in the US that bond issuers must carry a credit rating. However, this requirement does not apply to UK companies. In the context of signalling theory, De and Kale (1993) argue that financially stronger firms have the most to gain by transmitting information to the markets about their financial strength and therefore seek to be rated. Moreover, Moon and Stotsky (1993) and Gan (2004) posit that due to information asymmetry, credit ratings are seen as an important source of information to the market about a rated company. Similarly, Pottier and Sommer (1999, p. 626) contend

that the principal role of rating agencies is ‘the reduction of ex-ante uncertainty of informational asymmetry about a firm’s economic value and probability of financial distress’, while Rösch (2005) finds that credit ratings can accurately differentiate between failing and surviving firms.

In studies of municipal bonds, Lamb and Rappaport (1987) and Moon and Stotsky (1993) model the determinants of rating likelihood. Their empirical results suggest that outstanding debt is an important factor in the decision to solicit a rating; this is due to the prospective savings in interest costs that might arise from obtaining a favourable rating. Along the same lines, Cantor and Packer (1997) find that large firms with higher levels of outstanding debt are more likely to obtain an additional rating. They argue that to lower the interest rate on new debt issues, companies need to obtain a credit rating which will constitute an objective assessment of the creditworthiness of the company. Consequently, the rating dictates the firm’s cost of borrowing, lowering it if a favourable rating is assigned; this therefore implies that issuing bonds and obtaining a credit rating are inter-related processes.

Correspondingly, Pottier and Sommer (1999) and Kisgen (2006) posit that raising debt capital is a significant determinant of a firm’s decision to obtain a rating. They argue that access to capital markets is affected by the existence of a credit rating. In particular, Kisgen contends that a company might not be able to raise debt capital at certain ratings, such as speculative-grade ratings, in which case, additional costs would be incurred. In addition, he reports that changes in credit ratings affect the issuance and cost of debt and finds a strong relationship between availability and access to debt capital and the existence of a credit rating.

Informed by this literature, the following hypotheses are proposed:

H<sub>1</sub>: High levels of debt increase the likelihood of companies soliciting a credit rating.

H<sub>2</sub>: Companies issuing bonds are more likely to solicit a credit rating.

H<sub>3</sub>: Companies with a history of issuing bonds are more likely to solicit a credit rating.

Furthermore, Logue and Merville (1972, p. 41) contend that profitability can be considered as an ‘inverse surrogate for business risk’. Thus, high values of profitability can significantly reduce the systematic risk of a firm. Similarly, Adams *et al.* (2003, pp. 544-45) argue that higher profitability is often associated with lower insolvency risk and posit that profitability offers insights into ‘management’s ability to control expenses effectively’. Poon (2003) and Poon and Firth (2005) find that firms with solicited ratings boast higher profit margins and higher rates of return on assets when compared to firms with shadow ratings, (i.e. ratings assigned to a company without its active involvement in the rating process and therefore based entirely on public information). It is hypothesised that:

H<sub>4</sub>: Higher levels of profitability are associated with a greater propensity to solicit a credit rating.

With regard to the effect of leverage and the likelihood of companies obtaining a credit rating, there is a lack of consensus in the literature. Cantor and Packer (1997), for instance, posit that higher levels of financial leverage increase uncertainty regarding the firm. This provides firms with an extra incentive to solicit a new or an additional rating in order to signal their true credit risk. Similarly, Sommer and Pottier (1999) contend that high levels of leverage might be associated with greater uncertainty. Hence, highly geared companies are more likely to seek a credit rating to communicate their true probability of default. In contrast, others argue that higher levels of leverage are associated with higher values of business risk and thus highly leveraged companies will not actively seek a credit rating as this is likely to exacerbate market uncertainties about their ability to meet debt payments (Borde *et al.*, 1994; Adams *et al.*, 2003; Molina, 2005). Furthermore, Poon (2003) argues that due to the increased financial distress risk brought about by leverage, an inverse relationship might exist between leverage and the likelihood of obtaining a credit rating. Hence, on balance, the following hypothesis is proposed:

H<sub>5</sub>: Highly geared companies are less likely to solicit a credit rating.

Ganguin and Billardelo (2004) point out that financial flexibility constitutes an important measure of company financial risk. They contend that firm financial flexibility is positively related to profitability

and the quality of the assets on the balance sheet. Furthermore, financial flexibility, they add, drives the cash flow generation process, while its importance is accentuated in the event of financial distress when certain credit ratios become irrelevant and ‘the sole analytical focus should be on financial flexibility’ (p. 275). In addition, Gamba and Triantis (2008) argue that firms with financial flexibility are more likely to avoid financial distress in the event of negative shocks and are readily able to fund investment opportunities when they arise since they can access and restructure their debt at lower cost. Similarly, Poon (2003) finds that companies with solicited ratings are more financially flexible than those with unsolicited ratings. Thus, companies with ‘shadow’ ratings have higher short-term debt in their capital structure, less cash readily available for investment purposes and less invested funds. On this basis, the following hypothesis is proposed:

H<sub>6</sub>: Financially flexible companies are more likely to solicit a credit rating.

In relation to firm size, Koller *et al.* (2005) argue that larger firms are more likely to be diversified. Furthermore, size is a proxy for longevity and market power. Altamuro *et al.* (2009), for instance, find that larger companies are more likely to perform better during an economic downturn and are also more likely, due to diversification, to have a competitive advantage over smaller companies or market entrants. Additionally, bigger companies are more likely to maintain a prominent market position and a good reputation for sound corporate governance practices that the management may want to signal and protect (Adams *et al.*, 2003). Consequently, the following is hypothesised:

H<sub>7</sub>: Larger companies are more likely to solicit a credit rating.

When it comes to default risk, Cantor and Packer (1997) and Pottier and Sommer (1999) argue that companies solicit a credit rating if there is greater uncertainty about their true default risk. They hypothesise that greater uncertainty about a company, hence a higher probability of default, is a strong motive for firms to obtain a new or additional rating in an attempt to communicate information about their true credit quality. Similarly, Fama and French (1992) find an explicit link between the book-to-market (BTM) ratio and financial distress. They report that the market perceives companies with a high

BTM as having poorer prospects in relation to those with a low BTM; hence, BTM 'may capture the relative-distress effect' (p. 444). Building on this argument, Dichev (1998) contends that if bankruptcy is incorporated into systematic risk, it should be positively related to a company's BTM ratio. Therefore, the following hypothesis is proposed:

H<sub>8</sub>: Companies with high book-to-market ratios are more likely to solicit a credit rating.

Innovation is another factor that affects company risk and thus the soliciting of a credit rating. Piga and Atzeni (2007), for instance, argue that innovative firms find it difficult to access debt finance due to high information asymmetries, arising from the information advantage of the inventor over the investor. However, Czarnitzki and Kraft (2004) maintain that innovation, and consequently investment in research and design activity (R&D), is not as risky as it is portrayed. Thus, companies that invest in R&D and develop a knowledge stock have better chances of survival. In addition, they posit that R&D-intensive companies are more likely to communicate their commitment to the capital markets as a way of signalling potential future benefits. Moreover, Piga and Atzeni (2007) find that R&D-intensive firms are more likely to avoid facing credit constraints, whilst Czarnitzki and Kraft (2006) establish that the vast majority of companies in developed economies that engage in R&D activities reduce their risk of bankruptcy considerably. Hence, the following hypothesis is proposed:

H<sub>9</sub>: Higher R&D intensity companies are more likely to solicit a credit rating.

Another aspect for consideration when seeking a credit rating is institutional ownership as a corporate governance mechanism. Standard and Poor's (2004) perceive the extent of institutional ownership as a proxy for one aspect of corporate governance, that of ownership structure and influence of external stakeholders. The selection of this variable is informed by Shleifer and Vishny (1997), who argue that large institutional shareholders play an active role in corporate governance due to their general interest in profit maximisation and control over the firms they invest in. Further, Jensen (1993) maintains that institutional investors possess sufficient independence and voting power to put pressure on self-serving management, thus contributing to an efficient corporate governance system. Along the same lines,

Ashbaugh-Skaife *et al.* (2006, p. 203) contend that weak corporate governance can ‘impair a firm’s financial position’ and leave shareholders and bondholders vulnerable to losses. They find an inverse relationship between the quality of governance and debt financing costs, suggesting that a lack of appropriate control mechanisms results in higher interest costs. However, they posit that institutional ownership is such a mechanism that benefits company performance significantly. Consistent with this argument, Cornett *et al.* (2006) argue that institutional ownership limits managerial discretion. Significant levels of institutional ownership not only increase oversight of the firm but also ‘rein in’ aggressive use of accounting discretion. Therefore, the following hypothesis is proposed:

H<sub>10</sub>: Higher institutional ownership increases the likelihood of soliciting a credit rating.

The main studies in the area of credit rating are summarised in Table 1, alongside the summary of the variables which will be used in this study to test our hypotheses.

INSERT TABLE 1 ABOUT HERE

### 3. Methodology

#### 3.1. Model and Variables

The aim of this paper is to examine the main determinants of rating likelihood of UK companies. We estimate a binary probit model to determine the main drivers of a firm’s likelihood of obtaining a credit rating, consistent with the existing literature. The binary probit model considers the effect of a vector of explanatory variables  $x_{it}$  on a latent continuous variable  $d^*$ . The model can be written in general form as in Equation (1):

$$d_{it}^* = a'x_{it} + u_{it} \quad (1)$$



with  $u_{it}$  being a normally distributed random error [ $u_{it} \sim N(0,1)$ ] and  $a'$  the vector of coefficients to be estimated. The latent variable  $d^*$  in (1) can be interpreted as the propensity to be rated. However,  $d^*$  is observed only as a binary or dichotomous variable  $d$  which is defined by the threshold model:

$$d_{it} = \begin{cases} 1 & \text{if } d_{it}^* > 0 \\ 0 & \text{if } d_{it}^* \leq 0 \end{cases} \quad (2)$$

In (2), the binary variable  $d$  equals '0' for a company that has no rating and '1' for a firm with a rating.

The independent variables included in this study are defined in Table 2.

INSERT TABLE 2 ABOUT HERE

The contemporaneous pooled equation to be estimated is given as:

$$d_{it}^* = a_0 + a_1 ROA_{it} + a_2 GEAR_{it} + a_3 STDTD_{it} + a_4 LNSALES_{it} + a_5 LOGDEBT_{it} + a_6 BONDYN_{it} + a_7 BONDYBEF_{it} + a_8 BMV_{it} + a_9 RNDD_{it} + a_{10} INSTINV_{it} + u_{it} \quad (3)$$

whilst the predictive pooled equation to be estimated is as follows:

$$d_{it}^* = a_0 + a_1 ROA_{it-1} + a_2 GEAR_{it-1} + a_3 STDTD_{it-1} + a_4 LNSALES_{it-1} + a_5 LOGDEBT_{it-1} + a_6 BONDYN_{it-1} + a_7 BONDNEY_{it-1} + a_8 BMV_{it-1} + a_9 RNDD_{it-1} + a_{10} INSTINV_{it-1} + u_{it} \quad (4)$$

One alternative to conventional econometric methods not explored in this study is the application of neural network techniques. From a methodological perspective, the latter are:

- able to deal with incomplete or noisy data (Hawley *et al.*, 1990; Sharda, 1994)
- capable of determining the functional and variable interrelationships from the data itself (Perry, 1994; Huang *et al.*, 2004);
- robust to probability distribution assumptions (Sharda, 1994)

- better at pattern recognition, can learn incrementally (Hsieh, 1993; Widrow and Stearns, 1995) and do not require prior specification of theoretical models (Anders and Korn, 1999).

