Journal of Banking & Finance 40 (2014) 211–226

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

Default prediction with dynamic sectoral and macroeconomic frailties

Peimin Chen [a], Chunchi Wu [b,*]

[a] School of Economic Mathematics, Southwestern University of Finance and Economics, Chengdu, Sichuan 611130, China
[b] School of Management, State University of New York at Buffalo, Buffalo, NY 14260, USA

ARTICLE INFO

Article history:
Received 26 October 2012
Accepted 26 November 2013
Available online 11 December 2013

JEL classification:
G12
G14
G17

Keywords:
Default risk
Hazard rate function
Frailty
Distance to default
Tail loss
Monte Carlo expectations maximization (EM)
Gibbs sampler

ABSTRACT

This paper extends the macroeconomic frailty model to include sectoral frailty factors that capture default correlations among firms in a similar business. We estimate sectoral and macroeconomic frailty factors and their effects on default intensity using the data for Japanese firms from 1992 to 2010. We find strong evidence for the presence of sectoral frailty factors even after accounting for the effects of observable covariates and macroeconomic frailty on default intensity. The model with sectoral frailties performs better than that without. Results show that accounting for the sources of unobserved sectoral default risk covariations improves the accuracy of default probability estimation.

1. Introduction

One of the long-enduring issues in financial research is the question of how default probability is determined. Many models have been developed to address this issue. The traditional model of default is based on the structural approach of Black and Scholes (1973). Using this model, one can compute a covariate of distance to default. Estimates of this default covariate using accounting and market data for all publicly traded firms have been provided by Moody's KMV and are widely accepted in industry practices. However, Duffie and Lando (2001) show that if distance to default cannot be accurately measured, a filtering problem arises and the default intensity depends not only on the measured distance to default but also on firm-specific and macroeconomic covariates that can reveal additional information about the firm's conditional default probability. This justifies the use of a reduced-form model that specifies the likelihood of default as a function of the measured distance to default and other observable covariates.

Earlier default models include the discriminant model of Altman (1968) and the logit/probit models (Kao and Wu, 1990). Later work draws on the duration analysis or reduced-form formulation (see, for example, Shumway, 2001; Chava and Jarrow, 2004; Hillegeist et al., 2004; Bharath and Shumway, 2008). Duffie et al. (2007) propose a doubly stochastic model of default that incorporates the dynamics of firm-specific and macroeconomic covariates to estimate term structures of corporate default probabilities over multiple future periods. This model exploits the time-series dynamics of the explanatory covariates to improve the predictive performance.

Despite the tremendous progress in default risk modeling, conventional models are unable to fully explain the observed clustering of default and consistently underestimate the probability of extreme default losses (see Das et al., 2007; Koopman et al., 2012). In particular, conventional models fail to generate sufficient dependencies across obligors to capture the observed default cluster and tail loss. A potential problem with these models is their exclusive reliance on observed firm-specific or aggregate factors. To cope with this problem, Duffie et al. (2009) propose a model of frailty correlated default that consists of an unobserved risk factor that commonly affects default probabilities of firms. They find that a common dynamic latent factor explains a substantial portion of default risk variations missed by the standard models that incorporate only observable covariates. However, they also note that there could be more unobservable risk factors that drive defaults

* Corresponding author. Tel.: +1 716 645 0448; fax: +1 716 645 3823.
E-mail addresses: peimin.chen2010@gmail.com (P. Chen), chunchiw@buffalo.edu (C. Wu).

0378-4266/$ - see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.jbankfin.2013.11.036

and that a richer model could allow for the estimation of additional frailty factors, for example, at the sectoral level. Motivated by this observation and recent empirical findings of intraindustry default clusterings and credit contagion effects (see Jorion and Zhang, 2007, 2009; Hertzel and Officer, 2012), we explore the possibility of frailties at the sectoral level and implications for default estimation.

We propose a generalized frailty model that permits additional channels of common risk at the sectoral level to capture default correlations among firms in a similar business that often heavily cluster in time. The sectoral effect captured in this model is supported by empirical evidence (see, for example, Chava and Jarrow, 2004; Acharya et al., 2007; Jorion and Zhang, 2007; Hertzel and Officer, 2012). Firms in different businesses typically face different levels of competition and product cycles. As such, the likelihood of default can differ significantly for firms in different sectors even though they have similar balance sheets. Historically, default correlation often concentrates on firms in a similar business; for example, in 2002 the telecom sector accounted for 56 percent of all corporate bankruptcies. Jorion and Zhang (2007) and Hertzel and Officer (2012) document convincing evidence of an intraindustry effect in default clustering. Their findings suggest that there are important channels of default correlations at the sectoral level and ignoring them will lead to biased estimation of default correlation and tail losses.

