The Term Structure of Banking Crisis Risk in the United States:

A Market Data Based Compound Option Approach

Abstract

We use a compound option-based structural credit risk model to estimate banking crisis risk for the United States based on market data on bank stocks on a daily frequency. We contribute to the literature by providing separate information on short-term, long-term and total crisis risk instead of a single-maturity risk measure usually inferred by Merton-type models or barrier models. We estimate the model by applying the Duan (1994) maximum-likelihood approach. Strongly increasing total crisis risk estimated from early July 2007 onwards is driven mainly by short-term crisis risk. Banks that defaulted or were overtaken during the crisis have a considerably higher crisis risk (especially higher long-term risk) than banks that survived the crisis.

JEL classification: G21; G17; G32; G12; G18

Keywords: Banking crisis; Bank default; Option pricing theory; Compound option; Liability structure

1. Introduction

This paper derives short-term, long-term and total banking crisis risk indices for the United States using daily stock market data of the major US banks. This contributes to an emerging literature that aims to infer the probability of bank defaults and banking crises from stock price information by applying structural credit risk models. Several important and interesting papers apply the Merton (1974) options-based approach that assumes a firm where all debt becomes due at one single date in the future (see, for example, Chan-Lau et al., 2004; Gropp et al., 2004, 2006; Chen et al., 2006). The firm's equity is interpreted as a call option that enables the shareholders to buy the firm at maturity where the strike price of the call equals the face value of debt.

Geske (1977) advances the Merton framework by considering a multi-period debt payment framework applying compound option theory. This multi-period approach enables us to distinguish between short-term and long-term payments in the calculations and to capture the existing dependency between these payments. Furthermore, it makes it possible to determine separate default probabilities for short-term and long-term maturity in addition to the total probability to default at the first or the second payment date. We apply the Geske (1977) approach to the major US banks. Based on stock market data, we simultaneously estimate the unknown quantities of our structural model, i.e., the state variable (the bank's firm value) and the parameters of its stochastic process, which are needed to calculate the default probability. Here, we apply the estimation approach developed by Duan (1994) which relies on the maximization of the likelihood function for a time series of observed market data.

Our market based compound options approach may be interesting for supervisory agencies and policy makers for several reasons. Extracting information on market expectations about the likelihood of short- and long-term default sheds light on the potential problems banks face. This helps supervisory agencies to decide which instruments to use to rescue vulnerable banks. If, for example, the short-term probability of default rises but the long-term probability of default stays constant, supervisors may interpret this as evidence that the bank suffers from short-term problems, such as temporary financing and liquidity problems. An increase in the long-term probability of default, on the other hand, points to fundamental long-term or solvency problems. Supervisory agencies may use these market signals when evaluating which instruments to use to rescue vulnerable banks. A rising short-term probability of bank default calls for monetary easing, such as a reduction in interest rates and/or an expansion of the money supply, to improve the short-term financing and liquidity conditions of banks. Higher long-term default probabilities indicate structural problems that can only be solved by propping up the equity base, restructuring, or – as a last resort – nationalization of banks.

Another advantage of this approach results from the nature of the data used. Traditional bank monitoring systems use low-frequency balance sheet information to signal bank distress. Our approach uses stock market data available on a daily basis. This enables supervisors to react promptly to changing fundamentals. Market data is also, by nature, forward-looking: stock prices are based on expected future cash flows while balance sheet data reflect the bank's previous health. Thus, our approach may be interesting for supervisory purposes as stock prices signal future problems of banks that may be alleviated by implementing regulatory measures.

The rest of the paper is organized as follows. Section 2 reviews the literature on measuring and forecasting bank distress. Section 3 explains the multi-period debt service model. Section 4 discusses the estimation procedure. Section 5 presents the empirical application to the United States' banking system. Section 6 concludes.

2. Literature

Bank distress can be analyzed on the macroeconomic or on the bank-specific level. Papers that explain country-wide banking crises use a binary dependent variable that reflects whether a crisis in the banking sector occurs or not (see, for example, Demirgüc-Kunt and Detragiache, 1998, 2005; Davis and Karim, 2008). Using macroeconomic data these approaches have been applied to design early warning systems of banking crises with remarkable forecast ability.

To measure bank-specific distress, the literature relies on two types of data. One strand of the literature employs accounting data; the other uses market data. While using accounting data implies an *ex post* analysis of bank fragility, market data reflects market participants' perception of bank default risk *ex ante*.

Several papers focus on accounting data to forecast or explain bank distress. These approaches are interesting and insightful as they take the position of supervisory agencies – which use data on CAMEL variables (**c**apital adequacy, **a**ssets quality, **m**anagement quality, **e**arnings, and **l**iquidity) to quantify bank distress. Männasoo and Mayes (2009) find that CAMEL indicators play an important role in explaining bank distress. Using a sample of Eastern European banks, they are able to predict eight out of sixteen distress episodes during 2002-2004. Poghosyan and Cihak (2009) find that several CAMEL variables – especially asset quality and profitability – estimate the distress of banks located in the European Union (EU) particularly well. Arena (2008) finds for a set of East Asian and Latin American banks that CAMEL indicators have a remarkable explanatory power in predicting bank failure. He also concludes that macroeconomic variables such as economic growth or real exchange rate volatility can account for the regional differences in bank distress.

The use of market data, such as stock prices or subordinated debt spreads, has become popular in the literature to measure bank distress and exhibits several advantages.[1] First, market data is forward-looking as market participants set prices depending on their expectations about future cash flows. Second, data on practical banking regulation is available on a daily basis while accounting data is updated only monthly or quarterly. Thus, using market data would enable supervisory agencies to react quickly to problems adversely affecting banks.

Comparisons of different sources of information confirm that stock price information generally outperforms supervisory or rating agencies' balance sheet-based assessments of bank conditions. Berger et al. (2000) conclude that stock market and bond investors predict future bank performance more precisely than supervisors – except when the supervisor has recently inspected the bank. Bongini et al. (2002) find that stock market information, accounting data, and ratings have a similar ability to assess bank fragility although stock prices respond more quickly to changing bank conditions than ratings or balance sheet information. Gropp et al. (2006) find an asymmetric forecast ability of stock prices and subordinated debt spreads when the forecast window is considered. Stock prices perform best within a forecast window of six to 18 months before a rating downgrade. Spreads can predict downgrades within a forecast window of one year or less.

