The Rating Decision and the Determinants of Credit Ratings: A UK Empirical Investigation

Abstract

This study examines the determinants of the decision of UK non-financial companies to solicit a credit rating drawing upon the information asymmetry, signalling, agency and default literature. The paper extends the current literature on the determinants of corporate credit ratings by including key non-financial variables. The rating likelihood models are able to distinguish between rated and non-rated companies satisfactorily. Moreover, the estimated rating determinants models reveal that the inclusion of non-financial variables adds to their explanatory power. Finally, the study examines whether the unique attributes shared by rated companies drive their decision to solicit a credit rating. Using a two-stage sample selection framework the results indicate that self-selection is not dominant among UK non-financial companies.

1. Introduction

The collapse of Enron and a number of other high profile corporate defaults highlighted the importance of sound credit risk management and the shortcomings of the credit rating system. The financial crisis, 2008, and the severe economic costs of the consequent recession, brought about more criticism of the value of credit ratings. This study seeks to investigate the robustness or bias in ratings. We seek to establish whether the financial and non-financial characteristics of rated versus non-rated companies can be identified within a multivariate context to unveil consistency and transparency in extant ratings.

Credit ratings provide an independent evaluation of a company's ability to service its debts in a timely manner. As such, credit ratings can impact on firms' cost of debt and their financing structure; ultimately determining survival probability. Also, rated firms' business and financial strategies can potentially affect the rating and their future cost of capital (Graham and Harvey, 2001). Hence, rating agencies have not only been bestowed with the task of acting as quasi-regulators, by certifying the creditworthiness of companies worldwide, but are consistently used as inputs in financial institutions' internal credit risk assessment systems for risk management, and for regulatory purposes. For example, institutional investors, such as pension funds, have adopted credit ratings to ensure they maintain portfolios of sufficient credit quality (White, 2001; Steeman, 2002).

Nonetheless, credit rating agencies have been under fire for failing to anticipate major credit events worldwide. At the heart of such criticisms lies the rating methodology employed by rating agencies, described as a 'black box' by market participants (Pender, 1992) and academics alike (Sylla, 2001). Recently, their methodologies have been scrutinised and regulatory bodies in the USA (SEC) and Europe (IOSCO) have demanded that rating agencies become more transparent in their methods and their communication with investors and regulators.

The ‘opaque’ nature of the rating methodology has attracted researchers to gain an insight into the exact inputs of the rating agencies’ models. Horrigan (1966) attempted to replicate ratings assigned to corporate bonds by US rating agencies. This first empirical study aimed to provide transparency to the methods used by rating agencies; ultimately replicating their ‘end product’ as accurately as possible. In view of these developments and due to the academic interest that agencies' proprietary models have attracted over time, this study aims to address two important issues surrounding credit ratings. First, it explores the decision to obtain a credit rating by constructing a model that classifies accurately the likelihood of soliciting a credit rating. Secondly, it investigates the individual, as well as joint, significance of a number of financial and non-financial variables in the determination of credit ratings for UK companies.

The study contributes to the existing literature in a variety of ways. It provides an in-depth examination of the factors that lead UK companies to solicit credit rating. Only a few studies (Poon, 2003; Adams *et al*., 2003) have modelled the likelihood of companies obtaining credit rating. Nevertheless, Poon (2003) uses a restricted global sample (*excluding* the UK) and examine the dynamics in the context of solicited versus unsolicited ratings, whereas Adams *et al.* (2003) focus exclusively on the UK *insurance* industry. More recently, Gonis *et al.* (forthcoming) developed a conceptual framework, which borrows elements from signalling, information asymmetry, default and agency theories and which facilitates the empirical testing of rating likelihood across UK sectors. This study builds on it by testing a number of additional variables likely to affect the rating solicitation decision.

Furthermore, the majority of previous studies of credit determinants utilise US data, due to the wide use of credit ratings in the US capital markets. In the UK, however, there have only been few studies; Adams *et al.* (2003) study the determinants of credit ratings of UK insurance firms, whilst Doumpos and Pasiouras (2005) examine factors affecting UK credit scores. There are, to the authors’ belief, no studies that focus exclusively on the determinants of corporate credit ratings in a cross-industry UK context. This study, thus, contributes to the extant literature by presenting evidence on the determinants of letter ratings assigned to UK non-financial companies and provides a useful comparison for the predominantly US evidence.

Moreover, the paper contributes to the credit rating literature by incorporating a range of non-financial variables that are hypothesised to influence assigned credit ratings and by adopting a novel empirical strategy to determine the effects of these variables. Whereas a limited number of previous studies have examined the independent effects of non-financial firm attributes on corporate credit ratings (e.g. Czarnitzki and Kraft, 2004, 2006; Ashbaugh-Skaife *et al.*, 2006), this study examines the joint as well as the individual significance of these variables in an attempt to produce more comprehensive understanding of rating models.

The rest of this paper is structured as follows: Section 2 reviews the literature on the drivers of the rating decision and the determinants of credit ratings and sets forth the hypotheses to be tested. Section 3 presents the data and methods used to test the hypotheses, while Section 4 discusses the results. Section 5 concludes with a summary of the main findings.

1. Literature Review

1.1 Rating likelihood and rating determinants

The decision to obtain credit rating is not an *ad-hoc* decision by managers. De and Kale (1993) argue that companies have private knowledge relating to their financial strength, which can be shared with the public at a cost. They suggest that financially stronger firms have the most to gain and thus seek a rating, which signals good quality. In this context of signalling creditworthiness, Kisgen (2006) further maintains that ratings can act as a signal of firm quality, and if markets perceive them as adding value, then changes in credit ratings can signal changes in firms' underlying creditworthiness and provide discrete cost-benefits.

Meanwhile, Pottier and Sommer (1999) offer support to the information asymmetry argument by contending that the principal role of credit rating agencies is 'the reduction of *ex ante* uncertainty of informational asymmetry about a firm's economic value and probability of financial distress' (p. 626). Lastly, from a bankruptcy perspective, Rösch (2005) argues that credit ratings can accurately differentiate between failing and surviving firms, whilst Ambrose and Carroll (1994) report that insurer credit ratings are an effective, yet not very efficient, indicator of financial distress due to the insufficient advance warning they provide.

At the same time, ratings represent agencies' expert opinion on firms' business and financial risk. As such, they rely heavily on financial ratios and 'soft' factors to assess the underlying corporate creditworthiness. In fact, the majority of agencies vehemently argue that their rating methodologies are not exclusively dependent on statistical methods, but incorporate a number of subjective elements (Standard and Poor's, 2005).

Therefore, academic research into rating determinants has to respond by considering the issue of certain companies possessing unique characteristics that drive the process of rating solicitation, whilst simultaneously examining a wider range of letter rating determinants of both financial and non-financial nature. The proposed framework, including the variables considered therein, is considered in detail below.

1.2 Financial, non-financial determinants and hypotheses

It is widely regarded that firm age is negatively associated with its probability of default, and also inversely related to its idiosyncratic risk (Dunne *et al.*, 1988; Agarwal and Gort, 1996; Damodaran, 2001). In the same vein, Paul and Wilson (2007) argue that well-established firms are seen as less risky and more likely to remain solvent. On the other hand, Czarnitzki and Kraft (2004) and Sufi (2009) maintain that younger firms are more likely to apply for a credit rating, because the certification effect of indicating survival likelihood or even success trajectory is more valuable for younger firms that communicate information to previously uninformed market participants via ratings. *Therefore, younger companies are more likely to solicit credit ratings.*

Lamb and Rappaport (1987) and Moon and Stotsky (1993) contend that the volume of debt that firms have and/or are about to issue is key in rating solicitation; the cost of obtaining a rating may be offset by the saving in interest costs that might arise from obtaining a favourable credit rating. This is in line with studies that posit theoretically (Millon and Thakor, 1985) and show empirically (Minardi *et al.*, 2007) that credit ratings lower companies' cost of debt. Hence, it is hypothesised that *the higher the volume of debt, the greater the likelihood of soliciting credit rating* thus benefiting from interest costs savings.

