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Comparative Analysis of the Reduced form Model and the Structural Model in Credit Risk Modelling

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ABSTRACT: Credit risk models are statistical tools to infer the future default probabilities and loss distribution of values of a portfolio of debts. Credit risk modelling is prevalent in today's financial decision-making process. It turns out that both models of modelling credit risk contribute to explaining the default risk of listed firms, however, reduce-form model outperformances the structural model. Structural models are used to calculate the probability of default for a firm based on the value of assets and liabilities. The basic idea is that a company (with limited liability) defaults if the value of its assets is less than the debt of the company. The causal driver of defaults in structural model will choose to work with variables that help us explain what causes defaults. Default risk is endogenous in the structural model, this is so because the factors that causes defaults within a path are predictable. The structural model is an economic model with focus on options pricing, call option and put option. It provides clarity about the nature of defaults and how the various economic features that are chosen to relate with each other when defaults occur. The reduced form model is mostly concerned with prediction of when does defaults occurs? Default risk is exogenous to the reduced form model, can be caused by random events and most often comes as a surprise. Statistical models are used to observe the variables and help maximise the reduced form model.

The empirical result suggests that reduce-form model can better predict the firm's default risk.

KEYWORDS: Credit Risk, Default Risk, Poisson model, Merton Model.

INTRODUCTION

Risk is an intrinsic part of the business of any establishment and the greatest risks posed to businesses and financial institutions take the form of credit risk. Credit risk arises when a corporate or individual borrower fails to meet their debt obligations. It is the probability that the lender will not receive the principal and interest payments of a debt required to service the debt extended to a borrower. On the side of the lender, credit risk will disrupt its cash flows and increase collection costs, since the lender may be forced to hire a debt collection agency to enforce the collection. The loss may be partial or complete where the lender incurs a loss of part of the loan, or the entire loan extended to the borrower (CFI, 2015).

This study aims to examine the effectiveness of these two credit risk models in relation to one another. Credit risk modelling refers to data-driven risk models which calculate the probability of default on a loan. If a borrower fails to repay a loan, how much amount he/she owes at the time of default and how much the lender would lose from the outstanding amount. In other words, we need to build probability of default, loss given default and exposure at default models as per advanced IRB approach under Basel norms.

The role of the credit risk model is to take as input the conditions of the general economy and those of the specific firm in question and generate as output a credit spread. In this regard, there are two main classes of credit risk models – structural and reduced form models. Structural models are used to calculate the probability of default for firm based on the value of its assets and liabilities. A firm default if the market value of its assets is less than the debt it must pay. Reduced form models assume an exogenous random cause of default. For reduced form or default-intensity models, the fundamental modelling tool is a Poisson process. A default-intensity model is used to estimate the credit spread for contingent convertibles (Somnath, 2015).

The outcome of these models contributes significantly to risk management process and performance measurement processes of banks which include performance-based compensation, risk-based pricing, customer profitability analysis, capital structure decisions and active portfolio management (Basel, 1999).

Banks using the Internal Ratings Based approach depends on their own estimates of risk components in determining the capital requirements for a given exposure subject to certain conditions, disclosure requirements, and supervisory approval for its use. Under Foundation (IRB) approach, banks use their own estimates of probability of default and rely on the estimate provided by the supervisor for other risk components which are LGD and EAD. Banks using the advanced IRB approach calculate their own estimates of LGD, PD and EAD subject to the minimum standard of risk management specified by the national supervisor (Dun, 2010).

Scope of the Study

Credit risk analysis is essential to the survival and liquidity of any enterprise and companies attempt to improve the risk and return trade off in their decision-making processes. It may be difficult for firms to continue in operations without handling these risks as today's risk may become tomorrow's realities. This study aims at finding the most suitable credit risk modelling technique between the structural and reduced form models.

Structural models were initiated by Merton (1974) and use the Black-Scholes option pricing framework to characterize default behavior. They are used to calculate the probability of default of a firm based on its assets and liabilities. The main challenge with this approach is that one does not observe the market value of a firm's assets. A bank's annual report only provides an accounting version of its assets. But for any publicly listed bank, the market value of equity is observable, as is its debt. The analysis that follows is known as contingent claims analysis (CCA) and uses equity prices and accounting information to measure the credit risk of institutions with publicly traded equity.

In reduced form or default intensity models, the fundamental modelling tool is the Poisson process, and we begin by demonstrating its properties. We assume there are constant draws from the Poisson distribution and each draw brings up either a 0 or a 1. Most of the draws come up with 0. But when the draw throws up a 1, it represents a default. Poisson distribution specifies that the time between the occurrence of this event and the previous occurrence of the same event has an exponential distribution (Somnath Chatterjee, 2015).

