Iranian Journal of Management Studies (IJMS) 2022, 15(1): 169-188
RESEARCH PAPER

The Effect of Company's Interest Coverage Ratio on the Structural and Reduced-Form Models in Predicting Credit Derivatives Price

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(Received: November 30, 2020; Revised: April 23, 2021; Accepted: May 2, 2021)

Abstract
Derivative pricing models use either fixed or variable interest rates at the corporate level to compensate for the devaluation, which results in an estimated accounting profit caused by the cash inflation at the maturity date. These models also fail to take into account the lost opportunity costs, which are considered a deficiency. Accordingly, the present study set out to remove this problem by adding the company's Interest Coverage Ratio (ICR) to pricing models, which is the novelty of this study. The research data was extracted from the Bloomberg Terminal for an eight-year period from 2008 to 2015. The statistical population of the research included the North American and European companies recognized as the reference entities for Credit Default Swaps (CDS) in the given period, and the statistical sample consisted of 125 companies. The data was analyzed using four Artificial Neural Network (ANN) algorithms, namely ANFIS, NNARX, AdaBoost, and SVM. The research results indicated the increased predictive accuracy of the pricing models under scrutiny after adding the ICR. The findings also shed light on the superiority of the intensity model over the structural model in prognosticating the price of CDS contracts.

Keywords: Merton model, Reduced-form models, Credit default swaps, Interest coverage ratio, ANNs.

1. Introduction

As one of the key investment factors, credit risk has drawn considerable attention over recent years due to events such as the 2008 financial crisis as a manifest example of a credit crisis (Stout, 2011), and market practitioners are naturally looking for efficient means to cover such risks. Credit derivatives – e.g., swaps, options, and futures as the most common examples – are contracts that enable credit exposure management (Mengle, 2007). Credit default swap (CDS) contracts have ended up the most widely used credit derivatives over recent years, such that its market reached USD 60 trillion by the end of 2007 (Terzi & Ulucay, 2011). This impressive trading volume and striking welcome have paved the way for research on this very important instrument.

Pricing the derivative instruments, including CDS contracts, has continuously been a matter of great interest to researchers and capital market players. Price prediction of these contracts is vital for banks, investors, financial managers, speculators, and a wide range of capital market practitioners. The optimal capital structure provides a good example. Over the past few decades, various ways have been put forth for derivative securities pricing (Uhrig-Homburg, 2002). Indeed, the more accurate the pricing is, the more benefits the users will be

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endowed with. The incorrect or improper pricing of these instruments can potentially raise the credit risk and impose losses on various parts of the capital market, spreading to other markets and ultimately cause macroeconomic losses. This trend chiefly reminds the process the world witnessed in the 2008 crisis. Precise pricing of these instruments, contrariwise, can enhance its degree of liquidity (Pennacchi, 2008). Assuredly, the larger the volume of the trading of this tool, the lesser the credit risk and subsequently, the lesser the total market risk. Diminishing market risk can increase the volume of investment, and eventually, the prosperity of the capital market, which leads to potential profitability and macroeconomic growth (Terzi & Uluçay, 2011).

Derivative pricing models aim to cover the devaluation over the loan period using either fixed or variable interest rates of the normal cumulative distribution values (Hull, 2009). The resulting profit calculated through these models is the output of transaction price minus the price of derivative securities at the maturity date, which is a cash inflation-induced accounting profit and fails to cover interest expenses because the interest and inflation costs are on the rise during the loan period. Admittedly, this price difference cannot be regarded as the profit since the increased liquidity is less than the reduced purchasing power of money. The current value of money at the maturity date has failed to increase up as reflected in the accounting profit. It principally results from the failure to consider the opportunity costs, which fall into the category of economic profit (Jiang et al., 2018). It is possible that the loan process impose lost opportunity costs that fail to be taken into account in the structural and intensity pricing models.

On the other hand, one of the factors that indicates the company's credit worthiness is the Interest Coverage Ratio (ICR). The ICR is one of the financial ratios that indicate how many times a company can pay its current interest expenses with its available earnings. The higher the ICR, the lower the probability of default; thus, the company's debt securities are less likely to default (Dothan, 2006), and according to the theory of signaling, a positive signal is transmitted to the market, and consequently, investing in the given entity is less risky from the point of view of the people outside the organization (Connelly et al., 2011). In this way, individuals are less willing to purchase the covering bonds of that company due to the relative trust in the company's ability to meet its obligations (Afza & Alam, 2011). Accordingly, we concluded that the ICR is theoretically expected to have an inverse correlation with the price of CDS contracts related to a company.

Using the ICR of the company augments the economic justification of the interest expense. In other words, the company's ICR is an accounting ratio that somehow covers the increased interest rates and costs as well as the inflation during the loan period by taking into account the total company's interest expenses at the end of this period; hence it has an economic justification that considers the lost opportunity costs as well (Baños-Caballero et al., 2014). Based on the previous explanations, the present study intends to increase the predictive accuracy of some pricing models by adding the information associated with the ICR of the companies.

To the best of the authors' knowledge, there is currently a considerable gap in the existing literature – including content of the current journal – regarding the failure to consider opportunity costs in the pricing models of the derivative securities. Accordingly, the present study intends to fill this gap through adding the ICR to the information in CDS contracts which leads to more accuracy of the pricing models and this simultaneous use of the information is considered the novelty of the current study.

Given the theoretical framework and the relationship between CDS price and ICR, in the current research we hypothesized that the simultaneous use of the existing information in the CDS contracts and information associated with the ICR can increase the accuracy of the pricing models of this study in predicting the price of CDS contracts. This simultaneous use of the information on CDS and ICR is the innovation of the current study, which we expect to lead to more accuracy of the pricing models.

Based on the introduction, the current study aimed to assess the effect of adding ICR on the Merton and intensity models' prediction power by using the compound forms of ANN algorithms.

2. Research Terms and Definitions

2.1. Risk and Credit Risk

Risk can be defined as a series of probable losses caused by factors such as price changes. Credit risk is a type of risk that may be covered and is defined as the financial losses caused by the decreased credit quality of borrowers (Chau et al., 2018; Meissner, 2009).

2.2. Derivatives and Risk CoverageA

Derivatives are financial instruments whose values depend on a set of variables called basic variables, such as underlying assets, index, and reference rates. An underlying asset can be a stock, forex, commodity, etc. (Amuthan, 2014; Marthinsen, 2018). In financial literature, coverage refers to a set of operations that protect a party against financial losses (Šperanda & Tršinski, 2015). The derivative instrument can contribute to remove or manage all or part of the negative consequences resulting from the risk of price changes on profitability and cash flows (Amuthan, 2014).

2.3. Credit Default Swap (CDS)

CDS contract is the most popular and widely used credit derivative. It serves as a contract that protects a party against the credit risk imposed by a particular company. In this context, the company is referred to as a reference entity, and the company's default is denoted as the credit event. The protection seller agrees to purchase the securities issued for the reference entity at its nominal contingent upon a credit event by the reference entity. This contract will protect the buyer's right to sell the securities to the protection seller. The nominal value of the securities sold in the event of a default is referred to as the strike value of the default credit swap. The buyer of the CDS has to make periodic payments to the seller until the end of the life cycle of securities or until the occurrence of a credit event (Aragon & Li, 2019; Hull, 2009).