White (2001) highlights the importance of commissioning a credit rating in advance of bond issuances. While new issues of bonds in the US are required to bear at least two ratings from an approved list of NRSROs (SEC, 2003) the same is not true for UK companies. The increasing reliance of market participants on agencies' credit ratings and its incorporation in regulatory frameworks and investment policies, ultimately place considerable importance on soliciting credit ratings when new bonds are issued (Steeman, 2002). Cantor and Packer (1997) posit that the amount of time that companies are active in the public bond market is a significant determinant of its propensity to obtain rating. Therefore, *firms issuing bonds as a method of financing and those with a history of public debt issuance are more likely to solicit a credit rating.*

Financial flexibility constitutes an important measure of companies' financial risk, while its importance is accentuated in times of financial distress (Myers and Majluf, 1984; Ganguin and Billardelo, 2004). Modigliani and Miller (1963) argue that, to preserve their flexibility, companies tend not to maximise the use of debt in their capital structure. This flexibility is associated with low leverage, enhanced investment ability (Mura and Marchica, 2009) and commitment to growth (Pucia *et al.*, 2009). Baum *et al.* (2009) find that financial flexibility is inversely related to uncertainty, while Gamba and Triantis (2008) posit that financially flexible firms are more likely to avoid financial distress in the event of negative shocks. Hence, *financially flexible firms are more likely to solicit a credit rating.*

Cantor and Packer (1997) and Pottier and Sommer (1999) subscribe to the notion that companies solicit a credit rating if there is greater uncertainty about their true default risk. They hypothesise that 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. On the other hand, firms facing higher chances of bankruptcy are less likely to solicit a rating, since the resultant low rating and associated higher debt costs will outweigh any benefits. Hence, *a significant relation between default risk and rating propensity is expected.*

The assessment of companies' business risk lies at the heart of credit analysis. Its analysis includes an assessment of firms' industry characteristics and organisational factors (Amato and Furfine, 2004). Bradshaw *et al.* (2007) establish a direct relationship between business risk and uncertainty about a firm's prospects, which Reeb *et al.* (2001) associate with financial distress and lower credit ratings. Similarly, Fabozzi and Choudhry (2004) view increases in business risk as a strain on corporate cash-flow which impacts negatively on credit ratings. Hence, *increases in corporate business risk are related to a lower rating likelihood and lower credit ratings.*

An implicit element of business risk assessment is business growth. The positive signals sent by increases in business outweigh the potential shortcomings of high growth (Pottier and Sommer, 1999). However, companies' managers might actively, and sometimes aggressively, make decisions regarding the required growth rate in their own interest (Brush *et al.*, 2000). They pursue growth for purely personal benefits, since growth guarantees their employment and increases their salaries (Murphy, 1985). In the same vein, Garg *et al.* (2004) posit that business growth enhances corporate profitability and creditworthiness; a view echoed by Pottier and Sommer (1999) and Adams *et al.* (2003), who perceive growth in corporate activities as indicative of strong financial health. These arguments support a *positive relation between firm growth and the decision to solicit a rating,* as credit ratings contribute to the monitoring of companies' agents (Sylla, 2001). Moreover, *higher business growth rates are associated with better credit ratings.*

Business growth and firm size are interrelated in the context of credit ratings (Bottazzi *and Secchi,* 2006). Firm size is a proxy for longevity and market power (Pettit *et al.*, 2004). Also, larger companies are more likely to have prominent market positions (Adams *et al.*, 2003), achieve risk diversification due to the bigger scale of their operations (Koller *et al.*, 2005) and perform better during economic downturns (Altamuro *et al.*, 2009). Similarly, Altman and Rijken (2004) and Demirovic and Thomas (2007) report that size accurately represents survival potential and overall corporate creditworthiness. Hence, *bigger companies are more likely to solicit a credit rating*. Also, *firm size is positively related to credit ratings*.

Profitability is a clear indication of the level of risk that is associated with firms (Fink *et al.*, 2006) and their ability to service debt; it is also associated with companies' propensity to default (Altman, 1968; Logue and Merville, 1972). Adams *et al.* (2003) argue that higher profitability is related to lower insolvency risk, whilst Daniels *et al.* (2009) confirm that profitability plays an important role in facilitating access to capital markets. Galil (2003) maintains that profitability is inversely related to default propensity, which firms will seek to share with the market. Thus, *higher levels of profitability are associated with a greater propensity to solicit a credit rating and better credit ratings.*

Companies with established access to public capital markets, e.g. firms with credit ratings, are more likely to hold less liquid assets (Opler *et al.,* 1999). Credit-rated firms are perceived to exhibit lower firm-specific risk, have less incentive to hold more liquid assets (Baum *et al.*, 2008) and can minimise the propensity of accumulating cash (Shyam-Sunder and Myers, 1999) without deterring its credit quality. In addition, high levels of liquidity give managers the incentive to invest in negative NPV projects and may lead to principal-agent problems, as managers might increase their remuneration packages (Adams *et al.*, 2003). *Therefore, the higher the liquidity, the greater the likelihood of a firm soliciting a credit rating.* Also, *higher levels of liquidity are associated with higher credit ratings*. There is widespread disagreement regarding the effect of leverage on rating likelihood. Cantor and Packer (1997) and Pottier and Sommer (1999) posit that higher levels of financial leverage increase uncertainty, due to the risk of financial distress which provides firms with extra incentive to solicit new or additional ratings to signal their true credit risk. Adams *et al.* (2003), however, contend that highly leveraged companies will not actively seek a credit rating since securing a low rating 'is likely to exacerbate market uncertainties' (p. 544), while Poon (2003) posits that higher levels of leverage lead to an increase in a company's specific risk, which is consequently illustrated in lower ratings. Nevertheless, the inverse relationship between leverage and ratings is well documented in extant studies. Amato and Furfine (2004) maintain that increases in firms' indebtedness are indicative of lower ratings, whilst Shivdasani and Zenner (2005) distinguish between the impact of leverage on investment- and speculative-grade companies, highlighting that in most cases, levering up has a deteriorating effect on their ratings. This study proposes that *it is likely that highly geared companies are less likely to solicit a credit rating and more likely to have lower credit ratings.*

Nevitt and Fabozzi (2000) highlight the extensive use of coverage ratios by rating agencies for determining firms' ability to service their debt. Cash-flow ratios have the power to differentiate between failed and non-failed firms for up to five years before bankruptcy (Beaver, 1966). Moreover, sufficient ability to cover debt obligations is associated with companies' likelihood of obtaining a credit rating (Poon, 2003); and high volatility in coverage ratios might lead to insufficient cash-flow to service debts in time (Koller *et al.*, 2005). Similarly, Poon (2003) indicates that increasing coverage ratios are excellent indicators of earnings growth and financial flexibility, leading to higher ratings. Thus, *greater* *values of interest and cash-flow coverage are associated with a higher rating likelihood and better credit ratings.*

Czarnitzki and Kraft (2004) argue that companies that invest in successful R&D enjoy high revenues, exhibit an enhanced financial performance; in the long run, they have better chances of survival and are more likely to communicate this commitment to their commercial counterparties, lenders and capital markets. Similarly, Piga and Atzeni (2007) find that R&D intensive firms are more likely to avoid facing credit constraints. Moreover, a number of studies have established a link between *R&D expenditure* and improvements in corporate operating and financial performance (Capon *et al.*, 1990; Erickson and Jacobson, 1992; Roberts, 2001), which Czarnitzki and Kraft (2006) argue can be translated into a higher rating. Hence, *firms investing in R&D are more likely to solicit a credit rating.* Also, *higher levels of innovation are associated with better credit ratings.*

Ashbaugh-Skeife *et al.* (2006) maintain that weak corporate governance can damage a firm's financial position and leave bondholders vulnerable to losses due to increases in debt financing costs. Balling *et al.* (2005) argue that the prospect of obtaining and maintaining a credit rating provides companies with incentives to implement and follow good corporate governance practices. A review of the extant academic literature reveals that the assessment of corporate governance spans four main areas. Ownership structure is a fundamental criterion, as affiliations affect a company's credit quality. The study of a company's management and organisation focuses on assessing the competence of the management team as well as effectiveness of the control setup within an organisation. Furthermore, financial transparency and disclosure considerations are critical to reducing information asymmetries between firms and their capital suppliers. Finally, the study of their rights and relations reveals useful information about the treatment of various stakeholders by the company (Ashbaugh-Skaife *et al.*, 2006)

Jensen (1993) argues that institutional investors significantly contribute to a well-functioning governance system because of the unbiased view of management's strategies and the power to put pressure on management if they observe any agency problems arising. Similarly, Cornett *et al.* (2006) argue that institutional ownership, limits managerial discretion. Significant levels of institutional ownership increase oversight of firms and rein in aggressive use of accounting discretion. Nevertheless, Bhojraj and Sengupta (2003) contend that institutional owners and blockholders might influence management in order to secure benefits that are detrimental to bondholders.

The dimension of a company's management and its organisation deals primarily with the set-up of companies' governing boards and their role and ability to provide independent and impartial oversight of management performance. Fama and Jensen (1983) argue that independent directors bear a reputational risk if firm performance is poor. This leads them to monitor management actions more carefully in comparison to inside directors. Meanwhile, Minow and Bingham (1995) argue that increasing directors' shareholdings is likely to improve corporate performance due to sharing some of the financial risk of the company with other shareholders. Hence, *higher institutional ownership increases the likelihood of a company soliciting a credit rating and being awarded better ratings.* Also, *the more independent directors on a firm's board of directors, the better its credit rating.* Moreover, *the number of significant shareholders is negatively associated with credit ratings.* Lastly, *higher levels of director ownership are associated with lower ratings.* Finally, Kaplan and Urwitz (1979) argue that the assessment of corporate creditworthiness should in principle take place independently of any market dynamics. However, an increasing number of empirical studies have tested for the effect of beta, a proxy for systematic risk, on credit ratings, with the results affirming the importance of market risk in assigning credit ratings. Gan (2004) and Gray *et al.* (2006) propose that a firm with higher equity beta is expected to have lower credit ratings. Similarly, Allen and Saunders (2003) report that firms with higher ratings exhibit lower systematic risk. Therefore, *companies with higher equity beta are more likely to have lower ratings*.