Some authors use information on market-traded debt securities to infer expectations on bank distress. Evanoff and Wall (2001) show that yield spreads of subordinated debt predict changes in ratings of bank supervisors as well as or better than capitalization ratios drawn from a bank's balance sheet. Deyoung et al. (2001), by contrast, find that bank examinations provide relevant information to supervisory agencies several quarters before information about the bank's condition is reflected in subordinated debt yield spreads.

[1] Flannery (1998) reviews the different sources of market information that can help supervisory agencies assessing bank distress.

The literature that uses stock market information to measure bank fragility can be grouped into two branches. The first branch uses stock prices to infer probabilities of default. The second branch uses stock market information as an independent variable in regressions which aim to improve the understanding of supervisory rating changes (see, for example, Gunther et al., 2001; Curry et al., 2003; Distinguin et al., 2006). A common finding of the second branch is that stock market data helps explain rating downgrades or other forms of bank distress. Krainer and Lopez (2004) find that including stock market information in their forecast framework helps predict supervisory rating changes up to four quarters in advance.

Several important papers apply option pricing theory to derive the probability of bank default from stock price information (see, for example, Chan-Lau et al., 2004; Gropp et al., 2004, 2006; Chen et al., 2006). These approaches use the Merton (1974) model, which assumes that the equity of a bank is equivalent to a call option on the bank's assets and where the value of the debt represents the strike price. By employing information on stock prices, the bank's debt, its maturity, and the probability of default, i.e., the likelihood that the value of the assets falls short of the value of the debt at maturity can be derived.

A convenient indicator that can be derived from the basic options-based approach is the distance to default, i.e. the difference between the value of the bank's assets and debt at maturity (Crosbie and Bohn, 2003). Chan-Lau et al. (2004) use the distance to default measure to assess the fragility of 38 banks in 14 emerging economies. They are able to forecast rating downgrades up to nine months in advance in-sample and show that their model also performs well out of sample. Applying the distance to default measure to a sample of EU banks, Gropp et al. (2004, 2006) find that stock prices predict rating downgrades 6 to 18 months in advance. The forecast ability of stock prices is lower over the short-term. Chen et al. (2006) find that stock prices effectively forecast Estonian bank distress.

The approaches described above assume that the total debt is due at a single date. This enables them to derive a measure for the overall probability of default. We contribute to the literature by distinguishing between short-term and long-term debt. This enables us to derive short-term and long-term probabilities of default. This term structure of bank default risk may help supervisory agencies to address the bank's problems more accurately.

3. The Model Framework

3.1. A Compound-Option Approach to Model multiple Debt Service Payments

Our assessment of crisis risk for the US banking system is derived from the default probabilities estimated for the country's major banks. These default probabilities are derived from stock market data using the structural credit risk model of Geske (1977), which is a generalization of the Merton (1974) model to consider multiple debt service payments.

The pricing formulas are based on the assumption that the development of the firm's value, W, over time can be described by the following Ito stochastic process:

$$dW = \mu_W W dt + \sigma_W W dZ, \tag{1}$$

where μ_W is the constant drift rate, i.e., the expected rate of return on the firm's value, σ_W is the constant volatility, and dZ is a standard Gauss-Wiener process. It follows from Equation (1) that growth rates for equidistant time intervals $\Delta t = T - t$ are independently identically normally distributed:

$$w_{t,T} \sim \text{i.i.n.}[(\mu_W - \frac{\sigma_W^2}{2})(T-t); \sigma_W \sqrt{T-t}]. \tag{2}$$

Merton considers a situation where the firm's total debt becomes due at a single point in time. He shows that the firm's equity equals a call option for which the debt value is the strike price and the firm value is the underlying. Thus, the value of the firm's equity at any point in time, t (< T), can be calculated using the Black-Scholes formula for call options (see Black and Scholes, 1973). Geske (1977) provides a generalization of the Merton model that considers multiple debt service payments instead of only one. In our paper we use a version with two (short-term and long-term) debt service payments, B_1 and B_2, (due at T_1 respectively T_2) to derive the short-term and long-term default probability of banks. Geske (1977) shows that in a situation with two outstanding debt service payments the firm's equity equals a compound (call) option, i.e. a call option that gives the holder the right to by another (simple) call option. The latter equals the option considered in the Merton case, where B_2 is the strike price and T_2 is the expiry date. In T_1 ($< T_2$) the stock holders (as owners of the compound option) have the option right to by this option by paying the (first) strike price of the compound option, B_1, or to refuse to do so. Thus, at any date t before T_1 the equity holders own a compound option. The value of the equity can be calculated using the pricing formula for a compound call option (see Geske, 1979):

$$\begin{aligned} E_t &= W_t\, N_2(d_1 + \sigma_W \sqrt{T_1 - t}, d_2 + \sigma_W \sqrt{T_2 - t}; \rho) \\ &\quad - B_2\, e^{-r_s (T_2 - t)}\, N_2(d_1, d_2; \rho) - B_1\, e^{-r_s (T_1 - t)}\, N_1(d_1) \end{aligned}, \tag{3}$$

where: $d_1 = \dfrac{\ln(W_t / W_Q) + (r_s - \sigma_W^2 / 2)(T_1 - t)}{\sigma_W \sqrt{T_1 - t}}$,

$$d_2 = \frac{\ln(W_t / B_2) + (r_s - \sigma_W^2 / 2)(T_2 - t)}{\sigma_W \sqrt{T_2 - t}}, \text{ and } \rho = \sqrt{\frac{T_1 - t}{T_2 - t}}.$$

$N_1(d_1)$ and $N_2(d_1,d_2,\rho)$ describe the values of the one- and two-dimensional cumulative standard normal distribution for the arguments in parentheses, respectively, and r_s is the risk-less interest rate.

