The current issue and full text archive of this journal is available on Emerald Insight at:
www.emeraldinsight.com/0969-9988.htm

A method to evaluate credit risk for banks under PPP project finance

Xiuqin Wang, Lanmin Shi, Bing Wang and Mengying Kan
College of Management and Economics, Tianjin University, Tianjin, China

Received 20 June 2018
Revised 10 January 2019
Accepted 21 July 2019

Abstract

Purpose – The purpose of this paper is to provide a method that can better evaluate the credit risk (CR) under PPP project finance.

Design/methodology/approach – The principle to evaluate the CR of PPP projects is to calculate three critical indicators: the default probability (DP), the recovery rate (RR) and the exposure at default (EAD). The RR is determined by qualitative analysis according to Standard & Poor's Recovery Scale, and the EAD is estimated by NPV analysis. The estimation of the DP is the focus of CR assessment because the future cash flow is not certain, and there are no trading records and market data that can be used to evaluate the credit condition of PPP projects before financial close. The modified CreditMetrics model and Monte Carlo simulation are applied to evaluate the DP, and the application is illustrated by a PPP project finance case.

Findings – First, the proposed method can evaluate the influence of the project's cash flow uncertainty on the potential loss of the bank. Second, instead of outputting a certain default loss value, the method can derive an interval of the potential loss for the bank. Third, the method can effectively analyze how different repayment schedules and risk preference of banks influence the evaluating result.

Originality/value – The proposed method offers an approach for the bank to value the CR under PPP project finance. The method took into consideration of the uncertainty and other characteristics of PPP project finance, adopted and improved the CreditMetrics model, and provided a possible loss range under different project cash flow volatilities through interval estimation under certain confident level. In addition, the bank's risk preference is considered in the CR evaluating method proposed in this study where the bank's risk preference is first investigated in the CR evaluating process of PPP project finance.

Keywords Optimization, Engineering, Risk management, Simulation, Estimating

Paper type Research paper

Introduction

Numerous public infrastructure projects have been carried out by PPP model worldwide, where responsibilities, risks, rewards are substantially reallocated between public and private sectors (Zhang, 2005; Akintoye and Ezekiel, 2005). Under PPP model, a project company is usually set up by the private party, namely, special purpose vehicle (SPV) to finance, construct and operate the PPP project (Akintoye *et al.*, 1998; Bing, Akintoye and Hardcastle, 2005; Wang, Zhang, Wang and Feng, 2018; Yescombe, 2014). The maturity for substantial debt in PPP projects is usually longer than ten years, and the sponsors expect to separate their existing assets outside of the project from the repayment risk during the debt repayment period (Bing, Akintoye, Edwards and Hardcastle, 2005; Cheung and Chan, 2011; Wang *et al.*, 2007). The long maturity and limited recourse or non-recourse demand in PPP projects make conventional corporate finance seem rather limited, hence resulting in the preference for project finance (Sorge, 2004).

Project finance is the main financing model for PPP projects, under which the lending bank has no or limited recourse to the sponsors of the PPP project, and debt repayment mainly depends on cash flow during project operation period (World Bank, 2014). However, the cash flow of the PPP project is hard to predict, due to numerous project risk factors and long maturity (Beidleman *et al.*, 1990; Wang *et al.*, 2000, 2004; Zayed and Chang, 2002; Zhang *et al.*, 2016). Grimsey and Lewis (2002) argued that the uncertainty of predicted revenues does great harm to project viability, and the party providing the financing will bear the consequence because cash flow from the project is the source to service their loans

Engineering, Construction and Architectural Management
Vol. 27 No. 2, 2020
pp. 483-501
© Emerald Publishing Limited
0969-9988
DOI 10.1108/ECAM-06-2018-0247

(Finnerty, 2007). The lending banks do need to properly evaluate the credit risk (CR) of PPP projects under project finance.

Many CR evaluation models have been developed by financial institutions and agencies, which are mainly used in the corporate finance. However, project finance is vastly different from traditional corporate finance (complete recourse), which leads to the fact that the traditional CR assessment methods are not entirely applicable to PPP project finance due to the unique characteristics of PPP project finance. In addition, the newly established SPV has no historical credit data including financial data and credit records, which makes the traditional CR evaluation methods no longer applicable. Therefore, for banks, how to scientifically invest in PPP projects and how to comprehensively evaluate the CRs under PPP project finance is rather significant. It is undoubtedly necessary and urgent to develop a quantitative CR evaluation model for banks to decide whether or not to lend money to PPP projects under project finance.

The aim of this research is to provide a method that can better evaluate the CR under PPP project finance. Since the evaluation model is developed to serve the banks on loan decision making, it is obvious heterogeneity in the banks (risk tolerance and preference) should never be ignored so as to make the model developed more conditional on banks with different CR consideration.

This paper begins with literature review about traditional CR evaluation models. Next, detailed introduction on the advanced method under PPP project finance with the CreditMetrics model and Monte Carlo simulation (MCS) is provided. Then, an extension model based on the evaluation method has been developed which can be applied to explore the relationship between default probability (DP) and repayment schedule. Finally, a real case analysis with MCS technique is conducted to illustrate how to put this method into practice and some managerial insights for the banks to fund PPP projects are provided.

Literature review

Some researchers have studied bank lending under PPP project finance, and it was found that guarantees and political risks critically impacted on loan spreads (Blanc Brude and Strange, 2007; Girardone and Snaith, 2011; Bouzguenda, 2014; Buscaino *et al.*, 2012). They also pointed out the lenders relied on risk allocation in a contract's network and cash flow predictions to make lending decisions (Corielli and Steffanoni, 2010). This demonstrates that guarantees, political risks and the abundance of cash flow are all vital factors when it comes to making lending decisions, particularly with regard to evaluating CRs. Besides, Sorge (2004) also argued that the timing and the uncertainty of cash flow in the future also have a great influence on the CR. The cash flow in the future always represents the profitability of the PPP projects which will affect the probability of default (Lehlou *et al.*, 2014). For this reason, the uncertainty is vital for lenders to evaluate the CR (Donkor and Duffey, 2013).

The value of several project revenue configurations under the government guarantee and revenue-sharing strategies have been priced as real options in literature (Wibowo, 2004; Brandão and Saraiva, 2008; Ashuri *et al.*, 2011; Wang, Cui and Liu, 2018). Wibowo (2004) argued that while the government guarantee can help to attract the private investor, the contingent liabilities of government are increased when issuing guarantees. Brandão and Saraiva (2008) studied the option value of the minimum traffic guarantee in infrastructure projects. Ashuri *et al.* (2011) proposed a risk-neutral pricing approach to evaluate the value of the minimum revenue guarantee in BOT highway projects. Brandão *et al.* (2012) investigated the minimum demand guarantee in Metro Line 4 of the São Paulo subway system. Wibowo *et al.* (2012) set up a contingent liability model to evaluate the value of land cost guarantee and political risk guarantee. Li *et al.* (2017) studied the credit default swap (CDS) option, and proposed a risk-neutral valuation method to price the CDS. From the perspective of risk sharing, Wang, Cui and Liu (2018) argued that the minimum revenue guarantee value should be shared between the government and the private sector and derived the optimal distribution ratio which can satisfy both parties. It can be seen that those previous studies mainly focus on evaluating the option value of government guarantee from the perspective of the private sector and the government. Though banks can also have a better knowledge about the value of the project revenue configuration, the question how to evaluate the CR of PPP projects is still unresolved, which is the main concern for the bank to make lending decision.