2. Data and Methodology

2.1 Sample Selection and Data

The sample consists of a matched dataset of rated (86) and non-rated (159) listed UK non-financial companies during 1995-2006. This represents up to 2,782 and 752 firm years for the selection and outcome models respectively. In line with previous bankruptcy prediction (e.g. Beaver, 1966; Altman, 1968; Hamer, 1983; Gentry *et al.*, 1988; Charitou *et al.*, 2004) and self-selection studies (e.g. Moon and Stotsky, 1993; Adams *et al.*, 2003), this paper uses a matching procedure based on industry classification and size (i.e. every rated company is matched to a similarly sized non-rated company belonging to the same sector, as per the Industrial Classification Benchmark (ICB)). This procedure ensures homogeneity and allows for direct comparability between rated and non-rated companies. Nevertheless, the two sub-samples are not exactly matched in order to present variations that can be modelled with our range of independent variables in the multivariate estimations (Taffler, 1982).

The credit ratings are taken from S&P's Historical File and relate to solicited ratings initiated by UK companies during the period under investigation. Furthermore, firms are selected on the condition that their *main* activities are concentrated in the UK market. Where subsidiaries of firms have been assigned a separate rating, the study takes into account only the parent companies' credit rating. Also, the study includes only firms whose financial statements are available on the OSIRIS and Datastream databases. Certain non-financial data are hand-collected from companies' annual financial statements.

2.2 Methodology

$z_{it}^* = \gamma' w_{it} + u_{it}$

For the purposes of this study, the Heckman (1976) two-stage sample selection methodology is extended to deal with non-linearity of the outcome equation, due to the inherently qualitative and ordinal nature of credit ratings. This modification was developed by Dubin and Rivers (1990) and was discussed in more detail in Greene (2003). In short, the ordinal random variable measuring firms' creditworthiness is assessed for self-selection by testing the correlation between the error terms in two models. Thus, the sample selection methodology involves estimating two non-linear models:

i) an ordinary binary probit model (referred to as the rating likelihood equation) is fitted to obtain consistent estimates of the expected error of the parameters of the selected equation (ρ). To estimate this model, the dependent variable is a binary variable that equals one for firms that have the required observation on the dependent variable in year_t and zero otherwise. A set of independent variables are regressed against the dependent variable to obtain the estimated errors, which are consequently included in the second stage to eliminate the bias of limited dependent variables asymptotically;

ii) an ordered probit model (referred to as the rating determination equation) is estimated to include the correlation between the residual terms of the selection and outcome equations as an additional explanatory variable (ρ). The null hypothesis implies that self-selection does not exist ($\rho=0$). The independent variables in this model are of a quantitative (financial ratios and quantifiable non-financial variables) and of a qualitative (dummy variables) nature.

The rating likelihood probit model and the rating determination ordered probit model can be written in general form with the help of equations 1.1-1.4. Equations 1.1 and 1.2 represent the rating likelihood specification, while equations 1.3 and 1.4 portray the rating determination model:

$$z_{it}^* = \gamma' w_{it} + u_{it} \qquad \textbf{(1.1)}$$

$$z_{it} = \begin{cases} 1 \\ 0 \end{cases} \text{if} \begin{cases} z_{it}^* > 0 \\ z_{it}^* \leq 0 \end{cases} \qquad \textbf{(1.2)}$$

$$y_{it}^{*} = \beta^{'} x_{it} + \varepsilon_{it} \qquad \textbf{(1.3)}$$

$$y_{it} = \begin{cases} 0 & y_{it}^{*} \le \mu_0 \\ 1 & \mu_0 < y_{it}^{*} \le \mu_1 \\ 2 \text{ if} & \mu_1 < y_{it}^{*} \le \mu_2 \\ \cdots & \cdots \\ n & y_{it}^{*} > \mu_{n-1} \end{cases} \qquad \textbf{(1.4)}$$

$u_{it}, \varepsilon_{it} \sim N(0,0,1,1,\rho)$ and (y_{it}, x_{it}) is observed if and only if $z_{it} = 1$ (Adams *et al.*, 2003).

In the preceding models, z^{*} and y^{*} are continuous, latent variables. In the sample selection equation (equation 1.1), z^{*} is the 'propensity to get rated' (Adams *et al.* 2003, p. 551), while in the outcome equation (equation 1.3), y^{*} is the 'propensity to be assigned a particular rating' (*ibid*, p. 551). The binary variable z_{it} in equation 1.2 takes the value of zero for a non-rated company and one for a rated company. Meanwhile, the ordinal variable y_{it} in equation 1.4 measures the assigned credit ratings, as expressed on an n-point scale, where zero represents the lowest credit rating and n stands for the highest rating category.

Furthermore, in equations 1.1 and 1.3, w and x represent vectors of independent variables, while $\gamma^{'}$ and $\beta^{'}$ represent vectors of the coefficients to be estimated. The assumption of normal distribution with means equal to zero, variances equal to one and a correlation coefficient equal to ρ is made for the two disturbance terms, u_{it} and ε_{it}. Lastly, as the purpose of this study is to test the economic significance of hypotheses regarding the drivers of both the solicitation decision and the actual letter rating of UK non-financial companies, the econometric methods do not explicitly consider the direction of causality between the dependent and independent variables.

2.3 Models and Variables

The following rating likelihood binary probit model is estimated for the purposes of this study:

$$\begin{aligned}RNR_{it} &= \beta_0 + \beta_1 INTCOV_{it} + \beta_2 ROA_{it} + \beta_3 GEAR2_{it} + \beta_4 STDTD_{it} + \beta_5 CURRENT_{it} + \\ &+\beta_6 \ln SALES_{it} + \beta_7 \ln AGE_{it} + \beta_8 LOGDEBT_{it} + \beta_9 NDFTD_{it} + \beta_{10} BONDYN_{it} + \\ &+\beta_{11} BONDYBEF_{it} + \beta_{12} BREBIT5_{it} + \beta_{13} BREBIT12_{it} + \beta_{14} GROWTH_{it} + \\ &\beta_{15} BMV_{it} + \beta_{16} RNDD_{it} + \beta_{17} INSTINV_{it}\end{aligned} \qquad \textbf{(1.5)}$$

where:

RNR_{it} = dummy variable indicating whether a company is credit rated or not. This variable takes the value of one ($RNR_{it} = 1$) if a firm in the sample is rated in any given year and zero otherwise ($RNR_{it} = 0$),

β_0 = the intercept,

$INTCOV_{it}$ = interest coverage (EBIT to total interest expense for $year_t$)

ROA_{it} = profitability (net income over total assets for $year_t$)

$GEAR2_{it}$ = financial leverage (book value of total debt to total shareholders’ funds for $year_t$)

$STDTD_{it}$ = financial flexibility (total short-term debt by total debt for $year_t$)

$CURRENT_{it}$ = liquidity (current assets over current liabilities for $year_t$)

$\ln SALES_{it}$ = firm size (natural logarithm of a company’s sales for $year_t$)

$\ln AGE_{it}$ = firm age (natural logarithm of a company’s age since its incorporation)

$LOGDEBT_{it}$ = company overall indebtedness (logarithm of a company’s total debt for $year_t$)

$NCFTD_{it}$ = company cash-flow coverage (net cash-flow from operations to total debt for $year_t$)

$BONDYN_{it}$ = firm bond issuance. It is a dummy variable that equals one if a firm issued bonds during the period of the study ($BONDYN_{it} = 1$) and zero otherwise ($BONDYN_{it} = 0$)

$BONDYBEF_{it}$ = company past bond issuance. It is a dummy variable that equals one if a firm issued bonds in the last ten years to year$_t$ ($BONDYBEF_{it} = 1$) and zero otherwise ($BONDYBEF_{it} = 0$)

$BREBIT5_{it}$ = company historical short-term business risk. It is defined as the ratio of the standard deviation of earnings before interest and tax to average earnings before interest and tax for year$_t$ and the previous four years ($\frac{\sigma(EBIT_{t-4,t})}{\mu(EBIT_{t-4,t})}$)[1]

$BREBIT12_{it}$ = company historical long-term business risk. It is defined as the ratio of the standard deviation of earnings before interest and tax to average earnings before interest and tax for the entire sample period ($\frac{\sigma(EBIT_{t-11,t})}{\mu(EBIT_{t-11,t})}$)

$GROWTH_{it}$ = firm historical growth (rate of change of a firm's total assets over a one-year period ($\Delta TA_{t-1,t}$)[2])

BMV_{it} = company market-perceived distress risk (total shareholders' equity to market capitalisation for year$_t$[3])

$RNDD_{it}$ = company engagement with innovative activity. It is a dummy variable that takes the value of one if a company reports R&D expenditure in year$_t$ ($RNDD_{it} = 1$), and zero otherwise ($RNDD_{it} = 0$)

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[1] This measure of business risk is favoured by Ferri and Jones (1979) for its robustness and reliability over other measures, such as earnings volatility. Alternative periods were considered in the calculation of this measure of business risk, but the results in the sample selection models were qualitatively similar.
[2] Three-year growth rates were also calculated. This alternative measure of growth yielded similar results.
[3] Firms' market capitalisation values were calculated on their respective accounting year-end dates.

