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Forecasting US bond default ratings allowing for previous and initial state dependence in an ordered probit model

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ABSTRACT

In this paper we investigate the ability of a number of different ordered probit models to predict ratings based on firm-specific data on business and financial risks. We investigate models which are based on momentum, drift and ageing, and compare them with alternatives which take the initial rating of the firm and its previous actual rating into account. Using data on US bond issuing firms, as rated by Fitch, over the years 2000 to 2007, we compare the performances of these models for predicting the ratings both in-sample and out-of-sample using root mean squared errors, Diebold-Mariano tests of forecast performance and contingency tables. We conclude that both initial and previous states have a substantial influence on rating prediction.

1. Introduction

It is well known that ratings agencies provide independent assessments of the risk of a counterparty using information on the balance sheet, the profit and loss account, and private information on the management of the entity, summarized using a rating scale which runs from the highest rating, AAA, to the lowest, CCC. The analysis of credit risk, the probability of default and ratings has a long pedigree (see Horrigan, 1966; Kao & Wu, 1990; Kaplan & Urwitz, 1979; Pinches & Mingo, 1973; Pogue & Soldofski, 1969). This body of literature seeks to explain the relationship between ratings and financial or business risks, and has investigated applications to a wide range of sovereign countries, financial companies and corporations (Amato & Furfine, 2004; Blume, Lim, & MacKinlay, 1998; Rösch, 2005; van Gestel et al., 2007). We expect the ratings to be closely related to the default risk of the country or company being rated, or the instrument being issued, although rating agencies themselves claim to rate 'through the cycle', and seek to avoid any correlation with the business cycle. It is clear that frequent changes in ratings are undesirable from the points of view of long-term investors, governments and firms, whose financing options and costs may be affected by ratings through regulation, covenant provisions on loans or bonds, and the reduction of access to money and derivatives markets (see Pagratis & Stringa, 2009).

The examination of ratings behavior over time performed by Blume et al. (1998) showed that credit ratings became worse, on average, with the increased volatility in corporate creditworthiness during the mid-1980s and early 1990s being accompanied by downward momentum in credit ratings. This extended the approach developed by Carty and Fons (1993) for measuring the *ratings drift*. Because firms which were initially rated as AA on the basis of their risk characteristics were subsequently rated lower than AA, Blume et al. (1998) and others concluded that the standards of ratings agencies became more stringent over this period. However, ratings can also deteriorate because firms have a lower credit quality, for example if they becoming more leveraged, and a subsequent study by Amato and Furfine (2004) identified no secular change in rating standards in data over the period 1984–2001. Instead, their results implied that the ratings changes

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were driven by changes to business and financial risks rather than cycle-related changes to rating standards. Cantor and Mann (2003) confirmed that rating reversals are rare, even at a five-year horizon. At the same time, the large number of rating downgrades during the US corporate credit meltdowns in 2001–02 and 2007–09 casts some doubt on the extent to which ratings really see through the cycle. There are also other dynamics at work in ratings. Carty and Fons (1993) and Lando and Skodeberg (2002) found evidence that there is *momentum in ratings*, since a firm which has previously been upgraded has a different probability of upgrading in the next period to a firm which has previously been downgraded. Carty and Fons (1993) and Lando and Skodeberg (2002) also found evidence of *ageing in ratings*, which occurs when the current rating is dependent on the period of time that the firm spent in the previous rating category. The debate over the determinants of ratings is ongoing, and this paper compares various alternative models for forecasting the current rating classes of a number of US bond issuing firms.