Existing methods to evaluate the CR are mainly used in the corporate financing, e.g. KMV model, CreditRisk+ model, Credit Portfolio View model (McKinsey model). A neural net approach is also used to assess the CR of company (Tam and Kiang, 1992; Mcleod *et al.*, 1993). The basic idea of the KMV model is the option pricing model and risk neutrality, which is a CR assessment method based on analysis of stock market data. The CreditRisk+ model assumes that the default process is a Poisson distribution and estimates the portfolio default risk. The Credit Portfolio View model (McKinsey model) emphasizes the impact of economic conditions on CR, which is mainly used to estimate defaults and credit changes in a country or an industry. To use those above methods, the company's trading records or market data are necessary. While for PPP projects, the newly established company (SPV) has no trading records and market data before financial close (implementing the source of project construction funds) (Bing *et al.*, 2005; Yescombe, 2014). Therefore, the above credit evaluating methods which mainly rely on a company's previous trading data are no longer appropriate to evaluate the CR of PPP project finance (Kong *et al.*, 2008; Iyer and Purkayastha, 2017).

The real options analysis method can be used to price risk in infrastructure, in which the value of the project is assumed to follow a continuous diffusion process. Based on the seminal work of Leland and Toft (1996) and Leland (2012), the DP of the project can be mathematically derived. However, the real options analysis method partly ignores the characteristics of PPP project finance, and because it is a risk-neutral pricing method (Leland and Toft, 1996; Leland, 2012), the risk preference of the lending banks is not considered.

As another classical method, the CreditMetrics model takes into consideration dynamic credit rating changes, which is very much in line with the characteristics of project finance projects with large uncertainties. Besides, the credit rating transition matrix in this model can achieve probability calculation of credit rating changes in every year rather than just the beginning and the end of the loan period. In this way, the CreditMetrics model is more effective for process control of long-term PPP project finance. What is more, many institutions will publish the credit rating transition matrix, which makes up for the lack of historical data in PPP projects. At the same time, project information can be used as a correction factor to modify the basic credit rating transition matrix to be consistent with specific PPP projects. Therefore, we can see that the credit transfer matrix is especially suitable for PPP projects.

Although previous studies identified several factors that influence the CR of PPP projects, how to systematically evaluate the CR in PPP project finance has not been investigated, except the preliminary work of Kong *et al.* (2008), which analyzed the CR by calculating default exposure and DP according to potential credit rating change. However, the recovery rate (RR), which is also an important factor to assess the CR (Altman *et al.*, 2004; Scannella, 2012), was not taken into consideration. Standard & Poor (2014) also provided advice on these three elements, which demonstrates the importance of RR. In addition, the uncertainty of the project cash flow is not considered in the preliminary work of Kong *et al.* (2008).

Besides, Kong *et al.* (2008) judged the CR with the quantitative model only from the perspective of the specific project, neglecting the differences among the lending banks. It is necessary for a complete and scientific CR assessment model to take into account the uniqueness of the lending bank itself, e.g. the fact that the banks have different risk preferences.

Improved in this way, each lending bank can make lending decision under PPP project finance according to calculated CR range. Advance in this direction will be conducted to propose a method to better evaluate the CR of PPP project finance.

There are several prominent contributions in this research to advance the previous studies. First, taking into consideration of the uncertainty and risks of long-term and non-recourse or limited recourse under PPP project finance, MCS technique is adopted to predict the future cash flow and simulate the probability distribution of CR based on the input project financial variables, after which a possible loss range under different project cash flow volatilities can be provided through interval estimation under a certain confident level. Second, the bank's risk preference is also taken into consideration, so that the bank can make lending decision under PPP project finance according to its own preference. Besides, an extended model based on the evaluation method has been developed which can be applied to explore the relationship between DP and repayment schedule, providing suggestions for banks to optimize the repayment schedule.

CR evaluation model

As the lender in PPP project finance, the bank should pay more attention to the CR assessment due to the characteristics of long-term and no recourse or limited recourse. According to previous research, three key indicators to evaluate the CR of PPP projects are the DP, the RR in the event of default and the exposure at default (EAD) (Altman *et al.*, 2004; Scannella, 2012). The DP refers to the probability that the borrower fails to repay according to the contract, and it can be estimated with CreditMetrics model. The RR represents the portion of loss that can be recovered with insurance or asset liquidation in the event of default. The EAD can be interpreted as the debt that borrowers cannot repay according to repayment schedule, and it can be calculated by net present value (NPV) analysis with cash flow estimation.

In general, the DP is a variable directly related to the specific transaction parties, which is mainly determined by the credit rating of the debtor as the transaction party. Instead, the EAD and RR have the characteristics associated with a specific transaction rather than the parties, which is to say, they can be determined by the specific design and specific contract terms, such as the mortgage, guarantee and so on, rather than merely influenced by the debtor's credit rating.

The relationship between the CR and these three indicators can be expressed in Equation (1), and the process to evaluate the CR of PPP projects has been provided in Figure 1:

$$CR = EAD \times DP \times (1-RR). \tag{1}$$

As is shown in Figure 1, the complete CR assessment model can be divided into three sub models for calculation of three indicators, respectively. The input of the model is the financial indices and project information of specific projects and the output will be the probability distribution of CR.

The estimation of PPP project finance DP is the focus of CR assessment, and it is also the focus of this research. This paper will estimate the probability distribution of PPP project financing DP through CreditMetrics model and MCS based on the input distribution of project financial variables. EAD can be quantified by NPV analysis based on the loan repayment schedule. As for the default RR, many institutions such as Standard & Poor's have made suggestions for the estimation under project finance. Recommendations on the estimation of default RR will be provided based on the input project information with the help of existing project finance studies. Once these three important parameters are determined, the CR of project financing can be estimated.

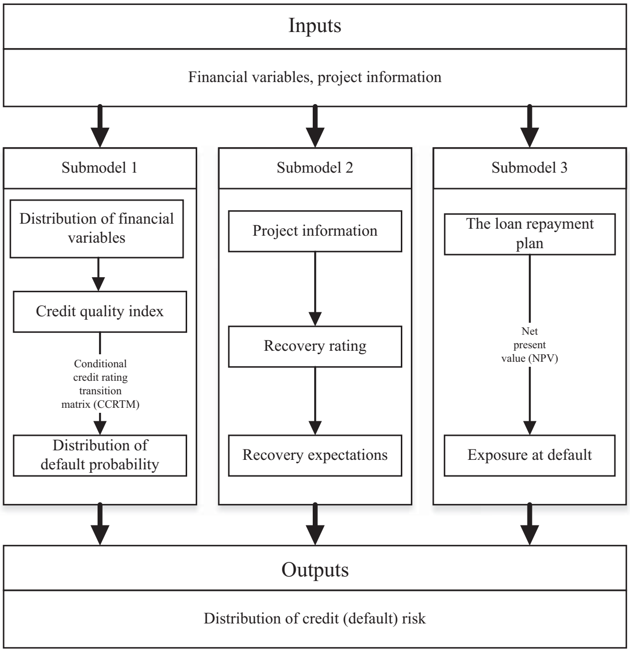

Figure 1.
The process of the credit risk evaluation model

Determining the EAD

As for the sub-model 3 in Figure 1, the EAD represents the maximum loss at default, and it is estimated by calculating how much money is still not repaid when the default occurs. In detail, assume that the repayment period is n years, and the repayment is d_j at jth year. If the borrowers cannot afford to repay at ith year, the default loss can be calculated by the following equation:

$$EAD_i = NPV_i = \sum_{j=i}^{n} \frac{d_j}{(1+r_j)^j} \quad \text{for } j = 1, 2, \ldots, n, \tag{2}$$

where EAD_i is the present value of the money after default occurs in year i; r_j is the discount rate at jth year.