$INSTINV_{it}$ = company institutional ownership (shares held by institutional investors to total number of shares for year$_t$)

Model 1.5 assumes a contemporaneous specification, in which the decision to obtain a credit rating is taken on the basis of current financial and non-financial information. We further estimate an alternative specification with the purpose of exploring the dynamics associated with this decision. The predictive specification assumes that the decision to obtain a credit rating depends on next year's forecasted financial and non-financial information and is established both theoretically (Nayar, 1993) and empirically (Czarnitzki and Kraft, 2004; Sufi, 2009). Hence, the following model is also estimated:

$$\begin{aligned}RNR_{it} &= \beta_0 + \beta_1 INTCOV_{it+1} + \beta_2 ROA_{it+1} + \beta_3 GEAR2_{it+1} + \beta_4 STDTD_{it+1} \\ &+\beta_5 CURRENT_{it+1} + \beta_6 \ln SALES_{it+1} + \beta_7 \ln AGE_{it+1} + \beta_8 LOGDEBT_{it+1} + \\ &+\beta_9 NDFTD_{it+1} + \beta_{10} BONDYN_{it+1} + \beta_{11} BONDNEY_{it} + \beta_{12} BREBIT5_{it+1} + \\ &+\beta_{13} BREBIT12_{it} + \beta_{14} GROWTH_{it+1} + \beta_{15} BMV_{it+1} + \beta_{16} RNDD_{it+1} + \\ &+\beta_{17} INSTINV_{it+1}\end{aligned} \qquad \mathbf{(1.6)}$$

As can be seen from Equations 1.5 and 1.6, both specifications use the same variables for reasons of direct comparability, with the exception of the $BONDYBEF_{it}$ variable, which is replaced in Model 1.6 by $BONDNEY_{it}$. $BONDNEY_{it}$ measures companies' future bond issuance. It is a dummy variable that equals one if a firm issues bonds in the next period relative to the rating decision ($BONDNEY_{it} = 1$) and zero otherwise ($BONDNEY_{it} = 0$). If the decision is assumed dependent on future events, then potential issuance of bonds in the future is more important than past bond issuance (Steeman, 2002). (Steeman, 2002).

In addition, the following rating determination ordered probit model is estimated:

$$\begin{aligned}CR_{it} &= \beta_0 + \beta_1 \ln TA_{it} + \beta_2 TDTA_{it} + \beta_3 INTCOV3_{it} + \beta_4 EBITDATD_{it} + \\ &+ \beta_5 EBITDAMA_{it} + \beta_6 CUTA_{it} + \beta_7 BETA_{it} + \beta_8 BREBIT12_{it} + \beta_9 GROWTH_{it} \\ &+ \beta_{10} RDREV_{it} + \beta_{11} INSTINV_{it} + \beta_{12} INDDR_{it} + \beta_{13} DIRSH_{it} + \beta_{14} NOSIGN_{it} + \\ &\beta_{15} INVAL_{it} + \beta_{16} YEND_{it}\end{aligned} \qquad \mathbf{(1.7)}$$

where:

CR_{it} = firm credit rating for year$_t$. It is a discrete variable that ranges between 9 (AA and above) and 0 (BB+ and below)[4]

$\ln TA_{it}$ = company size (natural logarithm of total assets for year$_t$)

$TDTA_{it}$ = company capital structure (total debt to total assets for year$_t$)

$INTCOV3_{it}$ = company interest coverage ability (net income and interest expense to interest expense for year$_t$[5])

$EBITDATD_{it}$ = company cash-flow coverage (EBITDA to total debt for year$_t$)

$EBITDAMA_{it}$ = company profitability (EBITDA to sales revenue for year$_t$)

$CUTA_{it}$ = company liquidity (current assets to total assets for year$_t$)

$BETA_{it}$ = company systematic risk for year$_t$. It is estimated for each company using the market model and 60 monthly observations based on the DATASTREAM database and centered on the year for which the financial ratios were computed[6]

$BREBIT12_{it}$ and $GROWTH_{it}$ = firm long-term business risk and historic growth for year$_t$ respectively. Their definition is the same as before.

$RDREV_{it}$ = R&D intensity (R&D expense to sales revenue for year$_t$)

$INSTINV_{it}$ = company institutional ownership (shares held by institutional investors to total number of shares for year$_t$)

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[4] For a breakdown of the different rating grades, refer to Appendix A.

[5] Following Blume *et al.* (1998), Amato and Furfine (2004) and Jorion *et al.* (2009), this study assumes a non-linear relationship between interest coverage and credit ratings.

[6] The market index used in the beta calculation was the FTSE-100 index. However, the FTSE-All Share index was also used to represent the wider UK market. The results obtained are qualitatively similar to the ones reported in this study.

$INDDR_{it}$ = company board independence (percentage of independent directors on the company board of directors for year$_t$)

$DIRSH_{it}$ = company board share ownership (percentage of share ownership by board directors for year$_t$)

$NOSIGN_{it}$ = company block ownership (number of significant shareholders, i.e. shareholders with a minimum of 3% share ownership for year$_t$)

Finally, following Blume *et al.* (1998) and Amato and Furfine (2004), all negative interest coverage values are eliminated and replaced by zero values. In addition, the interest coverage measure (*INTCOV3*) is allowed to have a non-linear effect on the assigned letter ratings for two reasons. If operating income is negative, then a decline in interest expense will only make the variable more negative, whereas this might be a positive development at the margin (Amato and Furfine, 2004). Furthermore, rating agencies place more emphasis on changes in interest coverage at lower levels, which are more likely to lead to a rating action than changes at higher levels of coverage that might immaterially impact a firm's rating(Standard and Poor's, 2005).. Hence, four new variables are created, $INTCOV3C_j$ (j=1,2,3,4), defined according to equations 1.8-1.11:

$$INTCOV3C1 = \begin{cases} INTCOV3 \\ 0 \end{cases} \text{if } \begin{cases} 0 < INTCOV3 < 5 \\ otherwise \end{cases} \qquad \textbf{(1.8)}$$

$$INTCOV3C2 = \begin{cases} INTCOV3 \\ 0 \end{cases} \text{if } \begin{cases} 5 \leq INTCOV3 < 10 \\ otherwise \end{cases} \qquad \textbf{(1.9)}$$

$$INTCOV3C3 = \begin{cases} INTCOV3 \\ 0 \end{cases} \text{if } \begin{cases} 10 \leq INTCOV3 < 20 \\ otherwise \end{cases} \qquad \textbf{(1.10)}$$

$$INTCOV3C4 = \begin{cases} INTCOV3 \\ 0 \end{cases} \text{if } \begin{cases} INTCOV3 \geq 20 \\ otherwise \end{cases} \qquad \textbf{(1.11)}$$

However, Unlike Gray's *et al.* (2006) and Amato and Furfine's (2004) values of interest coverage over 20 are not truncated since this is believed to be a very restrictive argument[7].

3. Empirical Results

3.1 Rated versus non-rated firm characteristics

Table 1 shows the averages and standard deviation values for the independent variables used in the rating likelihood equation for both rated and non-rated firms. It also reports the results of independent samples t-tests for the two categories of companies. Companies with credit ratings are, on average, bigger, more profitable with a higher proportion of institutional ownership. In addition, they invest more in R&D and have higher levels of debt in their capital structure and tend to issue more public debt in relation to their non-rated counterparts. Cash-flow coverage values for the two groups of companies appear considerably different; however, this difference is marginally economically significant. On the other hand, non-rated firms appear to have, on average, higher interest coverage ratios, lower long-term business risk and also exhibit higher growth rates.

INSERT TABLE 1 ABOUT HERE

3.2 Firm characteristics per rating category

Table 2 presents the medians for selected key financial and non-financial ratios per rating category. Higher-rated companies are on all accounts bigger companies. The difference in size is, however, less visible in the higher rating categories of "A" and "AA". Furthermore, they exhibit lower leverage ratios, with AA-rated companies carrying less than half the debt of their below BBB-rated counterparts. Nevertheless, firms in the two lower investment-

[7] Nevertheless, in line with earlier studies, models with restricted maximum interest coverage ratio values to 30 yielded consistent results.

grade categories exhibit almost identical leverage values. Moreover, low-rated companies generate enough cash to just cover their interest expenses, whereas higher-rated companies exhibit an enhanced ability of cash generation, which can be partly down to the lower amounts of debt higher-rated firms carry (Pinches and Mingo, 1973). The cash-flow coverage ratios further illustrate this point. Higher-rated companies generate higher free operating cash-flows consistent with debt servicing requirements.