W_Q is the (threshold) for which the stock holders will opt to exercise the option at the first payment date T_1, i.e. they will pay back the short-term debt and avoid a default if the firm value is higher or at least equal to the threshold W_Q. The determination of the threshold relies on the following consideration: The shareholders will service the debt only if the value of the option is positive at T_{1+}, i.e., immediately after that payment is made ($E_{T_{1+}} > 0$). Thus, the shareholders avoid a default at T_1 if the option value is higher than or at least equal to the required debt service payments: $E_{T_1} - B_1 \geq 0 \Rightarrow E_{T_1} \geq B_1$. By inserting the Black-Scholes formula for a call option (see Black and Scholes, 1973) for E_{T_1} into this formula, we can determine the threshold value at which a default occurs at T_1: The threshold value, W_Q, is the value of W_{T_1}, which turns the resulting formula into an equation:

$$B_1 = W_Q \cdot N_1(d + \sigma_W \sqrt{T_2 - T_1,}) - B_2 \cdot e^{-r_s(T_2 - T_1)} \cdot N_1(d)\,, \tag{4}$$

$$\text{where: } d = \frac{\ln(W_Q / B_2) + (r_s - \sigma_W^2 / 2)(T_2 - T_1)}{\sigma_W \sqrt{T_2 - T_1}}\,.$$

If W_{T_1} is less than W_Q, the right hand side of (4) is less than B_1, i.e., the value of the option is less than the price required to buy it, B_1. In this case, the shareholders refuse to buy the option. If W_{T_1} is greater than W_Q, the value of the option exceeds its price. In this case, the shareholders buy the option, i.e., they service the debt, and no default occurs.

3.2. The Default Probabilities

The default probability, PoD, is the probability that the firm's value at the respective payment date will be below the threshold value. The probability of defaulting is the opposite of the probability of not defaulting, i.e. the probability of surviving, PoS. The default probability is given by (see Delianedis and Geske, 1998):

$$PoD_{t,T_1} = 1 - PoS_{t,T_1} = 1 - N\left(\frac{\ln(W_t / W_Q) + (\mu_W - \sigma_W^2 / 2)(T_1 - t)}{\sigma_W \sqrt{T_1 - t}}\right). \tag{5}$$

Similarly, the joint default probability is the opposite of the joint survival probability, i.e., the probability that the borrower defaults neither at T_1 nor at T_2. In our model, this is the probability that the firm's value exceeds both the threshold at T_1, W_Q, and the threshold at T_2, B_2. This joint probability can be calculated using the two-dimensional standard normal distribution, $N_2(m_1,m_2,\rho)$ (see Delianedis and Geske, 1998). Thus, the joint default probability is given by:

$$PoD_{t,T_1,T_2} = 1 - PoS_{t,T_1,T_2} = 1 - N_2(m_1, m_2; \rho), \tag{6}$$

where: $m_1 = \dfrac{\ln(W_t / W_Q) + (\mu_W - \sigma_W^2 / 2)(T_1 - t)}{\sigma_W \sqrt{T_1 - t}}$,

$$m_2 = \frac{\ln(W_t / B_2) + (\mu_W - \sigma_W^2 / 2)(T_2 - t)}{\sigma_W \sqrt{T_2 - t}}, \text{ and } \rho = \sqrt{\frac{T_1 - t}{T_2 - t}}.$$

The joint survival probability, $PoS_{T_1,T_2,t}$, that a default occurs neither at T_1 nor at T_2 equals the probability that no crisis occurs in the short-run times the probability that no crisis occurs in the long run: $PoS_{T_1,T_2,t} = PoS_{T_1,t} \cdot PoS_{T_2,t}$ (see Delianedis and Geske, 1998). Rearranging shows that we can calculate the probability that no crisis occurs in the long run, $PoS_{T_2,t}$. by: $PoS_{T_2,t} = PoS_{T_1,T_2,t} / PoS_{T_1,t}$. The complementary probability gives the *conditional long-term default probability,* i.e. the probability of default at T_2 given that no default has occurred in the short-run, T_1:

$$P_{T_2,t} = 1 - \frac{PoS_{T_1,T_2,t}}{PoS_{T_1,t}} = 1 - \frac{N_2(m_1, m_2; \rho)}{N_1(m_1)}. \tag{7}$$

4. Estimation of the Model's Parameters

We derive the unknown quantities, i.e. the firm's value and the parameters of its stochastic process, from the observable market values of equity using the pricing Equation (3). If the actual value of the equity, E_t, and the debt service payments, B_i, the payment dates, T_i, and the risk-less interest rate, r_s, are given, the valuation equation can be used to calculate the firm's value, W_t, and volatility, σ_W. More precise, the pricing Equation (3) can be solved either for W_t or for σ_W (iteratively). However, both unobservable values must be estimated simultaneously using only one equation. This requires additional structure. We consider time series data (rather than observations from one date only) and estimate the firm value and its volatility using a maximum likelihood approach. This avoids some drawbacks of alternative approaches as explained below.

4.1. Common Estimation Approaches

One approach often applied uses a second equation (see McQuown, 1993; Delianedis and Geske, 1998). Thus, two unknown quantities can be derived from two equations. For example, the following equation describes the relationship between the volatility of equity (derivative security) and the volatility of the firm, if the equity value is given by Equation (3):

$$\sigma_E = \frac{\partial E}{\partial W}\frac{W}{E}\sigma_W = N_2(d_1 + \sigma_W\sqrt{T_1 - t}, d_2 + \sigma_W\sqrt{T_2 - t}; \rho)\cdot\frac{W}{E}\sigma_W . \qquad (8)$$

This relationship follows from the stochastic differential equation describing the dynamics of the equity value. This stochastic differential equation can be derived by applying Ito’s lemma on a derivative of an underlying – for which the stochastic process is given by Equation (1) (see Merton, 1974):

$$dE = \left[\frac{\partial E}{\partial W}\mu_W W + \frac{\partial E}{\partial t} + \frac{1}{2}\frac{\partial^2 E}{\partial W^2}\sigma_W^2 W^2\right]dt + \overbrace{\frac{\partial E}{\partial W}\sigma_W W}^{\sigma_E E}dZ . \qquad (9)$$

If the volatility, σ_E, of the derivative security could be estimated, Equations (8) and (3) could be solved for the two unknown variables, W_t and σ_W. In the papers mentioned above, the volatility of the derivative security (the equity value) is estimated using a time series of observed values of this security, whereby a sample estimator for the standard deviation is used:

$$\hat{\sigma}^*_{E,N,(\Delta t)} = \sqrt{\tfrac{1}{N}\sum_{n=0}^{N-1}(w_{t-n} - \hat{\mu}^*_{E,N,(\Delta t)})^2} \quad . \qquad (10)$$

Here, $\hat{\mu}^{*}_{E,N,(\Delta t)}$ is the common estimator for the mean of a sample with n elements. This approach implies the assumption that the volatility of the equity, σ_E, is constant. Equation (8) shows, however, that this cannot be true: since under the assumptions of the model σ_W is constant and the other quantities in (8) generally change over time (e.g., because the partial derivative depends on the time to maturity and, thus, changes with declining time to maturity). Thus, σ_E also cannot be constant under the model assumptions. So, the two-equations approach is problematic, because it's the assumptions conflict with the assumptions of the pricing model.