However, criticism is at times levelled that neural networks are ‘black box’ techniques, economically less readily transparent and can suffer from overfitting (Hill *et al.*, 1994, Krishnaswamy *et al.*, 2000); and whilst they may be superior in classification problems they do not always outperform conventional techniques in forecasting problems (Sharda, 1994). In the credit ratings literature, many (Dutta and Shekhar, 1988; Surkan and Singleton, 1990; Kim *et al.*, 1993; Moody and Utans, 1995) find that neural networks outperform conventional models, whilst others (Singleton and Surkan, 1995; Krishnaswamy *et al.*, 2000; Huang *et al.*, 2004) report that the former can present difficulties in distinguishing between multiple adjacent ratings subgroups. However, others still (Bennell *et al.*, 2006) argue that more efficient sovereign credit rating classification outcomes can be produced with neural networks, particularly where the risk assessment process lacks a well-defined theory. As our purpose is to propose a testable conceptual framework grounded in economic theory and we enjoy the benefit of a good quality dataset, we have decided to focus on a conventional econometrics approach.

### 3.2. Sample Selection and Data

Our sample consists of 245 UK listed non-financial companies over the period 1995 to 2006, inclusive. 86 firms are assigned credit ratings by Standard and Poor’s, while 159 companies are not rated by any of the four major rating agencies (Standard and Poor’s, Moody’s, Fitch Ratings and A.M. Best) over the 12-year period under investigation. This represents up to 2,872 firm years after allowing for missing observations. Many argue that empirical results obtained using a single agency’s ratings are representative due to the perceived homogeneity of the credit rating industry (Holthausen and Leftwich, 1986; Dichev and Piotroski, 2001; Beaver *et al.*, 2006). All 86 rated companies are, or have been, constituents of the FTSE-100 index over the studied period. Hence, non-rated companies from the FTSE-350 index are chosen to enable construction of a dataset matched by industry and size. This

practice is consistent with the majority of bankruptcy prediction studies (Beaver, 1966; Altman, 1968; Hamer, 1983; Gentry *et al.*, 1988; Charitou *et al.*, 2004) and earlier research in the area of self-selection in credit ratings (Moon and Stotsky, 1993; Adams *et al.*, 2003); it is also implemented with a view to ensuring homogeneity and allowing for direct comparability between rated and non-rated companies. Nevertheless, one should not lose sight of the potential bias that is introduced in the analysis by including only relatively big companies especially with respect to generalisability of results (Altman, 1968). Nonetheless, this is an issue in common with the overwhelming majority of credit rating studies due to the nature of the companies soliciting a credit rating (Sylla, 2001).

Financial statement information for the period is collected from OSIRIS, market data is collected from Datastream, and corporate governance information is manually collected from company annual reports.

Our initial analyses do not match for rated versus non-rated companies as we have, in common with other studies in the field (e.g. Adams *et al.*, 2003), more non-rated (159) than rated (86) companies in our sample by virtue of the characteristics of the population itself. In the related field of corporate failure, Taffler (1982) argues that exact matching not only severely restricts total sample size and degrees of freedom, but also inhibits representativeness in relation to the underlying population. Nevertheless, whilst the fact that the sample is not matched has little impact on the model itself, it is clearly capable of impacting upon the percentage of correct predictions in that a naïve model classifying all companies on a *prima facie* basis as non-rated could perform well where non-rated companies constitute a greater proportion of the sample. Our study explicitly addresses this issue by: a) constructing prediction tables for the fitted models with a percentage correct classification for both diagonal and off-diagonal categories; and b) repeating the analyses using a matched sample of rated and non-rated companies on the basis of total assets.

For model validation purposes, we partition the matched dataset into two parts in a proportion of 3:1, in line with prior studies in the field (Doumpos and Pasiouras, 2005; Chen and Shih, 2006). The first part

is used for training and model estimation exclusively, whilst the second part is used for testing. Moreover, our study reports both cross-sectional and time-series out-of-sample predictions. The former involves predicting the probability of rating solicitation for 25% of rated and non-rated companies respectively, randomly chosen from the matched dataset, whilst the latter relates to repeating the same prediction for all companies in the matched dataset over the last three years of the sample.

Using the Industrial Classification Benchmark (ICB), we identify ten industrial sectors, a summary of which is presented in Table 3. The majority of the companies in the sample are clustered in the consumer services and industrial sectors. Together, they account for 134 firms (55% of the sample). Table 3 also shows that rated and non-rated companies are matched well on a percentage basis, though with the number of non-rated companies in any industry in general exceeding the number rated. However, rated utility companies outnumber their non-rated counterparts; this observation is in common with existing empirical studies (Grier and Gatz, 1977; Pettit *et al.*, 2004); and is often attributed to the increased funding needs that relate to the ‘heavy capital expenditure programmes’ (Baker *et al.* 1999, p. 15) of utility firms that are serviced principally via the bond markets.

INSERT TABLE 3 ABOUT HERE

Panel A of Table 4 presents the number of rated and non-rated companies over the sample period. The results show an almost monotonic increase in the number of rated companies. In 2006, 74 companies bore a credit rating compared to only 30 in 1995. This represents an increase of 147%, evidencing the growing importance of credit ratings in the UK as well as the increasing willingness of firms to obtain a credit rating. The number of non-rated companies remains relatively stable over time, with a slight decrease that may be attributed to beginning of study sample companies obtaining a credit rating, delisting and/or going bankrupt. Panel B of Table 4 details the number of companies assigned specific ratings over the sample period. In all years, over 80% of Standard & Poor’s rated companies are

assigned an investment-grade rating (BBB- and above). The results also suggest that the credit quality of UK firms has been deteriorating: whereas in 1995, 83% of the credit rated companies are assigned 'good' ('A') and 'excellent' ('AA', 'AAA') ratings, only 35% of the businesses in 2006 are given such high ratings. The eventual monotonic rating deterioration might suggest that either the credit quality of UK firms has been deteriorating over the period or that tougher rating standards are being imposed by credit rating agencies over time. Blume *et al.* (1998) and Doherty and Phillips (2002) observe that the number of downgrades exceeded the number of upgrades in US companies and US property insurers, respectively, in the 1980s and 1990s, and find that this is attributable to an increase in rating stringency. However, Pottier and Sommer (2003) study US life insurance companies over the same period and determine that either increased stringency or a decrease in creditworthiness not reflected in the financial ratios modelled could explain the increasing prevalence of downgrades. More recently, Gonis and Taylor (2009) study UK firms and also find evidence consistent with either explanation. Furthermore, the reported figures in Panel B offer support to the argument that firms tend to converge upon the investment-grade threshold category (BBB) through time, a finding consistent with the transition matrix reported in Gonis and Taylor. Nevertheless, this seems to apply more to investment-grade and less to speculative-grade companies.

INSERT TABLE 4 ABOUT HERE

## **4. Results**

### 4.1. Descriptive Analysis

Panel A of Table 5 presents the means and standard deviations of the independent variables to be employed in this study. Separate figures are presented for the rated and non-rated companies in the sample. Examination of the figures reveals the presence of outliers in the sample that distort some of the

descriptive results due to the non-normality of the independent variables. As a result, we repeat this exercise for winsorised values of the independent variables (at the 5% level) in Panel B. Estimated skewness and kurtosis values for the winsorised variables evidence some correction towards the normal distribution for specific variables. A more important finding is that rated companies appear to be larger, marginally more profitable, significantly more geared and with a higher level of outstanding total debt than their non-rated counterparts. Also, non-rated companies invest, on average, twice the proportion of their sales in R&D activities compared to rated firms. Additionally, the degree of institutional ownership is significantly higher for rated companies whereas non-rated firms exhibit higher financial flexibility but at the same time are more susceptible to financial distress (as illustrated by the higher book to market values). Overall, the statistics in Table 5 indicate that rated companies have stronger financial profiles than their non-rated counterparts.

Panel C of Table 5 presents a Spearman correlation coefficients matrix for the independent variables included in the pooled model. The estimated correlation coefficients between pairs of independent variables are in general low. Nevertheless, the correlation coefficient between size (lnSALES) and outstanding debt appears to be both high and significant. However, the computed variance-inflation factors (VIFs), which account for potential multicollinearity between more than two independent variables, are all below the critical value of 10 (Gujarati, 2003). This indicates that multicollinearity is not a significant problem in this study.

INSERT TABLE 5 ABOUT HERE

Table 6 presents the means and associated standard deviations of the independent variables for the ten industrial sectors covered in this study as well as the average total assets and the market capitalisations of the companies in our dataset. We find that rated companies enjoy higher profitability in five sectors (oil and gas, basic materials, consumer goods, health care and consumer services), while non-rated firms are more profitable in the industrials, utilities and technology sectors. Consistent with the results

presented in Panel B of Table 5, the differences in firm profitability between rated and non-rated companies are statistically insignificant with the exception of companies in the health care and consumer goods industries. Furthermore, rated companies are higher geared than non-rated companies in the majority of industries, apart from real estate. Not surprisingly, we notice substantial differences in the average gearing levels across different industries. For example, companies in the oil and gas and health care industries have, on average, lower gearing whereas telecommunications and consumer services companies appear significantly more geared with levels of financial leverage exceeding 100%. Similarly, rated companies are larger and have significantly higher levels of outstanding debt than non-rated ones. Non-rated companies are more susceptible to financial distress (as proxied by higher book to market values) in seven industries with the difference being statistically significant in six of them, whilst they exhibit, on average, higher R&D intensity values, with the difference being statistically significant in only three sectors. The comparison of the absolute values of total assets reveals a consistent statistically significant difference between rated and non-rated companies, with the former exhibiting higher values. The same observation applies to market capitalisation. In summary, the findings illustrate a number of marked differences between industries, underlining the need to take industry effects into account when estimating the rating likelihood model.

INSERT TABLE 6 ABOUT HERE

#### 4.2. Rating Likelihood Models

Two specifications of the ‘rating likelihood’ binomial model are estimated. The first has a contemporaneous specification, thereby assuming that the effect of firm characteristics on the decision to solicit a credit rating is of a concurrent nature with companies reacting to changes in their circumstances within the same period. The contemporaneous specification is used by the majority of existing studies in the area of sample selection in credit ratings (Moon and Stotsky, 1993; Cantor and Packer, 1997; Pottier and Sommer, 1999; Adams *et al.*, 2003; Poon, 2003; Poon and Firth, 2005). The

second specification assumes that the decision to get a rating in year  $t$  is determined by company estimates for year  $t+1$ . Nayar (1993) hypothesises that managers can determine the quality of their projects one period in advance. Moreover, Czarnitzki and Kraft (2004) subscribe to this approach by estimating lead rating determinants models in their study of the effects of innovation on credit ratings in order to ‘ensure the causality runs from innovation to the rating’ (p. 379). The adoption of such an approach is supported by Sufi (2009), who estimates a *predictive model* assuming that expected firm characteristics in year  $t+1$  affect a company’s decision to obtain a rating in year  $t$ .