Determining the RR

As for the sub-model 2 in Figure 1, RR needs to be estimated. Standard & Poor has suggested that the RR of project should be considered from asset terms and condition, liquidation value, availability of collateral and capital structure (Standard and Poor, 2014). The term and conditions of assets play an important role in assessing the value of the project assets, which also affects the liquidating value of the assets at the time of default. The liquidation value considers whether the assets can be converted into liquidity in time to meet the needs of the debt repayment. The availability of collateral is very common for PPP project finance, which is an important measure to protect interests of creditors such as banks when default occurs. The effect of capital structure on the RR of default is mainly in the debt level, namely, the higher priority debt will bring up less risk and the corresponding RR will be higher.

Besides, credit enhancement is also essential to estimate the RR of PPP project finance. In the project finance loans, guarantees and commitment are important aspects for banks to evaluate the risk (Kleimeier and Megginson, 2000). Compared with conventional company finance, credit enhancement is more common in PPP project finance (Bouzguenda, 2014). Chowdhury *et al.* (2015) conducted a research on the credit enhancement factors and pointed out that the shareholders' credit enhancement and host government's credit enhancement are two of the most important factors. These credit enhancements always affect the compensation for banks at the default (Kleimeier and Megginson, 2000; Chowdhury *et al.*, 2015).

In sub-model 2, after the project information discussed above is obtained, the recovery rating can be determined by qualitative analysis according to Standard & Poor's Recovery Scale in Table I. and RR can be estimated consequently.

Determining the DP

The CreditMetrics model

The CreditMetrics model is developed by some large international banks, e.g. JP Morgan. It has been widely used to assess the CR of a company by considering its credit rating changes. The basic idea of CreditMetrics model is that the operating state of a company follows a Markov process, namely, for a discrete random sequence $\{X_n\}$, the value of X_{n+1} is mainly related to the previous state X_n. Besides, the CR depends on the borrower's credit status, and the credit status of the company is determined by the assessed credit rating, which means CR comes directly from changes in company credit ratings. What is more, credit evaluation system is effective, which means the impact of credit events on their repayment performance capabilities can be reflected in changes in credit ratings. Therefore, the basic method of the model is the analysis of changes in credit ratings.

Assume the credit rating sequence is $R = \{r_1, r_2, \ldots, r_m\}$. r_1 is the lowest rating, namely, default, and r_m is the highest rating (e.g., by Moody's convention, this would be "Aaa"). R_t is the credit rating at time t. The probability that the grade of project company is r_j at time t+1 (i.e. $R_{t+1} = r_j$), on the condition that the grade is r_i at time t, (i.e. $R_t = r_i$) is labeled as $\lambda_{i,j}^t$:

$$\lambda_{i,j}^t = P\{R_{t+1} = r_j | R_t = r_i\}. \tag{3}$$

Thus, the credit rating transition matrix at time t can be seen as λ^t:

$$\lambda^t = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,m} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,m} \\ \cdot & & & \\ p_{m,1} & p_{m,2} & \cdots & p_{m,m} \end{pmatrix}. \tag{4}$$

As for PPP projects, since its cash flow is hard to predict, some studies had assumed that it follows the Geometric Brown motion which is a special Markov process (Kong *et al.*, 2008). Therefore, it is suitable to use the CreditMetrics model to estimate the CR of PPP projects.

Table I.
Standard & poor's recovery scale

Net loss risk	Expected recovery rate (%)	Recovery rating
Extremely low risk	100	1
lower risk	75–100	2
Medium risk	50–75	3
higher risk	25–50	4
Extremely high risk	0–25	5

In the theoretical study of credit rating transition matrix, it is pointed out that the general credit rating transition matrix published regularly by the institution (Moody) does not necessarily conform to the specific PPP project. Therefore, the credit rating transition matrix should be improved by taking the information of the project into consideration. Therefore, the credit quality index is introduced to measure the future credit transition of a specific PPP project.

Credit quality index

The credit quality index is a combination of the PPP project's key financial indicators, i.e. the earnings before interest, tax, depreciation and amortization (EBITDA), the debt service coverage ratio (DSCR), the debt ratio and the total asset turnover. The relationship between the credit quality index in year t (Z_t) and the four key financial indicators is assumed to be as follows:

$$Z_t = a(R/A)_t + b(EBITDA/A)_t + c(DSCR)_t + d(D/A)_t + e, \tag{5}$$

where the parameters a, b, c, d, e are constant, and their value can be estimated by the banks' experienced data in previous PPP projects or expert interview.

In order to simplify the input parameters and avoid loss of any information, annual revenue can be divided into two categories, namely, operating revenue and incidental revenue. Annual cost can also be simplified to comprise two items, namely, maintenance cost and wages. It is assumed that the operational revenue in year i is OR_i, and incidental revenue is IR_i and, therefore, the total revenue in year i is $R_i = OR_i + IR_i$. The maintenance cost is OM_i, and wages and other expenses is IC_i. The asset value of finished project is A. d_j represents the money that should be repaid according to the repayment schedule in year j. The four financial indicators can be estimated as follows:

(1) The total asset turnover in year i is (R_i/A), for $i = 1, 2, \ldots, n$.

(2) The EBITDA in year I can be calculated as follows:

$$EBITDA_i = OR_i + IR_i - OM_i - IC_i \ldots \text{for } i = 1, 2, \ldots, n. \tag{6}$$

(3) The DSCR in year i is calculated as follows:

$$DSCR_i = \frac{EBITDA_i - TAX_i}{d_i} \quad \text{for } i = 1, 2, \ldots, n, \tag{7}$$

where TAX_i means the taxes in year i.

(4) The debt ratio in year i is (D_i/A), and D_i could be calculated as follows:

$$D_i = NPV_i = \sum_{j=i}^{n} \frac{d_j}{(1+r_j)^j} \quad \text{for } i = 1, 2, \ldots, n. \tag{8}$$

Because of the considerable uncertainty of the cash flow, it is necessary to adopt probability distribution for revenue and cost, which will be discussed later in the following part.

Estimation of the four financial indicators. Because of the considerable uncertainty of the cash flow, it is necessary to adopt probability distribution for revenue and cost. Following the studies of Jung and Kim (2001) and Wibowo and Kochendörfer (2005), it is supposed that the annual revenue and maintenance cost follow normal distribution, and the incidental revenue and wages and other expenses follow uniform distribution.

Among above distributions, the mean value of operating revenue and maintenance cost can be determined from the financial model and the standard deviation can be estimated by experts' experience. The mean value of incidental revenue and wages cost can be given from the financial model, and their maximum and minimum value can be estimated by experts. Once the above essentially distributional variables are determined, annual revenue and annual cost can be estimated with the use of MCS technique. After that, the four key indicators, namely, the total asset turnover, the EBITDA, the DSCR and the debt ratio, can be estimated.