2.4. Structural and Reduced Form Models

Merton was the first to present a precise and dynamic theory of corporate debt pricing. The backbone of his theory was the dynamic value of company assets that made the Black Scholes model for corporate debt pricing usable. Merton's structural model is the basis for many of the later models in pricing the demands that have the possibility of default. Some of the most prominent structural models presented in the expansion of the Merton model are given in Black and Cox (1976), Geske (1977), Kim et al. (1993), and Leland (1994), while reduced-form models are presented in studies such as Duffie and Singleton (1997), Jarrow et al. (1997), and Jarrow and Turnbull (1995). Unlike structural models, the reduced form models indicate that default is not considered dependent on the falling of the value of the asset to less than an already predetermined value. In fact, default happens based on some processes of the external default rate, and the model's timing of failure risk is a major difference here between the structural and the reduced-form strategies. Even though structural models assume that default befalls once and exogenously when the property value hits a certain lower level, the reduced-form ones apply an exogenous intensity method to postulate the default time. Therefore, the default in the first scenario is predictable; however, it turns out to be a completely random event in the second circumstance. The default time is formally the anticipated stopping time in structural models and the unanticipated stopping time in reduced-form ones (Marliese, 2002).

As mentioned above, many studies have tried to improve the Merton model accuracy as the current study does. Here are some recent studies that have innovations for improving the basic models with a variety of methods. Majewski et al. (2015) presented a general framework consisting of a broad class of discrete-time models with multi-component structures in terms of leverage and volatility and a flexible pricing kernel with multiple risk premiums. Byström (2019) investigated the effect of block chain technology in Bitcoin to improve credit risk modeling through enhanced reliability and better timing of accounting data releases. Leippold and Scharer (2016) argue that the classical option pricing theories are built upon the rules of a single price, overlooking the effect of market liquidity that may lead to significant bid-ask spreads. They developed a stochastic liquidity model in the framework of conic finance and extended the discrete-time constant liquidity model (Madan, 2010). Liang et al. (2016) priced a corporate zero-coupon bond having credit migration risk in an incomplete market. They determined the corporate bond price based on the indifference between two utility maximization problems of the investors. Brigo et al. (2017) applied a holistic approach for computing an OTC claim value. This value deals with credit and funding liquidity risks and their interactions rather than forcing individual price adjustments. Chen (2019) applied a normal and lognormal firm value diffusion process (FVDP) in order to present a series of formulas to price corporate liabilities. According to this research, unlike structural firm models that only allow for using positive firm values, in reality, a firm value can be negative because it may be subjected to losses that cannot be paid. Comparing these two models, Chen (2019) reported that the mean asset value volatility extracted using credit spreads based on the structural approach with a normal FVDP is very close to the prices empirically estimated based on asset value volatility.

Many of the pricing models proposed after Merton are derived from his model with some changes in the assumption. The structural model used in current research is the Black–Scholes–Merton model (Merton, 1974) and the reduced form model is based on Madan and Unal (1998). Below the models are described.

2.4.1. Financial Models: Valuing the CDS Contracts by Black–Scholes–Merton Pricing Formulas (Hull, 2009)

The furthermost prominent approach of the Black–Scholes–Merton model is the Black–Scholes–Merton formulations for European call /put options prices. These formularies are:

$$c = S_0 N(d_1) - Ke^{-rt} N(d_2) \tag{1}$$

$$p = Ke^{-rt} N(-d_2) - S_0 N(-d_1) \tag{2}$$

$$d_1 = \frac{\left[\ln\left(\frac{S_0}{k}\right) + \left(r + \frac{\sigma^2}{2}\right)T\right]}{[\sigma\sqrt{T}]} \qquad d_2 = \frac{\left[\ln\left(\frac{S_0}{k}\right) + \left(r - \frac{\sigma^2}{2}\right)T\right]}{[\sigma\sqrt{T}]} = d_1 - \sigma\sqrt{T}$$

In a standardized regular distribution, the function N(*x*) is the cumulative probability distribution[1]. A variable has a standard regular distribution, *Φ* (0, 1), of lower than *x*, as illustrated in Figure 1, in such a probability. The remaining parameters must be known. The variables c and p refer to the European call and European put price, S_0 is the stock price at time zero, *K* signifies the strike price, *r* indicates the constantly complex risk-free degree, $\boldsymbol{\sigma}$ symbolizes the stock price volatility, and *T* denotes the option maturity time. Risk-neutral valuation is regarded as an alternative approach. In a European call option, as an instance, the option value expected at maturity in a situation with neutral risk is:

$$\hat{E}\ [\max(S_t - K, 0)]$$

Where, as previously indicated, $\hat{E}$ represents the value anticipated in a world with neutral risk. According to the argument of risk-neutral valuation, the expected value is the European call option price c discounted at an interest rate that is free of risk, i.e.,

$$c = e^{-rt}\hat{E}[\max(S_t - K, 0)]$$

The terms in equation (1) can be interpreted by writing

$$\boldsymbol{C} = e^{-rt}\ [S_0 N(d_1) - Ke^{-rt}N(d_2)]$$

N (d_2) shows the probability according to which the option is utilized in a risk-neutral world, and *KN* (d_2) is the strike price that grows the paying possibility of it. $S_0 N_0\,(d_1)e^{rt}$ is the value anticipated in a variable risk-neutral world equal to S_T *if* $S_T > K$. Since quickly exercising an American call option has never been optimal on a non-dividend-paying stock, the equation (1) equals an American call option value on a non-dividend-paying stock. For an American put option value on a non-dividend-paying stock, no precise analytical formulation has been inopportunely established. Applying the Black–Scholes–Merton formula in practice, the interest rate r is established as equivalent to the interest zero-coupon risk-free rate for a maturity *T*. If *r* is a time popular function, this is theoretically rationale. Suppose the interest rate is stochastic in circumstance of the lognormal stock price at time T and properly picking up the volatility factor. In that case, it is also true in a theoretical opinion. It must be mentioned that time is typically measured as the number of remaining trading days in the option, separated based on the trading days in a year (Hull, 2009).

2.4.1.1. Estimating Default Probabilities from Bond Prices

The default likelihood in a firm can be predictable by the prices of issued bonds. The typical motive that a company bond sells for less than a comparable risk-free one is the default likelihood. In general

$$\bar{\lambda} = \frac{s}{1 - R}$$

where λ is the annual hazard mean rate (default intensity), s is the firm bond distribution yield over the risk-free rate, and R is the estimated recovery ratio.

2.4.2. Reduced-Form Model

In this research, as the reduced form model, we have used the model of Madan and Unal (1998) which has been simplified in Uhrig-Homburg (2000) model that consists of forward

1. The table for the Cumulative Regular Distribution Values is presented in the Appendix.

and stops swaps. However, we have forward swaps in our methodology. A model that allows stochastic recovery rates is presented by Madan and Unal (1998). They presume that the default intensity is determined by the company's stock price evolution s (t) in the money market account units. They took up the subsequent stochastic under the valuation measure Q

$$d_s(t) = \sigma s dz$$

where **σ** is the constant volatility and z is a standard Brownian motion. Madan/Unal presume a default intensity:

$$\lambda(s,t) = \frac{a}{\ln\left(\frac{s}{s_{crit}}\right)^2} 1_{\{\tau > t\}}$$

with positive constants a and s_{crit}. In theory, s may be above or unders_{crit}.