Table 7 presents the results of the contemporaneous specification. Model I excludes dummies while Models II and III include industry and time dummies respectively, and Model IV includes both time and industry dummies. In all four models, the estimated coefficients of the independent variables are all statistically significant, with the exception of BMV in Models I and III. Profitability, size, financial flexibility, outstanding debt, bond issuance, R&D intensity and institutional ownership all exert a statistically significant influence (at the 1% level, two tail) on the propensity to be rated, whilst leverage is statistically significant at the 5% level. However, when industry dummies are included in the contemporaneous likelihood specification (Models II and IV), the estimated coefficients increase in statistical significance (1%, two tail). This supports the statistics presented in Table 6 which imply that leverage is greatly influenced by industry factors and thus needs to be taken into account when modelling the determinants of rating likelihood. Likewise, when industry effects are incorporated into the rating propensity models, the estimated coefficient of the book-to-market variable is significant at the 10% level. Our results would therefore appear to support prior empirical findings that financial leverage and default risk vary greatly across industries and are therefore expected to vary in their influence upon the firm’s decision to solicit a rating.

The signs of the estimated coefficients are all as hypothesised, with the exception of profitability that displays a significant negative sign, indicating that UK firms with higher levels of profitability have a lower propensity to be rated. Less profitable firms may be more likely to solicit a credit rating as they



perceive the whole process as a way of signalling their creditworthiness to the markets in an attempt to secure access to capital (Adams *et al.*, 2003). An alternative explanation is offered by Cantor and Packer (1997) who argue that higher profitability is associated with reduced uncertainty about a firm. Based on this argument, we can argue that more profitable firms do not need to use a rating agency to certify their strong financial position. More importantly, however, Shyam-Sunder and Myers (1999) find that more profitable companies are less inclined to borrow funds externally. This has implications for the solicitation of a credit rating since profitable companies might not perceive the benefit of obtaining a credit rating if they do not have need to access the financial markets for funds.

The marginal effects are presented in Panel B of Table 7. Increases in profitability and leverage tend to increase the likelihood of being non-rated, whereas increases in firm financial flexibility, size, default risk, outstanding debt and institutional ownership lead to a higher propensity of being rated. Further, companies with current and a history of past public debt issuance and involvement in R&D are more likely to obtain a credit rating. The statistics listed in Panel C include the  $\chi^2$  statistic that tests the null hypothesis that the regression coefficients (excluding the constant term) are all zero. The estimated values for all models reject this hypothesis. Moreover, the Hosmer-Lemeshow  $\chi^2$  statistic, used for model validation, indicates that the proposed models fit the data satisfactorily, while the computed (adjusted) McFadden  $R^2$  values suggest reasonably good fits.

Table 8 presents the results for the predictive specification. As with the contemporaneous specification, Model V excludes dummies, Models VI and VII include industry and time dummies respectively, whilst Model VIII includes both dummies. Size, financial flexibility, outstanding debt, public debt issuance, financial distress risk, R&D intensity and institutional ownership all have the hypothesised signs and are statistically significant. Leverage has the hypothesised sign and is statistically significant in all four models, but only marginally statistically significant in the model incorporating the time dummy. Similarly, future bond issuance, which replaces past bond issuance in the predictive models, is only statistically significant in three out of four models. An explanation for this is that industry dummies in

Model VI proxy the same effect that is measured by the future public debt issuance variable. This finding is supported by the sample statistics in Table 3 and the ensuing discussion, which collectively imply that bond issuance is driven by industry-specific factors. Profitability retains its significant negative sign in the predictive specification. Therefore, our findings indicate that companies with high levels of expected profitability do not see the benefit of obtaining a credit rating, especially when their expected profits can be retained to finance new projects and hence circumvent the need for external funding.

One notable difference between the contemporaneous and predictive model specifications relates to forecasted outstanding total debt. The estimated coefficient is lower in the predictive specification, reflecting the fact that future as opposed to current financing needs are harder to predict. The marginal effects presented in Panel B of Table 8 indicate that increases in expected profitability and leverage decrease the likelihood of being rated; whereas increases in a firm's financial flexibility, size, default risk, outstanding debt and institutional ownership lead to a higher propensity of being rated. Similarly, companies with current and expected future public debt issuance and high R&D intensity are more likely to obtain a credit rating. The estimated  $\chi^2$  statistic values for all of the predictive specification models, as shown in Panel C of Table 8, reject the hypothesis that the independent variables together are not different from zero. Moreover, both the Hosmer-Lemeshow  $\chi^2$  statistic and the (adjusted) McFadden  $R^2$  values suggest satisfactory fits respectively.

INSERT TABLE 7 ABOUT HERE

INSERT TABLE 8 ABOUT HERE

Finally, Table 9 presents within-sample classification performance statistics for all eight models. The contemporaneous specification models achieve a minimum within-sample correct classification rate of 92.28% and a maximum of around 93.33%. The predictive specification models achieve slightly lower

values of 91.62% and 92.56%, respectively. For both specifications, the models which include the industry dummies achieve the highest correct classification rates, further illustrating the importance of explicitly accounting for industry-specific effects. In terms of classification ability, the models in this study perform significantly better in terms of reported classification results than Van Roy's (68.9%) and Adams *et al.*'s (80.38%). Interestingly, both of these existing studies focus on a specific individual industry alone, whereas the study detailed here examines the rating likelihood determinants across all UK non-financial industries, leading to a greater generalisation of results.

INSERT TABLE 9 ABOUT HERE

As a robustness test, we run the analyses again using a balanced panel of rated and non-rated companies. All 159 non-rated companies are ranked according to average total assets over the sample period and the top 86 are chosen to match as closely as possible their rated counterparts. Tables 10 and 11 present the results of the contemporaneous and predictive specifications respectively. The fitted coefficients are qualitatively similar to those reported in Tables 7 and 8 respectively. Interestingly, in both specifications, the BMV coefficient is statistically more significant than in the non-matched sample. This difference can be attributed to the exclusion of a significant number of small, more default-prone companies that might have been distorting the results. Further, the marginal effects in Panel B of Tables 10 and 11 are different from those reported in Tables 7 and 8. More specifically, the majority of marginal effects of the predictive specification of the matched sample (Models XIII – XVI) are statistically significant and of a more meaningful size. Long (1997) argues that the magnitude of marginal effects depends on the values of all model variables and their coefficients, since the generating function depends on the interaction of effects and variables in the dataset. This can explain the reported change in the restricted, matched sample.

INSERT TABLE 10 ABOUT HERE

INSERT TABLE 11 ABOUT HERE

For model validation purposes, we split our entire matched dataset into training and testing samples. Table 12 shows four different versions of the contemporaneous and predictive models. Models XVII and XIX exclude the last three years (2004-2006) from both specifications, whilst models XVIII and XX exclude an equal number of randomly chosen rated (22) and non-rated (22) companies respectively, both representing 25% of the sample. Our results illustrate the robustness of the coefficients in these different specifications. Profitability retains its negative sign, whilst leverage is highly statistically significant in both specifications. Default risk, as proxied by book-to-market ratio, is statistically significant in all specifications, albeit marginally so in the first three models. Meanwhile, R&D intensity, institutional ownership, bond issuance (including past and future), financial flexibility, size and the extent of outstanding debt are all statistically significant and appear with the hypothesised signs. Model statistics reveal that the models are correctly specified and achieve good fits on the basis of adjusted McFadden  $R^2$  values.

INSERT TABLE 12 ABOUT HERE

Table 13 illustrates that the estimated models exhibit significantly high out-of-sample prediction rates. Specifically, both contemporaneous and predictive models achieve, on average, an 85% correct prediction rate when the last three years are excluded from the training set. Meanwhile, the models perform even better, achieving a 90% correct prediction rate, when classifying the randomly chosen companies belonging to the testing set. It is worth noting that whereas the Type II errors in Models XVIII (7.43%) and XX (7.56%) relate to companies which the model predicted as rated whilst they were non-rated, these companies all eventually solicited a rating, thereby further supporting the underlying strength of the model. Indeed, when these firms are not taken into account, each model misclassifies

only two firms. Hence, we can argue that our models are well specified to predict the solicitation of a credit rating and that their predictive capacity is considerable.

INSERT TABLE 13 ABOUT HERE

The models' predictive ability is further supported by Figure 1, which portrays the Receiver Operating Curve (ROC) for Model XVIII. ROCs are proving increasingly helpful in credit rating studies because they plot the proportion of outcomes correctly predicted for different values of a binary classification system's discrimination threshold (Satchell and Xia, 2006). In other words, the ROC describes a model's ability to correctly predict outcomes by plotting the true positive rate (sensitivity) of a model against its false positive rate ( $1 - \text{specificity}$ ). Satchell and Xia go on to argue that a rating model's performance is 'the better the steeper the ROC curve at the left end and the closer the ROC curve's position is to the point (0,1)' (8). Model XVIII's ROC fits that pattern. Moreover, the reported Area Under the Curve (AUC) statistic for Model XVIII is 0.88, indicating that this model exhibits good discriminatory power between rated and non-rated companies. Non-reported AUC statistics for the remaining models in Table 12 are consistently above 0.78, which further supports the efficiency of the different specifications of our rating likelihood models.

INSERT FIGURE 1 ABOUT HERE

## **5. Conclusions**

This study is among the few that investigate the determinants of the rating likelihood of companies, rather than the determinants of a given rating. Moreover, its novelty lies in the fact that it does so for UK non-financial companies over a relatively long period of time (1995-2006). In addition, the study pays specific attention to the time dimension for the factors that drive the rating decision. Five key findings arise from the empirical analysis. Firstly, the likelihood of obtaining a rating is negatively related to a

company's leverage and positively related to its financial flexibility, lending support to the studies of Pottier and Sommer (1999) and Adams *et al.* (2003, p. 564) that show that companies seek to obtain credit ratings with the purpose of reducing the 'ex ante uncertainty about their future levels of financial risk and solvency'. The increased uncertainty (Cantor and Packer, 1997) and higher chances of financial distress (Adams *et al.*, 2003) associated with higher values of financial leverage are strong incentives for not soliciting a credit rating. Nevertheless, this study establishes that the propensity to be rated is negatively related to firm profitability. This result is consistent with the bankruptcy theory that posits that companies with lower profitability have more to gain from the certification exercise (Gan, 2004), and challenges the assumed relationship between profitability and firm uncertainty (Cantor and Packer, 1997; Pottier and Sommer, 1999).

Secondly, outstanding debt, the choice of bonds as a financing method, and past/future issuance of public debt, are all positively related to soliciting credit ratings. Companies that exploit public debt markets to borrow funds are more likely to obtain a credit rating in the hope that it is accompanied by lower interest costs (Lamb and Rappaport, 1987; Moon and Stotsky, 1993). Furthermore, this offers empirical support to anecdotal claims that firms obtain a credit rating for the exclusive purpose of lowering the cost of borrowing via bonds.

Thirdly, default risk, as proxied by the book to market ratio, is significant across the specifications and different models. This illustrates that market-perceived financial distress risk is an important driver of the decision to obtain a rating in order to signal true firm credit quality to the markets (Fama and French, 1992; Dichev, 1998). In addition, we find that institutional ownership positively affects the likelihood of obtaining a credit rating. Institutional investors are more likely to make use of credit ratings when monitoring the firms in which they invest as such ratings should minimise the principal-agent problem (White, 2001). Finally, the extent of engagement in innovative activity (R&D) is a strong determinant of the decision to apply for a credit rating; the resulting tangible (innovative products) and intangible

benefits (increase in market share, decrease of firm-specific risk) associated with R&D increase the likelihood of a firm soliciting a credit rating.

Fourthly, in terms of model specification, this study finds that the contemporaneous and predictive specifications provide similar results and are equally efficient in classifying accurately the propensity to get rated within-sample. More importantly, the estimated models perform significantly well in out-of-sample classification tests, predicting correctly, on average, 9 out of 10 cases, lending greater support to the robustness of our model. These results taken together lend some support to the argument that the decision to obtain a rating, and the rating process itself, is by nature forward-looking (Standard and Poor's, 2005).