We fit the sectoral frailty model to Japanese default data in our empirical investigation. According to recent default studies by Standard & Poor's, US and foreign companies share many common characteristics and the time-series pattern of default rates in Japan is similar to those in the US and other industrial countries (see, for example, S&P default and rating transitions study 2011). This suggests that the hazard rate model can be used to explain the default behavior in different countries. Like the US default studies, past studies based on Japanese and other foreign data typically use similar financial and macroeconomic covariates in the default model (see Fukuda et al., 2009; Naifar, 2011; Harada et al., 2010; Lu et al., 2013). However, as Duffie et al. (2009) indicate, this type of default models based on only observable covariates cannot fully capture default clustering and tail risk. Our model improves these default models by introducing unobservable risk factors at both aggregate and sectoral levels.

We find that our model explains the behavior of corporate defaults very well. This finding demonstrates the generality of the frailty model to predict defaults in different economies. Empirical evidence strongly suggests the existence of sectoral frailties beyond observable risk factors and a single macroeconomic frailty factor. We find that accounting for sectoral frailties significantly reduces the bias in default risk estimation and improves the forecasting performance of the hazard rate model. Estimates of default probability are important for corporate bond and credit derivatives pricing, credit rating, portfolio analysis and risk management (see, for example, Koopman et al., 2008; Jarrow et al., 2010). Our results suggest that sectoral factors should be taken into account in order to obtain more accurate estimation of default correlation and to improve the predictive ability of the hazard rate model.

Recently, Koopman et al., 2012 have developed a high-dimensional and partly nonlinear non Gaussian dynamic factor model for decomposing systematic default risk into various components to shed light on the sources of systematic default risk variations over time. Similar to our study, they model default risk as a function of observed covariates, and common frailty and industry-specific factors. However, our paper differs from theirs in several key aspects. First, our paper uses a frailty approach to estimate the exposure of firms within the same industry to an unobservable industry risk factor. This contrasts the model of Koopman et al. (2012) that uses a factor approach to estimate industry-specific factors from the observed data. The industry frailty factor extracted from our model captures default clustering within an industry over and beyond that can be explained by observed macroeconomic and financial variables. Second, our model specification and empirical methodology are different. In our model, the industry frailty factor follows an Ornstein–Uhlenbeck (OU) process and is estimated by the EM algorithm and the Gibb sampler. By contrast, Koopman et al. (2012) specify the industry-specific factor as an autoregressive dynamic process and estimate the parameters of their model using the method of importance sampling suggested by Durbin and Koopman (2001). Moreover, we evaluate the explanatory power of our sectoral frailty model using the posterior odd ratio as opposed to the pseudo R^2. Third, we provide both in-sample and out-of-sample forecasts. The out-of-sample forecasts allow us to evaluate the model's ability to predict default rates out-of-sample, which is important in default forecasting for various purposes such as predicting individual firm defaults, managing portfolio risk, assessing adequate capital requirement and providing early warning signals. Lastly, we estimate default rates for individual firms using Japanese data. Our empirical analysis complements the Koopman et al. study which uses the US data and focuses on default prediction for rating groups instead of individual firms.

Considering sectoral default correlations allows us to trace different channels of default correlations across firms. Portfolio loss distributions depend on the correlating influences of observable and unobservable factors. Identifying the additional sources of default correlations and risk factors at the sectoral level helps improve the estimate of the portfolio loss distribution. For example, a CDO may be composed of a portfolio of collateral debt instruments from different sectors or regions. Comovements in the credit quality of the borrowers represented in the collateral pool affect default correlation and the tail of the total loss distribution for the portfolio. If a pool of instruments has more heavy sectoral or regional concentration, it will have higher default correlation and tail losses, and thus requires more conservative overcollateralization. Uncovering the channels of correlations among obligors and unobserved risk factors at the sectoral level allows modelers to better estimate default correlations among borrowers in the CDO collateral pool and to deliver more accurate estimates of tail losses consistent with true underlying correlation across borrowers in the pool. By capturing comovements of credit quality of borrowers in similar businesses, our model provides a more suitable framework for estimating portfolio loss distribution and the required amount of collateralization for senior tranches of CDOs and other tranched products.

The remainder of this paper is organized as follows. Section 2 describes the model and empirical methodology. Section 3 discusses the data and presents empirical results. Here we compare the performance of various default models with different specifications and variables, and conduct model specification tests. Section 4 evaluates the in-sample and out-of-sample forecasting performance of alternative frailty factor models. Finally, Section 5 summarizes main findings and concludes the paper.

2. Model and estimation

In this section, we propose a frailty model that permits additional channels of default correlations at the sectoral level. Frailty may occur because some important risk factors are unobservable, measured with errors, or subject to unexpected shocks. Frailties can exist at the sectoral level for a number of reasons. First, firms in the same industry may experience common shifts in the level of default intensity. Second, through business relations and trade