Here, the more genuine case of $s > s_{crit}$was focused, where the default intensity is reduced by s. At that point, as long as the company remains active, its standardized value may never fall under this critical level. Madan and Unal (1998) initiate with certain arbitrary payment X (t) at a potential default time t and decide its value in T to design the stochastic recovery rate.

$$X(T) = e^{\int_t^T r(s)ds} X(t)$$

after which, they presume X (T) does not rely on the default time, and that is distributed freely and equally through interest-rate modes. This supposition, at first sight, appears to be slightly odd. However, this equates to defining a recovery rate autonomously and equally distributed recovery rate φ used as a reference value (recovery-of-treasury-value supposition) in else equal, default-free bond.

The independence suppositions made by Madan and Unal (1998) result in the following pricing formulation for defaultable zero-coupon bonds, contrary to some previous models that apply the recovery-of-face value supposition to catch associations among the recovery and the default-free interest rates:

$$v(t,T) = p(t,T)(E(\varphi) + (1 - E(\varphi))Q(\tau > T))$$

Therefore, the above equation is based on the predictable recovery ratio E (φ), and for certain assumed model factors may be estimated. For practical goals, however, the model factors should be defined by market prices of defaultable tools that are yet again quite complex.

In all reduced-form systems discussed so far, the fundamental supposition is the independence between the default interest rate and the timing risks. The motive behind such a premise is not empirical, rather the desire to get an effortlessly flexible model. However, these correlations are crucial for many reasons.

2.5. Interest Coverage Ratio

This ratio evaluates how many times a firm's EBIT may cover its interest payments. A high ICR suggests better profitability, providing a higher guarantee based on which the firm may deal with its debt (i.e., bank debt, bonds, and notes) from effective incomes in a similar period (Robinson et al., 2015). The following equation displays the general method to calculate this ratio:

$$\text{ICR (Interest Coverage Ratio)} = \frac{EBIT\ (Earning\ Before\ Interest\ and\ Taxes)}{Interest\ Expenses}$$

The total sum of interest spending, both the capitalized and the cost portions, must be used to give the right image of the interest-bearing coverage in estimating the interest-bearing ratios. Moreover, the revenue must be adapted in order to reduce the impact on the depreciation if a firm is devaluing interest, which is capitalized in an earlier period. In general, a better assessment of the solvency in a firm is possible by counting capitalized interest in the ICR estimation. Rating agencies comprise capitalized interest in coverage ratios in the assignment of credit evaluations.

A financial deal is most often included on the bank loan that maintains the minimum ICR. The firm's credit agreement describes the coverage ratio. The concept is pertinent since the capitalized interest treatment in coverage ratio estimation would influence the valuation of how close the actual ratios of a firm are to the levels determined via its financial agreements, and thus, those covenants' breach likelihood.

2.6. Statistic Models: Artificial Neural Networks (ANNs)

Mathematically speaking, any issue may be simulated; Artificial Neural Network (ANN) is an effort to perform the estimation. Like the actual human brain, the neural network has the essential capacity for learning and can apply the attained novel experiences from new and analogous activities. ANNs have certain properties that mark them privileged in specific application capabilities, such as pattern separation and flexibility to learn the networks by linear and nonlinear plotting where the learning is needed. As with the hominid brain, a neural network may learn practices through different strategies that may involve learning by memory, parameter adjustment after random result prediction, and categorization (Malik et al., 2018). In this study, four algorithms are used as statistical models, namely AdaBoost (Shen et al., 2017), SVM (Zhang et al., 2015), ANFIS (Raja et al., 2016), and NNARX (Matkovskyy & Bouraoui, 2019). Readers, who look for a detailed explanation of the algorithms, are referred to mentioned references. Beytollahi and Zeinali (2020) have explained a detailed explanation of the architectures and functions of the four mentioned algorithms.

3. Theoretical Framework and Research Hypotheses

Interest rates are among the most crucial factors affecting investment risk. Changes in interest rates denote a change in inflation that directly affects investment. A decline in the interest rate causes a loss, while a rise in the interest rate leads to a gain in investments subjected to interest rate risk. Changes in inflation subsequently culminate in changes in the value of money. A rise in inflation may cause a decline in the investment value; hence, people determine the type of their stock based on the future interest rates when entering the capital market (Dupor, 2001).

The Black-Scholes-Merton formula uses the difference in prices at the purchase and maturity dates to define the value of the bonds (Watson, 2007). However, as we discussed in previous parts, it fails to consider a crucial macroeconomic factor, i.e., interest rate. Unlike some variables, such as inflation, the corporate interest rate is a macroeconomic variable that can be calculated based on the debt-to-investment rate at the company level, which is effective on the price obtained by the Black-Scholes-Merton model. Accordingly, the price estimated by the model at the maturity date is different from the actual price. We propose that this problem can be eliminated to a great extent by adding ICR to the model.

As mentioned earlier, the bond pricing models cover the depreciation over the loan period using both fixed and variable interest rates at the corporate level and the normal cumulative distribution values (Hull, 2009). As argued in the introduction part, the profit obtained from these models is an accounting profit calculated by transaction price minus the maturity date price of the bonds (i.e., company's total revenues and total expenses), which is also influenced by the cash inflation. This profit fails to cover the interest expenses because the interest and inflation costs will rise during the loan period. Unquestionably, all this revenue generated from the price changes cannot be considered profit because the changes in the increased liquidity are less than those in the reduced purchasing power of the money (Pavan et al., 2008) and the current value of money at the end of the loan period has failed to rise as reflected in the accounting profit. This is mostly since the opportunity costs – which fall into the category of economic profit – fail to be considered in derivatives pricing models. Using the ICR augments the economic justification of the interest expense. In other words, the ICR is an accounting ratio that somehow covers the increased interest rates and costs and also the inflation during the loan period by taking into account the total interest expenses at the end of this period; hence it has an economic justification as it considers the lost opportunity costs as well (Ji, 2019). As mentioned in previous parts, the ICR is an internal ratio of the companies, and this study does not focus on the interest rates of the market.

Some macroeconomic factors are useful in microeconomics. For instance, an interest rate is defined in macroeconomics as the rate that the central banks request for loans (Borio & Gambacorta, 2017). However, it is regarded in microeconomics as the companies' payment in exchange for debt development, except the equities (Tucker, 2016). It is necessary to mention that the ICR considered in the current study is the ratio of the companies included in the research statistical sample, which affects the shareholders' equity and should be distinguished from the market interest rates (Mengle, 2007).

The present research chiefly sought to investigate the effect of adding the ICR to the information of the CDS contracts on the predictability of the structural and intensity models. Then, the main inquiries of this study were as follows:

1. Does the addition of the ICR increase the accuracy of the Merton model (as a representative of structural models) in predicting the CDS bonds price?

2. Does the addition of the ICR increase the accuracy of the Madan intensity model (as a representative of structural models) in predicting the CDS bonds price?