Finally, we address a notable omission in the credit rating literature by providing a testable conceptual framework for the modelling of rating likelihood. This framework is based on signalling to financial markets via credit ratings for the purpose of reducing information asymmetry in relation to firm uncertainty.

A number of areas for further research might include extending this study to US credit ratings data to determine whether the models drawn from our conceptual framework are capable of wider generalisation, a comparison of the probit approach employed in this study with an equivalent neural networking methodology, and an examination of how credit ratings responded to the recent global financial crisis in the US and UK.

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**Table 1: Overview of the Existing Literature**

Study	Variable	Definition of variable	Hypothesised direction	Empirical evidence direction
Moon and Stotsky (1993)	Outstanding debt	Natural logarithm of debt	Positive	Positive <sup>a</sup>
	Region	4 dummy variables for US regions	N/A	Negative <sup>a</sup>
	Population	3 dummy variables for population	Positive	Positive <sup>a</sup>
	Leverage	[Long-term debt+current liabilities+(8xrent)]/total assets	Positive	Negative <sup>b</sup>
	Profitability	Net income/total assets	Positive	Negative <sup>b</sup>
	Coverage	(Net income+interest+rent)/(interest+rent)	Negative	Positive <sup>b</sup>
Cantor and Packer (1997)	Years of public debt	Dummy variable for 10 years of public debt	Positive	Positive <sup>b</sup>
	Long-term debt	Long-term debt outstanding	Positive	Positive <sup>b</sup>
	Default risk (Uncertainty)	Weighted average ratings x average credit spreads	Positive	Negative
	Regulation	Absolute rating difference 3dummy variables for regulatory issues	N/A	Positive <sup>b</sup> , Negative <sup>b</sup>
	Leverage	Statutory capital/total assets	Positive	Negative <sup>a</sup>
	Profitability	Net income/total assets	Positive	Positive <sup>a</sup>
Pottier and Sommer (1999)	Size	Natural logarithm of direct premiums written	Positive	Positive <sup>a</sup>
	Liquidity	(Cash+short-term investments)/invested assets	Negative	Negative <sup>a</sup>
	Reinsurance	Reinsurance ceded/direct premiums written	N/A	Positive <sup>a</sup>

	Business growth	% change in net premiums written	N/A	Negative <sup>a</sup>
	Leverage	Accumulated reserves /total assets	Negative	Negative <sup>b</sup>
	Profitability	(Annual income+unrealised capital gains)/statutory capital	Positive	Positive <sup>b</sup>
	Liquidity	Current assets/current liabilities	Positive	Positive <sup>b</sup> , Negative <sup>b</sup>
Adams, Burton and Hardwick (2003)	Growth	Absolute change in annual reported surplus	Positive	Positive <sup>b</sup>
	Company size	Deflated natural logarithm of total assets	Positive	Negative <sup>b</sup>
	Organisational form	0 if stock company, 1 if mutual company	N/A	Negative
	Reinsurance	Annual reinsurance ceded/Annual premiums written	Negative	Negative <sup>b</sup>
	Business Activity	0 if life insurer, 1 if general and composite insurer	N/A	Positive <sup>b</sup>
	Liquidity	Current assets/current liabilities	Positive	Positive
Poon (2003)	Profitability	Net income/total assets	Positive	Positive <sup>a</sup>
		EBIT/interest expense		
	Leverage	Total debt/shareholders' funds	Negative	Positive
	Financial flexibility	Short-term debt/total debt	Negative	Negative <sup>a</sup>

Notes: <sup>a</sup>, <sup>b</sup>, <sup>c</sup> denote significance at the 1%, 5% and 10% respectively. N/A indicates the lack of stated hypothesis.

**Table 2: Definition of the Model Variables**

<b>Variable</b>	<b>Label</b>	<b>Definition</b>
Profitability	ROA	Ratio of net income to total assets
Leverage	GEAR	Ratio of total debt to total shareholder funds (Poon, 2003) - proxies financial risk
Financial flexibility	STDTD	Total short-term debt divided by total debt – proxies uncertainty
Company size	lnSALES	Natural logarithm (because of the highly skewed distribution of total sales, as per existing literature)
Firm indebtedness	LOGDEBT	Logarithm of total debt - captures the potential interest saving effect from obtaining a rating
Period bond issue	BONDYN	Dummy variable: '1' if company issues public debt during the study period, and '0' if it does not
History of bond issues	BONDYBEF	Dummy variable: '1' if company has outstanding public debt for 10 years at the time of study, and '0' if it does not
Future bond issuance	BONDNEY	Dummy variable: '1' if company issues public debt in the next period, and '0' if it does not
Default risk	BMV	Book to market value = ratio of total shareholder equity to market capitalisation
Research and development	RDREV	Research and Development intensity = R&D expenditure to total sales
Institutional ownership	INSTINV	Proportion of ordinary shares owned by institutional investors, as reported in the company's annual report

**Table 3: Industry Classification by Rating Status**

Industry Classification (ICB)	Rated firms (2)	Relative frequency (%) (3)	Non-rated firms (4)	Relative frequency (%) (5)
Oil and Gas	4	5	6	4
Basic Materials	7	8	8	5
Industrials	15	17	49	31
Consumer Goods	13	15	13	8
Health Care	2	2	9	6
Consumer Services	26	30	44	28
Telecommunications	5	6	6	4
Utilities	11	13	3	2
Real Estate	1	1	17	11
Technology	2	2	4	3
<i>Totals</i>	<i>86</i>	<i>100</i>	<i>159</i>	<i>100</i>

*Note:* Column (1) presents the ten industrial sectors as per the ICB classification. Columns (2) and (3) provide numbers and relative frequencies for rated companies, while columns (4) and (5) concern non-rated companies.

**Table 4: Firm Count and Credit Ratings****Panel A: Count of Rated and Non-rated Companies**

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	<i>Total</i>
Non-rated	165	183	191	172	175	170	167	162	160	160	160	155	<b>2020</b>
Rated	30	31	37	61	62	69	74	78	79	79	78	74	<b>752</b>
<i>Total</i>	<i>195</i>	<i>214</i>	<i>228</i>	<i>233</i>	<i>237</i>	<i>239</i>	<i>241</i>	<i>240</i>	<i>239</i>	<i>239</i>	<i>238</i>	<i>229</i>	<b>2772</b>

**Panel B: S&P Ratings, 1995-2006**

	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	<i>Total</i>
<BB+	2	2	2	3	4	4	5	7	9	12	12	15	<b>77</b>
<BB+ (%)	7	6	5	5	6	6	7	9	11	15	15	20	<b>10</b>
BBB	3	4	4	15	18	25	28	34	39	38	38	33	<b>279</b>
BBB (%)	10	13	11	25	29	36	38	44	50	48	49	45	<b>37</b>
A	18	18	21	30	29	31	34	29	26	25	24	23	<b>308</b>
A (%)	60	58	57	49	47	45	46	37	33	32	31	31	<b>41</b>
AA, AAA	7	7	10	13	11	9	7	8	5	4	4	3	<b>88</b>
AA, AAA (%)	23	23	27	21	18	13	9	10	6	5	5	4	<b>12</b>
<i>Total</i>	<i>30</i>	<i>31</i>	<i>37</i>	<i>61</i>	<i>62</i>	<i>69</i>	<i>74</i>	<i>78</i>	<i>79</i>	<i>79</i>	<i>78</i>	<i>74</i>	<b>752</b>
<i>Total (%)</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>	<i>100</i>	<b>100</b>

Notes: Numbers of rated and non-rated companies and number of companies being assigned specific ratings. The broad rating categories (e.g. BBB) include the finer rating classifications (i.e. BBB-, BBB and BBB+).

**Table 5: Descriptive Statistics for the Sample of UK Companies****Panel A: Key Summary Statistics for the Sample**

<i>Variables</i>	Rated companies		Non-rated companies		Comparison of means	
	<i>Mean</i>	<i>SD</i>	<i>Mean</i>	<i>SD</i>	<i>t-statistic</i>	<i>p-value</i>
ROA	0.045	0.117	0.030	0.166	2.328	0.020
GEAR	1.592	11.638	1.090	13.030	0.977	0.329
STDTD	0.249	0.210	0.370	0.329	-9.390	0.000
lnSALES	21.945	1.203	19.108	1.898	38.174	0.000
LOGDEBT	9.141	0.484	7.563	1.036	39.979	0.000
BMV	4.121	48.557	0.594	0.798	3.165	0.002
RDREV	0.021	0.037	2.462	39.393	-1.332	0.183
INSTINV	0.900	0.065	0.878	0.091	5.497	0.000

**Panel B: Key Summary Statistics for the Sample (winsorised)**

<i>Variables</i>	Rated companies		Non-rated companies		Comparison of means	
	<i>Mean</i>	<i>Skewness</i>	<i>Mean</i>	<i>Skewness</i>	<i>t-statistic</i>	<i>p-value</i>
	<i>(SD)</i>	<i>(Kurtosis)</i>	<i>(SD)</i>	<i>(Kurtosis)</i>		
ROA	0.049	-0.773	0.045	-0.953	1.356	0.175
	(0.067)	(1.432)	(0.072)	(0.973)		
GEAR	1.025	1.412	0.664	2.052	10.240	0.000
	(0.908)	(1.258)	(0.791)	(4.161)		
STDTD	0.250	1.183	0.373	0.731	-9.456	0.000
	(0.212)	(1.143)	(0.329)	(-0.823)		
lnSALES	21.849	-1.442	19.185	-0.001	40.363	0.000
	(1.051)	(3.310)	(1.690)	(-0.689)		
LOGDEBT	9.105	-1.578	7.620	-0.183	42.970	0.000
	(0.427)	(3.955)	(0.907)	(-0.812)		
BMV	0.478	1.220	0.584	0.934	-5.651	0.000
	(0.385)	(1.278)	(0.452)	(-0.061)		

RDREV	0.021 (0.037)	2.677 (6.978)	0.043 (0.069)	2.228 (3.578)	-6.160	0.000
INSTINV	0.900 (0.057)	-0.923 (0.129)	0.889 (0.054)	-1.394 (1.677)	3.972	0.000

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**Panel C: Correlation Coefficient Matrix and Variance-Inflation Factors (VIFs)**

	GEAR	STDTD	lnSALES	LOGDEBT	BMV	INSTINV	RDREV
ROA	-0.184 <sup>a</sup>	0.146 <sup>a</sup>	0.081 <sup>a</sup>	-0.101 <sup>a</sup>	-0.348 <sup>a</sup>	0.023	-0.059
GEAR	1.000	-0.322 <sup>a</sup>	0.259 <sup>a</sup>	0.494 <sup>a</sup>	-0.010	-0.038	-0.239 <sup>a</sup>
STDTD		1.000	-0.048 <sup>b</sup>	-0.321 <sup>a</sup>	-0.136 <sup>a</sup>	0.009	0.138 <sup>a</sup>
lnSALES			1.000	0.805 <sup>a</sup>	-0.188 <sup>a</sup>	0.133 <sup>a</sup>	-0.320 <sup>a</sup>
LOGDEBT				1.000	-0.038	0.126 <sup>a</sup>	-0.376 <sup>a</sup>
BMV					1.000	0.038	-0.203 <sup>a</sup>
VIFs	1.081	1.873	3.320	4.484	1.247	1.353	1.169

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*Notes:* This table presents summary statistics for the sample of non-financial company data used in the sample. The sample consists of an unbalanced panel of 86 rated companies and 159 non-rated companies. Panels A and B provide descriptive data for rated and non-rated companies (unrestricted and winsorised respectively). Independent samples t-test testing  $H_0 = \mu_{rated} - \mu_{non-rated} = 0$ . Levene's test for equality of variances was used to determine the homogeneity of variances between rated and non-rated firms. Panel C shows the correlation matrix and variance-inflation factors for the independent variables used in the study. The correlations are measured using the Spearman rank coefficient. VIFs are calculated by regressing each independent variable on the remaining independent variables and then calculating  $1/(1-R^2)$ . ROA is the ratio of net income to total assets. GEAR is the ratio of total debt to shareholders' funds. STDTD is the ratio of short-term debt to total debt. lnSALES is the natural logarithm of annual sales. LOGDEBT is the logarithm of a company's outstanding total debt. BMV is the ratio of total shareholder equity to market capitalisation. INSTINV is the proportion of ordinary shares held by institutional investors. RDREV is the ratio of R&D expenditure to total sales. <sup>a</sup>, <sup>b</sup>, <sup>c</sup> denote significance at the 1%, 5% and 10% respectively.