A second important approach applies the (extended) Kalman filter to exploit information from time series data (see, for example, Claessens and Pennacchi, 1996; Keswani, 2000). This application requires a linear approximation of the model equation: The Kalman filter estimates unobservable quantities (e.g. the firm's value and volatility) from a time series of observable quantities (e.g. the market value of equity) – which are covered by some noise. This requires a model to connect the observable quantity (equity) with the unobservable quantity (the firm value) as described in the pricing Equation (3). The Kalman filter was originally designed for linear model equations. Applying the filter to non-linear equations (as Equation (3)) requires a linear approximation, e.g. a Taylor-approximation – which may cause errors. The Kalman filter also relies on certain assumptions which have to be made in addition to the model assumptions explained in Section 3. These concern the distribution of the variables and the noise. First, the error terms – which arise if the model's equation (e.g. the pricing equation) is used to calculate the latent quantities from observable quantities – are assumed to be normally distributed and serially independent. Second, the state variable is assumed to follow an arithmetic Brownian motion. Third, the residuals of the Brownian motion are assumed to be independent from the error terms.

4.2. Maximum Likelihood Estimation of the Model's Parameters

Despite their drawbacks, the approaches explained so far provide interesting results and are widely used and well accepted in the literature. We nevertheless avoid the drawbacks of these approaches by applying the time series maximum likelihood approach proposed by Duan (1994) – who estimated the Vasicek (1977) model for the term structure of risk-free interest rates and insurance contracts for bank deposits. This approach has rarely been applied in the literature and has never been applied to estimate the Geske (1977) model for bank assets. Recently, Duan et al. (2003) applied this approach to estimate the Merton (1974) model for corporate liabilities where the firm's value is determined by the equity value.

If the value of the volatility, σ_W, is known, the firm's value can be calculated by inserting the market value of equity into the pricing Equation (3). This can be done for a time series of market values of equity, E_{t_n} (n = 0,…,N). We obtain a time series of the firm's value, W_{t_n} where the value of σ_W is arbitrary but constant over time. This follows from the assumption regarding the stochastic process (see, Equation (1)), which implies that the volatility, σ_W, is a constant parameter, i.e. it does not change over time.

The estimator of the volatility is chosen by maximization of a likelihood function for the observed time series. Again, we use the assumption on the stochastic process of the firm value, which implies that the growth rates of the firm's value for equidistant time intervals are independently identically normally distributed (see Equation (2)). If the growth rates of the firm's value were observable, the likelihood function which corresponds to the normal distribution would be used. Since the growth rates of the firm's value are not directly observable, but are instead derived from the observable equity values for a given volatility, the likelihood function of the observable equity values – expressed in terms of growth rates of the firm's value – is used. Assuming that the state variable follows the stochastic process described by Equation (1) and that the connection between the state variable and the equity value can be calculated using Equation (3), the log-likelihood function is given by (see Duan (1994)):

$$LLF = \sum_{n=0}^{N-1} -\ln(\sqrt{2\pi}) - \ln(\hat{\sigma}_{w(\Delta t)}) - \frac{1}{2}\left(\frac{w_{t-n} - \hat{\mu}^{*}_{w,N,(\Delta t)}}{\hat{\sigma}_{w(\Delta t)}}\right)^{2} - \sum_{n=0}^{N-1} \ln\left(\frac{\partial E_{t-n}}{\partial W_{t-n}}\right) - \sum_{n=0}^{N-1} \ln W_{t-n} \,. \quad (11)$$

In Equation (11) the firm value W_{t_n} and its observed growth rates w_{t_n}, their mean μ_w and their standard deviation σ_w and the values of the partial derivative of E_{t_n} with respect to W_{t_n} are required. If pricing Equation (3) is used, the partial derivative can be calculated by:

$$\frac{\partial E_{t_n}}{\partial W_{t_n}} = N_2(d_1 + \sigma_W \sqrt{T_1 - t}, d_2 + \sigma_W \sqrt{T_2 - t}; \rho) \,. \quad (12)$$

The standard deviation of the time series can be determined using Equation (2) and the value of the volatility parameter σ_W:

$$\hat{\sigma}_{w(\Delta t)} = \sigma_W \sqrt{\Delta t} \,. \quad (13)$$

The mean is estimated from the observed growth rates by:

$$\hat{\mu}^{*}_{w,N,(\Delta t)} = \frac{1}{N} \sum_{n=0}^{N-1} w_{t-n} \,. \quad (14)$$

To find the best estimator for the volatility, the (initially) arbitrary volatility value is iterated. For each volatility value, the corresponding time series of growth rates of the firm's value is calculated using the observed time series of the market values of equity. The necessary input data, i.e., the partial differential and the parameters, are then calculated. Finally, the value of the likelihood function (11) is determined for each volatility value. The volatility value that yields the maximum value of the likelihood function is chosen as the estimator. The corresponding time series for the firm's value, W_{t_n}, provides the estimation for the values of the firm. The estimator for the drift parameter, μ_W, is derived from the mean estimator using Equation (2):

$$\hat{\mu}_W = \frac{\hat{\mu}^*_{w,N,(\Delta t)}}{\Delta t} + \frac{\hat{\sigma}^2_W}{2}. \tag{15}$$

Having specified the time series of the firm value and the corresponding parameters for volatility and drift, we can estimate the default probabilities as explained in Section 3.3.

5. Empirical Application: The Banking Crisis Risk in the United States

This section applies the model and the estimation approach outlined in the previous sections to derive banking crisis risk indices for the United States in two steps. First, we estimate the individual default probabilities for the major banks in the considered countries. Second, we average these default probabilities to estimate the banking crisis risk for the country as a whole.

5.1. Input Data and Estimation Procedure

To estimate the default probabilities of banks with our structural model the following input data are required: the market value of equity, data on the amount of liabilities, their term structure, and the risk-less interest rate. This section discusses the availability of this data and how we used them to specify the input parameters for the model estimation. All data are drawn from Thomson Financial's Datastream®.