Credit change indicator

In order to reflect the credit rating transition, underlying, continuous credit change indicator, Y_t, is defined (Belkin *et al.*, 1998a, b). As in Belkin *et al.* (1998a, b), Y_t can be decomposed into two parts: a (scaled) idiosyncratic component Z_t, unique to a borrower, and a (scaled) systematic component ε_t, shared by all borrowers. It is assumed there is a linear relationship between credit change indicator and credit quality index. The linear relation is expressed as the following equation:

$$Y_t = \gamma Z_t + \sqrt{1-\gamma^2}\varepsilon_t, \tag{9}$$

where Z_t is credit quality index at time t; γ is a correlation coefficient, and its value can be estimated according to the study of Belkin *et al.* (1998a, b); and ε_t is a standard random error term which follows a standard normal distribution.

The credit quality index is obtained through the specific financial data of the project. The credit change indicator calculated from the credit quality index can embody the improvement on the general credit rating transition matrix by the specific project information. Under the influence of project uncertainty, credit change indicator follows a probability distribution rather than a fixed value.

Credit change indicator is usually considered to follow normal distribution (Belkin *et al.*, 1998a, b). Then, conditional on an initial credit rating r_i at the beginning of a year, we partition the Y_t values into a set of disjoint bins (y_j, y_{j+1}). The credit rating at the end r_j will be:

$$r_j = \begin{cases} r_1, & \text{if} \quad Y_t \leqslant y_1 \\ r_2, & \text{if} \quad y_1 < Y_t \leqslant y_2 \\ \cdots & \\ r_{m-1}, & \text{if} \quad y_{m-2} < Y_t \leqslant y_{m-1} \\ r_m, & \text{if} \quad y_{m-1} < Y_t \leqslant y_m \end{cases}, \tag{10}$$

where r_1 is the lowest rating, namely, default, and r_m is the highest rating.

The bins are defined such that the probability of Y_t falling within a given interval equals the corresponding historical average transition rate. According to the historical credit rating transition matrix, the interval of credit quality index can be obtained, and the transition probability and interval relation can be expressed as follows:

$$p^t_{i,j} = \Phi\left(y^t_{j+1}\right) - \Phi\left(y^t_j\right), \tag{11}$$

where $p^t_{i,j}$ denotes the historical average transition probability and $\Phi(\cdot)$represents the standard normal cumulative distribution function. The default bin has a lower threshold of $-\infty$. The highest bin has an upper threshold of $+\infty$. The remaining thresholds are fit to the observed transition probabilities.

According to the relationship between credit change indicator and credit quality index in Equation (9), the credit transition probability is as follows:

$$\begin{aligned}\lambda_{i,j}^{t} &= P\{y_{j-1} < Y_t \leqslant y_j\}\\ &= P\left\{y_{j-1} < \gamma Z_t + \sqrt{1-\gamma^2} \leqslant y_j\right\}\\ &= P\left\{\frac{y_{j-1}-\gamma Z_t}{\sqrt{1-\gamma^2}} < \varepsilon_t \leqslant \frac{y_j-\gamma Z_t}{\sqrt{1-\gamma^2}}\right\}.\end{aligned} \tag{12}$$

Since ε_t is a standard random error term which follows a standard normal distribution, the formulas can be changed as follows:

$$\lambda_{i,j}^{t} = \begin{cases} \Phi\left(\frac{y_j-\gamma Z_t}{\sqrt{1-\gamma^2}}\right), & j=1 \\ \Phi\left(\frac{y_j-\gamma Z_t}{\sqrt{1-\gamma^2}}\right)-\Phi\left(\frac{y_{j-1}-\gamma Z_t}{\sqrt{1-\gamma^2}}\right), & 1<j\leqslant m-1 \\ 1-\Phi\left(\frac{y_{j-1}-\gamma Z_t}{\sqrt{1-\gamma^2}}\right), & j=m \end{cases}. \tag{13}$$

Since this paper is concerned with the DP, the focus is on the situation when the credit rating changes to default, r_1, namely, Y_t, is less than or equal to the y_1. Then, Equation (12) can be transformed into:

$$\begin{aligned}\lambda_{i,1}^{t} &= P\{Y_t \leqslant y_1\}\\ &= P\left\{\gamma Z_t + \sqrt{1-\gamma^2} \leqslant y_1\right\}\\ &= P\left\{\varepsilon_t \leqslant \frac{y_1-\gamma Z_t}{\sqrt{1-\gamma^2}}\right\}.\end{aligned} \tag{14}$$

According to Equation (13), the DP can be calculated as follows:

$$DP = \Phi\left(\frac{y_1-\gamma Z_t}{\sqrt{1-\gamma^2}}\right). \tag{15}$$

We can see from the above formula that DP has a certain relationship with credit quality index which is determined by the key indicators of the project. Therefore, the DP of specific projects can be obtained through the improvement on general credit rating transition matrix with the credit quality index. Based on Equation (15), the banks and sponsors of PPP project can estimate the DP of project in future based on the current project's operating condition.

Monte Carlo simulation (MCS)

MCS is a classical method used to deal with uncertainty and is widely used in PPP project research (Wibowo and Kochendörfer, 2005; Chang and Ko, 2014; Moore and Weatherford, 2001). Chang and Ko (2014) applied the MCS to the risk analysis of build-operate-transfer projects, proving the broader use of MCS compared with the NPV approach in improving project appraisals. Taking the uncertainties in PPP project finance into consideration, cash flow estimation simply based on financial model might deviate from the reality, resulting in great loss to lenders. Therefore, MCS is adopted in this research to simulate the distribution of key indicators.

Compared with fixed result of traditional methods without consideration of uncertainty and probability distribution, the interval estimation under certain confident level through Monte Carlo can bring more comprehensive CR evaluation basis for banks. Improved in this way, banks can choose the data within the estimated interval as the basis of CR evaluation according to their own risk tolerance and risk preference. For banks with higher risk preference or higher risk tolerance, the lower value of the CR interval may be used as the evaluation data, and the bank is optimistic about the future operation of the project. On the contrary, banks with risk aversion or low risk tolerance tend to take higher value of the CR interval as the basis of loan decision, and tend to be pessimistic for the future operation of the project and make more prudent lending decisions. Different banks have different pursuit of risk and revenue, development and business strategy. MCS can help banks to make lending decisions according to their own preference and make more comprehensive analysis.

Oracle Crystal Ball is an advanced application based on spreadsheet for predicting modeling, forecasting, simulation and optimization. Crystal Ball can perform MCS to analyze the risks and uncertainties associated with Microsoft Excel spreadsheet models. The study was conducted based on Oracle Crystal Ball 11.1.2.4 version. By identifying the probability distribution of the input variables and the financial model, a simulation will be performed as identified and probability distribution of the output indices will be automatically provided. Result through MCS by Crystal Ball can provide in-depth understanding of CR distribution since it takes into consideration of the great uncertain cash flow prediction.

Influence of repayment schedule and risk preference of banks

The loan repayment schedule is one of the vital elements in a bank's loan decision and greatly influences the DP of project. The model discussed above can deal with the problem of CR estimation under certain and fixed repayment schedule, which is to say, the repayment in every year is predetermined. Banks can calculate the estimated CR interval they are exposed in the project to be invested in the future and make lending decisions according to their risk tolerance and risk preference. However, there can be various repayment schedules for one specific PPP project based on the mutual understanding between banks and borrowers. The method proposed in this extended research can be used to analyze how different loan repayment schedules influence the DP of PPP projects with the use of MCS technique.

Consideration on bank heterogeneity

Generally speaking, there is heterogeneity in the banks, e.g. different risk preference. Therefore, they tend to have different attitudes for the same repayment period. which is to say, the importance of DP in every year may vary for different banks with different demand in the CR evaluation.