**Table 6. Ratio Means by Industry**

	Oil and Gas		Basic Materials		Industrials		Consumer Goods		Health Care	
	Rated	Non-rated	Rated	Non-rated	Rated	Non-rated	Rated	Non-rated	Rated	Non-rated
TOTAL ASSETS (£M)	32,331 <sup>a</sup> (42,541)	2,827 <sup>a</sup> (9,284)	10,612 <sup>a</sup> (7,424)	1,662 <sup>a</sup> (3,469)	5,339 <sup>a</sup> (4,697)	458.8 <sup>a</sup> (665.2)	8,143 <sup>a</sup> (7,265)	1,961 <sup>a</sup> (5,617)	14,332 <sup>a</sup> (7,099)	52.13 <sup>a</sup> (70.12)
MARKET CAP (£M)	35,540 <sup>a</sup> (48,110)	2,491 <sup>a</sup> (8,112)	8,714 <sup>a</sup> (8,193)	1,411 <sup>a</sup> (2,845)	3,677 <sup>a</sup> (2,945)	576 <sup>a</sup> (1,102)	8,784 <sup>a</sup> (7,365)	1,492 <sup>a</sup> (3,191)	53,288 <sup>a</sup> (27,408)	110.64 <sup>a</sup> (113.47)
ROA	0.05 (0.05)	0.01 (0.24)	0.04 (0.06)	0.03 (.013)	0.04 (0.08)	0.06 (0.11)	0.08 <sup>a</sup> (0.06)	0.04 <sup>a</sup> (0.09)	0.15 <sup>a</sup> (0.04)	-0.25 <sup>a</sup> (0.44)
GEAR	0.57 <sup>b</sup> (0.37)	0.35 <sup>b</sup> (0.54)	1.29 <sup>a</sup> (0.69)	0.43 <sup>a</sup> (0.32)	0.98 <sup>a</sup> (0.37)	0.18 <sup>a</sup> (0.28)	1.55 <sup>a</sup> (1.18)	0.61 <sup>a</sup> (0.41)	0.49 (0.40)	0.30 (1.58)
STDTD	0.29* (0.18)	0.40* (0.34)	0.30 (0.16)	0.33 (0.21)	0.28 (0.20)	0.45 (0.34)	0.32 (0.20)	0.35 (0.32)	0.31 <sup>a</sup> (0.15)	0.42 <sup>a</sup> (0.31)
lnSALES	22.66 <sup>a</sup> (2.07)	17.44 <sup>a</sup> (2.21)	22.46 <sup>a</sup> (0.71)	18.47 <sup>a</sup> (2.46)	21.46 (0.83)	19.28 (1.42)	22.3 <sup>a</sup> (0.77)	19.2 <sup>a</sup> (2.11)	23.15 <sup>a</sup> (0.61)	16.06 <sup>a</sup> (2.10)
LOGDEBT	9.47 <sup>a</sup> (0.50)	7.15 <sup>a</sup> (1.00)	9.29 <sup>a</sup> (0.33)	7.52 <sup>a</sup> (0.91)	8.85 (0.45)	7.30 (1.01)	9.26 <sup>a</sup> (0.40)	7.48 <sup>a</sup> (1.09)	9.16 <sup>a</sup> (0.45)	6.46 <sup>a</sup> (0.97)
BMV	81.6 <sup>b</sup> (40.57)	0.71 <sup>b</sup> (0.60)	0.66 <sup>a</sup> (0.58)	1.06 <sup>a</sup> (1.05)	0.44 (0.50)	0.45 (1.02)	0.28 <sup>a</sup> (0.29)	0.79 <sup>a</sup> (0.59)	0.13 <sup>b</sup> (0.06)	0.27 <sup>b</sup> (0.48)
RDREV	0.01 (0.01)	0.01 (0.01)	0.01 <sup>c</sup> (0.01)	0.02 <sup>c</sup> (0.02)	0.03 (0.03)	0.02 (0.02)	0.01 <sup>b</sup> (0.02)	1.85 <sup>b</sup> (6.82)	0.14 (0.03)	13.97 (98.14)
INSTINV	0.93 (0.05)	0.92 (0.03)	0.91 <sup>b</sup> (0.05)	0.89 <sup>b</sup> (0.04)	0.90 (0.08)	0.88 (0.07)	0.90 <sup>a</sup> (0.05)	0.85 <sup>a</sup> (0.09)	0.92 <sup>a</sup> (0.03)	0.90 <sup>a</sup> (0.02)
<i>No of firms</i>	4	6	7	8	15	49	13	13	2	9
	<b>Consumer</b>		<b>Telecoms</b>		<b>Utilities</b>		<b>Real Estate</b>		<b>Technology</b>	



	Services									
	Rated	Non-rated	Rated	Non-rated	Rated	Non-rated	Rated	Non-rated	Rated	Non-rated
TOTAL ASSETS (£M)	5,268 <sup>a</sup> (4,074)	794.6 <sup>a</sup> (1,280)	34,494 <sup>a</sup> (51,280)	928.4 <sup>a</sup> (1,963)	6,311 <sup>a</sup> (5,012)	2,155 <sup>a</sup> (2,262)	874.5 (239.3)	736.5 (1,301)	407.2 (235.5)	345.2 (411.9)
MARKET CAP (£M)	5,090 <sup>a</sup> (3,898)	819.8 <sup>a</sup> (1,811)	31,532 <sup>a</sup> (41,984)	1,518 <sup>a</sup> (3,012)	3,614 <sup>a</sup> (3,148)	1,090 <sup>a</sup> (1,231)	428.8 (198.7)	345.1 (562.7)	210.4 (247.8)	543.6 (592.5)
ROA	0.05 (0.09)	0.04 (0.15)	-0.02 (0.19)	-0.05 (0.13)	0.03 (0.18)	0.07 (0.05)	0.03 (0.04)	0.03 (0.05)	-0.02 (0.15)	0.01 (0.03)
GEAR	1.39 (0.29)	1.36 (0.76)	4.91 (5.66)	4.28 (1.54)	1.95 (0.40)	2.51 (0.80)	0.74 <sup>a</sup> (0.07)	0.93 <sup>a</sup> (0.91)	19.38 (14.26)	0.65 (0.14)
STDTD	0.31 <sup>a</sup> (0.24)	0.38 <sup>a</sup> (.032)	0.20 (0.15)	0.28 (0.32)	0.17 (0.17)	0.26 (0.32)	0.00 <sup>a</sup> (0.00)	0.15 <sup>a</sup> (0.21)	0.24 <sup>c</sup> (0.19)	0.40 <sup>c</sup> (0.36)
lnSALES	21.90 <sup>a</sup> (0.97)	19.41 <sup>a</sup> (1.59)	22.06 <sup>a</sup> (1.86)	18.19 <sup>a</sup> (1.73)	21.20 <sup>a</sup> (0.81)	18.98 <sup>a</sup> (1.68)	17.62 (0.21)	17.79 (1.16)	19.75 <sup>a</sup> (0.80)	18.59 <sup>a</sup> (1.55)
LOGDEBT	8.89 <sup>a</sup> (0.42)	7.54 <sup>a</sup> (0.95)	9.28 <sup>a</sup> (0.64)	7.34 <sup>a</sup> (1.04)	9.20 <sup>a</sup> (0.44)	7.86 <sup>a</sup> (1.24)	8.53 <sup>a</sup> (0.10)	7.94 <sup>a</sup> (0.90)	7.97 <sup>a</sup> (0.34)	7.07 <sup>a</sup> (0.98)
BMV	0.40 <sup>a</sup> (0.58)	0.53 <sup>a</sup> (0.53)	0.65 (0.69)	0.74 (0.84)	-1.03 (15.37)	0.58 (0.42)	1.17 (0.24)	1.03 (0.45)	-0.17 <sup>b</sup> (1.89)	0.51 <sup>b</sup> (0.22)
RDREV	0.01 (0.02)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 <sup>c</sup> (0.01)	0.01 <sup>c</sup> (0.01)	0.01 (0.01)	0.01 (0.01)	0.05 (0.06)	0.05 (0.05)
INSTINV	0.90 <sup>a</sup> (0.06)	0.88 <sup>a</sup> (0.08)	0.88 <sup>a</sup> (0.08)	0.81 <sup>a</sup> (0.16)	0.87 (0.05)	0.88 (0.02)	0.98 <sup>a</sup> (0.01)	0.85 <sup>a</sup> (0.16)	0.85 <sup>a</sup> (0.08)	0.77 <sup>a</sup> (0.08)
<i>No of firms</i>	26	44	5	6	11	3	1	17	2	4

Notes: Ratio means for each industry for the entire sample period. Values in parentheses represent standard deviations. <sup>a, b, c</sup>

denote significance at the 1%, 5% and 10% respectively and relate to the comparison of means using an independent samples

t-test ( $H_0 = \mu_{rated} - \mu_{non-rated} = 0$ ).

