International Review of Financial Analysis 37 (2015) 129–139

Contents lists available at ScienceDirect

International Review of Financial Analysis

Credit contagion in the presence of non-normal shocks

Enrique Batiz-Zuk [a], George Christodoulakis [b,*,1], Ser-Huang Poon [b,1]

[a] Central Bank of Mexico, Mexico
[b] Manchester Business School, University of Manchester, Manchester M15 6PB, United Kingdom

ARTICLE INFO

Article history:
Received 2 July 2013
Received in revised form 13 November 2014
Accepted 21 November 2014
Available online 28 November 2014

JEL classification:
C13
C16
C22
G21
G32

Keywords:
Vasicek–Merton credit loss distribution
Single factor model
Contagion
Basel
Non-Gaussian distributions
Skew-Normal
Skew-Student *t*

ABSTRACT

We generalize existing structural credit risk models that account for contagion effects across economic sectors, to capture the impact of neglected skewness and excess kurtosis in the asset return process, on the shape of the credit loss distribution. We specify Skew-Normal and Skew-Student *t* densities for the underlying asset return process and estimate the derived credit loss density using sector default rates based on proprietary data from the Central Bank of Mexico for six firm sectors. We show that, out of the six sectors analyzed, there is a significant contagion effect in 'Commerce', 'Services' and 'Transport'. Moreover, we show that the non-Gaussian modelling of the common factor provides a better characterization than its Gaussian counterpart for the 'Services' sector. This result has a significant impact on the shape and the corresponding Value-at-Risk levels of the 'Services' credit loss distribution. In this context, traditional Basel and vendor-based credit risk models are inadequate as these do not consider the individual or the joint impact of contagion and non-Gaussian asset returns.

1. Introduction

A major challenge for any credit risk model is to capture and forecast the impact of default clustering that arises especially during economic recessions. The shape of the credit loss distribution and its corresponding tail depend on a number of factors that are difficult to capture. In particular, default clustering arises because of complex interactions between macroeconomic, microeconomic as well as idiosyncratic factors of random nature. The macroeconomic factors take into account the influence of the business cycle on firms, whilst the microeconomic component accounts for microstructure and contagion effects across business related firms. Banks must secure sufficient capital reserves against default clustering to survive during periods of financial stress. Under the Basel regulatory framework, see Basel Committee on Banking Supervision (2005, 2006, 2010), a bank may choose the internal ratings-based approach that utilizes risk weights derived from Vasicek's (1987, 2002)–Merton (1974) framework. The credit loss distribution in the standard Vasicek–Merton model is derived under the assumptions of portfolio homogeneity and Gaussian asset returns, whilst it ignores the impact of microeconomic dependence or contagion effects. Non-Gaussian returns and contagion may play a crucial role during periods of economic stress. Thus, regulators, bank risk managers and credit risk pricing analysts are interested in designing models that can capture the interaction of macroeconomic and microeconomic factors over the credit loss distribution, especially in the presence of extreme circumstances.

In this paper we consider the Rösch and Winterfeldt (2008) single factor contagion model which is based on the Vasicek–Merton framework and extend analytically and empirically to account for neglected non-normality. We argue that neglected non-normality in the underlying obligor asset return process can have a significant impact on the shape of the derived credit loss distribution, especially in the presence of contagion effects. We examine the relevance of our arguments for the case of the Mexican banking sector using proprietary aggregate default data. Mexico constitutes a large G20 open economy with a developed banking sector, which evolved significantly during the 1990s and the 2000s, thus extending significant implications for the international financial stability. Using monthly default rates for six Mexican sectors from 2005 to 2009, we find that non-normality is present in two of

* Corresponding author.
E-mail addresses: ebatiz@banxico.org.mx (E. Batiz-Zuk), George.Christodoulakis@mbs.ac.uk (G. Christodoulakis), Ser-Huang.Poon@mbs.ac.uk (S.-H. Poon).
[1] Tel.: +44 161 306 6404; fax: +44 161 275 4023.

http://dx.doi.org/10.1016/j.irfa.2014.11.014
1057-5219/

them, contagion is significant in three sectors, whilst non-Gaussianity and contagion are both significant for one sector. The latter result highlights that the joint presence of contagion and non-normality can massively change the shape of the credit loss distribution and the value-at-risk.

The remainder of this paper is organized as follows. Section 2 provides a brief literature review on credit risk single factor models that include contagion. Section 3 describes the model framework, the statistical properties of the Skew Normal and the Skew Student's *t* densities as well as the estimation procedure. Section 4 describes the data sets. In Section 5, we present the estimation results and assess the impact of contagion and non-Gaussianity on the loss distribution. Finally, Section 6 provides some concluding remarks.

2. Literature review

The literature on contagion can be classified according to firm type in 'financial firms' (interbank market) and 'non-financial firms' through the institution of trade credits. Allen and Gale (2000) provide a microeconomic discussion of interbank market contagion, whilst Kiyotaki and Moore (1997) provide a discussion of non-financial firms. In addition, studies on contagion may focus on contagion across: (i) countries (i.e. developed vs. emerging economies); (ii) economic sectors; and (iii) equity markets or credit markets. Kaufman (1994) provides a good review of the theory and evidence of bank contagion and Dungey, Fry, González, and Martin (2005) provide an early review of methodologies for empirical modelling of contagion.