The value of the option E_t at a specific date t is given by the market capitalization of a banks equity, which is provided by Datastream in daily frequency. Datastream also provides information about banks' liabilities. Although the Geske approach would enable us to consider every single debt service payment required, such exact data on the debt service payments is not available. The available data only enables us to distinguish between short-and long-term liabilities.[2] Although a more detailed consideration of debt service payments would be preferable, even distinguishing between short- and long-term debt, however, advances the existing literature on banking crisis risk. The existing literature (see the discussion in Section 2) typically relies on the single-payment assumption where only one payment date is considered. Nevertheless, this approach is well-accepted and applied in many important contributions that provide interesting results. Our approach improves risk assessment since it captures the influence of the term structure of liabilities on default risk. Applying a stringent model, it also enables us to estimate short-term and long-term default risk which may be influenced by different factors. Due to different contracts and consumer portfolios, each bank's debt has its own maturity. In the application, we apply an average maturity for both short-term and long-term debt. We assume that the maturity of short-term liabilities is one year.[3] The maturity of long-term debt is assumed to be three years on average.

Short- and long-term debt must be assigned a risk-less interest rate. Geske (1977) specifies the model with identical risk-less interest rates for all maturities. It is possible, however, to consider different rates for different time spans between the observation date and the date of maturity (see, for example, Delianedis and Geske, 1998). We use the term structure of interest rates (derived from government bonds) of the United States to derive the interest rates for the short-term and long-term maturity, i.e. one-year and three-year interest rates.

Market data, as interest rates and stock market data are provided in daily frequency. Data on the debt structure is updated only annually. In the application, we derive time series in daily frequency since we are interested in the most current assessment of default risk. We

[2] As Datastream also other data providers (Bankscope, Bloomberg) only provide data that distinguish between short-term and long-term payments. More detailed data is not available.
[3] Papers applying the basic Merton (1974) model to forecast bank default typically assume a maturity of one year debt for the short-term debt and do not distinguish between short- and long-term default probabilities.

consider daily time series of interest rates and market values of equity inferred from stock prices. The liability information is updated at the beginning of the respective year, when the information becomes available. Since annual data provided by Datastream® refers to the end of each year, we apply these end-of-the-year values to the following year.

We only include variables for a specific date that are observable at these specific dates and not data that became observable at later dates. Thus, our approach is applied as a tool for forecasting banking crises. Since we only use data available at a specific date in the past where the forecast is made, we obtain the same estimates of crisis risk than those that would have occurred by applying the approach at these past prognosis dates. The results are not biased by including data of variables that became observable at later dates. We do not interpolate the liability values since this implies that values for the next year (or the end of the respective year) must be known.

In the following we discuss the results of applying our approach to the United States' banking system. In the discussion of the results we mainly focus on the crisis period 2007-2009. Since the required data are available for the most banks for longer time periods we also consider data for the pre-crisis years. Until the financial crisis the US banking system was characterized by the existence of pure investment banks, on the one hand, and more or less pure commercial banks, on the other. To paint a complete picture, we include the most important players of each category in our estimation of the US banking crisis risk. These are the most important commercial banks, Bank of America, Citibank, JPMorgan Chase & Co. and Wells Fargo, and most important investment banks, Bear Stearns & Co., Merrill Lynch & Co., Morgan Stanley, Lehman Brothers and Goldman Sachs Group. Additionally we consider the two important mortgage banks, Fannie Mae and Freddie Mac.

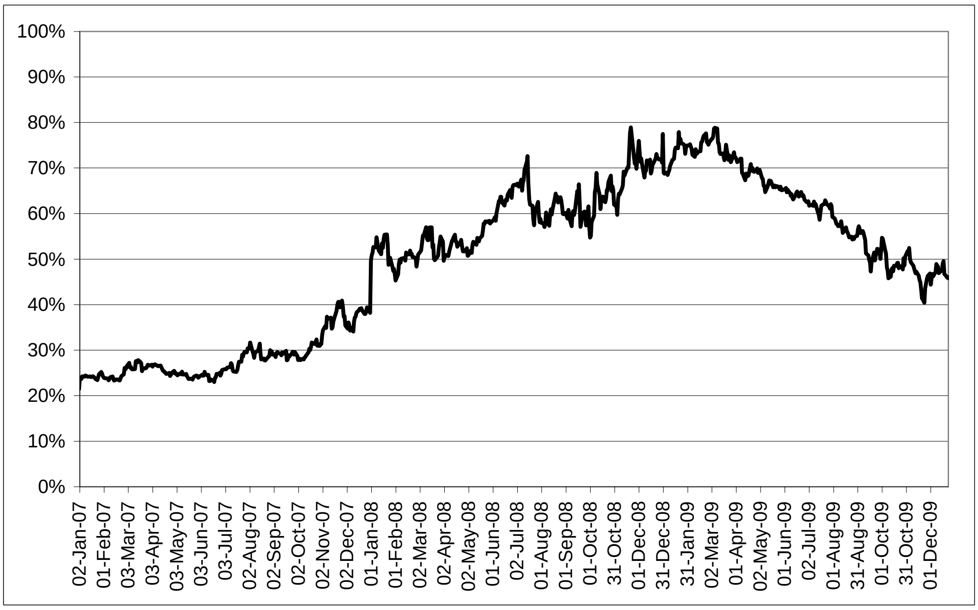
The Geske (1977) model allows us to estimate a term structure of default risk rather than a single default probability. We, thus, can calculate short-term default risk and the overall default probability, i.e., the risk that the bank will default either on its short-term liabilities at T_1 or on its long-term liabilities at T_2. We further estimate the (conditional) long-term risk, i.e., the probability that the bank will default on its long-term liabilities given no default at T_1. Using the estimation procedure explained in the last section we infer a market data based assessment of default risk for every bank on an individual level. By calculating the (weighted) average we provide an indicator for the US banking crisis risk. In the averaging of the bank individual data we use the total bank assets as weights to control for the importance of the considered banks.

5.2. The Overall Crisis Risk for Entire United States' Banking System

This section discusses our results for the *overall banking crisis* risk in the United States, i.e. the joint risk of suffering a banking crisis in the short-run or in the long-run. The overall banking crisis is determined by averaging the *bank individual overall default probabilities* for the banks mentioned above, which are calculated using Equation (6), i.e. the probability of defaulting at the short-run or at the long-run. Figure 1 displays the total risk indicator for the crisis years 2007-2009. The dots on the line represent overall crisis risk indicator at the corresponding dates on the x-axis.