In addition, low-rated firms carry more debt in their capital structures and are less profitable compared those with higher ratings. However, this difference in relative indebtedness is less prominent in the low investment-grade categories (i.e. “BBB” and “A”), whilst the difference in profitability is not considerable between speculative-grade companies (below BBB) and firms on the investment-grade threshold category (BBB). Also, higher-rated companies hold less liquid assets than their lower-rated counterparts. With reference to firm growth, no consistent pattern can be established suggesting that growth is not a differentiating factor when assigning credit ratings, as growth rates are industry-specific (Pettit *et al.*, 2004). However, speculative-rated companies experience very similar growth rates to those achieved by the highest-rated companies in the sample. These results are consistent with Peavy and Edgar (1983) and Tang (2006); the latter reports that rating upgrades lead to higher rates of asset growth, especially with companies on the lower end of the rating spectrum.

Furthermore, a company’s market risk and its probability of financial distress are negatively associated with its credit rating. Higher-rated companies exhibit, on average, lower systematic risk (beta) than those with either speculative-grade ratings (below BBB) or in the threshold investment-grade category (BBB). The declining book-to-market ratio suggests that companies with higher credit ratings are less likely to run into financial problems. Finally, the (*PE*) ratio indicates that high quality companies are in greater demand by equity investors than those of lower quality. However, the speculative-grade firms (below

BBB) in the sample exhibit higher P/E values than those in the lowest investment-grade category. This can be, however, attributed to the varying degrees of risk appetite by investors, with fast-growing, low-rated firms being preferred on the basis of their potential future returns.

INSERT TABLE 2 ABOUT HERE

3.3 Rating likelihood results

Table 3 provides a matrix of correlation coefficients and variance-inflation factors for all the independent variables included in the rating likelihood model. The correlation coefficients between pairs are generally low with some notable exceptions between interest coverage and profitability, sales and amount of debt and debt and bond issuance. Nevertheless, the variance inflation factors (VIFs) are all less than 10, which indicate low degrees of multicollinearity and does not pose a problem to model estimation (Gujarati, 2003).

INSERT TABLE 3 ABOUT HERE

Tables 4 and 5 present the regression results and marginal effects pertaining to a number of alternative versions of the estimated rating likelihood models. Model I, a contemporaneous specification, assumes that the effect of firm characteristics on the decision to solicit credit ratings is of a simultaneous nature with companies reacting to changes in their circumstances instantly (Moon and Stotsky, 1993; Cantor and Packer, 1997; Pottier and Sommer, 1999; Adams *et al.*, 2003, Poon, 2003; Poon and Firth, 2005). The majority of variables appear with the hypothesised sign and are statistically significant. Size is significantly positive, indicating the strong relationship between firm size and rating likelihood, which can be either attributed to the benefits of bigger size (diversification, operational efficiency, etc.) documented in the extant literature (Adams *et al.*, 2003) or linked to the greater levels of uncertainty that might be associated with bigger companies (Johnson and Kriz, 2002).

Our results suggest that companies that issue more debt are more likely to proceed with soliciting credit rating in the hope that they can lower their borrowing costs. The marginal effects in Table 5 for Model I illustrate that an increase in companies' debt burden leads to a considerable increase of 9% in the rating likelihood. Equally, bond issuance is positively related to the possibility of soliciting credit ratings. Thus, companies that issue bonds are more likely to apply for credit rating as opposed to those that do not raise capital in this way. The marginal effects in Table 5 also show that the issue of bonds considerably increases the likelihood of soliciting credit rating by over 11%. This is further supported by the fact that, unlike US companies, UK companies are not faced with the regulatory task of obtaining a rating before they consider raising finance through bond issuance. Similarly, *BONDYBEF* is positive and statistically significant and indicative of the market-imposed requirement that a company has to sport credit rating if it is to raise capital via bond issue.

Financial flexibility is inversely related to the likelihood of a firm obtaining credit rating. The estimated coefficient is significant at 1% indicating that companies that take on additional short-term debt in relation to their overall indebtedness are, *ceteris paribus,* less able to access and restructure their finance at a lower cost and therefore more vulnerable to financial distress in the face of negative shocks (Gamba and Triantis, 2008). This presents companies with an incentive against soliciting credit rating since the probable assignment of a low rating will most likely accentuate the problem of financial fragility (Kisgen, 2006). Moreover, financial leverage is of the expected sign and statistically significant (though weak at 10%) implying that an increase in companies' gearing may lead to financial distress and thus lowers the likelihood of obtaining credit rating. This inverse relationship is also illustrated by the marginal effects coefficient in Table 5, which carries a negative sign and is statistically significant (weak at 11%).

Consistent with our hypothesis and earlier studies (Dichev, 1998), the book-to-market variable is positive and statistically significant suggesting that companies with a higher book-to-market ratio are more likely to show signs of financial distress and, hence, might benefit most from soliciting credit rating to certify their true default risk. Institutional ownership is highly significant and positively related to the rating likelihood showing that institutional investors perceive the certification by rating agencies as a valuable monitoring tool, which can even replace their practices of due diligence (Ashbaugh-Skaife *et al.*, 2006).

Surprisingly, profitability has a negative and strongly significant sign, suggesting that less profitable companies are more likely to solicit credit rating, as opposed to their profitable counterparts. The result can be explained in the context of Shyam-Sunder and Myers (1999), who establish an inverse relationship between profitability and firms' propensity to obtain external debt finance. They find that more profitable companies are less inclined to borrow funds externally, thus offering further support to the pecking order theory. This bears implications regarding the solicitation of credit rating since profitable companies might not see the benefit of obtaining credit rating if they are not accessing the markets to borrow funds. An alternative explanation is offered by Cantor and Packer (1997), who argue that profitability might be negatively related to uncertainty about firms. On that basis, more profitable firms need not use the services of a rating agency to certify their strong financial position.

Model II assumes that the decision to solicit credit ratings might be made by companies in anticipation of their future performance, and on the basis of forward-looking internally generated information which companies seek to disseminate to the markets (Thompson and Vaz, 1990). The concept of using forward-looking information is at the heart of the rating process (S&P, 2005). The predictive specification of Model II assumes that the decision to get a rating in year *t* is determined by companies' estimates for year *t+1* (Czarnitzki and Kraft, 2004; Sufi, 2009).

The results of Model II are similar to those of Model I, with the estimated coefficients being robust to this alternative specification. Due to its predictive nature, Model II includes a variable that captures the decision of a company to issue bonds in the next period (*BONDNEY*). This replaces the backward-looking variable *BONDYBEF*, which indicates whether a company has issued bonds in the last ten years. The substitution yields consistent results: the decision to issue bonds in the future offers companies a strong incentive to seek credit rating.

Unlike the contemporaneous specification, the R&D variable in Model II is statistically significant (though weak at 10%) suggesting that if the decision to obtain credit rating is truly forward-looking then investment in innovative receives a significantly higher weighting. Nayar (1993) offers conceptual support to this finding. He posits that it is possible for managers to place an informed estimate on the value of their firms' future projects today. Therefore, engagement in innovative activities might feature more heavily in the decision to solicit credit rating.

INSERT TABLE 4 ABOUT HERE

INSERT TABLE 5 ABOUT HERE

With reference to the models' goodness-of-fit, the McFadden (1973) pseudo-R^2 reported in Table 4 for Model I is 65.78%, while the Kullback-Leibler pseudo-R^2 is 53.65%. Both measures indicate a very good fit between the data and the model, suggesting a robust model specification. Model II achieves a 60.89% pseudo-R^2. Meanwhile, the Akaike (1974) information criterion and the statistically significant χ^2 statistics further indicate a robust model specification for both models.

Table 6 presents some in-sample classification statistics for the estimated models. Model I correctly classifies 92.53% of all cases in the sample. The accuracy rate of Model II almost equals that of the contemporaneous model. The predictive specification accurately classifies 86% of rated and almost 94% of non-rated firms, while achieving a 92% overall correct classification rate (a mere 0.53% behind the contemporaneous model). This means that the decision to solicit credit rating can be modelled using either a contemporary or forward-looking specification.

INSERT TABLE 6 ABOUT HERE

3.4 Rating determinants results

Table 7 presents the results of the rating determinants models. Panel A presents the fitted coefficients. The last variable in Panel A is the correlation coefficient (ρ) between the error terms of the rating likelihood and the rating determinants equations. Furthermore, Panel B shows the estimated partition points (μ_i) for each model, while Panel C presents useful model diagnostics information.

Model III is of a contemporaneous nature and is estimated using the contemporaneous rating likelihood specification (Model I). Consistent with the hypotheses, firm size, profitability, cash-flow coverage and liquidity are positively related to letter credit ratings and statistically significant. On the other hand, financial leverage and business risk carry negative signs and are both strongly significant, suggesting that firms with higher earnings volatility are considered more risky due to their susceptibility to business cycles (Shin and Moore, 2003; Amato and Furfine, 2004).