Accordingly, the research hypotheses were formulated as follows:

1. The addition of the ICR increases the precision of the Merton model in predicting the price of CDS bonds.

2. The addition of the ICR increases the precision of the Madan intensity model in predicting the price of CDS bonds.

4. Research Design and Methodology

The present research intended to investigate the effect of the addition of ICR to the information in the CDS contracts on the prediction accuracy of the structural and intensity models. To this end, the Black-Scholes-Merton financial model and Madan model were used as the structural and intensity models, respectively, for pricing the CDS contracts. Data analysis and prediction were conducted using four Hybrid Artificial Neural Networks (HNNAs), namely ANFIS, NNARX, AdaBoost, and SVM, and data was analyzed in MATLAB software using codes optimized for financial analysis. The statistical population of the research included North American and European companies recognized as the reference entities for CDS contracts during the 2008-2015 period. Finally, the contracts associated with 125 companies were selected as the statistical sample by applying the following filters:

- Companies must be active from the beginning of 2009 until the end of 2015,
- Companies had to be recognized as reference entities for concluding CDS contracts during the period under scrutiny,
- Companies must be a Single-A credit rating or higher, and
- The financial information required to investigate the company must be fully accessible.

The algorithms contain some codes that need some variables as input, and they generate some variables as outputs. At first, some codes were used to feed the data that Merton and intensity models need for calculating the price of CDS contracts as the output. To this end, first some random data was used to train the algorithms for calculating the previous year's CDS prices in order to compare them with actual prices and determine the accuracy of the models. In the current study, the algorithms were trained with the data available for the 8 years to minimize the error of the outputs, which here are the CDS prices. Then the data of ICR was added to input variables in order to train algorithms for the second time and calculate the prices. Adding the ICR data to the CDS data decreased the training time and increased the accuracy of the models. This admitted that the actual prices are not just derived by the Merton and Intensity model factors, but other factors such as interest rates are vital factors that affect the CDS prices. The advantage of adding ICR to CDS contracts is in line with the theoretical framework and the hypotheses explained in the previous section.

In the first phase of the present study, the predictions were made based on the existing historical data. In the second phase, the results of the first phase predictions – due to their high accuracy – were added to the historical data, and both were considered the basis for the forecasts. The historical and actual information associated with the ICR and CDS contracts of the companies selected as the statistical sample for the given period was used to train the algorithms that prognosticated the contracts' prices for the years 2016 and 2017 based on the Merton and intensity models. Given a large number of records in the training set, the output of the algorithms for the two years mentioned above had both a considerably high predictive accuracy and a considerably low error rate, such that the predicted prices for these years were considered real data for forward predictions. In addition, in the subsequent phase, 2016 and 2017 were considered the base years for predicting contract prices for the next three years. The estimated prices related to 2016 were used to forecast contract prices during the 2017-2019 period. Likewise, the estimated prices for 2017 were considered the basis for predicting contract prices during the 2018-2020 period.

In the next section, the results associated with the pricing models, the selected algorithms, and the base years are presented. Finally, in line with the research objectives and hypotheses testing, the findings and outputs yielded from the algorithms were compared to determine which algorithm had the minimum error rate and the maximum predictive accuracy. The results also showed the effect of adding ICR to CDS data on the models' prediction accuracy, which is the novelty of this study.

5. Research Findings

This part of the paper is dedicated to the research findings. Here we present the numerical findings and discuss how the statistics are in line with the study hypotheses which are based on our theoretical framework. The following tables present the results of the data analysis divided by the ANFIS, NNARX, AdaBoost, and SVM algorithms. The tables are related to the structural and intensity models that predicted the prices using four algorithms based on two base years and two scenarios, i.e., the presence or absence of the ICR. In the first rows, the accuracy of the algorithm for each of the three next years and the average predictive accuracy of the three years are presented. The last column of each table shows the average changes in the accuracy of the algorithms after adding the ICR to the model aggregately for the two base years.

Tables 1-4 demonstrate the results of Merton model – as one of the structural forms of the pricing models – with different ANN algorithms of the current study used for predicting the CDS contract prices for three years ahead. Each table demonstrates the outputs of a single algorithm.

Table 1. The Results of Merton Model With ANFIS

Base year	Prediction method	1 year ahead	2 years ahead	3 years ahead	Average prediction accuracy	Aggregated average change in prediction accuracy
2016	Merton model	98/39	97/99	97/10	97/82	0/700
	CDS-ICR Method	98/98	98/69	97/93	98/53	
	Change in accuracy	0/59	0/7	0/83	0/71	
2017	Merton model	97/11	96/11	95/93	96/38	
	CDS-ICR Method	98/11	97/10	96/02	97/07	
	Change in accuracy	1	0/99	0/09	0/69	

Table 2. The Results of Merton Model With NNARX

Base year	Prediction method	1 year ahead	2 years ahead	3 years ahead	Average prediction accuracy	Aggregated average change in prediction accuracy
2016	Merton model	97/90	97/20	96/51	97/20	0/765
	CDS-ICR Method	98/41	98/16	97/29	97/95	
	Change in accuracy	0/51	0/96	0/78	0/75	
2017	Merton model	97/19	96/71	95/99	96/63	
	CDS-ICR Method	97/91	97/61	96/71	97/41	
	Change in accuracy	0/72	0/9	0/72	0/78	

Table 3. The Results of Merton Model With AdaBoost

Base year	Prediction method	1 year ahead	2 years ahead	3 years ahead	Average prediction accuracy	Aggregated average change in prediction accuracy
2016	Merton model	94/88	91/95	91/19	92/67	3/365
	CDS-ICR Method	97/19	96/11	95/19	96/16	
	Change in accuracy	2/31	4/16	4	3/49	
2017	Merton model	94/08	91/01	90/60	91/89	
	CDS-ICR Method	96/03	95/24	94/12	95/13	
	Change in accuracy	1/95	4/23	3/96	3/24	

Table 4. The Results of Merton Model With SVM

Base year	Prediction method	1 year ahead	2 years ahead	3 years ahead	Average prediction accuracy	Aggregated average change in prediction accuracy
2016	Merton model	9351	91/40	90/59	91/83	2/675
	CDS-ICR Method	96/99	95/91	94/90	95/93	
	Change in accuracy	3/48	4/51	4/31	4/1	
2017	Merton model	99/27	90/93	90/49	93/56	
	CDS-ICR Method	95/81	94/65	93/89	94/81	
	Change in accuracy	-3/46	3/72	3/4	1/25	

As demonstrated in the tables above, except for the SVM prediction for one year ahead in 2017 base year, all the other results show that the combined method of CDS-ICR has increased the prediction accuracy of the algorithms for three years ahead and in the case of both base years aggregately, the numbers which are in line with the study hypotheses. The most significant rise in the prediction accuracy after adding the ICR to CDS data belongs to the AdaBoost, followed by the SVM, which respectively showed 3/365 and 2/675 percent of improvement in prediction accuracy. NNARX and ANFIS with 0/765 and 0/700 have the least change in prediction accuracy through the combined method.

Tables 5-8 contains the results of Madan model – as the reduced-form of pricing models – utilized for predicting the CDS prices through the four mentioned algorithms for three years ahead. The tables are distinguished by the utilized algorithm.