Since there will be a long maturity for substantial debt in PPP projects, banks are more involved in the project finance than other financing modes. Banks has to bear considerable losses in the event of contract default. Therefore, it is also the goal of the banks to prevent the project from excessive negative impact on the operation due to excessive debt repayment pressure in the earlier period, thus avoiding defaults. Banks with this consideration may choose to reduce the loan repayment amount from the borrowers in early years.

However, there is another consideration for other banks, namely, financial liquidity. As a financial institution, banks have to take into account the financial liquidity problem in its business activities. The lack of liquidity will result in severe consequence such as cash cannot satisfy the use of the depositors, which will lead to confidence decline in the bank and will further aggravate the reduction of deposits, deteriorate the lack of liquidity and form a vicious spiral. As a way of capital outflow, loans will lead to a decline in financial liquidity. Therefore, some banks will recover loans as soon as possible to protect financial liquidity and avoid the liquidity gap.

In addition, there is a certain trade-off between liquidity and profitability. Generally speaking, in order to ensure liquidity, more capital resources are needed, thus reducing profitability, while the pursuit of profitability often results in liquidity risk.

According to the discussion above, it is obvious that heterogeneity in the banks (risk preference) should never be ignored, thus making the model in this paper more conditional on banks with different CR consideration. Banks can make lending decisions according to their conditional risk preference. This consideration can be reflected by the weight of DP in different years. The weighted DP is used to get the comprehensive DP.

Comprehensive DP

To capture this heterogeneity in the banks, the vector $Q = (q_1, q_2, \ldots, q_n)$ is set to represent the risk preference of the bank to the repayment period $D = (d_1, d_2, \ldots, d_n)$, where q_i means the risk aversion level of bank to the repayment d_i in the year i. In the whole repayment schedule, the bank may have different risk aversion level in different years. Since the model aims to satisfy different banks with different risk preferences, to make it comparable among different banks, the normalized total degree of risk aversion level of bank is supposed to be 1, which is to say $\sum_{i=1}^{n} q_i = 1$. The weight has been distributed in the repayment period and the risk preference of banks can be reflected through the various weights in different years.

Setting the probability of default in year i is DP_i, and $\overline{DP}$ is the weighted mean DP combining the risk preference of banks. Then, based on the multiplication rule, the DP under different repayment schedules can be estimated by the following equation:

$$\min \overline{DP} = DP_1^{q_1} \times DP_2^{q_2} \times \cdots \times DP_n^{q_n}, \tag{16}$$

subjected to conditions:

$$\begin{cases} Z_i = e + a\left(\frac{R}{A}\right)_i + b\left(\frac{EBITDA}{A}\right)_i + c\left(\frac{EBITDA-TAX}{d}\right)_i + d\left(\frac{D}{A}\right)_i \\ DP_i = \Phi\left(\frac{y_1 - \gamma Z_i}{\sqrt{1-\gamma^2}}\right) \\ \sum_{i=1}^{n} q_i = 1. \end{cases} \tag{17}$$

The first and the second constrain condition are used to calculate the DP every year. The third constrain condition means the normalized total degree of risk aversion level of bank is 1. Through the model set above, the influence of different repayment schedules and different risk preference can be revealed. Banks can make repayment schedule considering their risk preference.

Case analysis

Estimation of CR

The case analyzed here is a Chinese PPP highway project located in Hebei province and the real data are disguised. In this PPP project, the tax rate was 25 percent. This highway project's asset value is evaluated with the method of present return value in which net cash flow in the whole concession period is discounted at 8 percent as the basic discount rate. The total value of the highway project is estimated at about CNY 799,193,700. The mean revenue and cost are determined according to the financial model. The deviation is given by experts' comprehensive analyses. The information is shown as Table II.

The total debt is CNY 508,490,500. The loan term is 14 years. The construction period is two years and the repayment will start in the first year of the operation period. We mainly focus on evaluating the CR in the operation period. The cash flow was estimated according to the financial model and is shown in Table III.

The EAD is calculated according to the repayment money A_j in year j with the use of NPV:

$$EAD = NPV_i = \sum_{j=i}^{n} \frac{A_j}{(1+r_j)^j},$$

Table II.
Estimation of four financial variables (thousands of CNY)

Year	Operating revenue		Incidental revenue			Operating and maintenance costs		Wages and other expenses		
	Mean	SD	Mean	Min.	Max.	Mean	SD	Mean	Min.	Max.
1	–	–	–	–	–	–	–	–	–	–
2	–	–	–	–	–	–	–	–	–	–
3	60,580	15,150	45,470	44,670	46,270	7,050	650	4,050	3,550	4,550
4	73,050	17,680	44,600	43,800	45,400	6,810	640	4,500	4,000	5,000
5	85,210	16,350	45,320	44,520	46,120	7,150	680	4,370	3,870	4,870
6	90,320	19,450	45,610	44,810	46,410	7,120	640	4,720	4,220	5,220
7	97,290	20,650	44,260	43,460	45,060	7,430	720	4,630	4,130	5,130
8	10,2140	31,250	4,5270	44,470	46,070	7,340	710	4,950	4,450	5,450
9	109,150	30,450	44,360	43,560	45,160	7,680	730	4,830	4,330	5,330
10	115,330	21,430	44,530	43,730	45,330	7,720	740	5,030	4,530	5,530
11	11,7910	21,050	45,370	44,570	46,170	8,050	760	5,060	4,560	5,560
12	121,650	21,350	45,130	44,330	45,930	8,680	820	4,670	4,170	5,170
13	125,090	24,050	45,270	44,470	46,070	8,870	830	4,730	4,230	5,230
14	128,450	22,350	45,560	44,760	46,360	9,040	870	4,820	4,320	5,320

Table III.
Financial prediction (thousands of CNY)

	Revenue		Cost						
Year	Operating revenue	Incidental revenue	Wages and other expenses	Operating and maintenance cost	Tax	EBITDA	Money to repay the loan	Repayment schedule	EAD
1									
2									
3	60,580	45,470	4,050	7,050	23,737.5	94,950	71,212.5	55,500	508,490.50
4	73,050	44,600	4,500	6,810	26,585	106,340	79,755	35,150	493,669.70
5	85,210	45,320	4,370	7,150	29,752.5	119,010	89,257.5	47,500	498,013.30
6	90,320	45,610	4,720	7,120	31,022.5	124,090	93,067.5	61,820	490,354.40
7	97,290	44,260	4,630	7,430	32,372.5	129,490	97,117.5	77,800	467,762.70
8	102,140	45,270	4,950	7,340	33,780	135,120	101,340	86,750	427,383.80
9	109,150	44,360	4,830	7,680	35,250	141,000	105,750	32,600	374,824.50
10	115,330	44,530	5,030	7,720	36,777.5	147,110	110,332.5	104,400	372,210.40
11	117,910	45,370	5,060	8,050	37,542.5	150,170	112,627.5	115,500	297,587.30
12	121,650	45,130	4,670	8,680	38,357.5	153,430	115,072.5	122,350	205,894.20
13	125,090	45,270	4,730	8,870	39,190	156,760	117,570	75,980	100,015.80
14	128,450	45,560	4,820	9,040	40,037.5	160,150	120,112.5	34,600	32,037.00

where $r = 8$ percent. The repayment in the operation period and the EAD results can be seen in Table III.