The results relating to the interest coverage are quite interesting. The negative coefficient on *INTCOV3C1* is strongly statistically significant. However, the remaining three interest coverage variables (*INTCOV3C2, INTCOV3C3, INTCOV3C4*) have positive sings[8] but only the first two are significant. These findings indicate that companies are more likely to receive a higher credit rating as their interest coverage ability increases. While these results are broadly consistent with extant literature (Ashbaugh-Skaife *et al.*, 2006; Gray *et al.*, 2006), two observations need to be made. First, in Blume *et al.* (1998) and Amato and Furfine (2004) the signs of *INTCOV3C1* and *INTCOV3C4* appear with opposite signs compared to the ones in our study. This illustrates the higher relative importance of *INTCOV3C1* because marginal changes at low levels of interest coverage are indicative of a considerably enhanced ability to cover interest expense. However, this is not the case in this study. Secondly, and similarly to earlier studies, the statistical significance of the interest coverage variables decreases monotonically since marginal changes at higher levels of coverage values do not significantly contribute to the possibility of a company achieving a higher rating.

Model III also contains the non-financial variables that are held to influence the credit rating of a company. R&D intensity is positive and strongly significant. This illustrates that rating agencies perceive innovative activities as potentially beneficial to firms' future prospect and ultimately creditworthiness. The number of blockholders and independent directors on the board of directors have positive signs and are significant at 1% and 10% respectively. The former result is inconsistent with the stated hypothesis and earlier studies (Bhojraj and Sengupta, 2003; Ashbaugh-Skaife *et al.*, 2006) as it suggests that the concentrated involvement of institutional investors encourages more efficient monitoring by the management and the benefits from such monitoring are shared by shareholders and bondholders, leading to an increase in companies' credit rating (Barclay and Holderness, 1992).

Moreover, the percentage of institutional ownership has a negative sign and is statistically significant implying that agencies are more likely to assign lower ratings to

[8] It is reminded that *INTCOV3C1* is bound between 0 and 4.99, *INTCOV3C2* between 5 and 9.99 and *INTCOV3C3* between 10 and 19.99. *INTCOV3C4* assumes values over 20.

companies, where ownership is concentrated in the hands of institutional owners. In principle, Shleifer and Vishny (1986) support an inverse relationship and argue that institutional investors have incentives to monitor corporate performance and take corrective action when their wealth is threatened by decisions that benefit bondholders instead. Thus rating agencies might see such behaviour as an obstacle towards the timely payment of debt obligations due to the conflicting interests of the two groups of companies' stakeholders. Also, the variable that captures directors' shareholdings in the company has a significant negative sign (1%) suggesting that rating agencies do not favour directors owning higher portions of firms since they can make critical decisions at the expense of bondholders, creditors and even shareholders.

The estimate of the error correlation coefficient (ρ) in Model III is negative and statistically insignificant. This suggests that self-selection is not present in the sample of rated companies when a contemporaneous specification is employed. Furthermore, Model III is highly significant with a likelihood ratio χ^2 of 590.347. Additionally, the pseudo-R^2 measure of 43.98% is among the highest ones in studies in this empirical field[9].

Model IV is of a predictive specification and uses the predictive rating likelihood model for the examination of self-selection (Model II). The results are qualitatively similar to those of the contemporaneous specification. Also, the coefficients of the four scaled interest coverage variables have the same signs as in Model III. However, a monotonic increase in the magnitude of the interest coverage coefficients (*INTCOV3C3>INTCOV3C2*) can be observed, suggesting that rating agencies tend to place more emphasis on higher predicted values of interest coverage. This might be indicative of the nature of credit ratings, which are used as a tool to asses companies' ability to service their debt on time. Nevertheless,

[9] Indicatively, Bouzouita and Young (1998) achieve a 36.88% goodness-of-fit measure, while Purda (2003) reports a pseudo-R^2 value of 27%. However, there are studies that report higher values due to their focus on specific markets. For example, Shin and Moore (2003) report a pseudo-R^2 measure of 62% for Japanese companies' credit ratings.

INTCOV3C4 is still statistically insignificant, indicating that considerably high coverage capacity does not materially affect credit ratings.

Contrary to our hypothesis, the growth variable in the predictive specification has a negative sign and is significant (1% level), implying that higher predicted growth rates have a negative impact on companies' credit rating. Pottier and Sommer (1999) report a similar negative, though statistically insignificant, growth coefficient. In principle, Adams *et al.* (2003) argue that there is a possibility that forecasted growth can have an inverse effect on companies' future creditworthiness, especially in cases where this growth is not properly supported and can lead to uncertain future cash-flows; a view shared by S&P (2005). Lastly, Model IV reveals that in a predictive specification, institutional ownership and board independence have only a very weak impact on credit ratings. However, directors' shareholdings and the number of significant shareholders are strongly negatively and positively associated with credit ratings respectively.

5. Conclusions

Overall, rated firms appear to have stronger financial profiles; they are bigger, older and more profitable than their non-rated counterparts. In line with the literature, (Gan, 2004; Poon and Firth, 2005) non-rated companies, however, hold, on average, more liquid assets due to their relatively poorer ability to access capital markets. Rated firms are, on average, more highly geared than non-rated firms, issue significantly more bonds and exhibit lower interest coverage ability. The results further suggest that the two groups are distinctively different in the funding approach they adopt (Poon, 2003). Non-rated firms are riskier and demonstrate faster growth rates than rated firms, which in turn are owned to a greater extent by institutional investors. However, non-rated firms in the sample have a higher number of significant shareholders, who control a higher percentage of company shares. This suggests that investors of non-rated companies are more actively involved in the monitoring of the firm, due to the lack of credit ratings that can play this role (Sylla, 2001).

Our results have potentially a number of significant implications for UK companies, regulators, policy makers and various other market participants. Through the comparison between rated and non-rated firms, this study offers managers a useful set of rating benchmarks against which they can measure themselves and act as guidelines in firms' quest for a rating solicitation. Our study also offers regulators an invaluable insight into the motives behind the decision to become rated, and the actual rating determinants, which can further help with establishing better criteria in investment-related supervisory mandates as well as ratings-based rules for institutional investors.

The empirical results of the rating likelihood models illustrate that the contemporaneous and predictive specifications are robust and also efficient in predicting the likelihood of obtaining a rating accurately. Both contemporaneous and predictive models achieve pseudo-R^2 values of 66% and 61% respectively. More importantly, however, they can classify 93% and 92% of the sample correctly respectively. This indicates that the proposed models capture the data generating process satisfactorily. In addition, the results with regard to the different specifications estimated confirm that the rating process is truly forward-looking.

The majority of the results are consistent with the proposed hypotheses. Firm size is found to be an important factor in the decision to solicit credit ratings. Furthermore, outstanding debt, choosing bonds as a financing method and past issuance of bonds are all positively related to soliciting credit rating. This suggests that companies that use the public debt markets to borrow funds are more likely to obtain credit rating in the hope the acquired rating brings about a benefit in the form of lower interest costs (Lamb and Rappaport, 1987; Moon and Stotsky, 1993).

Our study further establishes that increased uncertainty and higher chances of financial distress associated with higher values of financial leverage are strong incentives against applying for credit rating. Furthermore, the models illustrate that market-perceived distress risk is an important driver of the decision to obtain a rating in order to signal the firm's true credit quality to the markets. Additionally, institutional ownership is found to positively affect the likelihood of obtaining credit rating. Engagement in innovative activity (R&D) is also a strong determinant of the decision to apply for credit rating. This means that 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 credit rating.

However, profitability is inversely related to the rating likelihood, thus profitable companies are less likely to solicit credit rating. A possible explanation for those companies could be that the costs might outweigh the benefits and therefore the need for a rating is not as strong as in less profitable firms. In addition, the findings align more with the bankruptcy theory, which posits that companies with lower profitability have more to gain from this certification exercise (Gan, 2004).

In this context, our study provides market participants with the opportunity to observe any gaps that might exist between managers' perception and the actuality of the rating process. Similarly to Adams *et al.* (2003), we show that some determinants of the actual letter ratings are not important in the initial decision to solicit a rating, e.g. business risk. This thus allows for the differences in perceptions to shine through; managers might not perceive business risk as important in the wider context of the firm's industry perhaps, whilst rating agencies certainly recognise this as a contributing factor to the company's survival and eventual creditworthiness.