By end of June 2007, i.e. on the onset of the international financial crisis the crisis risk for the US banking system started to rise. The increase within 2007 was caused by deteriorating stock prices of the banks since the nominal value of outstanding debt used in the calculations did not change till the beginning of 2008. It shows that the use of market data in crisis prediction enables us to build a quickly reacting risk indicator, in particular in comparison with forecasts based on balance sheet information. The average of overall default probabilities increased to more than 30% at the end of July 2007. By the end of November, the overall default probability rose to almost 40%, reflecting a deepening of the crisis and growing uncertainties about the future of the US economy and especially the banking system.

Figure 1: Indicator of Overall Banking Crisis Risk for the US in the crisis years 2007-2009



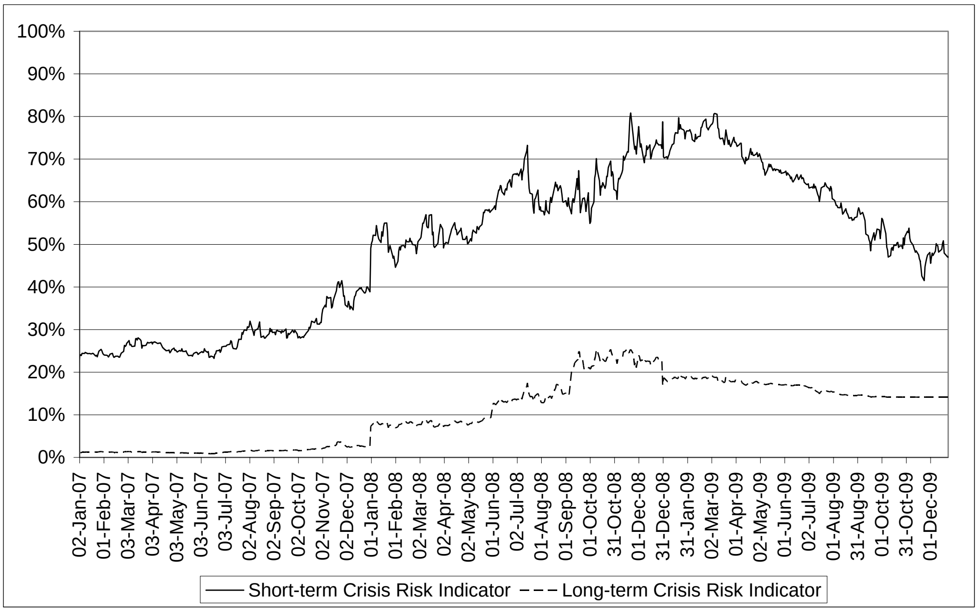
At the beginning of 2008, we observe a jump in the crisis risk to over 50%. This jump is a result of new information on the liabilities rather than stock prices, since at this date the annual liability data included in the estimations is up-dated. It clearly shows the influence of the liabilities and the liability structure on crisis risk. In January 2008, the overall crisis probability decreased somewhat because of stock market information. In February the crisis risk started to rise again – despite of the enacting of the US "economic stimulus act of 2008" – and reached a temporary pike at mid March. At this time the first major bank, Bear Stearns & Co., was de-facto bankrupt and was rescued from de-jure bankruptcy only by JPMorgan Chase's takeover. At this time also rumours about problems of Lehman Brothers were afloat. Till mid of July the risk increased further reaching levels of over 70%. In the following period the value of bank stocks increased somewhat (after heavy losses in the first half of the year). Thus, the banking crisis risk indicator decreased to 60%. In September, however, the crisis became even worse: Fannie Mae and Freddie Mac were de facto bankrupt and overtaken on

September 7 by the Federal Housing Finance Agency, a governmental institution. Lehman Brothers became de-jure bankrupt on September 15, when also Merrill Lynch & Co. was overtaken and rescued from formal bankruptcy by Bank of America. Triggered by these events, the crisis risk started to rise again finally reaching levels of 80 % in early November 2008. From March 9, 2009 onwards the risk started to decline to levels below 50 % at the end of 2009.

5.3. The Term Structure of Crisis Risk: Short-term versus Long-term Crisis Probabilities

One of the major advantages of using a compound options approach instead of a Merton type single-payment model is that it enables us to decompose the overall crisis risk into risks for short-term and long-term maturity and, thus, to provide a (simple) term structure of crisis risk. The solid line in Figure 2 displays the short-term crisis indicator, which is the weighted average of the short-term default probabilities of the considered banks calculated by Equation (5). The dashed line displays the conditional long-term crisis risk of the banking system. It results from averaging the conditional long-term default probabilities, i.e. the probability to default in the long-run given that no default has occurred in the short-run. These bank individual probabilities are calculated by Equation (7). As explained in Section 3 the total default probability of defaulting in the short-run or in the long-run, which we discussed in the last subsection, is not the sum of the short-term and long-term default probabilities. Rather there is a multiplicative relation in a sense that the overall probability of survival is the product of short-term and (conditional) long-term probability of survival (for further discussion see Section 3 or Delinanedis and Geske, 1998). This relation is valid for single banks but does not perfectly hold for risk indicators resulting from averaging individual default probabilities.

Figure 2: Short-term and Long-term Banking Crisis Risk Indices for the US in the crisis years 2007-2009