Table 5. The Results of intensity Model With ANFIS

Base year	Prediction method	1 year ahead	2 years ahead	3 years ahead	Average prediction accuracy	Aggregated average change in prediction accuracy
2016	Merton model	97/22	97/26	95/93	96/80	0/695
	CDS-ICR Method	98/19	97/35	96/74	97/42	
	Change in accuracy	0/97	0/09	1/08	0/71	
2017	Merton model	95/93	94/88	95/15	95/32	
	CDS-ICR Method	97/38	95/84	94/78	96/00	
	Change in accuracy	1/45	0/96	-0/37	0/68	

Table 6. The Results of Intensity Model With NNARX

Base year	Prediction method	1 year ahead	2 years ahead	3 years ahead	Average prediction accuracy	Aggregated average change in prediction accuracy
2016	Merton model	97/05	95/83	96/84	96/45	0/365
	CDS-ICR Method	97/36	97/33	96/59	97/09	
	Change in accuracy	0/31	1/5	-0/25	0/64	
2017	Merton model	95/88	95/72	95/04	95/54	
	CDS-ICR Method	97/14	96/55	95/68	96/45	
	Change in accuracy	1/26	0/83	0/64	0/91	

Table 7. The Results of Intensity Model With AdaBoost

Base year	Prediction method	1 year ahead	2 years ahead	3 years ahead	Average prediction accuracy	Aggregated average change in prediction accuracy
2016	Merton model	93/67	90/71	90/72	91/70	3/250
	CDS-ICR Method	96/35	94/88	94/33	95/18	
	Change in accuracy	2/68	4/17	3/61	3/48	
2017	Merton model	93/24	90/52	89/91	91/22	
	CDS-ICR Method	94/97	94/30	93/45	94/24	
	Change in accuracy	1/73	3/78	3/54	3/02	

Table 8. The Results of Intensity Model With SVM

Base year	Prediction method	1 year ahead	2 years ahead	3 years ahead	Average prediction accuracy	Aggregated average change in prediction accuracy
2016	Merton model	92/44	90/39	90/02	90/95	2/895
	CDS-ICR Method	96/04	94/96	93/68	94/89	
	Change in accuracy	3/6	4/57	3/66	4/3	
2017	Merton model	98/37	90/04	89/57	92/66	
	CDS-ICR Method	94/62	93/77	93/17	93/85	
	Change in accuracy	-3/75	3/73	3/6	1/19	

As demonstrated in the findings, which confirm the research hypotheses, all the results affirm that the combination of the ICR and CDS data increases the prediction accuracy of the reduced-form model. Prediction with the SVM in 2017 based year is the only exception. The highest enhancement of the prediction power after mixing the ICR and CDS data for future price prediction belong to the AdaBoost and SVM with 3/250 and 2/895 percent of growth in prediction accuracy, respectively. Nonetheless, NNARX and ANFIS with 0/365 and 0/695 percent of growth have demonstrated minimum change in prediction accuracy in case of the combined method. In the conclusion part, we discuss more about the research findings and their relevance to the hypothesis and theoretical framework.

Figures 1 and 2 below exhibit a schematic comparison of the average predictive accuracy of the algorithms used in this research by structural and intensity models in the two mentioned scenarios for 2016 and 2017 base years. The first scenario uses the information in the CDS contracts to predict prices. The second scenario is adding the information associated with the ICR to the first scenario. As it is visible in the graphs, the addition of the ICR has increased the accuracy of future price prediction.

Despite the training of neural networks with the training sets composed of eight-year information, as shown in the above tables and graphs, in the case of using just the data of CDS contracts, the accuracy of both structural and intensity models in predicting the future prices is less than that of the proposed scenario which uses the compound method. For both base years and utilizing all four intelligent statistical models, the simultaneous use of the information in CDS contracts and the information associated with the ICR increased the predictive accuracy of the models compared with the case wherein only the information of CDS contracts was used for prediction.

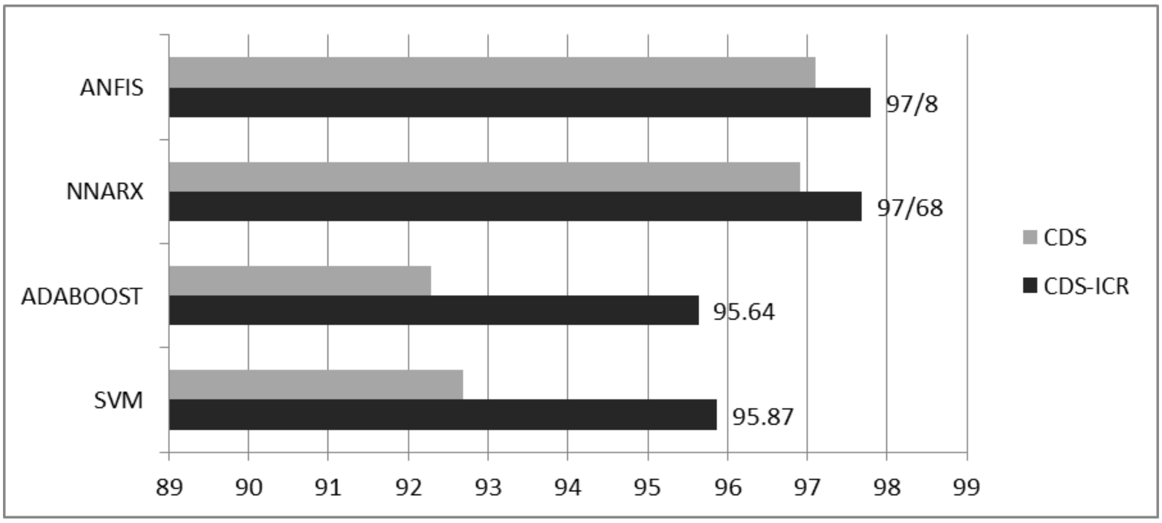

Figure 1. The Two-Year Average Predictive Power of Algorithms With the Merton Model (Percentage)

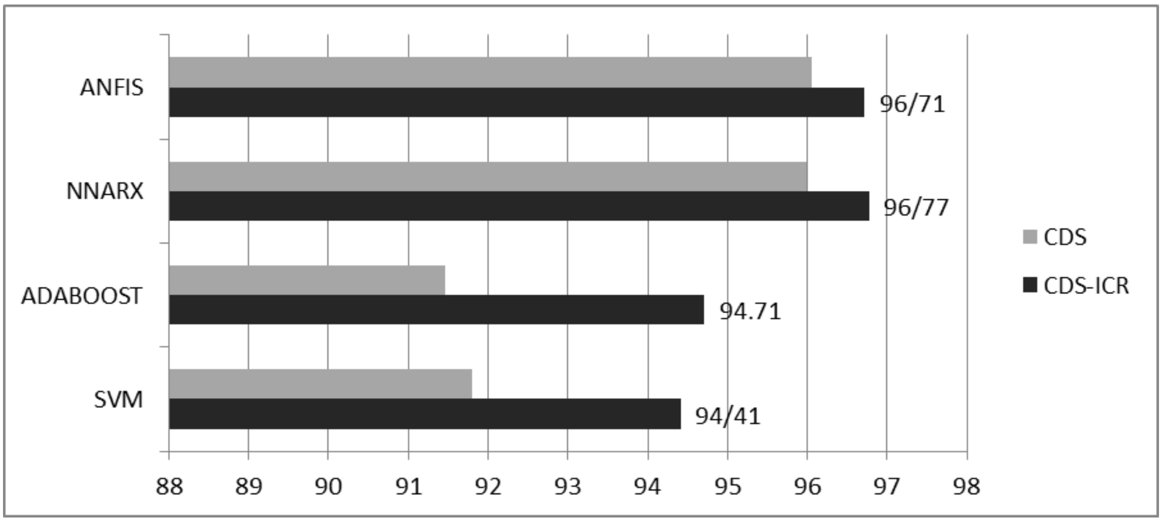

Figure 2. The Two-Year Average Predictive Power of Algorithms With the Reduced-Form Model (Percentage)

Based on the theoretical framework discussed in previous parts, it seems that the increased accuracy in the second scenario can be attributed to the fact that the addition of the company's ICR to the CDS contract information can enable the lost opportunity costs during the loan period to be taken into account. The results of the data analysis are in line with the research hypotheses and confirm them.