This project is located in China where the government promotes PPP projects. This project has collateral from sponsors according to Standard & Poor's Recovery Scale, as shown in Table I. The recovery rating can be determined as 4, which is the average recovery considering the comprehensive project information. The recovery expectations, which represent the RR, can be given as 30 percent according to Standard & Poor's Recovery Scale.

The probability of default will be estimated according to the method established above. The relationship between credit quality index and a project's key indicators can be estimated by the banks' experienced data in previous PPP projects or expert interview. In this case, the formula which represents the relationship between credit quality index and a project's key indicators is given according to Kong *et al.*'s (2008) research:

$$Z_t = -0.157 + 3.41(R/A)_t + 1.70(EBITDA/A)_t + 0.383(DSCR)_t - 2.16(D/A)_t.$$

In this case, the correlation coefficient of linear regression in Equation (9) is 0.0244. The basic matrix uses the smoothed version of the 1981–1997 historical average transition matrix tabulated by Standard & Poor's. The corresponding bins threshold values of different credit grades can be obtained by Equations (10) and (11). Based on the basic matrix, this study modifies and adjusts the matrix suitable for the specific PPP project. Because the probability distribution of key indicators is easy to obtain, the probability distribution of DP based on key indicators can be obtained. The associated bins can then be calculated. The probability of default can be estimated with the use of MCS technique. The probability of default in the first year varies from 1.597 to 1.635 percent under 80 percent probability. The variation under 80 percent probability of the DP in other years is shown in Table IV.

The RR is 30 percent (as discussed above) and EAD is shown in Table III. According to the relationship between RR, EAD and RR:

$$CR = EAD \times DP \times (1 - RR).$$

As an example, the simulation result of CR under 80 percent probability in the third year can be seen in Figure 2. The simulation result shows that if default occurs in the project, the bank's loss varies from CNY 569,100 to CNY 588,100, and the variation is about CNY 19,000 because of the uncertainty. Compared with the CNY 553,327 calculated without

	DP (‰)		Credit risk (thousands of CNY)	
Year	Min.	Max.	Min.	Max.
1	–	–	–	–
2	–	–	–	–
3	1.520	1.590	569.10	588.10
4	1.456	1.534	499.60	533.90
5	1.473	1.536	510.60	538.50
6	1.483	1.549	505.80	534.50
7	1.483	1.547	482.80	509.60
8	1.455	1.548	435.30	463.30
9	1.323	1.455	347.40	382.40
10	1.450	1.508	377.80	393.20
11	1.431	1.485	297.80	309.40
12	1.401	1.455	201.90	209.80
13	1.334	1.402	93.40	98.10
14	1.226	1.312	27.50	29.40

Table IV. Simulation result of DP and credit risk under 80 percent confident level

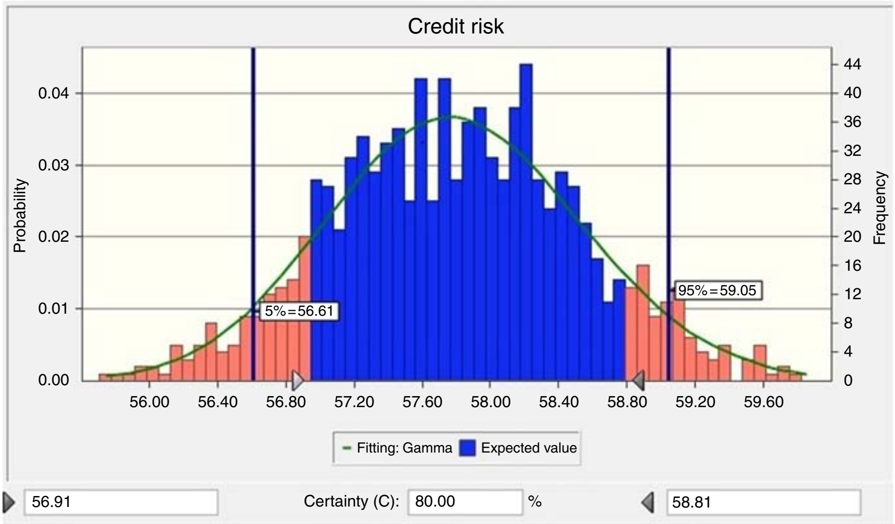

Figure 2.
Sample: the simulation result of credit risk under 80 percent probability in the third year

consideration of the uncertainty, the uncertainty would increase at least amount of CNY 157,73 default loss for the bank, the increased ratio is nearly 2.9 percent. The variation under 80 percent probability of other years is shown in Table IV.

Based on the above result, it can be seen that uncertainty is one of the main considerations to take when making a loan decision for the bank, and the CR evaluating method can help banks to evaluate the influence of the project's cash flow uncertainty on their potential loss quantitatively. Besides, instead of outputting a certain default loss value, the CR evaluating method proposed in this study can derive an interval of the potential loss for the bank, which can provide a reference for the bank to make a lending decision. Which is to say, if the loss-bearing value of the bank is within the interval, the bank can consider to lend money for the project; otherwise, the bank should not lend money for the project.

Influence of repayment schedules and risk preference of banks

The calculation above provides the CR interval range, given that the repayment schedule in every year is predetermined. Further discussion with MCS technique is to be provided in this section to analyze how different repayment schedules and risk preference affect the DP.

Assume the total repayment is CNY 90,650,000. The variation of repayment in the first half of the repayment period is from CNY 45,500,000 to CNY 65,500,000. The variation of the second half of the repayment period year is from CNY 25,150,000 to CNY 45,150,000.

Assume the risk preference of bank to each repayment of the first half and second half of the repayment period is 0.3 and 0.7, respectively, which means banks aim to protect from excessive negative impact on the operation due to excessive debt repayment pressure in the earlier period and thus avoiding defaults. Then, the DP can be calculated as follows: $\overline{DP} = DP_1^{0.3} \times DP_2^{0.7}$. The DP can be estimated on the basis of different repayments made in each year using MCS technique. The variation is shown in Figure 3, with the horizontal axis indicating the repayment in the second half of the repayment period. Banks could choose the minimum probability according to their acceptable range of repayment. In Figure 3, the minimum probability occurs when the repayment of the first half is CNY 25,150,000 and CNY 65,500,000 in the second half. Banks intending to protect the project and avoid defaults may make repayment schedule according to this result.

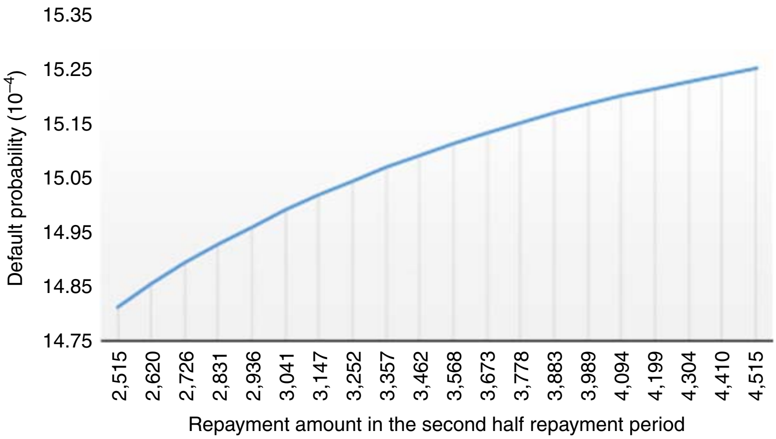

Figure 3.
Impact of repayment schedules on default probability given $q_1 = 0.3$, $q_2 = 0.7$

The measured DP is certainly affected by the bank's risk preference. Assume the weight of each of first half and second half of the repayment is 0.8 and 0.2, respectively, which means banks aim to protect financial liquidity and avoid the liquidity gap. Then, the DP of project can be estimated as follows: $\overline{DP} = DP_1^{0.08} \times DP_2^{0.2}$. The variation is shown in Figure 4. The change in weight creates a different variation relationship. The minimum DP occurs when the repayment of the first half is CNY 45,500,000 and CNY 45,150,000 in the second half. Banks intending to recover the loan in early years can arrange the repayment schedule based on this.