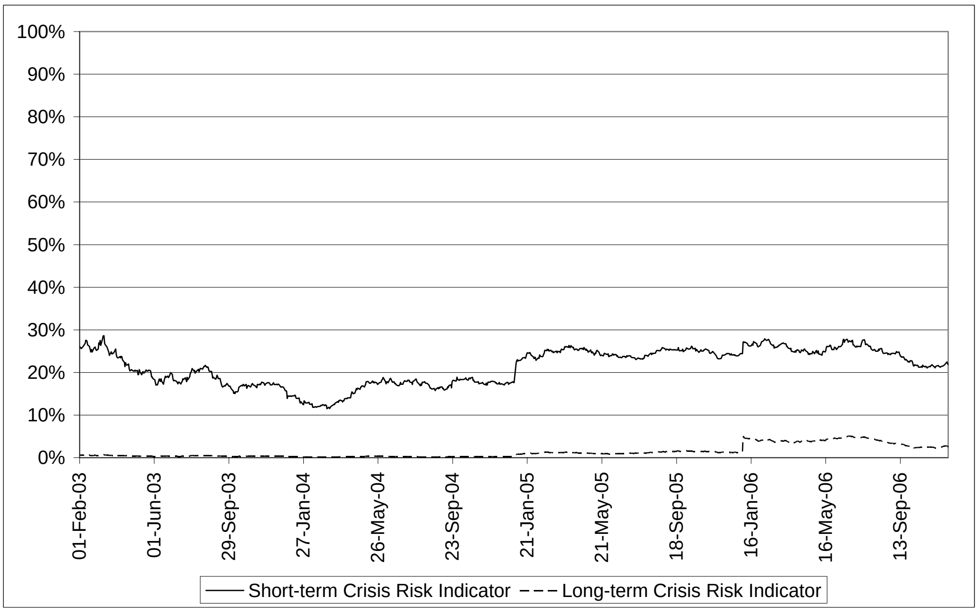
Considering the short-term and long-term risk we find that the high overall crisis risk discussed in the last subsection was driven largely by the short-term risk. The long-term crisis risk (conditional on no default in the short-run) was on a much lower level. The first increase in risk starting in summer 2007 was especially to large extent because of an increase in the short-term default probabilities. Only new balance sheet information included in the calculations at the beginning of 2008 increased the long-term crisis risk. A further deterioration of the long-term perspectives further increased the long-term crisis risk also within the year 2008. In particular the events in September of 2008 increased the long-term crisis risk. With new balance sheet data at the beginning of 2009 the long-term perception of risk started to improve.

The fact that short-term risk is much higher than long-term risk may be seen as evidence that the banking crisis was caused to a large extend from illiquidity than solvency problems. This matches conventional wisdom that banks are especially prone to liquidity risk (see Diamond and Dybvig, 1983) because the major part of there liabilities is short-term. It further provides evidence to the point of view that the existing problems in the mortgage market, which in fact impact the banks' solvency, where outranged by the liquidity problems. This liquidity issue was the major problem (for the majority of banks), which was only triggered by the doubts about solvency (because of problems in the mortgage market). Thus, our findings support the view that by injecting liquidity and actions to restore confidence the Federal Reserve and the US government undertook the right action during the crisis.

5.4. The Risk in the Pre-crisis Period

Although our main focus is on the crisis period, we also consider the pre-crisis years. Figure 3 shows the respective results for the time since 2003. In the aftermath of the dotcom crisis the banking crisis risk in 2003 was on a relatively high level. During this time the overall crisis risk indicator is driven almost exclusively by the short-term default probabilities. Contrary to the crisis of 2007 and the following years, the long-term crisis risk was close to zero, meaning that almost no solvency problems are observed. Problems are more or less pure liquidity problems. In the following years the banking crisis indicator started to decline to levels of about 12%. This level of crisis risk in the relatively tranquil period 2004 may reflect the well-known theoretical result of the Diamond and Dybvig (1983) model that banks and banking systems always face a considerable liquidity-driven default risk since the major part of their liabilities is short-term, whereas a large part of their assets consists of long-term investments. In the pre-crisis years 2005 and 2006 the crisis risk increased somewhat, in particular the long-term perspectives worsened slightly.

Figure 3: Short-term, and Long-term Crisis Risk Indices for the US in the pre-crisis years



5.5. Defaulters versus Non-Defaulters

Another interesting question regarding the assessment of crisis risk is whether or to what extent our estimation approach enables us to distinguish between good and bad banks, i.e. the banks that survived the crisis as independent entities and those that did not survive. To analyze this issue we calculated two sub-indices of crisis risk resulting from grouping the banks into a non-defaulter and defaulter group. The first resulted from the banks that finally survived the crisis as independent entities. These are six banks, Bank of America, Citibank, Goldman Sachs, JPMorgan Chase & Co., Morgan Stanley and Wells Fargo. The second group comprises all banks that did not survive, be it because of a formal act of bankruptcy, as in the case of Lehman Brothers, or since they ran into problems and were overtaken by a competitor (Bear Stearns and Merrill Lynch) or a US governmental institution (Fannie Mae and Freddie Mac).

Figure 4: Joint Banking Crisis Risk Indices for the Default and Non-default Group

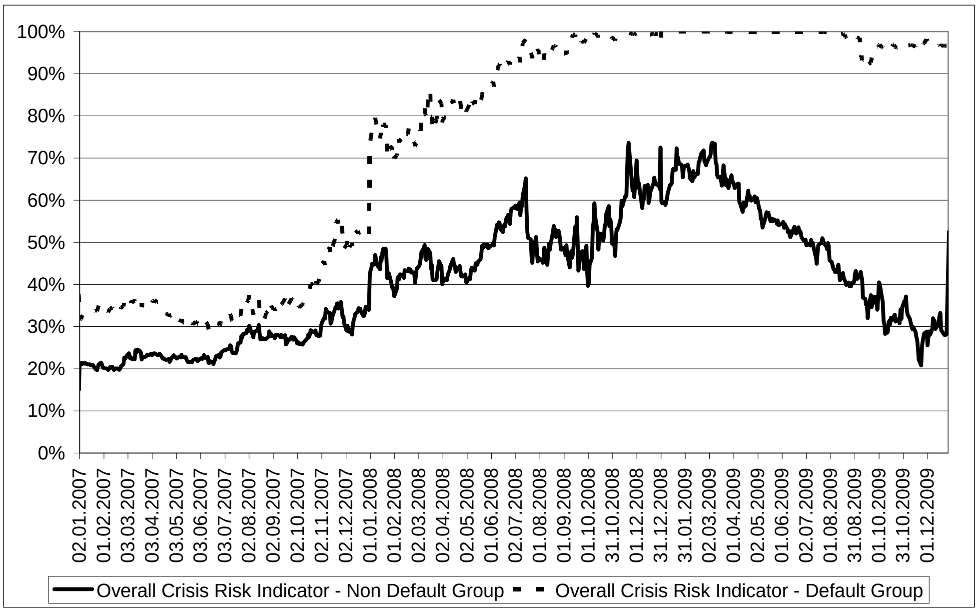
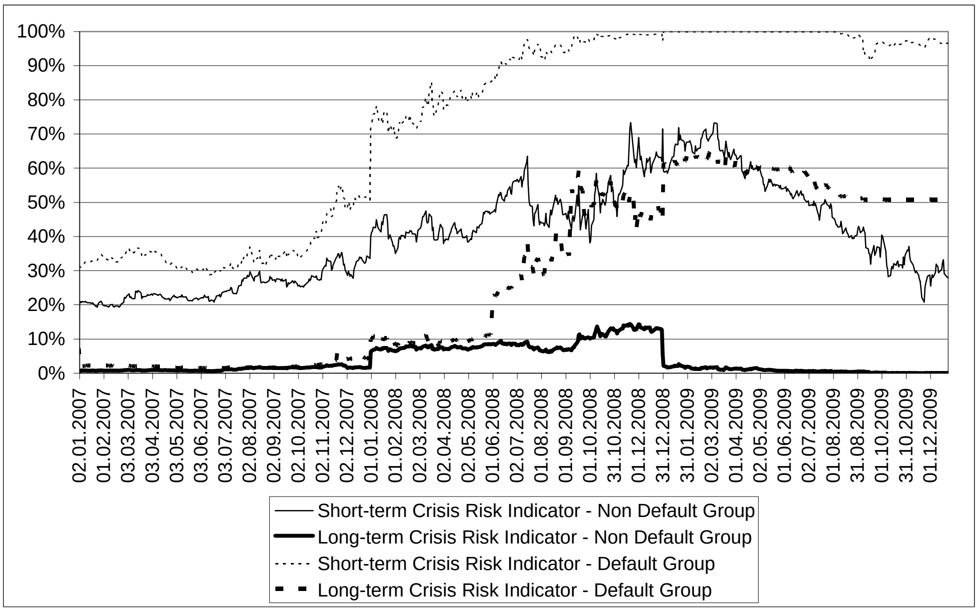