The highest average predictive accuracy belongs to the ANFIS algorithm with 97.8% and 96.7% for structural and intensity models, respectively, followed by the NNARX algorithm placed in the second rank with a slight difference. Contrariwise, AdaBoost has the least degree of accuracy compared with other algorithms. Notably, following the addition of the ICR, the accuracy of the ANFIS algorithm had a slight increase compared with the three other algorithms, reflecting the relative accuracy of the ANFIS compared with three others. Another point that deserves mentioning is that the intensity model had more accuracy than the structural model before the addition of ICR, while, as observed in the respective tables, the structural model accuracy had a relatively higher increase following the addition of ICR to the model. It shows that in the case of using the proposed model of this study, the structural models may show a better proficiency than the reduced-form models. Regarding the ANN algorithms as the statistical models, ANFIS shows a high degree of accuracy, which can be due to the fuzzy interference and usage of both numerical and linguistic knowledge. In the paper written by the authors of the current study, which was referenced in the above parts, the advantages of ANFIS compared with the other ANN models are explained in detail Beytollahi and Zeinali (2020).

6. Discussion and Conclusion

As theoretically expected, and as observed in the numerical results, the findings indicate that adding the company's ICR to the Merton and intensity models can increase the accuracy of these models in predicting the price of CDS contracts. One of the disadvantages of the conventional form of these models, as pointed out earlier, is the failure to consider the lost opportunity costs, which causes a difference between real prices and prices obtained from the model. The cost of the lost opportunity has a significant impact on the calculation of the economic profit; hence, the failure to consider this cost can result in the deviation of the predicted prices from the real prices. This deviation leads to unreal forecasted prices higher than the real prices and finally reduces the accuracy of the market assessment. This failure is due to the fact that the reduction in money value over time is more than what the interest rates provide. One of the most important elements that lead to this difference is the non-inclusion of the opportunity cost in the conventional financial models. Taking into account the cost of lost opportunity through the company's ICR can partly remove this problem, and this is considered as the novelty of current study. As observed in the numerical results, adding the respective ratio to the pricing models can increase their accuracy, which confirms the veracity of the theoretical framework and that of the research hypotheses.

In the present study, four hybrid neural network algorithms, namely ANFIS, NNARX, AdaBoost, and SVM, were used to augment data analysis precision. ANFIS had the highest two-year predictive accuracy, followed by the NNARX algorithm with a slight difference. The superiority of ANFIS over other algorithms can be attributed to the simultaneous use of the advantages of the artificial neural networks and the fuzzy logic rules, which endow ANFIS with other advantages such as fast learning potential, high adaptability, and the ability to understand the nonlinear process. In the NNARX algorithm, the future values of the endogenous output signal are regressed on the previous values of the exogenous input and output signals, and this is one of the reasons for the high accuracy of this algorithm.

Traditional financial models rely just on information in the contracts conclude to predict the future price of the derivative securities; thus, they fail to have good efficiency in predicting the price of upcoming contracts. Smart models such as various algorithms of the neural network are capable of precisely learning, recognizing, and forecasting the trends relying upon the historical data through a machine learning process; therefore, these models are highly capable of prognosticating the price of future contracts. Accordingly, combining traditional financial models and intelligent algorithms leads to a high level of accuracy.

Structural and reduced form models have been among the most accepted and widely used models for pricing financial derivatives, but there have also been many different attempts to enhance them. Among the most significant studies for improving reduced form models are Jarrow and Turnbull (1995), Das and Tufano (1995), Jarrow et al. (1997), Madan and Unal (1998), and Duffie and Singleton (1997). These studies concentrated on timing and recovery risk of default and the interest rate risk to improve the pricing models and presented some models for default time based on assuming constant intensity, intensity depending on rating, intensity depending on stock price, and intensity depending on some state variables. There have been also different efforts for improving structural models such as Merton. Here we mention some of the most significant studies for expanding and improving such models. Studies such as Kim et al. (1993), Nielsen et al. (1993), Longstaff and Schwartz (1995), Briys and Devarenna (1997) and Schöbel (1999) have proposed models focused on timing and recovery risk of default and the interest rate risk, and especially in the case of interest rate they worked on variables such as mean-reversion parameter, long-term mean, and volatility parameter of the interest rate models.

Most recently, Cont (2006) suggested two different approaches. First, he envisaged a group of probable models each calibrated to all related market derivatives and then used them to price a certain portfolio of exotic derivatives. He assumed the observed level of difference in the prices as an indicator of the inherent uncertainty related to modeling the portfolio's price. Secondly, he took into consideration this fact that not all models are compliant to calibration to market financial derivatives, and compared the models through penalizing them for the pricing error linked to calibration instruments. He discussed that the pricing mistakes for multiple derivatives may be merged utilizing different choices of norm, giving rise to a number of possible measures of model risk. Glasserman and Xu (2014) have design another attitude based on mixing the model error subject to a limitation on the degree of reasonability. The attitude begins from a baseline model and searches for the worst-case error that may happen through a divergence from the baseline model, indicating an exact limit on the credibility of the deviation. Employing comparative entropy to constrain model distance resulted to a clear characterization of worst-case model errors. This enabled them to calculate upper bounds on model error. They demonstrated how this attitude is useful to the difficulties of portfolio risk assessment, credit risk, delta hedging, and counterparty risk assessed by credit valuation adjustment (CVA). In a review, Morini (2011) criticized the deficit of the model risk literature and came down against the exceeding usage of mathematical formalism and numbers which may lead to obscure the all-significant association between certain modeling assumptions and the difference of prices that really appear thereof. He proposed a middle path between that and formal compliance or simple methods to construct acceptable numbers for putting in reports, but it lacks the quantitative attitude necessary for understanding models profoundly. Turfus (2018) suggested a structure for quantifying the model risk in credit derivatives pricing in situation where the association between rates and credit is either unclear in its value or not included in the calculation. The study considered specifically the situations of an interest rate swap extinguisher, a contingent CDS on an interest rate swap underlying, and an extinguisher with capped or floored Libor flows. The study derives obvious analytical expressions for the model risk as a subordinate of the level of uncertainty related with the correlation, under an asymptotic consideration of the interest rate and the credit default intensity being small as well as taking into account the possible impact of correlation on model calibration.

As some of the most significant studies, we mention foregoing research projects among numerous studies that have tried to improve the financial models through different ways such as adding economic parameters or using new mathematical approaches, with almost all of them concluding that the proposed models could increase the accuracy of the models. Something that the present study does by adding an accounting ratio to the financial models (but like no other previous study) is that this study adds an accounting ratio (ICR) to the CDs contracts information to assess its effect on improving pricing models. To the best of the authors' knowledge, this issue has not been considered previously in the literature and this is the novelty of the current study compared with the previous efforts.

In the case of using intelligent algorithms as statistical methods for analyzing current and predicting future prices of the financial bonds, Artificial Neural Networks (ANNs) have drawn significant attention in research areas from the first days they were introduced.