Based on the above result, it can be seen that the CR evaluating method can effectively analyze how different repayment schedules and risk preference of banks influence the DP of the project. Therefore, banks can evaluate the CR of the project based on their own risk preference and make lending decision correspondingly. Default under project finance is very destructive to the PPP project. The reasonable determination of loan repayment schedule can not only reduce the DP as much as possible, but also play an important role in ensuring the smooth operation of the PPP project. Through the above methods, some reference can be provided for banks to reduce DP.

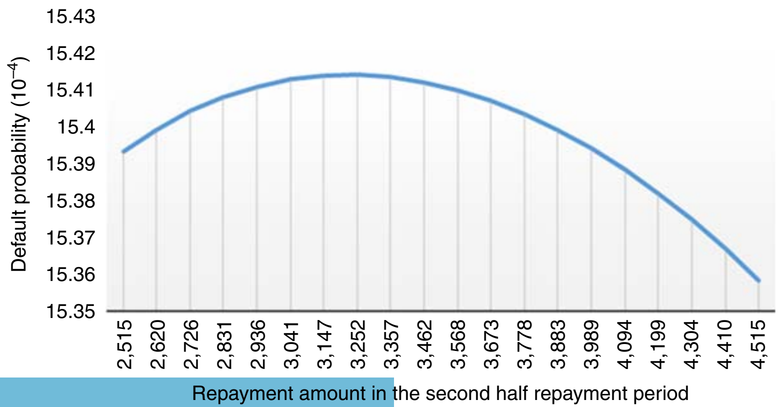

Figure 4.
Impact of repayment schedules on default probability given $q_1 = 0.8$, $q_2 = 0.2$

Conclusion

This research aims to pursue the solution for banks to better evaluate the CRs to serve the lending decision. A quantitative analysis method based on CreditMetrics model and MCS technique has been developed and the interval estimation of CR under a certain confident level can bring more comprehensive CR evaluation basis for banks. The extended model of evaluation method proposed in this study analyzed how different loan repayment schedules and risk preference influence the DP of PPP projects with the use of MCS technique. It can help the banks to optimize their loan repayment schedule according to their risk preference and play more active role in PPP projects. Many insights can be provided through case analysis on the PPP project in Hebei Province in China. First, the CR evaluating method can help banks to quantitatively evaluate the influence of the project's cash flow uncertainty on their potential loss in the project. Second, instead of outputting a certain default loss value, the CR evaluating method proposed in this study can derive an interval of the potential loss for the bank, which can provide a reference for the bank to make a lending decision. Thirdly, the CR evaluating method can effectively analyze how different repayment schedules and risk preference of banks influence the DP of the project. Therefore, banks can correctly value the CR of the project based on their own risk preference and make lending decision correspondingly.

However, there are still some limitations for this method. First, different PPP projects vary in the relationship between the key indicators of the project and the credit quality index, which can be further explored with increased implementation of the PPP projects and disclosure of relevant information. Besides, some indicators used in this method are based on expert's evaluation, which is subjective and constrained to the experience and knowledge of experts. Some objective methods can be used in the future to improve the accuracy of these indicators' calculation.

References

Akintoye, A. and Ezekiel, C. (2005), "Private finance initiative in the healthcare sector: trends and risk assessment", *Engineering, Construction and Architectural Management*, Vol. 12 No. 6, pp. 601-616.

Akintoye, A., Taylor, C. and Fitzgerald, E. (1998), "Risk analysis and management of private finance initiative projects", *Engineering Construction & Architectural Management*, Vol. 5 No. 1, pp. 9-21.

Altman, E., Resti, A. and Sironi, A. (2004), "Default recovery rates in credit risk modelling: a review of the literature and empirical evidence", *Economic Notes*, Vol. 33 No. 2, pp. 183-208.

Ashuri, B., Kashani, H., Molenaar, K.R., Lee, S. and Lu, J. (2011), "Risk-neutral pricing approach for evaluating BOT highway projects with government minimum revenue guarantee options", *Journal of Construction Engineering and Management*, Vol. 138 No. 4, pp. 545-557.

Beidleman, C.R., Fletcher, D. and Veshosky, D. (1990), "On allocating risk: the essence of project finance", *Sloan Management Review*, Vol. 31 No. 3, pp. 47-55.

Belkin, B., Suchower, S.J. and Forest, L.R. (1998a), "A one parameter representation of credit risk and transition matrices", *CreditMetrics Monitor*, Vol. 1 No. 3, pp. 46-56.

Belkin, B., Suchower, S. and Forest, L.R. (1998b), "The effect of systematic credit risk on loan portfolio value-at-risk and loan pricing", *CreditMetrics Monitor*, pp. 17-28.

Bing, L., Akintoye, A. and Hardcastle, C. (2005), "Critical success factors for PPP/PFI projects in the UK construction industry", *Construction Management & Economics*, Vol. 23 No. 5, pp. 459-471.

Bing, L., Akintoye, A., Edwards, P.J. and Hardcastle, C. (2005), "The allocation of risk in PPP/PFI construction projects in the UK", *International Journal of Project Management*, Vol. 23 No. 1, pp. 25-35.

Blanc Brude, F. and Strange, R. (2007), "How banks price loans to public-private partnerships: evidence from the European markets", *Journal of Applied Corporate Finance*, Vol. 19 No. 4, pp. 94-106.

Bouzguenda, N. (2014), "Project finance: determinants of the bank loan spread", *International Journal of Business and Social Science*, Vol. 5 No. 5, pp. 144-155.

Brandão, L.E., Bastian-Pinto, C., Gomes, L.L. and Labes, M. (2012), "Government supports in public–private partnership contracts: metro line 4 of the Sao Paulo Subway system", *Journal of Infrastructure Systems*, Vol. 18 No. 3, pp. 218-225.

Brandão, L.E.T. and Saraiva, E. (2008), "The option value of government guarantees in infrastructure projects", *Construction Management and Economics*, Vol. 26 No. 11, pp. 1171-1180.

Buscaino, V., Caselli, S., Corielli, F. and Gatti, S. (2012), "Project finance collateralised debt obligations: an empirical analysis of spread determinants", *European Financial Management*, Vol. 18 No. 5, pp. 950-969.

Chang, C.Y. and Ko, J.W. (2014), "A new advance in the application of Monte Carlo simulation to the risk analysis of build-operate-transfer projects", working paper, Bartlett School of Construction and Project Management, University College London, London.

Cheung, E. and Chan, A.P.C. (2011), "Risk factors of public-private partnership projects in China: comparison between the water, power, and transportation sectors", *Journal of Urban Planning & Development*, Vol. 137 No. 4, pp. 409-415.