The empirical results concerning the determinants of UK corporate credit ratings reveal that firm size, financial leverage, profitability, liquidity, business risk and growth are all statistically significant determinants of UK firms' credit ratings. The empirical results are consistent with the proposed hypotheses and a significant number of earlier empirical studies. Furthermore, interest coverage is positively related to credit ratings. Nevertheless, the analyses reveal that increases at low values of interest coverage are more likely to result in lower ratings. This is inconsistent with the proposed hypothesis, which assumes that an overall increase in the ability of companies to service their debt is accompanied by improvements in their credit quality. It is, however, contrary to empirical results by Amato and Furfine (2004), Gray *et al.* (2006) and Jorion *et al.* (2009), who establish that marginal changes at low levels of interest coverage are a strong positive determinant of companies' credit rating. As all the earlier studies examine foreign datasets, the results of this study indicate that rating agencies might use different weightings with regard to the interest coverage dimension of UK companies.

In relation to the non-financial determinants of credit ratings, the results suggest that agencies reward companies for engaging in R&D projects by way of higher letter ratings. Similarly, the results confirm the importance of the corporate governance dimension as a factor in determining firm ratings. The results of the four measures representing different aspects of corporate governance are however surprising. Director shareholdings and institutional ownership are negatively related to credit ratings and consistent with the proposed hypotheses. Taken together, these results indicate that rating agencies do not assess favourably the aspects of corporate governance that benefit shareholders or directors rather than bondholders and other creditors and incorporate that in their credit analysis. Furthermore, the independent oversight of companies' operations and management team that independent directors provide ensures that interests of a wide variety of stakeholders are met and the company is less likely to engage in risky activities (Bhojraj and Sengupta, 2003). This is reflected in higher ratings. The number of large shareholders is significantly positively related to credit ratings, contrary to the proposed hypothesis and existing studies (Ashbaugh-

Skaife *et al.*, 2006). This indicates that accumulation of ownership by a larger number of institutional investors is more likely to result in better credit rating.

Our findings indicate that the financial determinants of UK firm credit ratings are broadly the same as in the majority of existing academic and trade literature, spanning a number of industries and countries. This highlights the uniformity of the rating process, which Fight (2004) criticises for causing a lack of appreciation of industry- or country-specific attributes. Nevertheless, the inclusion of non-financial firm attributes enhance the overall performance of the models and hence provides an insight into the rating analysts' expert judgement that rating agencies argue they possess and enables them to command such high premiums for their services.

Finally, the fitted models indicate that self-selection is not an issue among non-financial UK companies. The estimated error correlation coefficient is in all models statistically insignificant and suggests that, while rated and non-rated companies have significantly different financial and non-financial profiles, these differences and the associated benefits from having credit rating (e.g. lower funding costs) do not necessarily drive the decision to obtain a rating.

Appendix A

Fine Grading	
AAA AA+	9
AA	8
AA-	7
A+	6
A	5
A-	4
BBB+	3
BBB	2
BBB-	1
BB+ BB BB- B+ B B- CCC+ CCC CCC- CC C D	0

Note: Fine grading of numerical ratings. Rating structure is as per Standard and Poor's. BBB- is the investment-grade threshold rating category.

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Table 1. Descriptive statistics and comparison of means for selected ratios for rated and non-rated firms

Variable	*Rated firms*	*Non-rated firms*	*Comparison of means#* *t-statistic*	*d.f.*	*p-value*
INTCOV	10.018	51.415	2.408	1,750	0.016**
	(7.011)	(48.137)			
ROA	0.048	0.026	-4.015	2,771	0.000***
	(0.117)	(0.167)			
GEAR2	0.523	0.381	10.687	1,172	0.000***
	(0.159)	(0.109)			
STDTD	0.273	0.371	8.840	2,548	0.000***
	(0.211)	(0.328)			
CURRENT	1.221	1.728	9.119	2,528	0.000***
	(0.359)	(0.467)			
lnSALES	14.894	11.945	-49.564	2,463	0.000***
	(1.202)	(1.897)			
lnAGE	3.659	3.232	-9.951	2,175	0.000***
	(1.080)	(1.094)			
lOGDEBT	9.141	7.564	-53.332	2,580	0.000***
	(0.484)	(1.035)			
NCFTD	1.089	20.204	1.735	1,698	0.083*
	(1.740)	(18.305)			
BONDCO	80	29	21.429	1,054	0.000***
	(n.a.)	(n.a.)			
BONDYN	0.930	0.183	-55.864	2,938	0.000***
	(0.214)	(0.438)			
BONDYBEF	0.630	0.110	18.348	1,687	0.000***
	(n.a.)	(0.313)			
BREBIT5	0.322	0.370	0.180	1,838	0.857
	(5.541)	(7.601)			
BREBIT12	0.818	0.605	-1.703	2,756	0.089*
	(1.889)	(4.705)			
GROWTH	0.122	0.409	-1.707	2,702	0.044**
	(0.417)	(4.898)			
BMV	0.338	0.171	1.989	2,660	0.023**
	(0.412)	(0.797)			
RNDD	0.620	0.280	-16.584	1,237	0.000***
	(0.486)	(0.797)			
INSTINV	0.900	0.876	-6.211	1,699	0.000***
	(0.064)	(0.091)			
No of firms			***86 rated, 159 non-rated***		

Notes: The values in parentheses represent standard deviations. # Independent samples t-test testing $H_0 = \mu_{rnon-rated} - \mu_{rated} = 0$. Levene's test for equality of variances was used to determine the homogeneity of variances between rated and non-rated firms. ***, **, * denote significance at the 1%, 5% and 10% respectively.

Table 2. Selected ratio medians per broad rating category

		Rating Category			
Dimension	*Variables*	Below BBB	BBB	A	AA, AAA
Size	lnTA	21.32	21.91	22.63	22.84
	lnSALES	20.65	21.78	22.26	22.51
Financial leverage	TDTA	47.97%	32.62%	29.67%	22.20%
	GEAR2	89.13%	77.17%	77.08%	48.80%
Interest coverage	INTCOV	1.63	3.50	4.48	8.42
	INTCOV3	1.36	2.89	3.44	6.33
Cash-flow coverage	FOTD	4.36%	13.21%	9.58%	23.02%
	EBITDATD	26.99%	39.62%	50.87%	95.80%
Profitability	ROA	0.89%	4.38%	5.32%	8.07%
	ROC	19.39%	19.56%	27.43%	31.00%
	EBITDAMA	13.68%	15.44%	22.84%	34.21%
Liquidity	CURRENT	1.67	1.13	1.06	0.97
	CUTA	24.76%	31.20%	30.32%	28.43%
Growth	GROWTH	4.07%	2.36%	5.85%	4.77%
R&D intensity	RDTA	0.45%	0.47%	0.17%	0.49%
	RDREV	0.72%	0.54%	0.44%	1.12%
Market	BMV	0.42	0.40	0.39	0.36
	BETA	1.79	1.09	0.78	0.76
	PE	14.10	14.05	15.2	17.8
Corporate governance	INSTINV	89.70%	92.80%	91.00%	89.80%
	NOSIGN	4	3	3	2
	DIRSH	0.29%	0.09%	0.02%	0.02%
	INDDR	62.5%	58.33%	55.56%	57.14%

Notes: Median values of key ratios for the 86 rated companies included in the sample. Variables are defined as follows: *lnTA:* natural logarithm of total assets, *lnSALES:* natural logarithm of sales, *TDTA:* Total debt/total assets, *GEAR2:* Total debt/total equity, *INTCOV:* EBIT/interest expense, *INTCOV3:* (Net income + Interest expense)/interest expense, *FOTD:* Free operating cash-flow/total debt, *EBITDATD:* EBITDA/total debt, *ROA:* Net income/total assets, *ROC:* EBIT/total equity, *EBITDAMA:* EBITDA/sales, *CURRENT:* Current assets/current liabilities, *CUTA:* Current assets/total assets, *GROWTH:* $\Delta TA_{t-1,t}$, *RDTA:* R&D expense/total assets, *RDREV:* R&D expense/sales, *BMV:* Book value of equity/market capitalisation, *BETA:* market-derived beta, *PE:* Price per share/earnings per share, *INSTINV:* Equity held by institutional investors/total equity, *NOSIGN:* Number of shareholders owning more than 3% of a firm's equity, *DIRSH:* Equity held by board of directors/total equity and *INDDR:* Independent directors/total number of board directors.