**Table 7: The Rating Likelihood Probit Model: Estimation Results for the Contemporaneous Specification**

<b>Panel A: Parameter estimates (contemporaneous specification)</b>									
Independent variables	<b>Model I</b>		<b>Model II</b>		<b>Model III</b>		<b>Model IV</b>		
	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	
Intercept	-12.4	-16.4 <sup>a</sup>	-12.9	-13.8 <sup>a</sup>	-13.4	-16.5 <sup>a</sup>	-13.7	-14.1 <sup>a</sup>	
ROA	-1.30	-12.4 <sup>a</sup>	-1.19	-10.3 <sup>a</sup>	-1.34	-12.5 <sup>a</sup>	-1.22	-10.3 <sup>a</sup>	
GEAR	-0.01	-2.2 <sup>b</sup>	-0.01	-2.9 <sup>a</sup>	-0.01	-2.3 <sup>b</sup>	-0.01	-2.97 <sup>a</sup>	
STDTD	-0.90	-11.0 <sup>a</sup>	-0.92	-9.6 <sup>a</sup>	-0.90	-10.8 <sup>a</sup>	-0.92	-9.4 <sup>a</sup>	
lnSALES	0.28	8.3 <sup>a</sup>	0.29	6.4 <sup>a</sup>	0.30	8.7 <sup>a</sup>	0.31	6.7 <sup>a</sup>	
LOGDEBT	0.90	11.0 <sup>a</sup>	0.91	9.6 <sup>a</sup>	0.90	10.8 <sup>a</sup>	0.91	9.4 <sup>a</sup>	
BONDYDYN	1.01	9.9 <sup>a</sup>	0.90	8.1 <sup>a</sup>	1.04	10.0 <sup>a</sup>	0.90	8.0 <sup>a</sup>	
BONDYBEF	0.01	7.4 <sup>a</sup>	0.01	7.4 <sup>a</sup>	0.01	7.9 <sup>a</sup>	0.01	7.8 <sup>a</sup>	
BMV	0.01	1.4	0.01	1.8 <sup>c</sup>	0.01	1.5	0.01	1.8 <sup>c</sup>	
RDREV	0.01	6.3 <sup>a</sup>	0.01	4.3 <sup>a</sup>	0.01	6.6 <sup>a</sup>	0.01	4.7 <sup>a</sup>	
INSTINV	0.01	13.5 <sup>a</sup>	0.01	13.4 <sup>a</sup>	0.01	10.3 <sup>a</sup>	0.01	10.5 <sup>a</sup>	
Industry dummies	<i>NO</i>		<i>YES</i>		<i>NO</i>		<i>YES</i>		
Time dummies	<i>NO</i>		<i>NO</i>		<i>YES</i>		<i>YES</i>		
<b>Panel B: Marginal effects</b>									
Intercept	-1.19	-9.0 <sup>a</sup>	-1.01	-7.5 <sup>a</sup>	-1.27	-8.6 <sup>a</sup>	-1.10	-7.2 <sup>a</sup>	
ROA	-0.12	-5.5 <sup>a</sup>	-0.09	-4.6 <sup>a</sup>	-0.13	-5.5 <sup>a</sup>	-0.09	-4.6 <sup>a</sup>	
GEAR	-0.01	-2.1 <sup>b</sup>	-0.01	-2.6 <sup>a</sup>	-0.01	-2.2 <sup>b</sup>	-0.01	-2.7 <sup>a</sup>	
STDTD	-0.09	-7.5 <sup>a</sup>	-0.07	-5.8 <sup>a</sup>	-0.09	-7.3 <sup>a</sup>	-0.07	-5.7 <sup>a</sup>	
lnSALES	0.03	6.8 <sup>a</sup>	0.02	5.7 <sup>a</sup>	0.03	6.7 <sup>a</sup>	0.02	5.7 <sup>a</sup>	
LOGDEBT	0.09	7.5 <sup>a</sup>	0.07	5.8 <sup>a</sup>	0.09	7.3 <sup>a</sup>	0.07	5.7 <sup>a</sup>	
BONDYDYN	0.10	4.9 <sup>a</sup>	0.07	3.9 <sup>a</sup>	0.10	4.9 <sup>a</sup>	0.07	3.9 <sup>a</sup>	

BONDYBEF	0.01	5.4 <sup>a</sup>	0.01	4.9 <sup>a</sup>	0.01	5.4 <sup>a</sup>	0.01	4.8 <sup>a</sup>
BMV	0.01	1.4	0.01	1.7 <sup>c</sup>	0.01	1.5	0.01	1.7 <sup>c</sup>
RDREV	0.01	4.8 <sup>a</sup>	0.01	3.6 <sup>a</sup>	0.01	4.9 <sup>a</sup>	0.01	3.7 <sup>a</sup>
INSTINV	0.01	6.9 <sup>a</sup>	0.01	5.9 <sup>a</sup>	0.01	6.4 <sup>a</sup>	0.01	5.5 <sup>a</sup>

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**Panel C: Selected model statistics**

$\chi^2$ statistic	2,150.4 <sup>a</sup>	2,201.3 <sup>a</sup>	2,179.8 <sup>a</sup>	2,228.1 <sup>a</sup>
Hosmer-Lemeshow $\chi^2$	86.66 <sup>a</sup>	69.03 <sup>a</sup>	73.19 <sup>a</sup>	75.64 <sup>a</sup>
Log-likelihood	-545.1	-519.7	-530.4	-506.3
No of observations	2,772	2,772	2,772	2,772
Akaike I.C.	0.40	0.39	0.40	0.39
Pseudo-R <sup>2</sup> $\diamond$	66.36%	67.93%	67.26%	68.75%
Adjusted pseudo-R <sup>2</sup> *	65.62%	67.18%	66.52%	68.03%

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*Notes:* The dependent variable of all binary probit models is the dummy variable RNR, which takes the value of 1 if a company is rated by S&P or 0 otherwise. All significance levels are determined using two-tailed Z-tests. <sup>a</sup>, <sup>b</sup>, <sup>c</sup> denote significance at the 1%, 5% and 10% respectively.  $\diamond$  This measure of goodness-of-fit is a simple computational statistic (

$R^2 = 1 - \frac{\text{Log}(L_{UR})}{\text{Log}(L_R)}$ ) proposed by McFadden (1973). \* McFadden's adjusted pseudo-R<sup>2</sup> adjusts for the number of

predictors in a model ( $R^2 = 1 - \frac{\text{Log}(L_{UR}) - K}{\text{Log}(L_R)}$ ).

**Table 8: The Rating Likelihood Probit Model: Estimation Results for the Predictive Specification**

<b>Panel A: Parameter estimates (predictive specification)</b>									
Independent variables	Model V		Model VI		Model VII		Model VIII		
	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	
Intercept	-12.5	-16.6 <sup>a</sup>	-13.0	-14.3 <sup>a</sup>	-13.6	-16.6 <sup>a</sup>	-13.9	-14.5 <sup>a</sup>	
ROA	-1.33	-10.4 <sup>a</sup>	-1.15	-8.3 <sup>a</sup>	-1.48	-11.0 <sup>a</sup>	-1.29	-9.0 <sup>a</sup>	
GEAR	-0.01	-2.1 <sup>b</sup>	-0.01	-2.6 <sup>a</sup>	-0.01	-1.8 <sup>c</sup>	-0.01	-2.3 <sup>b</sup>	
STDTD	-0.82	-9.9 <sup>a</sup>	-0.88	-9.2 <sup>a</sup>	-0.80	-9.5 <sup>a</sup>	-0.84	-8.6 <sup>a</sup>	
lnSALES	0.25	7.4 <sup>a</sup>	0.23	5.4 <sup>a</sup>	0.28	8.0 <sup>a</sup>	0.27	6.0 <sup>a</sup>	
LOGDEBT	0.81	9.9 <sup>a</sup>	0.88	9.1 <sup>a</sup>	0.79	9.6 <sup>a</sup>	0.83	8.6 <sup>a</sup>	
BONDYN	0.89	8.1 <sup>a</sup>	0.77	6.6 <sup>a</sup>	0.96	8.6 <sup>a</sup>	0.84	7.1 <sup>a</sup>	
BONDNEY	0.20	2.0 <sup>b</sup>	0.14	1.4	0.24	2.3 <sup>b</sup>	0.18	1.7 <sup>c</sup>	
BMV	0.01	1.8 <sup>c</sup>	0.01	2.1 <sup>b</sup>	0.01	1.9 <sup>c</sup>	0.01	2.1 <sup>b</sup>	
RDREV	0.01	6.0 <sup>b</sup>	0.01	4.3 <sup>a</sup>	0.01	6.6 <sup>a</sup>	0.01	4.8 <sup>a</sup>	
INSTINV	0.01	10.9 <sup>a</sup>	0.01	10.8 <sup>a</sup>	0.01	8.6 <sup>a</sup>	0.01	8.7 <sup>a</sup>	
Industry dummies	<i>NO</i>		<i>YES</i>		<i>NO</i>		<i>YES</i>		
Time dummies	<i>NO</i>		<i>NO</i>		<i>YES</i>		<i>YES</i>		
<b>Panel B: Marginal effects</b>									
Intercept	-0.0321	-1.43	-0.0426	-1.42	-0.0211	-1.34	-0.0276	-1.33	
ROA	-0.0034	-1.46	-0.0038	-1.47	-0.0023	-1.36	-0.0026	-1.37	
GEAR	-0.0001	-1.19	-0.0002	-1.26	-0.0008	-1.09	-0.0001	-1.16	
STDTD	-0.0021	-1.41	-0.0029	-1.38	-0.0012	-1.31	-0.0017	-1.29	
lnSALES	0.0006	1.40	0.0008	1.39	0.0004	1.33	0.0005	1.32	
LOGDEBT	0.0021	1.41	0.0029	1.38	0.0012	1.31	0.0017	1.29	
BONDYN	0.0023	1.65 <sup>c</sup>	0.0025	1.69 <sup>c</sup>	0.0015	1.51	0.0017	1.51	

BONDNEY	0.0005	0.93	0.0005	0.80	0.0004	0.95	0.0002	0.84
BMV	0.00001	1.09	0.00001	1.13	0.00001	1.07	0.00001	1.09
RDREV	0.00001	1.37	0.00002	1.30	0.00001	1.30	0.00001	1.24
INSTINV	0.00003	1.44	0.00003	1.44	0.00001	1.35	0.00003	1.34

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**Panel C: Selected model statistics**

$\chi^2$ statistic	1,928.85 <sup>a</sup>	1,969.81 <sup>a</sup>	1,966.99 <sup>a</sup>	2,007.17 <sup>a</sup>
Hosmer-Lemeshow $\chi^2$	42.93 <sup>a</sup>	41.13 <sup>a</sup>	42.30 <sup>a</sup>	37.03 <sup>a</sup>
Log-likelihood	-600.54	-580.06	-581.47	-561.01
No of observations	2,782	2,782	2,782	2,782
Akaike I.C.	0.44	0.43	0.43	0.43
Pseudo-R <sup>2</sup> $\diamond$	61.63%	62.93%	62.84%	64.12%
Adjusted pseudo-R <sup>2</sup> *	60.86%	62.17%	62.08%	63.38%

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*Notes:* The dependent variable of all binary probit models is the dummy variable RNR, which takes the value of 1 if a company is rated by S&P or 0 otherwise. All significance levels are determined using two-tailed Z-tests. <sup>a</sup>, <sup>b</sup>, <sup>c</sup> denote significance at the 1%, 5% and 10% respectively.  $\diamond$  This measure of goodness-of-fit is a simple computational statistic (

$R^2 = 1 - \frac{\text{Log}(L_{UR})}{\text{Log}(L_R)}$ ) proposed by McFadden (1973). \* McFadden's adjusted pseudo-R<sup>2</sup> adjusts for the number of

predictors in a model ( $R^2 = 1 - \frac{\text{Log}(L_{UR}) - K}{\text{Log}(L_R)}$ )