Obviously, it is easy to implement the credit scoring models but they have lower prediction accuracy compared to other models. The structural models (also called market-based models) provide an alternative and potentially superior source of information compared to the credit scoring models. The information contained in the financial statements may not be enough to accurately estimate future default probability. The structural models thus add stock prices, which aggregate information from the market in addition to the financial statements, into the models. However, the main concern is that the structural model may not perform well due to the inclusion of market prices which may lower the estimation accuracy for the market value of the asset. Another shortcoming is that the stock price may not efficiently include all publicly available default-related information. In addition, Sloan (1966) argues that the market does not accurately include all the information in financial statements while the structural model estimation is based on stock price. Thus, it is ultimately an empirical question if the market-based default models or accounting-based default models can achieve more accurate estimates (Hillegeist et al., 2004).

Most recent papers apply a reduced-form model (logit model or the Poisson model) with some exogenous variables which are assumed to capture traditional risk factors and DTD as determinants of firm's default probability. For example, Chava and Jarrow (2004), Hillegeist et al., (2004), Shumway (2001) estimates a discrete-time hazard model with yearly data and directly predict one-year default probabilities. Chava and Jarrow (2004), and Campbell et al. (2008) estimate default probability using the logistic regression models. Duffie et al. (2007), Duffie et al. (2009) and Duan et al. (2012) develop a Poisson intensity approach with common risk factors and firm-specific attributes to estimate corporate defaults.

Reduced form model

Reduced form models typically assume an exogenous cause of default. It model default as a random event without any focus on the firm's balance sheet. This random event of default is described as a Poisson event. As Poisson models look at the arrival rate, or intensity, of a specific event, this approach to credit risk modelling is also referred to as default intensity modelling.

Under the Basel II IRB framework, the probability of default (PD) per rating grade is the average percentage of obligors that will default over a one-year period. Exposure at default (EAD) gives an estimate of the amount outstanding if the borrower defaults. Loss given default (LGD) represents the proportion of the exposure (EAD) that will not be recovered after the default. Assuming a uniform value of LGD for a given portfolio, EL can be calculated as the sum of individual ELs in the portfolio.

$$EL= \sum_{i=1}^{N} PD_i LGD_i EAD_i$$

Structural model

The structural approach to credit risk modeling focuses on modeling bankruptcy from a firm's asset value, in contrast to the reduced form approach in which default probabilities are modeled as stochastic processes. Here, the credit default event occurs when the assets of a firm drop below a certain pre-defined level.

Structural models assume complete knowledge of a very detailed information set. In most cases, this informational assumption implies that a firm's default time is predictable. In contrast, reduced-form models assume knowledge of a less detailed information set, akin to that observed by the market.

Extensions and improvement on the Merton's model

Ever since the works of Black, Scholes and Merton started the literature of structural credit risk modelling, many researchers have proposed extensions to Merton model, which has been criticized for basing on several simplifying assumptions. The extended structural models represent important improvements for Merton's original framework as they are more realistic and able to better align with market data (e.g., CDS spreads). Some of these areas of improvements are introduced below:

In Merton's framework, a company could only default at its debt maturity date. The model can be modified to allow for early defaults by specifying a threshold level such that a default event occurs when asset value A^* falls below this critical level.

CONCLUSION

Structural approach, led by Merton model, has the highly appealing feature of connecting credit risk to underlying structural variables. It provides both an intuitive economic interpretation and an endogenous explanation of credit defaults, and allows for applications of option pricing methods. As a result, structural models not only facilitate security valuation, but also address the choice of financial structure.

The downside of structural model lies in the difficulty of implementation. For example, the continuous tradability assumption for corporate assets is unrealistic, and calibrating stochastic asset processes using publicly available information is sometimes more difficult than anticipated. Furthermore, although improved structural models have addressed several limitations of earlier models, they tend to be analytically complex and computationally intensive.

Reduced form models do not consider endogenous cause of defaults; rather, they rely on exogenous specifications for credit default and debt recovery. This feature is both a strength and a weakness—while these models suffer from the lack of economic insights about default occurrence, they offer more degrees of freedom in functional form selection. Such flexibility contributes to analytical tractability and ease of implementation and calibration (compared to structural models). However, reduced form models' dependence on historical data may result in good in-sample fitting properties but limited out-of-sample predictive power.

In general, structural models are particularly useful in areas such as counterparty credit risk analysis, portfolio/security analysis and capital structure monitoring, while the difficulty in calibration limits their presence in front office environments. Reduced form models, on the other hand, are widely used on credit security trading floors where traders require fast computation tools to help them react to market movements quickly.

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