Davis and Lo (2001) develop a contagion model from a pure probabilistic binomial approach. The authors show that even a small infection probability leads to a tail increase of the loss distribution and that the distribution loses its unimodality feature in severe cases as the infection probability increases. Although Davis and Lo (2001) model provides an interesting alternative to the binomial expansion technique used by Moody's (see Cifuentes and Wilcox (1998) and Cifuentes and O'Connor (1996)), the model has important practical shortcomings that constraint its applicability in large portfolios. Mistrulli (2011) provides an assessing of financial contagion in the Italian interbank market using the maximum entropy versus observed interbank lending patterns. It was found that, depending on the structure of the interbank linkages, the recovery rates of interbank exposures and banks' capitalisation, the maximum entropy approach tends to overrate the scope for contagion. Hasman and Samartin (2008) build a framework similar to Allen and Gale (2000) in which contagion and financial crises are the result of information gathering by depositors, weak fundamentals and an incomplete market structure of banks.

Giesecke and Weber (2004) were the first to study contagion under a single factor model approach. The authors find theoretical evidence supporting the view that heavy tails of the loss distribution depend on the degree of connectedness between firms in the economy. The less connected, the lower is the contagion-induced additional risk of large losses. Egloff, Leippold, and Vanini (2007) use a macroeconomic model in conjunction with a hierarchical interdependence structure (also known as neural network like connections). Although their results support the theoretical findings of Giesecke and Weber (2004), the model is difficult to apply in practice. Neu & Kühn (2004) generalize structural credit risk models and resort to Monte Carlo simulations to study the salient features of their model. The main virtue of their study is that their model is useful to assess the impact of avalanches of default events and arrive at the same findings as Davis and Lo (2001). Based on the findings of Davis and Lo (2001) and Neu & Kühn (2004), Rösch and Winterfeldt (2008) proposed a Gaussian single factor framework to model credit contagion across business sectors, and use historical U.S. bond rating data to estimate the model through Maximum Likelihood. The main virtue of their work is that they derive at a loss density with contagion effects whose parameters are suitable for empirical estimation using real world data. They find that a significant contagion effect leads to a loss distribution with fatter tails.

3. Non-Gaussian contagion model and estimation framework

Our model, which is described in this section, is based on the Vasicek–Merton framework and generalizes the approach of Rösch and Winterfeldt (2008) to introduce a contagion credit loss distribution with a non-Gaussian common factor. Then, we define the contending non-Gaussian distribution and we review some of its fundamental properties.

3.1. Theoretical model and estimation framework

The model assumes a default mode with a discrete time horizon for any given set of firms $\mathbb{F}_t$ in time period t and the individual default is based on Merton (1974). It is assumed that individual default of firm i in time period t, where $(i \in \mathbb{F}_t, t = 1, \ldots, T)$, occurs when the firm asset return process $(R_{i,t})$ is below some threshold (K_i) which is also known as a default barrier:

$$R_{i,t} < K_i \quad \Rightarrow \quad D_{i,t} = 1 \tag{3.1}$$

where

$$D_{i,t} = \begin{cases} 1 & \text{firm i defaults in period t} \\ 0 & \text{otherwise} \end{cases}. \tag{3.2}$$

$D_{i,t}$ is the default indicator $(i \in \mathbb{F}_t, t = 1, \ldots, T)$, and $R_{i,t}$ is a continuous random variable.

We assume that for each sector of the economy the original set of firms $\mathbb{F}_t$ is composed of two mutually exclusive sets of firms $(\mathbb{F}_t = \mathbb{I}_t \cup \mathbb{C}_t)$. The set $(\mathbb{I}_t)$ contains the 'infecting' firms for any time period t, whilst the set $(\mathbb{C}_t)$ contains the 'contaminated' or 'infected' firms. All firms can be assigned to either the infecting firms set or the contaminated set. The asset return process for each set of firms is driven by a single common factor Y_t and an idiosyncratic noise component ε_t as:

$$R_{i,t}^{I} = \sqrt{\rho^I} Y_t + \sqrt{1-\rho^I} \varepsilon_{i,t} \tag{3.3}$$

$$R_{j,t}^{C} = \sqrt{\rho^C} Y_t + \sqrt{1-\rho^C} \varepsilon_{j,t} - \beta \left(\frac{D_t^I(y_t)}{N_t^I} \right) \tag{3.4}$$

where $R_{i,t}^I$ $(i \in \mathbb{I}_t, t = 1, \ldots, T)$ and $R_{j,t}^C$ $(j \in \mathbb{C}_t, t = 1, \ldots, T)$ are the asset return processes for the infecting and infected firms, respectively; Y_t and $\varepsilon_{k,t}$ are assumed to be mutually and serially independent random variables, where Y_t is assumed to be $G(y_t)$ distributed and $\varepsilon_{k,t}$ follows a Gaussian distribution $N(0, 1)$ for all k, where $k \in \{I, C\}$; parameters $\sqrt{\rho^k}$ and $\sqrt{1-\rho^k}$ are the corresponding factor loadings, where $k \in (I, C)$; $D_t^I(y_t) = \sum_{i \in_t} D_{i,t}^I(y_t)$ is the number of defaulting infecting firms at time t; N_t^I is the total number of firms in the infecting set at time t; and β denotes an unknown coefficient that captures the impact of contagion of the infecting firms over the asset return process of the contaminated firms. Note that under this specification, the multivariate asset return distribution function will depend on the choice of $G(\cdot)$. In this framework, default events of the infecting firms may cause a decrease in the asset return of contaminated firms, but not vice versa. Therefore, if β is statistically different from zero, there is a clear sign of contagion, whereas in the case that $\beta = 0$, the model reduces to the standard factor model.

To describe the default behaviour through an appropriate distribution function, let us depart with the concept of a conditional default probability which for each set of firms, given a realization of the common risk factor, is given by:

$$PD_i^I(y_t) = \text{Prob}\left(R_{i,t}^I < K_i^I | Y_t = y_t \right) = \Phi\left(\frac{K_i^I - \sqrt{\rho^I} y_t}{\sqrt{1-\rho^I}} \right) \tag{3.5}$$