Recently, the efficiency of the conventional forms of ANNs has been questioned by the researchers. For example, over-fitting of the data set is one of the drawbacks of ANNs. Many studies have attempted to overcome this issue, such as Sariev and Germano (2020) who proposed a Bayesian regularization approach instead of the classical back-propagation algorithm for training feed-forward networks. Other studies such as Gündüz and Uhrig-Homburg (2011), Feser and Broby (2020), and Jing et al. (2021) have also assessed the efficiency of the different forms of ANNs. Almost all of them agree that the compound forms of neural networks, such as SVM and others mentioned in this study, have shown a higher accuracy in predicting financial derivatives.

Axiomatically, there are limitations on the course of any research project, and removing these limitations can pave the way for future studies. The limitations of the present study are mentioned in the following lines. This study investigated eight years while expanding the period under scrutiny is concomitant to a rise in the predictive accuracy of models. In addition, in this study, only four algorithms were used to analyze the data, while using other intelligent algorithms can yield different results. Moreover, the pricing models have multiple shortcomings, but only one of them, i.e., the failure to consider the cost of lost opportunity, was dealt with in the present study; accordingly, future works are recommended to address other deficits of these models. Finally, the study's statistical population was limited to the North American region and Europe, while such research can also be conducted in the context of other geographical areas.

7. Scientific and Practical Implications

Increasing the accuracy of pricing models will reduce the risk and increase the predictive accuracy related to derivatives market. Accordingly, the volume of transactions and liquidity of the credit derivative market subsequently increases, which will directly mitigate the risk of the entire market and increase the volume of investment, and will ultimately lead to the improvement of macroeconomic variables at the global market level. As to the best knowledge of the authors, there has not yet been a study to address the disadvantage caused by the failure to consider the opportunity costs in pricing models. Thus, the present study intends to fill this considerable gap in the existing literature. Pricing models for defaultable obligations in various fields of financial science are highly important. These models can be applied, for instance, in pricing new products of the capital market, such as credit derivatives – a market that witnessed a striking growth over the past decade. These models can also help risk managers identify credit exposures and ultimately deepen insight into corporate finance decisions. That is why these models end up useful in analyzing traditional corporate finance issues, e.g., optimal capital structure. Enhancing the accuracy of these models reduces the risk and increases the prosperity of the derivatives market, including the credit derivatives market. Different entities and individuals potentially benefit from the increased predictive accuracy of the given models, such as investment companies which can calculate more accurate future prices and improve their hedging policies, market players such as credit speculators who can use these more accurate prices for financial benefits, and financial managers who (through the better insight over the future market) can design better management for the financial risk and risk-covering institutions which benefit from both credit hedging and financial benefits of this new approach.

References

Afza, T., & Alam, A. (2011). Determinants of corporate hedging policies: A case of foreign exchange and interest rate derivative usage. *African Journal of Business Management*, *5*(14), 5792-5797.

Amuthan, R. (2014). *Financial derivatives*. Himalaya Publishing House.

Aragon, G. O., & Li, L. (2019). The use of credit default swaps by bond mutual funds: Liquidity provision and counterparty risk. *Journal of Financial Economics*, *131*(1), 168-185.

Baños-Caballero, S., García-Teruel, P. J., & Martínez-Solano, P. (2014). Working capital management, corporate performance, and financial constraints. *Journal of Business Research*, *67*(3), 332-338.

Beytollahi, A., & Zeinali, H. (2020). Comparing prediction power of artificial neural networks compound models in predicting credit default swap prices through Black–Scholes–Merton model. *Iranian Journal of Management Studies*, *13*(1), 69-93.

Black, F., & Cox, J. C. (1976). Valuing corporate securities: Some effects of bond indenture provisions. *The Journal of Finance*, *31*(2), 351-367

Borio, C., & Gambacorta, L. (2017). Monetary policy and bank lending in a low interest rate environment: Diminishing effectiveness? *Journal of Macroeconomics*, *54*, 217-231.

Brigo, D., Buescu, C., & Rutkowski, M. (2017). Funding, repo and credit inclusive valuation as modified option pricing. *Operations Research Letters*, *45*(6), 665-670.

Briys, E., & De Varenne, F. (1997). Valuing risky fixed rate debt: An extension. *Journal of Financial and Quantitative Analysis*, *32*(2), 239-248.

Byström, H. (2019). Blockchains, real-time accounting, and the future of credit risk odeling. *Ledger*, *4*. https://doi.org/10.5195/ledger.2019.100

Chau, F., Han, C., & Shi, S. (2018). Dynamics and determinants of credit risk discovery: Evidence from CDS and stock markets. *International Review of Financial Analysis*, *55*, 156-169.

Chen, J. (February 6, 2019). Can a normal firm value diffusion process improve the performance of the structural approach to pricing corporate liabilities? *SSRN Electronic Journal*. http://dx.doi.org/10.2139/ssrn.2738706

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of Management*, *37*(1), 39-67.

Cont, R. (2006). Model uncertainty and its impact on the pricing of derivative instruments. *Mathematical Finance*, *16*(3), 519-547.

Das, S. R., & Tufano, P. (1995). Pricing credit sensitive debt when interest rates, credit ratings and credit spreads are stochastic. *Journal of Financial Engineering, 50*(2), 789–819.

Dothan, M. (2006). Costs of financial distress and interest coverage ratios. *Journal of Financial Research, 29*(2), 147-162.

Duffie, D., & Singleton, K. J. (1997). An econometric model of the term structure of interest-rate swap yields. *The Journal of Finance*, *52*(4), 1287-1321.

Dupor, B. (2001). Investment and interest rate policy. *Journal of Economic Theory*, *98*(1), 85-113.

Feser, J. A., & Broby, D. (2020). *The Determinants of Credit Default Swap Premia and the Use of Machine Learning Techniques for their Estimation*. (pp. 1-26). University of Strathclyde

Geske, T. G., & Rossmiller, R. A. (1977). The politics of school fiscal reform in Wisconsin. *Journal of education finance*, *2*(4), 513-532.

Glasserman, P., & Xu, X. (2014). Robust risk measurement and model risk. *Quantitative Finance*, *14*(1), 29-58.

Marthinsen, J. (2018). *Risk takers: uses and abuses of financial derivatives*. Walter de Gruyter GmbH & Co KG.

Gündüz, Y., & Uhrig-Homburg, M. (2011). Predicting credit default swap prices with financial and pure data-driven approaches. *Quantitative Finance*, *11*(12), 1709-1727.

Hull, J. (2009). *Options, futures and the other derivatives*. Prentice Hall.

Jarrow, R. A., Lando, D., & Turnbull, S. M. (1997). A Markov model for the term structure of credit risk spreads. *The Review of Financial Studies*, *10*(2), 481-523.

Jarrow, R. A., & Turnbull, S. M. (1995). Pricing derivatives on financial securities subject to credit risk. *The Journal of Finance*, *50*(1), 53-85.

Ji, H. (2019). The impact of interest coverage ratio on value relevance of reported earnings: Evidence from South Korea. *Sustainability*, *11*(24), 7193. MDPI AG. Retrieved from http://dx.doi.org/10.3390/su1124719

Jiang, S. J., Lei, M., & Chung, C. H. (2018). An improvement of gain-loss price bounds on options based on binomial tree and market-implied risk-neutral distribution. *Sustainability*, *10*(6), 1942.

Jing, J., Yan, W., & Deng, X. (2021). A hybrid model to estimate corporate default probabilities in China based on zero-price probability model and long short-term memory. *Applied Economics Letters*, *28*(5), 413-420.

