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The ordered qualitative model for credit rating transitions ☆

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Abstract

Information on the expected changes in credit quality of obligors is contained in credit migration matrices which trace out the movements of firms across ratings categories in a given period of time and in a given group of bond issuers. The rating matrices provided by Moody's, Standard & Poor's and Fitch became crucial inputs to many applications, including the assessment of risk on corporate credit portfolios (CreditVar) and credit derivatives pricing. We propose a factor probit model for modeling and prediction of credit rating matrices that are assumed to be stochastic and driven by a latent factor. The filtered latent factor path reveals the effect of the economic cycle on corporate credit ratings, and provides evidence in support of the PIT (point-in-time) rating philosophy. The factor probit model also yields the estimates of cross-sectional correlations in rating transitions that are documented empirically but not fully accounted for in the literature and in the regulatory rules established by the Basle Committee.

JEL classification: C23; C35; G11
Keywords: Credit rating; Migration; Migration correlation; Credit risk; Probit model; Latent factor; Business cycle

1. Introduction

Agency rating of credit quality provides an important measure of credit risk. The corporate ratings are routinely performed and updated by agencies such as the Moody's, Standard & Poor's and Fitch. The records of past and present ratings document the movements of a firm from one rating category to another, and arise as direct indicators of risk dynamics. Information on the future expected changes in credit quality is contained in the credit migration matrices which trace out the movements of firms in a given group of bond issuers across rating categories in a given period of time. This information is used for computing the risk on portfolios of corporate credits, including the CreditVar, and for credit derivatives pricing. Therefore, the methods used in the banking sector for modeling and prediction of risk migration matrices have an important effect on the performance of internal credit pricing models (CPM) and the functioning of risk monitoring systems.

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Recent literature has explored the variation of credit rating matrices in time (see e.g. Altman and Kao, 1991) and investigated the links between the rating dynamics and the underlying macroeconomic conditions (see Nickell et al., 2000; Bangia et al., 2002; Rosch, 2005). A common feature of recent contributions to the literature is the dependence of credit migration dynamics on observable macroeconomic variables such as, for example, a proxy of the stage of the business cycle (see Nickell et al., 2000; Bangia et al., 2002), a riskfree interest rate or the unemployment rate (Rosch, 2005). Our study explores the dynamics of credit rating matrices from a different perspective. We do not assume a priori that the rating matrices are driven by a particular, observed variable. Instead, we introduce an unobservable (latent) factor that allows the data to reveal their own intrinsic driving process. The estimated path of the factor can then be compared to relevant macroeconomic variables and interpreted. Our result confirms the link between credit quality changes and the underlying state of the economy, but points to the continuously valued GDP growth rate as the leading process rather than to the business cycle indicator. In the context of the on-going debate on the PIT (point-in-time) versus TTC (through-the-cycle) rating philosophy our findings clearly support the PIT approach.

The analysis is carried out in the framework of an ordered qualitative variable model (see Basle Committee on Banking Supervision, 2002, 2003, 2004; Cheung, 1996; Nickell et al., 2000). This approach explicitly allows for discreteness of ratings and accommodates naturally the ordering from low to high credit quality.

The paper is organized as follows. Section 2 introduces the notation and basic assumptions. Section 3 presents the time-varying parameter probit and stochastic factor probit models for rating transition probabilities. In Section 4, we compare both models and emphasize the important features of the stochastic factor probit. One of them is cross-sectional correlation in credit quality migration among obligors. The correlation arises from joint migrations when several firms are jointly down- or up-graded. Statistical inference is discussed in Section 5 for both specifications. In particular, we propose the simulated maximum likelihood as a consistent and efficient estimation method for the stochastic factor model. Practitioners may however find this method complicated and possibly time consuming. Therefore, as an alternative approach, we develop a simplified estimation method based on a linear approximation of the non-linear factor model. It is not only easier to implement, but also preserves the consistency and asymptotic efficiency properties of the estimator due to the large cross-sectional dimension of the dataset. In Section 6, the methodology is applied to data on aggregate transition frequencies reported by the Standard & Poor's. Estimation of both types of probit models, and various summary statistics produced by the models, such as " average risk" and "risk volatility" per rating category, are discussed in the sequel. A one factor probit model is used in Section 7 to predict future ratings and correlations in rating transitions at different horizons. We observe that migration correlations depend on the time it takes to migrate, on the current economic environment and on the ratings in which the migration starts and in which it ends. These dependencies are not taken into account in the most recent document issued by the Banking Supervisory Committee in Basle. Also, we find that the estimated correlations are different, and in most cases much lower than the fixed input values provided by the Basle Committee in 2003 to banks for computation of the minimum capital reserve. This suggest that the current capital reserves are likely overestimated, and the cost of corporate credit is artificially increased. Section 8 concludes. Additional estimation results are available at http://www.econ.yorku.ca/jasiakj.

2. Specification of credit rating dynamics

2.1. Observed transition matrices

The object of our analysis is a sequence of square matrices with positive elements formed by the frequencies of transitions between states. The dimension of each matrix can be of the order of 8 by 8 up to 10 by 10, depending on the number of states considered in the analysis.[1] The states, denoted k $k=1,\ldots,K$ represent credit ratings, assigned by a credit rating agency, such as the Standard & Poor's, for example, for a fixed period of time. Accordingly, K is equal to the number of credit categories including default.[2] In our study $k=1$ indicates the highest rating while $k=K$ indicates default. The rating matrices are updated and reported, at a fixed frequency of 1 year. Therefore a typical sequence in an

[1] For credit ratings, the regulators require the number of states to lie between 8 and 10 (including default).

[2] Standard & Poor's use the following ratings: AAA, AA, A, BBB, BB, B, CCC, CC, C, D. The three C-type of categories are often aggregated into a single category CCC. AAA is the best credit quality rating, C is the worst one, and D stands for default.