

Longitudinal predictive models for SMEs¹

Modelli longitudinali per la previsione del rischio di insolvenza di piccole medie imprese

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Riassunto: L’idea di questo lavoro nasce dalla constatazione delle novità in arrivo in ambito finanziario dettate da Basilea II, che stabilisce nuove regole per aumentare la sensibilità al rischio e la capacità di misurarlo attraverso l’introduzione dei sistemi di rating interni.

Il presente lavoro ha lo scopo di proporre modelli di valutazione e mitigazione del rischio di credito con particolare riferimento all’analisi delle piccole medie imprese.

Keywords: Default probabilities, Credit risk, Model comparison

1. Introduction

The process of credit scoring is very important for banks as they need to discriminate good SMEs” from bad SMEs” (SMEs, Small and Medium Enterprises) in terms of their creditworthiness. This is a classic example of asymmetric information, where a bank has to reveal hidden data about its customer. Seminal contributions to default prediction are Altman (1968), and recent ones include Shumway (2001) and Chava and Jarrow (2004). According to Basel II capital accord, financial institutions require transparent benchmarks of creditworthiness to structure their risk control systems, facilitate risk transfer through structured transactions and comply with impending regulatory changes.

Concerning the causes of default, it is possible to identify a number of components that can generate such a behaviour: a *static component*, determined by the characteristics of the SME, a *dynamic component* that encloses trend and the contacts of the SME with the bank over different years, a *seasonal part*, tied to the period of investment and external factors, that include the course of the markets. To take into account this aspects, we consider many different methods to obtain a predictive tool to model the default.

The longitudinal “two-dimensions” character of SMEs data, both a cross-section dimension and a time dimension, has not been considered in the financial empirical literature,

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so far. This leads us to propose the use of panel data models to predict default probabilities for SMEs, considering both classical random effects and random coefficients models. Furthermore, we propose a Bayesian extension of these models in order to include prior knowledge, such as analysts recommendations.

By using a panel data set of German SMEs of 1000 firms, we compare the previous set of classical and Bayesian models in terms of forecasting performances. To assess the performance of the different models, we consider both of threshold-dependent performance criteria as described in Fielding and Bell (1997) and a threshold-independent performance criteria such as the Area-Under-the-ROC-Curve (AUC) together with bootstrapped confidence interval as discussed in Buckland et al. (1997). We also consider different ways to find the optimal probability cut-off values according to criteria proposed in the empirical literature (see Hand, 1997, Hand et. al. 1997 and Giudici, 2003).

However, the main weakness of the previous criteria is not to take the financial costs of a wrong decision into account. To measure the costs of an incorrect classification, we propose a particular financial loss function that considers the missed profits as well as the loss given default sustained by the bank (or loan issuer in general). Therefore, we choose the best predictive models taking into account both the predictive classification matrix and the lower financial loss function. For sake of space, we do not report the results of the models, but they are available from the authors upon request.

2. Future research

Our research can be improved following three directions: first, larger datasets should be considered to confirm the evidence emerging out of this work. Second, new financial ratios could be considered and derived from the balance sheet, for example considering business expertise and BACH (Bank of the Accounts of Companies Harmonized), that is a database containing harmonized annual accounts statistics of SMEs for 11 European countries, Japan and the United States. Finally, another avenue of future research is to include different qualitative information, such as questionnaire as well as external analysts recommendations. For SMEs, it is well known that subjective information is an important supplementary tool for credit scoring.

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