**Table 9: Within-Sample Classification Model Performance**

<b>Model I</b>					<b>Model II</b>				
		<i>Predicted</i>		<i>Totals</i>			<i>Predicted</i>		<i>Totals</i>
		<b>0</b>	<b>1</b>				<b>0</b>	<b>1</b>	
<i>Actual</i>					<i>Actual</i>				
<b>0</b>	1,894 (93.76%)	126 (6.23%)	2,020		<b>0</b>	1,911 (94.60%)	109 (5.40%)	2,020	
<b>1</b>	88 (11.70%)	664 (88.30%)	752		<b>1</b>	76 (10.11%)	676 (89.89%)	752	
<i>Totals</i>	1,982	790	2,772		<i>Totals</i>	1,987	785	2,772	
Correct classification rate: 92.28%					Correct classification rate: 93.33%				
<b>Model III</b>					<b>Model IV</b>				
		<i>Predicted</i>		<i>Totals</i>			<i>Predicted</i>		<i>Totals</i>
		<b>0</b>	<b>1</b>				<b>0</b>	<b>1</b>	
<i>Actual</i>					<i>Actual</i>				
<b>0</b>	1,902 (94.16%)	118 (5.84%)	2,020		<b>0</b>	1,910 (94.55%)	110 (5.45%)	2,020	
<b>1</b>	85 (11.30%)	667 (88.70%)	752		<b>1</b>	80 (10.64%)	672 (89.36%)	752	
<i>Totals</i>	1,987	785	2,772		<i>Totals</i>	1,990	782	2,772	
Correct classification rate: 92.68%					Correct classification rate: 93.15%				
<b>Model V</b>					<b>Model VI</b>				
		<i>Predicted</i>		<i>Totals</i>			<i>Predicted</i>		<i>Totals</i>
		<b>0</b>	<b>1</b>				<b>0</b>	<b>1</b>	
<i>Actual</i>					<i>Actual</i>				
<b>0</b>	1,957 (93.82%)	129 (6.18%)	2,086		<b>0</b>	1,959 (93.91%)	127 (6.09%)	2,086	
<b>1</b>	91 (13.07%)	605 (86.93%)	696		<b>1</b>	80 (11.49%)	616 (88.51%)	696	
<i>Totals</i>	2,048	734	2,782		<i>Totals</i>	2,050	732	2,782	
Correct classification rate: 92.09%					Correct classification rate: 92.56%				
<b>Model VII</b>					<b>Model VIII</b>				

	<i>Predicted</i>			<i>Totals</i>		<i>Predicted</i>			<i>Totals</i>
	<b>0</b>	<b>1</b>				<b>0</b>	<b>1</b>		
<i>Actual</i>					<i>Actual</i>				
<b>0</b>	1,956 (93.77%)	130 (6.23%)		2,086	<b>0</b>	1,966 (94.24%)	120 (5.76%)		2,086
<b>1</b>	103 (14.80%)	593 (85.20%)		696	<b>1</b>	88 (12.64%)	608 (87.36%)		696
<i>Totals</i>	2,059	723		2,786	<i>Totals</i>	2,054	728		2,782
	Correct classification rate: 91.62%					Correct classification rate: 92.52%			

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*Note:* Analysis of binary choice model predictions based on a 0.5 threshold.

**Table 10: The Rating Likelihood Probit Model: Estimation Results for the Contemporaneous Specification of a Matched Sample of Rated and Non-rated Firms**

<b>Panel A: Parameter estimates (contemporaneous specification)</b>									
Independent variables	Model IX		Model X		Model XI		Model XII		
	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	
Intercept	-11.6	-14.3 <sup>a</sup>	-11.5	-11.6 <sup>a</sup>	-12.5	-14.6 <sup>a</sup>	-12.4	-11.9 <sup>a</sup>	
ROA	-1.31	-12.0 <sup>a</sup>	-1.16	-9.8 <sup>a</sup>	-1.36	-12.2 <sup>a</sup>	-1.20	-9.9 <sup>a</sup>	
GEAR	-0.01	-2.2 <sup>b</sup>	-0.01	-2.8 <sup>a</sup>	-0.01	-2.3 <sup>b</sup>	-0.01	-2.8 <sup>a</sup>	
STDTD	-0.86	-10.2 <sup>a</sup>	-0.91	-9.2 <sup>a</sup>	-0.86	-10.0 <sup>a</sup>	-0.90	-9.0 <sup>a</sup>	
lnSALES	0.26	7.4 <sup>a</sup>	0.24	4.8 <sup>a</sup>	0.28	7.7 <sup>a</sup>	0.26	5.1 <sup>a</sup>	
LOGDEBT	0.85	10.2 <sup>a</sup>	0.90	9.2 <sup>a</sup>	0.85	10.0 <sup>a</sup>	0.89	9.0 <sup>a</sup>	
BONDYDYN	1.05	9.9 <sup>a</sup>	0.93	8.1 <sup>a</sup>	1.01	9.9 <sup>a</sup>	0.94	8.1 <sup>a</sup>	
BONDYBEF	0.01	7.1 <sup>a</sup>	0.01	7.2 <sup>a</sup>	0.01	7.7 <sup>a</sup>	0.01	7.6 <sup>a</sup>	
BMV	0.01	1.5	0.01	2.1 <sup>b</sup>	0.01	1.6	0.01	2.1 <sup>b</sup>	
RDREV	0.01	6.5 <sup>a</sup>	0.01	4.5 <sup>a</sup>	0.01	6.9 <sup>a</sup>	0.01	4.8 <sup>a</sup>	
INSTINV	0.01	13.6 <sup>a</sup>	0.01	13.3 <sup>a</sup>	0.01	10.2 <sup>a</sup>	0.01	10.2 <sup>a</sup>	
Industry dummies	<i>NO</i>		<i>YES</i>		<i>NO</i>		<i>YES</i>		
Time dummies	<i>NO</i>		<i>NO</i>		<i>YES</i>		<i>YES</i>		
<b>Panel B: Marginal effects</b>									
Intercept	-4.44	-15.6 <sup>a</sup>	-4.52	-15.2 <sup>a</sup>	-4.83	-15.7 <sup>a</sup>	-4.75	-15.8 <sup>a</sup>	
ROA	-0.51	-10.5 <sup>a</sup>	-0.51	-10.5 <sup>a</sup>	-0.53	-10.7 <sup>a</sup>	-0.53	-11.0 <sup>a</sup>	
GEAR	-0.01	-2.2 <sup>b</sup>	-0.01	-2.1 <sup>a</sup>	-0.01	-2.3 <sup>b</sup>	-0.01	-2.3 <sup>a</sup>	
STDTD	-0.33	-11.0 <sup>a</sup>	-0.32	-10.6 <sup>a</sup>	-0.33	-10.7 <sup>a</sup>	-0.34	-10.8 <sup>a</sup>	
lnSALES	0.10	7.4 <sup>a</sup>	0.10	7.5 <sup>a</sup>	0.11	7.7 <sup>a</sup>	0.11	7.9 <sup>a</sup>	
LOGDEBT	0.32	10.9 <sup>a</sup>	0.33	10.7 <sup>a</sup>	0.33	10.7 <sup>a</sup>	0.33	11.0 <sup>a</sup>	
BONDYDYN	0.40	8.7 <sup>a</sup>	0.40	8.7 <sup>a</sup>	0.41	8.9 <sup>a</sup>	0.41	8.8 <sup>a</sup>	



BONDYBEF	0.01	7.1 <sup>a</sup>	0.01	7.0 <sup>a</sup>	0.01	7.6 <sup>a</sup>	0.01	7.5 <sup>a</sup>
BMV	0.01	1.5	0.01	1.6	0.01	1.6	0.01	1.7 <sup>c</sup>
RDREV	0.01	6.6 <sup>a</sup>	0.01	6.8 <sup>a</sup>	0.01	6.9 <sup>a</sup>	0.01	6.8 <sup>a</sup>
INSTINV	0.01	13.9 <sup>a</sup>	0.01	12.5 <sup>a</sup>	0.01	10.5 <sup>a</sup>	0.01	11.6 <sup>a</sup>

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**Panel C: Selected model statistics**

$\chi^2$ statistic	1,562.7 <sup>a</sup>	1,582.7 <sup>a</sup>	1,556.3 <sup>a</sup>	1,609.9 <sup>a</sup>
Hosmer-Lemeshow $\chi^2$	93.17 <sup>a</sup>	86.83 <sup>a</sup>	101.8 <sup>a</sup>	90.81 <sup>a</sup>
Log-likelihood	-538.8	-510.8	-523.9	-497.2
No of observations	1,954	1,954	1,954	1,954
Akaike I.C.	0.56	0.54	0.58	0.54
Pseudo-R <sup>2</sup> $\diamond$	58.63%	60.78%	59.76%	61.82%
Adjusted pseudo-R <sup>2</sup> *	57.78%	59.24%	58.07%	60.00%

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*Notes:* The dependent variable of all binary probit models is the dummy variable RNR, which takes the value of 1 if a company is rated by S&P or 0 otherwise. All significance levels are determined using two-tailed Z-tests. <sup>a</sup>, <sup>b</sup>, <sup>c</sup> denote significance at the 1%, 5% and 10% respectively.  $\diamond$  This measure of goodness-of-fit is a simple computational statistic (

$R^2 = 1 - \frac{\text{Log}(L_{UR})}{\text{Log}(L_R)}$ ) proposed by McFadden (1973). \* McFadden's adjusted pseudo-R<sup>2</sup> adjusts for the number of

predictors in a model ( $R^2 = 1 - \frac{\text{Log}(L_{UR}) - K}{\text{Log}(L_R)}$ ).

**Table 11: The Rating Likelihood Probit Model: Estimation Results for the Predictive Specification of a Matched Sample of Rated and Non-rated Firms**

<b>Panel A: Parameter estimates (predictive specification)</b>									
Independent variables	Model XIII		Model XIV		Model XV		Model XVI		
	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	
Intercept	-11.6	-14.4 <sup>a</sup>	-11.5	-11.7 <sup>a</sup>	-11.9	-14.2 <sup>a</sup>	-11.6	-11.5 <sup>a</sup>	
ROA	-1.36	-10.2 <sup>a</sup>	-1.14	-8.1 <sup>a</sup>	-1.48	-10.7 <sup>a</sup>	-1.28	-8.7 <sup>a</sup>	
GEAR	-0.01	-2.1 <sup>b</sup>	-0.01	-2.5 <sup>b</sup>	-0.01	-1.7 <sup>c</sup>	-0.01	-2.1 <sup>b</sup>	
STDTD	-0.77	-9.1 <sup>a</sup>	-0.87	-8.7 <sup>a</sup>	-0.75	-8.7 <sup>a</sup>	-0.82	-8.2 <sup>a</sup>	
lnSALES	0.23	6.5 <sup>a</sup>	0.17	3.6 <sup>a</sup>	0.25	7.0 <sup>a</sup>	0.20	4.1 <sup>a</sup>	
LOGDEBT	0.77	9.1 <sup>a</sup>	0.86	8.7 <sup>a</sup>	0.74	8.7 <sup>a</sup>	0.82	8.2 <sup>a</sup>	
BONDYN	0.91	8.1 <sup>a</sup>	0.80	6.6 <sup>a</sup>	0.95	8.4 <sup>a</sup>	0.85	7.0 <sup>a</sup>	
BONDNEY	0.22	2.2 <sup>b</sup>	0.18	1.7 <sup>c</sup>	0.28	2.7 <sup>a</sup>	0.23	2.2 <sup>b</sup>	
BMV	0.01	1.9 <sup>c</sup>	0.01	2.3 <sup>b</sup>	0.01	2.0 <sup>b</sup>	0.01	2.4 <sup>a</sup>	
RDREV	0.01	6.2 <sup>a</sup>	0.01	4.5 <sup>a</sup>	0.01	6.6 <sup>a</sup>	0.01	4.9 <sup>a</sup>	
INSTINV	0.01	11.1 <sup>a</sup>	0.01	10.9 <sup>a</sup>	0.01	9.6 <sup>a</sup>	0.01	9.5 <sup>a</sup>	
Industry dummies	<i>NO</i>		<i>YES</i>		<i>NO</i>		<i>YES</i>		
Time dummies	<i>NO</i>		<i>NO</i>		<i>YES</i>		<i>YES</i>		
<b>Panel B: Marginal effects</b>									
Intercept	-0.54	-2.0 <sup>b</sup>	-0.71	-2.1 <sup>b</sup>	-0.51	-1.9 <sup>c</sup>	-0.54	-1.9 <sup>c</sup>	
ROA	-0.07	-2.1 <sup>b</sup>	-0.07	-2.1 <sup>b</sup>	-0.06	-2.0 <sup>b</sup>	-0.07	-2.0 <sup>b</sup>	
GEAR	-0.01	-1.5	-0.01	-1.4	-0.01	-1.3	-0.01	-1.5	
STDTD	-0.04	-2.0 <sup>b</sup>	-0.05	-2.1 <sup>b</sup>	-0.04	-1.9 <sup>c</sup>	-0.04	-1.8 <sup>c</sup>	
lnSALES	0.01	1.9 <sup>c</sup>	0.01	1.9 <sup>c</sup>	0.01	1.9 <sup>c</sup>	0.01	1.7 <sup>c</sup>	
LOGDEBT	0.04	2.1 <sup>b</sup>	0.05	2.0 <sup>b</sup>	0.03	2.0 <sup>b</sup>	0.04	1.8 <sup>c</sup>	
BONDYN	0.05	2.5 <sup>b</sup>	0.05	2.6 <sup>b</sup>	0.04	2.4 <sup>b</sup>	0.04	2.5 <sup>b</sup>	

