Journal of Banking & Finance 60 (2015) 209–223

Contents lists available at ScienceDirect

Journal of Banking & Finance

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

Risk assessment based on the analysis of the impact of contagion flow

Chanaka Edirisinghe [a,*], Aparna Gupta [a], Wendy Roth [b]

[a] Lally School of Management, Rensselaer Polytechnic Institute, 110 Eighth Street, Troy, NY 12180, USA
[b] J. Mack Robinson College of Business, Georgia State University, 35 Broad Street, Atlanta, GA 30303, USA

ARTICLE INFO

Article history:
Received 10 March 2014
Accepted 8 August 2015
Available online 14 August 2015

JEL classification:
G32
C63
D85

Keywords:
Contagion
Bond defaults
Factor models
Firm-level risk assessment

ABSTRACT

This paper presents a new framework to model and calibrate the process of firm value evolution when an unanticipated exogenous event impacting one firm can contagiously affect other firms. The nature of propagation of such contagion is determined by the underlying connections between firms, which can adversely affect the tail risks of firm value, hence the securities issued by the firm. This paper combines the insights gained from the existing firm-value models and historical events into a structural model for flow of contagion among firms using a network-based approach. Rather than using stylized networks, we develop a data-driven approach for network construction where we define and calibrate several contagion variables to model the spread of contagion. This framework is applied for assessing firm-level risk under downside risk measures. Using actual data, our model illustrates how connections between firms can lead to heavy-tailed default distributions and default clustering observed in practice.

1. Introduction

Investments in equities or corporate bonds are impacted by the fundamental financial well-being of the underlying firms issuing those securities. Thus, before an equity or debt security is considered in an investment portfolio, a comprehensive risk assessment of the firm becomes an important ingredient in any overall risk management strategy. Understanding the firm's risk of default is a crucial part of this assessment, especially in the case of corporate bonds, but may also be instructive for tail risk in equity of the firm.

Altman et al. (2000) and Altman and Bana (2004) analyzed data from defaults occurring between 1971 and 2003. The results showed default rates ranging from 0.158% to 12.795% per year, with a weighted average default rate of 5.453%, see Fig. 1 for default rates during 1971–2007. In addition, during the time period covered by the study, the losses under default increased substantially, with a record par value default of 96.858 billion dollars in 2002. High variability in default rates increases the challenge of accurate risk assessments.

Historically, investors have relied on credit rating agencies to give accurate assessments of a firm's likelihood of a default. The financial crisis of 2007, involving mortgage-backed securities, however, highlighted credit rating agencies' inability to timely and accurately predict the risk of default. The issue of accuracy of such ratings was also raised by 'fallen angels', as discussed in Altman and Bana (2004). Fallen angels are companies whose bond ratings are downgraded from investment to speculative grade subsequent to the actual drop in the bond's price, reinforcing the position that ratings are often a lagging indicator of default risk.

To help understand the possible causes of default risk, several models have been developed in the literature. Models of default often rely on the double stochastic assumption, that is, conditioned on certain risk factors, default intensities of firms are independent Poisson arrivals with conditionally deterministic intensity paths. Das et al. (2007) analyzed default and corporate data from 1979 to 2004 to test the above assumption. However, results fail to support a double stochastic default intensity model, leading to the conclusion that better models for defaults are required for capturing default clustering observed in practice. Macroeconomic factors and changes in an industry/sector are cited as the causes of clustering of defaults, leading to bankruptcies. Moreover, Marchesini et al. (2004) studied accounting models to determine the accuracy in predicting bond defaults. Results were only slightly better than flipping a coin, again indicating that additional influences are missing in current models.

* Corresponding author. Tel.: +1 518 276 3336.
E-mail addresses: edirin@rpi.edu (C. Edirisinghe), guptaa@rpi.edu (A. Gupta), wroth@gsu.edu (W. Roth).

http://dx.doi.org/10.1016/j.jbankfin.2015.08.015
0378-4266/

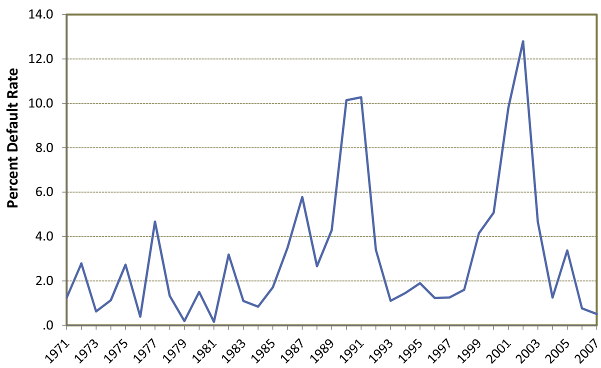

Fig. 1. Default rate 1971–2007.