Chowdhury, A.N., Chen, P.H. and Tiong, R.L.K. (2015), "Credit enhancement factors for the financing of independent power producer (IPP) projects in Asia", *International Journal of Project Management*, Vol. 33 No. 7, pp. 1576-1587.

Corielli, F. and Steffanoni, A. (2010), "Risk Shifting through nonfinancial contracts: effects on loan spreads and capital structure of project finance deals", *Journal of Money Credit & Banking*, Vol. 42 No. 7, pp. 1295-1320.

Donkor, E.A. and Duffey, M. (2013), "Optimal capital structure and financial risk of project finance investments: a simulation optimization model with chance constraints", *Engineering Economist*, Vol. 58 No. 1, pp. 19-34.

Finnerty, J.D. (2007), *Project Financing: Asset-Based Financial Engineering*, 3rd ed., Wiley, New York, NY.

Girardone, C. and Snaith, S. (2011), "Project finance loan spreads and disaggregated political risk", *Applied Financial Economics*, Vol. 21 No. 23, pp. 1725-1734.

Grimsey, D. and Lewis, M.K. (2002), "Evaluating the risks of public private partnerships for infrastructure projects", *International Journal of Project Management*, Vol. 20 No. 2, pp. 107-118.

Iyer, K.C. and Purkayastha, D. (2017), "Credit risk assessment in infrastructure project finance: relevance of credit ratings", *The Journal of Structured Finance*, Vol. 22 No. 4, pp. 17-25.

Jung, D.W. and Kim, H.J. (2001), "A study on the financial risk assessment of SOC private investment projects: focused on light rail transit projects", *Korean Journal of Architectural Engineering*, Vol. 17 No. 5, pp. 109-116.

Kleimeier, S. and Megginson, W.L. (2000), "Are project finance loans different from other syndicated credits?", *Journal of Applied Corporate Finance*, Vol. 13 No. 1, pp. 75-87.

Kong, D., Tiong, R.L., Cheah, C.Y., Permana, A. and Ehrlich, M. (2008), "Assessment of credit risk in project finance", *Journal of Construction Engineering & Management*, Vol. 134 No. 11, pp. 876-884.

Lehlou, S., Tebourbi, I. and Bouslimi, L. (2014), "Internal governance mechanism and default probability: evidence from US public firms", *International Journal of Corporate Governance*, Vol. 5 Nos 1/2, pp. 83-102.

Leland, H.E. (2012), "Predictions of default probabilities in structural models of debt", in Fong, H.G. (Ed.), *The Credit Market Handbook: Advanced Modeling Issues*, Chapter 2, Wiley, New York, NY, pp. 39-64.

Leland, H.E. and Toft, K.B. (1996), "Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads", *The Journal of Finance*, Vol. 51 No. 3, pp. 987-1019.

Li, S., Abraham, D. and Cai, H. (2017), "Infrastructure financing with project bond and credit default swap under public-private partnerships", *International Journal of Project Management*, Vol. 35 No. 3, pp. 406-419.

Mcleod, R.W., Malhotra, D.K. and Malhotra, R. (1993), "Predicting credit risk: a neural network approach", *Journal of Retail Banking*, Vol. 27 No. 5, pp. 37-44.

Moore, J. and Weatherford, L. (2001), *Decision Modeling with Microsoft Excel*, 6th ed., Prentice Hall, Englewood Cliffs, NJ.

Scannella, E. (2012), "Bank lending in project finance: the new regulatory capital framework", *Social Science Electronic Publishing*, Vol. 5 No. 1, pp. 218-227.

Sorge, M. (2004), "The nature of credit risk in project finance", *BIS Quarterly Review*, December, pp. 91-102.

Standard & Poor (2014), *Standard & Poor's Project Finance Ratings Criteria Reference Guide: Project Finance Framework Methodology*, Standard & Poor's America, San Francisco, CA.

Tam, K.Y. and Kiang, M.Y. (1992), "Managerial applications of neural networks: the case of bank failure predictions", *Management Science*, Vol. 38 No. 7, pp. 926-947.

Wang, B., Zhang, S., Wang, X. and Feng, Z. (2018), "The influence of quality benefit and marginal contribution on the optimal equity structure of the PPP projects: balancing public and private benefits", *Construction Management and Economics*, Vol. 36 No. 11, pp. 611-622.

Wang, S.Q., Dulaimi, M.F. and Aguria, M.Y. (2004), "Risk management framework for construction projects in developing countries", *Construction Management & Economics*, Vol. 22 No. 3, pp. 237-252.

Wang, S.Q., Tiong, R.L.K., Ting, S.K. and Ashley, D. (2000), "Evaluation and management of foreign exchange and revenue risks in China's BOT projects", *Construction Management & Economics*, Vol. 18 No. 2, pp. 197-207.

Wang, W.X., Qi-Ming, L.I., Deng, X.P. and Jing-Hua, L.I. (2007), "Critical success factors of infrastructure projects under PPP model in China", *International Conference on Wireless Communications, Networking and Mobile Computing, WiCOM*, pp. 4965-4969.

Wang, Y., Cui, P. and Liu, J. (2018), "Analysis of the risk-sharing ratio in PPP projects based on government minimum revenue guarantees", *International Journal of Project Management*, Vol. 36 No. 6, pp. 899-909.

Wibowo, A. (2004), "Valuing guarantees in a BOT infrastructure project", *Engineering, Construction and Architectural Management*, Vol. 11 No. 6, pp. 395-403.

Wibowo, A. and Kochendörfer, B. (2005), "Financial risk analysis of project finance in Indonesian toll roads", *Journal of Construction Engineering & Management*, Vol. 131 No. 9, pp. 963-972.

Wibowo, A., Permana, A., Kochendörfer, B., Kiong, R.T.L., Jacob, D. and Neunzehn, D. (2012), "Modeling contingent liabilities arising from government guarantees in Indonesian BOT/PPP toll roads", *Journal of Construction Engineering and Management*, Vol. 138 No. 12, pp. 1403-1410.

World Bank (2014), *"Public-Private Partnerships: Reference Guide Version 2.0 (English)*, World Bank Group, Washington, DC.

Yescombe, E.R. (2014), *Principles of Project Finance*, Academic Press, New York, NY.

Yun, S., Han, S.H., Kim, H. and Ock, J.H. (2009), "Capital structure optimization for build–operate–transfer (BOT) projects using a stochastic and multi-objective approach", *Canadian Journal of Civil Engineering*, Vol. 36 No. 5, pp. 777-790.

Zayed, T.M. and Chang, L.M. (2002), "Prototype model for build-operate-transfer risk assessment", *Journal of Management in Engineering*, Vol. 18 No. 1, pp. 7-16.

Zhang, X. (2005), "Financial viability analysis and capital structure optimization in privatized public infrastructure projects", *Journal of Construction Engineering & Management*, Vol. 131 No. 6, pp. 656-668.

Zhang, S., Zhang, S., Gao, Y. and Ding, X. (2016), "Contractual governance: effects of risk allocation on contractor's cooperative behavior in construction projects", *Journal of Construction Engineering and Management*, Vol. 142 No. 6, p. 04016005.

Further reading

Brandimarte, P. (2003), *Numerical Methods in Finance: A MATLAB-Based Introduction*, Wiley and Sons, New York, NY.

Hassan, M.K. and Soumaré, I. (2014), "Guarantees and profit-sharing contracts in project financing", *Journal of Business Ethics*, Vol. 130 No. 1, pp. 1-19.

Corresponding author
Bing Wang can be contacted at: w_bing@tju.edu.cn