BONDNEY	0.01	1.2	0.01	1.2	0.01	1.3	0.01	1.1
BMV	0.01	1.4	0.01	1.5	0.01	1.4	0.01	1.3
RDREV	0.01	1.9 <sup>c</sup>	0.01	1.8 <sup>a</sup>	0.01	1.9 <sup>c</sup>	0.01	1.7 <sup>c</sup>
INSTINV	0.01	2.1 <sup>b</sup>	0.01	2.0 <sup>b</sup>	0.01	2.0 <sup>b</sup>	0.01	2.0 <sup>b</sup>

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**Panel C: Selected model statistics**

$\chi^2$ statistic	1,364.9 <sup>a</sup>	1,416.2 <sup>a</sup>	1,395.2 <sup>a</sup>	1,446.4 <sup>a</sup>
Hosmer-Lemeshow $\chi^2$	64.50 <sup>a</sup>	64.97 <sup>a</sup>	53.58 <sup>a</sup>	55.72 <sup>a</sup>
Log-likelihood	-594.40	-568.76	-579.22	-553.64
No of observations	1,964	1,964	1,964	1,964
Akaike I.C.	0.62	0.60	0.61	0.59
Pseudo-R <sup>2</sup> $\diamond$	53.50%	55.45%	54.64%	56.63%
Adjusted pseudo-R <sup>2</sup> *	52.58%	53.89%	52.99%	54.21%

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*Notes:* The dependent variable of all binary probit models is the dummy variable RNR, which takes the value of 1 if a company is rated by S&P or 0 otherwise. All significance levels are determined using two-tailed Z-tests. <sup>a</sup>, <sup>b</sup>, <sup>c</sup> denote significance at the 1%, 5% and 10% respectively.  $\diamond$  This measure of goodness-of-fit is a simple computational statistic (

$R^2 = 1 - \frac{\text{Log}(L_{UR})}{\text{Log}(L_R)}$ ) proposed by McFadden (1973). \* McFadden's adjusted pseudo-R<sup>2</sup> adjusts for the number of

predictors in a model ( $R^2 = 1 - \frac{\text{Log}(L_{UR}) - K}{\text{Log}(L_R)}$ ).

**Table 12: The Rating Likelihood Probit Model: Estimation Results for the Contemporaneous and Predictive Specification of a Matched Training Sample of Rated and Non-rated Firms**

<b>Panel A: Parameter estimates</b>								
Independent variables	<b>Contemporaneous specification</b>				<b>Predictive specification</b>			
	<b>Model XVII</b>		<b>Model XVIII</b>		<b>Model XIX</b>		<b>Model XX</b>	
	<b>(excl. 2004-2006)</b>		<b>(excl. firms)</b>		<b>(excl. 2004-2006)</b>		<b>(excl. firms)</b>	
	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat	Coef	Z-stat
Intercept	-10.9	-8.9 <sup>a</sup>	-14.6	-10.8 <sup>a</sup>	-9.4	-8.2 <sup>a</sup>	-13.6	-10.6 <sup>a</sup>
ROA	-1.16	-7.4 <sup>a</sup>	-1.70	-6.1 <sup>a</sup>	-1.24	-6.7 <sup>a</sup>	-1.65	-6.0 <sup>a</sup>
GEAR	-0.01	-2.6 <sup>a</sup>	-0.01	-2.9 <sup>a</sup>	-0.01	-1.8 <sup>c</sup>	-0.01	-2.0 <sup>b</sup>
STDTD	-0.98	-7.9 <sup>a</sup>	-0.53	-2.4 <sup>b</sup>	-0.86	-7.0 <sup>a</sup>	-0.59	-2.6 <sup>a</sup>
lnSALES	0.16	2.7 <sup>a</sup>	0.29	4.3 <sup>a</sup>	0.10	1.9 <sup>c</sup>	0.24	3.6 <sup>a</sup>
LOGDEBT	0.97	7.9 <sup>a</sup>	0.97	6.2 <sup>a</sup>	0.85	6.9 <sup>a</sup>	0.89	5.8 <sup>a</sup>
BONDYN	1.01	6.5 <sup>a</sup>	0.96	6.4 <sup>a</sup>	0.90	5.5 <sup>a</sup>	0.83	5.4 <sup>a</sup>
BONDYBEF	0.01	7.2 <sup>a</sup>	0.01	6.3 <sup>a</sup>	-	-		
BONDNEY	-	-			0.26	2.2 <sup>b</sup>	0.28	2.2 <sup>b</sup>
BMV	0.01	1.8 <sup>c</sup>	0.01	1.7 <sup>c</sup>	0.01	1.7 <sup>c</sup>	0.01	2.3 <sup>a</sup>
RDREV	0.01	3.9 <sup>a</sup>	0.01	4.4 <sup>a</sup>	0.01	3.8 <sup>a</sup>	0.01	4.7 <sup>a</sup>
INSTINV	0.01	10.4 <sup>a</sup>	0.01	7.6 <sup>a</sup>	0.01	9.8 <sup>a</sup>	0.01	7.1 <sup>a</sup>
Industry dummies	<i>YES</i>		<i>YES</i>		<i>YES</i>		<i>YES</i>	
Time dummies	<i>YES</i>		<i>YES</i>		<i>YES</i>		<i>YES</i>	

**Panel B: Marginal effects**

Intercept	-3.90	-10.1 <sup>a</sup>	-1.74	-6.5 <sup>a</sup>	-0.01	-1.2	-3.86	-1.6
ROA	-0.42	-5.9 <sup>a</sup>	-0.18	-3.3 <sup>a</sup>	-0.08	-1.3	-0.42	-1.6
GEAR	-0.01	-2.6 <sup>a</sup>	-0.01	-2.6 <sup>a</sup>	-0.04	-1.2	-0.01	-1.5
STDTD	-0.35	-8.9 <sup>a</sup>	-0.10	-2.8 <sup>a</sup>	-0.05	-1.2	-0.17	-1.4
lnSALES	0.06	3.1 <sup>a</sup>	0.05	3.1 <sup>a</sup>	0.06	1.6	0.10	1.6

LOGDEBT	0.35	8.9 <sup>a</sup>	0.10	3.7 <sup>a</sup>	0.05	1.3	0.19	1.5
BONDYN	0.36	5.1 <sup>a</sup>	0.11	3.1 <sup>a</sup>	0.06	1.6	0.23	1.5
BONDYBEF	0.01	6.9 <sup>a</sup>	0.01	3.5 <sup>a</sup>	-	-		
BONDNEY	-	-			0.01	1.6	0.08	1.6
BMV	0.01	1.5	0.01	1.3	0.01	1.5	0.01	1.4
RDREV	0.01	4.2 <sup>a</sup>	0.01	3.2 <sup>a</sup>	0.01	1.6	0.01	1.6
INSTINV	0.01	10.2 <sup>a</sup>	0.01	8.5 <sup>a</sup>	0.01	1.3	0.01	1.3

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**Panel C: Selected model statistics**

$\chi^2$ statistic	1,230.1 <sup>a</sup>	1,275.0 <sup>a</sup>	1,041.5 <sup>a</sup>	1,145.4 <sup>a</sup>
Hosmer-	50.19 <sup>a</sup>	40.80 <sup>a</sup>	16.80 <sup>b</sup>	40.79 <sup>a</sup>
Lemeshow $\chi^2$				
Log-likelihood	-337.63	--339.32	-391.97	-386.40
No of observations	1,463	1,456	1,468	1,462
Akaike I.C.	0.51	0.50	0.57	0.56
Pseudo-R <sup>2</sup> $\diamond$	65.00%	65.26%	57.06%	59.71%
Adjusted pseudo-R <sup>2</sup> *	61.61%	62.08%	54.09%	56.48%

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*Notes:* The dependent variable of all binary probit models is the dummy variable RNR, which takes the value of 1 if a company is rated by S&P or 0 otherwise. All significance levels are determined using two-tailed Z-tests. <sup>a</sup>, <sup>b</sup>, <sup>c</sup> denote significance at the 1%, 5% and 10% respectively.  $\diamond$  This measure of goodness-of-fit is a simple computational statistic (

$R^2 = 1 - \frac{\text{Log}(L_{UR})}{\text{Log}(L_R)}$ ) proposed by McFadden (1973). \* McFadden's adjusted pseudo-R<sup>2</sup> adjusts for the number of

predictors in a model ( $R^2 = 1 - \frac{\text{Log}(L_{UR}) - K}{\text{Log}(L_R)}$ ).

**Table 13: Out-of-Sample Classification Model Performance for matched Rated (86) and Non-rated Companies (86)**

<b>Model XVII</b>				<b>Model XVIII</b>			
<b>(contemporaneous excl. 2004-2006)</b>				<b>(contemporaneous excl. firms)</b>			
	<i>Predicted</i>		<i>Totals</i>		<i>Predicted</i>		<i>Totals</i>
	<b>0</b>	<b>1</b>			<b>0</b>	<b>1</b>	
<i>Actual</i>				<i>Actual</i>			
<b>0</b>	214	46	260	<b>0</b>	299	24 (7.43%)	323
	(82.31%)	(17.69%)			(92.57%)		
<b>1</b>	25	206	231	<b>1</b>	23	163	186
	(10.82%)	(89.18%)			(12.37%)	(87.63%)	
<i>Totals</i>	239	252	491	<i>Totals</i>	322	187	509
	Correct prediction rate: 85.54%				Correct prediction rate: 90.77%		

  

<b>Model XIX</b>				<b>Model XX</b>			
<b>(predictive excl. 2004-2006)</b>				<b>(predictive excl. firms)</b>			
	<i>Predicted</i>		<i>Totals</i>		<i>Predicted</i>		<i>Totals</i>
	<b>0</b>	<b>1</b>			<b>0</b>	<b>1</b>	
<i>Actual</i>				<i>Actual</i>			
<b>0</b>	215	47	262	<b>0</b>	318	26 (7.56%)	344
	(82.06%)	(17.94%)			(92.44%)		
<b>1</b>	25	211	236	<b>1</b>	21	139	160
	(10.59%)	(89.41%)			(13.13%)	(86.88%)	
<i>Totals</i>	240	258	498	<i>Totals</i>	339	165	504
	Correct prediction rate: 85.54%				Correct prediction rate: 90.67%		

*Note:* Analysis of binary choice model predictions based on a 0.5 threshold.

**Figure 1: Receiver Operating Curve (ROC) for Model XVIII (Matched Sample Contemporaneous Specification Excluding 25% of Rated and Non-rated Firms)**