Table 3. Correlation coefficient matrix and variance-inflation factors

		Correlations													
	VIFs	ROA	GEAR2	STDTD	CURRENT	lnSALES	lnAGE	LOGDEBT	NCFTD	BONDYN	BONDYBEF	BREBIT5	BREBIT12	GROWTH	BMV
INTCOV	1.536	**0.778*** **	-0.362***	0.272***	0.088***	0.001	0.025	-0.262***	0.656***	-0.124***	-0.212***	0.039**	-0.012	0.182***	-0.231***
ROA	1.513	1	-0.185***	0.146***	0.052	0.081***	0.076***	-0.313***	0.516***	-0.022	-0.053	0.028	-0.045**	0.179***	-0.348***
GEAR2	1.062		1	-0.322***	-0.194***	0.259***	0.070***	0.494***	-0.413***	0.245***	0.309***	0.055***	0.016	-0.012	-0.010
STDTD	1.443			1	-0.094***	-0.048**	0.070***	-0.321***	0.290***	-0.140***	-0.224***	0.045**	0.059***	-0.027	-0.137***
CURRENT	1.099				1	-0.222***	0.025	-0.223***	0.015	-0.184***	-0.123	0.022	0.058***	-0.072***	0.124***
lnSALES	**4.717**					1	0.322***	**0.800** **	0.083***	0.598***	0.497***	0.003	-0.094***	-0.132***	-0.188***
lnAGE	1.143						1	0.213***	0.029	0.173***	0.178***	0.021	-0.112***	-0.160***	0.005
LOGDEBT	**6.849**							1	-0.272***	**0.687*** **	0.596***	-0.050**	-0.135***	-0.106***	-0.037
NCFTD	1.645								1	-0.076***	-0.124	0.039**	0.009	0.054***	-0.169**
BONDYN	2.062									1	0.509***	-0.042**	-0.097***	-0.064***	-0.079***
BONDYBEF	1.667										1	0.049	-0.105	-0.012	0.076
BREBIT5	1.337											1	0.402***	0.040**	0.039**
BREBIT12	1.142												1	-0.003	0.090***
GROWTH	1.091													1	-0.100***
BMV	1.048														1

Notes: Correlations involving non-metric variables are measured using the Spearman rank coefficient. ***, ** denote significance at the 1% and 5% respectively.

Table 4. Rating likelihood model time specification results

Panel A: Parameter estimates

		Contemporaneous (Model I)		**Predictive (Model II)**	
Independent variables	*Hypothesised sign*	*Coefficient*	*Z-stat*	*Coefficient*	*Z-stat*
Intercept		-13.5664	-17.22***	-13.5629	-17.54***
INTCOV	+	-0.0002	-0.53	-0.0002	-0.07
ROA	+	-1.4250	-13.26***	-1.4547	-11.33***
GEAR2	–	-0.0047	-1.63*	-0.0045	-1.61*
STDTD	–	-0.8966	-10.84***	-0.8081	-9.89***
CURRENT	+	-0.0190	-1.23	-0.0144	-1.01
lnSALES	+	0.3279	9.48***	0.2861	8.42***
lnAGE	+	0.0024	0.96	0.0026	0.85
LOGDEBT	+	0.8895	10.85***	0.8018	9.90***
NCFTD	+	0.0004	0.71	0.0003	0.37
BONDYN	+	1.1061	10.85***	0.9628	8.85***
BONDYBEF	+	0.0015	7.22***	-	-
BONDNEY	+	-	-	0.2089	2.12**
BREBIT5	+	-0.0032	-1.37	-0.0017	-0.86
BREBIT12	+	-0.0212	-1.41	-0.0187	-1.28
GROWTH	+	0.0031	1.33	0.0035	0.80
BMV	+	0.0005	1.97**	0.0005	1.94*
RNDD	+	0.0006	1.13	0.0008	1.69*
INSTINV	+	0.0015	13.00***	0.0012	10.34***
Panel B: Selected model statistics					
χ^2 statistic			2,127.859***		1,905.792***
Hosmer-Lemeshow χ^2			75.52***		42.05***
Log-likelihood			-556.393		-612.07
Restr. log-likelihood			-1,620.323		-1,620.323
No of observations			2,772		2,782
Akaike I.C.			0.414		0.453
Pseudo-R^2 ◊			65.66%		60.89%

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. ***, **, * denote significance at the 1%, 5% and 10% respectively. ◊ This measure of goodness-of-fit is a simple computational statistic ($R^2 = 1 - \frac{Log(L_{UR})}{Log(L_R)}$) proposed by McFadden (1973).

Table 5. Marginal effects of rating likelihood model time specification results

		Contemporaneous (Model I)		Predictive (Model II)	
Independent variables	*Hypothesised sign*	*Coefficient*	*Z-stat*	*Coefficient*	*Z-stat*
Intercept		-1.3147	-9.08***	-0.0207	-1.24
INTCOV	+	-0.0002	-0.53	-0.0000003	-0.07
ROA	+	-0.1381	-5.72***	-0.0022	-1.27
GEAR2	–	-0.0005	-1.58	-0.00007	-1.00
STDTD	–	-0.0868	-7.40***	-0.0012	-1.23
CURRENT	+	-0.0018	-1.19	-0.0002	-0.78
lnSALES	+	0.0318	7.27***	0.0004	1.23
lnAGE	+	0.0002	0.95	0.00004	0.71
LOGDEBT	+	0.0862	7.41***	0.0012	1.23
NCFTD	+	0.0004	0.71	0.000005	0.36
BONDYN	+	0.1071	5.07***	0.0015	1.37
BONDYBEF	+	0.0002	5.33***	-	-
BONDNEY	+	-	-	0.0003	0.89
BREBIT5	+	-0.0003	-1.36	-0.00003	-0.71
BREBIT12	+	-0.0021	-1.39	-0.0003	-0.94
GROWTH	+	0.0003	1.33	0.00005	0.82
BMV	+	0.0005	1.87*	0.000008	1.00
RNDD	+	0.0006	1.13	0.00001	1.01
INSTINV	+	0.0001	6.74***	0.00002	1.25

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. ***, **, * denote significance at the 1%, 5% and 10% respectively.

Table 6. Prediction statistics of rating likelihood model time specifications

Contemporaneous (Model I)				Predictive (Model II)			
	Predicted		*Totals*		*Predicted*		*Totals*
Actual	**0**	**1**		*Actual*	**0**	**1**	
0	1,903	117	2,020	**0**	1,957	129	2,020
1	90	662	752	**1**	96	600	752
Totals	1,993	779	***2,772***	*Totals*	2,053	729	***2,772***
Prediction success							
Actual 1s correctly predicted			88.03%	Actual 1s correctly predicted			86.21%
Actual 0s correctly predicted			94.21%	Actual 0s correctly predicted			93.82%
Prediction failure							
False +s for true -s			5.79%	False +s for true -s			6.18%
False -s for true +s			11.97%	False -s for true +s			13.79%
Prediction statistics							
Correct prediction rate			92.53%	Correct prediction rate			91.91%
False prediction rate			7.47%	False prediction rate			8.09%

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

Table 7. Rating determinants results

Panel A: Parameter estimates

Independent variables	Hypothesised sign	**Contemporaneous (Model III)** Coefficient	Z-statistic	**Predictive (Model IV)** Coefficient	Z-statistic
Intercept		-8.2179	-9.33***	-9.0016	-9.46***
lnTA	+	0.4768	12.15***	0.5100	12.09***
TDTA	–	-1.8296	-7.85***	-1.3264	-5.38***
INTCOV3C1	+	-0.0420	-3.34***	-0.0480	-3.55***
INTCOV3C2	+	0.0213	2.02**	0.0185	1.65*
INTCOV3C3	+	0.0175	1.82*	0.0187	1.84*
INTCOV3C4	+	0.0016	0.73	0.0093	1.91*
EBITDATD	+	0.0028	3.27***	0.0003	0.27
EBITDAMA	+	0.8994	4.84***	0.9900	4.96***
CUTA	+	0.4391	2.15**	0.3886	1.76*
BETA	–	0.0001	0.23	-0.0002	-0.29
BREBIT12	–	-0.1373	-5.02***	-0.1236	-4.42***
GROWTH	+	0.0005	0.79	-0.5726	-4.57***
RDREV	+	0.0007	7.96***	0.0007	7.57***
INSTINV	+	-0.0005	-1.75*	-0.0004	-1.02
INDDR	+	0.0013	1.72*	0.0010	0.90
DIRSH	–	-0.0017	-4.52***	-0.0017	-4.31***
NOSIGN	–	0.0023	4.70***	0.0022	4.11***
Error correlation (ρ)		*-0.47*	*-0.10*	*-0.40*	*-0.12*
Panel B: Upper boundary for rating category					
BB+ and below		0.000	–	0.000	–
BBB-		0.369	6.32***	0.342	5.57***
BBB		1.123	13.69***	1.090	12.20***
BBB+		1.720	18.92***	1.692	17.32***
A-		2.178	23.13***	2.147	21.19***
A		2.684	26.49***	2.653	24.63***
A+		3.347	29.39***	3.316	27.89***
AA-		3.879	26.71***	3.882	25.48***
AA		4.126	27.28***	4.148	26.51***
AA+, AAA		$+\infty$	–	$+\infty$	–
Panel C: Selected model statistics					
Log-likelihood			-1,391.148		-1,293.992
Restr. log-lik.			-1,686.322		-1,605.360
No of obs.			752		696
χ^2 statistic			590.347***		622.735***
Pseudo-R^2 ◊			43.98%		47.22%

Notes: The dependent variable of all ordered probit models is the categorical variable CR1. All significance levels are determined using two-tailed Z-tests. ***, **, * denote significance at the 1%, 5% and 10% respectively. ◊ This measure of goodness-of-fit is a simple computational statistic [pseudo-$R^2 = \frac{\chi^2}{\chi^2 + N}$] proposed by Aldrich and Nelson (1984).