Figure 4 shows the overall crisis risk indicator for both groups. It can be seen that the crisis index for the defaulters is considerably higher than that of the non-defaulters at each date. Whereas in summer 2007 the difference is rather small, the increase in crisis risk in autumn 2007 is much stronger in the defaulter group. Since the liability data is not up-dated at this time the stronger increase in estimated crisis risk results from a stronger decrease in stock prices. One could interpret this result as evidence that stock markets perceived the inferior situation of the (finally) defaulting banks which became worse more rapidly than in the other group. Already at the end of 2007 the risk index of the defaulter group is on a level of more than 50%. Including new balance sheet data for the liabilities at the beginning of 2008 increases the risk index even more to levels close to 80%. In early March 2008, when Bear Stearns & Co. was close to bankruptcy, the risk index is above 85%. The situation worsened till July, when the perceived risk is well-above 90%. This clearly indicates the upcoming defaults of the included banks that occurred in September 2008 when the default risk materializes and the risk index is almost 100%. The perceived risk of the non-defaulter group is much lower. Even in summer 2008 it is far from the high values of the defaulter group, varying around 50%. Only in autumn 2008 when the most of the defaults of the bad banks have occurred the perceived crisis risk in the non-defaulter group was about 70%. But it starts to decrease in early 2009 and reached rather moderate levels at the end of the year.

Figure 5: Short-term and Long-term Banking Crisis Risk Indices for the Default and Non-default Group



In Figure 5 we provide the results for the short-term and long-term crisis risk index of both groups. It can be seen that both types of crisis risk are higher for the group of defaulters. Starting in autumn 2007 the short-term risk in the defaulter group increases much faster than the risk in the non-defaulter group. The most striking feature in this figure is that the long-term risk increases much stronger in the defaulter group within 2008. Thus, according to our model the situation in the defaulter group is not only inferior to the non-defaulters in the short run, but also the long-term perspectives of the defaulter group are clearly inferior and became worse during the crisis. For the non-default banks, by contrast, the long-term perspectives decreased only gradually in 2008 and became much better again in 2009. This may be seen as indication that they faced rather a short-run or liquidity problem – maybe caused by losses of confidence because of the problems of the defaulting banks – rather than long-term or solvency problem.

6. Conclusion

We apply the Geske (1977) compound option model to derive banking crisis risk indices for short-term and long-term risk in addition to a total crisis risk index for the US banking system from stock prices of the major US banks. Market data-based risk assessment is well-suited to signal an imminent banking crisis due to its high frequency and forward-looking nature. By distinguishing between short- and long-term default risk, it is possible to determine whether short-term liquidity problems or long-term solvency problems exist.

Applying the Duan (1994) maximum likelihood approach to estimate the model, we obtain several interesting results. After a period of low crisis risk in the middle of the decade we observe a slight increase in the years before the current crisis (2005 and 2006). In 2007 the risk starts to increase considerably, especially from end of June 2007 onwards. At the beginning of 2008 it was above 50% and in September 2008 above 60%. By distinguishing between surviving and non-surviving banks we find that banks which ran into problems and became bankrupt or were overtaken have a considerably higher crisis risk. Here the risk index is close to 100% already in July 2008, i.e. before the majority of defaults or rescue mergers occurred in September 2008.

The results of the compound options approach with respect to separate information on short-term and long-term crisis risk show that the high and strongly increasing total crisis risk in the entire system is driven mainly by short-term crisis risk in 2007. The long-term crisis risk (conditional that no default occurred in the short-run) also increased during the crisis, especially from 2008 onwards, but remains on lower levels. With respect to good versus bad banks our results indicate that there were considerable differences not only in the amount, but also in the composition of crisis risk between banks that did not survive the crisis and the surviving banks. Both types of risk are considerable higher for the non-surviving banks. The long-term or solvency risk increases dramatically for the non-surviving banks, whereas it remains on rather low levels for the banks that finally survived the crisis. Whereas our results indicate that the non-surviving banks faced serious long-term problems in addition to short-term problems, the problems in the surviving group were rather short-term liquidity problems. This is in line with the basic bank (crisis) theories that even sound banks are prone to substantial default risk because of liquidity problems in crisis situations.

By indicating the importance of liquidity problems (even for solvent banks) our results underpin that measures to ease these liquidity risks would be an important step towards a less risky future of international banking system. Of course, liquidity risk is an inherent risk of the banking industry (see Diamond and Dybvig, 1983), but the problem could be eased to some extend by regulatory measures. Especially, improving the amount of equity in relation to liabilities could lower the banking crisis risk in the future.

Our results may be interpreted as support for the thesis that the Federal Reserve took a good approach by providing liquidity to the markets to ease the liquidity issue, which finally saved the sound banks that were not conflicted by major solvency problems. The stock market data based compound option approach proposed here makes it possible to provide detailed information on short-term and long-term risk in high frequency. Thus, it may be a useful tool that could be applied by central banks and supervising agencies in addition to their traditional balance-sheet-based approaches as early warning system for upcoming difficulties.

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