Despite the many competing arguments which seek to explain ratings, it is agreed that ratings do seem to show state dependence. This contravenes the assumptions of the simple stationary Markov chains which are often used to make predictions of ratings transitions, although more complex models involving mixtures of Markov chains or models with non-Markovian features such as drift, momentum and ageing can be more informative than simple Markov models. In this paper we examine the role of state dependence in predicting credit ratings by first estimating the determinants of credit ratings using linear measures of business and financial risks from the balance sheet. We then allow for the possibility that some variables influence the rating in a nonlinear manner, supplementing the linear model with nonlinear terms, following van Gestel et al. (2007). We also introduce models of drift, momentum and ageing. Then we allow the model to register the initial rating of the firm and the previous actual rating of the firm, creating persistence through state dependence (initial and previous states). This marks a break with previous studies, which have used ordered probit or logit models without considering the influence of the previous rating history on the current rating. We show that there is a very considerable amount of evidence that allowing for state dependence in ratings improves the prediction of current ratings. Even by the standards of the earlier models, which evaluate the relative performances of alternative models in terms of an informal goodness-of-fit indicator, the performance of the model with state dependence in predicting the current rating is superior. When we examine the predictive ability both in-sample and out-of-sample using the root mean squared error with the Diebold and Mariano (1995) prediction test, and evaluate the proportion of correct predictions using Merton's correct prediction statistic (Merton, 1981), we find that the state dependence model is better than the alternatives based on this measure as well. The alternative models which we consider include the momentum, drift and ageing hypotheses for predicting ratings.

The remainder of the paper is organized as follows. Section 2 discusses the extensive body of literature on credit risk, the probability of default and ratings; Section 3 describes the methodology which we use in this paper; Section 4 presents the data used in our empirical analysis; and Sections 5 and 6 report the results, model predictions and forecast evaluations. Section 7 concludes the paper.

2. Literature

The body of literature on credit risk and default prediction, of which the analysis of credit ratings forms a part, is vast. This literature review will provide the context for our analysis, while necessarily leaving many of the details for the reader to follow up using the references cited. We start with a discussion of credit risk and default probabilities, before considering the analysis of ratings, ratings transitions and the relationship between ratings and cycles.

2.1. Credit risk and the probability of default

If we suppose that the probability of default can be connected with the characteristics (covariates) of the firm recorded in the matrix X_{it}, then one approach to analyzing the probability of default is the logit regression. Taking $y_i = 1$ as the default outcome observed for firm i, the probability of default is defined as $\Pr(y_i = 1|X_{it}) = \Phi(\alpha + X_{it}\beta) = \frac{\exp(\alpha+X_{it}\beta)}{1+\exp(\alpha+X_{it}\beta)}$, where α and β are matrices of parameters to be estimated. The estimation can be undertaken using maximum likelihood methods, where the likelihood function is defined as

$$L = \prod_{i=1}^{N} \Pr(y_i = 1 \mid X_{it}, \beta, \alpha)^{y_i} \Pr(y_i = 0 \mid X_{it}, \beta, \alpha)^{1-y_i}.$$

Anderson (1984) shows that this approach is closely connected to discriminant analysis. It is assumed that we can observe both firms which survive ($y_i = 0$) and those which default ($y_i = 1$), and can see what their characteristics are in a training sample of data. If these groups have different means, μ^0 and μ^1 respectively, a common variance covariance matrix, Σ, and densities of ϕ_0 and ϕ_1 respectively, then the discriminant function $d(X) = X'\Sigma^{-1}(\mu^0-\mu^1)-\frac{1}{2}(\mu^0-\mu^1)'\Sigma^{-1}(\mu^0-\mu^1)$ allocates firms to group 0 if $d(X) \geq \log K$, and group 1 otherwise, based on their information from a second sample of data. This discriminant function ensures that the costs of allocating the firm to the 'wrong' group are minimized. Anderson (1984) shows that following this approach is equivalent to estimating a logit regression, where we restrict $\Pr(y_i = 1|X_{it}) = \Phi(\alpha + X_{it}\beta) = \frac{\exp(\alpha+X_{it}\beta)}{1+\exp(\alpha+X_{it}\beta)}$, with $\alpha = \log(\frac{\exp(q_1)}{1+\exp(q_1)}) + (X_{it} - \frac{\mu^0+\mu^1}{2})'\Sigma^{-1}(\mu^0 - \mu^1)$ and $\beta = \Sigma^{-1}(\mu^0 - \mu^1)$. Duffie and Singleton (2003) and Lando (2004) point out that the Z-score derived by Altman (1968) is essentially a form of discriminant analysis, where the X_{it} covariates are financial ratios from the firm's balance sheet recorded over time. An example of the use of discriminant analysis for assessing the default probability is given by Lo (1986), who found that this method was as successful as a logit model in discriminating between bankrupt firms in a sample of US firms. Lennox (1999) found a similar result on a sample of 949 UK firms between 1987 and 1994, in which the covariates included firm-specific variables