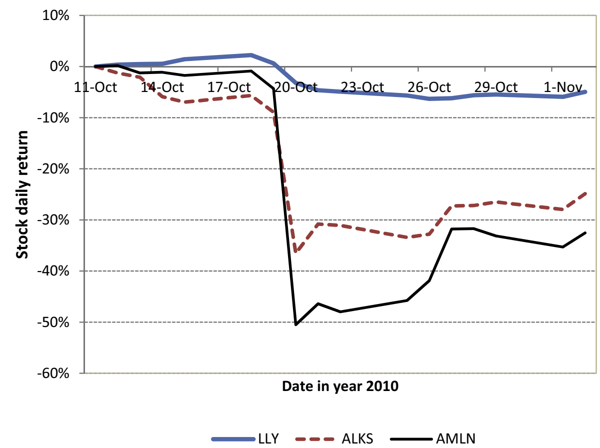

Fig. 2. Stock performance of connected firms impacted by an unanticipated event.

An approach called the Conditional Probability of Default (CoPoD) methodology is used to model the empirical default likelihood using identifiable macroeconomic and financial variables conditional on the business cycle. CoPoD method allows one to measure evolution of risk through time as macroeconomic conditions change incorporating econometric and economic perspectives. See Basurto (2006) who develops the CoPoD method for modeling the probability in the context of loan defaults for small and medium size enterprises. As the author states in the paper, the CoPoD methodology does not incorporate firm specific fundamental information into the explanatory (macroeconomic) variables, a key piece of information in our treatment of modeling firm defaults. On the other hand, Lucas et al. (2012) use conditional probabilities to model Euro area sovereign default risk based on CDS data. Results show risk dependence varies over time and there are considerable spillover effects between countries in the likelihood of sovereign failures. For our work, this is construed as evidence supporting a methodology that incorporates contagion factors in models of default risk, as we shall follow in this paper.

We subscribe to the notion that for a model of default to be useful, its output must agree with empirical data, specifically the actual observed clustering of defaults. To exemplify, consider the stock performance of three firms in the pharmaceutical industry, see Fig. 2. The drop in the stock price of the three firms was the result of a surprise rejection announcement by the FDA of a new drug. News headlines stated, "Amylin shares crater after FDA rejects Bydureon application." Amylin was the focus of the negative publicity, however, this FDA decision also affected two other firms, Alkermes and Eli Lilly. These three firms were related by a joint venture. This example illustrates how an exogenous event can contagiously spread from one firm to other firms creating an impact substantially greater than that explained by macroeconomic or sector factors alone.

While the risks due to factors that are common for all firms in a given market sector can be expected to be priced in the equities, there do exist connections among certain subsets of firms in the sector that may present elevated risks that are not priced-in. Risk due to firm connection in the form of a joint venture, depicted in Fig. 2, is such an example. However, in general, the nature of these connections can be multifaceted, and they can be less obvious. According to Altman and Bana (2004), in 2002, 36% of bankruptcies were of telecom-related firms. In the same year, 24% of bankruptcies were related to alleged fraud. When a case of fraud was revealed at a firm, all firms using the same auditor as the fraudulent firm were at increased risk, in this case, "same auditor" being the connection between firms. This risk was not priced until the initial event occurred and the potential impact of connections between the firms became apparent.

The focus of this paper is on the risk due to an unanticipated (negative) event impacting one firm spreading to other firms contagiously due to underlying, but often less apparent, firm connections. The term *contagion* is often used to describe the spreading of impact of a negative event, although there is no single definition of what constitutes a contagion. Forcardi and Fabozzi (2004) define contagion as a sudden and unexplained increase in correlation levels. Egloff et al. (2007) use contagion in the context of credit deterioration of a counterparty triggering the credit deterioration of other counterparties through micro-structural channels.

Contagion spreading through the international banking system is considered in the seminal work by Allen and Gale (2000), where contagion is not viewed as a random event, but rather driven by real shocks and linkages between banks. A network of banks and the impact of a liquidity crisis are used to illustrate a contagion spreading through the banking system. The size of the liquidity shock and the structure that connects the banks determine the impact of the contagion's spread, ranging from complete dissipation to causing total network failure. Research on the impact of financial contagion includes examining its spread between countries (see Pericoli and Sbracia (2003), Corsetti et al. (2005), and Stiglitz (2010)), across markets (see Kodres and Pritsker (2002)), between sovereign bond markets (see Bhanot et al. (2011)), and among hedge funds (see Boyson et al. (2010)). This systemic risk is often modeled via two components – a random shock and a network that allows the transmission (see Martinez-Jaramillo et al. (2010)).

The credit crisis of 2007 continued to show for several subsequent years how shocks spread between linked nations and banks. Using the data from this time period, Baur (2012) supports the notion of financial contagion spreading from the financial sector to the real economy, within and across countries. In addition, the latter research provides evidence that not all sectors in an economy are impacted equally by contagion, indicating that there are unique factors within a sector that influence the spread of contagion. The impact of contagion on banks or countries can become quite extreme, hence the need to understand the process of contagion flow better.

The impact of contagion in the case of non-financial firms has also been analyzed. Schellhorn and Cossin (2004) developed a structural model where random and cyclical network structures were considered. Other stylized models of contagion have also been proposed, for instance Giesecke and Weber (2006), Kraft and Steffensen (2009), and Horst (2007); also see Hull and White (2008) for a default model including contagion effects. Bernoulli random variables are used in Davis and Lo (2001) to model a