Kim, I. J., Ramaswamy, K., & Sundaresan, S. (1993). Does default risk in coupons affect the valuation of corporate bonds? A contingent claim model. *Financial Management*, 22(3), 117-131.

Leippold, M., & Schärer, S. (2017). Discrete-time option pricing with stochastic liquidity. *Journal of Banking & Finance*, *75*, 1-16.

Leland, H. E. (1994). Corporate debt value, bond covenants, and optimal capital structure. *The journal of finance*, *49*(4), 1213-1252

Liang, J., Zhao, Y., & Zhang, X. (2016). Utility indifference valuation of corporate bond with credit rating migration by structure approach. *Economic Modelling*, *54*, 339-346.

Longstaff, F. A., & Schwartz, E. S. (1995). A simple approach to valuing risky fixed and floating rate debt. *The Journal of Finance*, *50*(3), 789-819.

Madan, D. B. (2010). Pricing and hedging basket options to prespecified levels of acceptability. *Quantitative Finance*, *10*(6), 607-615.

Madan, D. B., & Unal, H. (1998). Pricing the risks of default. *Review of Derivatives Research*, *2*(2-3), 121-160.

Majewski, A. A., Bormetti, G., & Corsi, F. (2015). Smile from the past: A general option pricing framework with multiple volatility and leverage components. *Journal of Econometrics*, *187*(2), 521-531.

Malik, H., Srivastava, S., Sood, Y. R., & Ahmad, A. (2018). Applications of artificial intelligence techniques in engineering. *SIGMA*, *vol 1*.

Matkovskyy, R., & Bouraoui, T. (2019). Application of neural networks to short time series composite indexes: Evidence from the nonlinear autoregressive with exogenous inputs (NARX) model. *Journal of Quantitative Economics*, *17*(2), 433-446.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance*, *29*(2), 449-470.

Meissner, G. (2009). *Credit derivatives: Application, pricing, and risk management*. John Wiley & Sons.

Mengle, D. (2007). Credit derivatives: An overview. *Economic Review-Federal Reserve Bank of Atlanta*, *92*(4), 1-24

Morini, M. (2011). *Understanding and managing model risk: A practical guide for quants, traders and validators*. John Wiley & Sons.

Nielsen, L. T., Saà-Requejo, J., & Santa-Clara, P. (1993). Default risk and interest rate risk: The term structure of default spreads. In *Journées Internationales de Finance*. 1-21.

Pavan, A., Segal, I., & Toikka, J. (2008). Dynamic mechanism design: Revenue equivalence, profit maximization and information disclosure, 82(2), 601-653

Pennacchi, G. G. (2008). *Theory of asset pricing*. Pearson/Addison-Wesley.

Raja, P., & Pahat, B. (2016). A review of training methods of ANFIS for applications in business and economics. *International Journal of u-and e-Service, Science and Technology*, *9*(7), 165-172.

Robinson, T. R., Henry, E., Pirie, W. L., and Broihahn, M. A. (2015). *International financial statement analysis*. John Wiley and Sons.

Sariev, E., & Germano, G. (2020). Bayesian regularized artificial neural networks for the estimation of the probability of default. *Quantitative Finance*, *20*(2), 311-328.

Schöbel, R. (1999). *A note on the valuation of risky corporate bonds. OR-Spektrum, 21(1-2), 35-47.*

Shen, F., Zhao, X., Lan, D., & Ou, L. (2017, July). A Hybrid Model of AdaBoost and Back-Propagation Neural Network for Credit Scoring. In *International Conference on Management Science and Engineering Management* (pp. 78-90). Springer.

Cham.Šperanda, I., & Tršinski, Z. (2015). Hedging as a business risk protection instrument. *Ekonomski Vjesnik: Review of Contemporary Entrepreneurship, Business, and Economic Issues*, *28*(2), 551-565.

Stout, L. A. 2011b. Derivatives and the legal origin of the 2008 credit crisis. Harvard Business Law Review, 1(1): 1–38

Terzi, N., & Ulucay, K. (2011). The role of credit default swaps on financial market stability. *Procedia-Social and Behavioral Sciences*, *24,* 983-990.

Tucker, I. B. (2016). *Microeconomics for today*. Cengage Learning.

Turfus, C. (2018). Analytic pricing of quanto cds.

C. Turfus. Analytic Pricing of Quanto CDS. Working Paper, ResearchGate, 2018c. URL https://www.researchgate.net/publication/325070862_Analytic_Pricing_of_Quanto_CDS.

Uhrig-Homburg, M. (2002). Valuation of defaultable claims—A survey. *Schmalenbach Business Review*, *54*(1), 24-57.

Watson, M. (2007). Searching for the Kuhnian moment: The Black-Scholes-Merton formula and the evolution of modern finance theory. *Economy and Society*, *36*(2), 325-337.

Zhang, L., Hu, H., & Zhang, D. (2015). A credit risk assessment model based on SVM for small and medium enterprises in supply chain finance. *Financial Innovation*, *1*(1), 1-21.

Appendix A

Cumulative Regular Distribution

d	*N(d)*	*d*	*N(d)*	*d*	*N(d)*	*d*	*N(d)*	*d*	*N(d)*	*d*	*N(d)*
		−2.00	.0228	−1.00	.1587	.00	.5000	1.00	.8413	2.00	.9773
−2.95	.0016	−1.95	.0256	−.95	.1711	.05	.5199	1.05	.8531	2.05	.9798
−2.90	.0019	−1.90	.0287	−.90	.1841	.10	.5398	1.10	.8643	2.10	.9821
−2.85	.0022	−1.85	.0322	−.85	.1977	.15	.5596	1.15	.8749	2.15	.9842
−2.80	.0026	−1.80	.0359	−.80	.2119	.20	.5793	1.20	.8849	2.20	.9861
−2.75	.0030	−1.75	.0401	−.75	.2266	.25	.5987	1.25	.8944	2.25	.9878
−2.70	.0035	−1.70	.0446	−.70	.2420	.30	.6179	1.30	.9032	2.30	.9893
−2.65	.0040	−1.65	.0495	−.65	.2578	.35	.6368	1.35	.9115	2.35	.9906
−2.60	.0047	−1.60	.0548	−.60	.2743	.40	.6554	1.40	.9192	2.40	.9918
−2.55	.0054	−1.55	.0606	−.55	.2912	.45	.6735	1.45	.9265	2.45	.9929
−2.50	.0062	−1.50	.0668	−.50	.3085	.50	.6915	1.50	.9332	2.50	.9938
−2.45	.0071	−1.45	.0735	−.45	.3264	.55	.7088	1.55	.9394	2.55	.9946
−2.40	.0082	−1.40	.0808	−.40	.3446	.60	.7257	1.60	.9459	2.60	.9953
−2.35	.0094	−1.35	.0855	−.35	.3632	.65	.7422	1.65	.9505	2.65	.9960
−2.30	.0107	−1.30	.0968	−.30	.3821	.70	.7580	1.70	.9554	2.70	.9965
−2.25	.0122	−1.25	.1057	−.25	.4013	.75	.7734	1.75	.9599	2.75	.9970
−2.20	.0139	−1.20	.1151	−.20	.4207	.80	.7881	1.80	.9641	2.80	.9974
−2.15	.0158	−1.15	.1251	−.15	.4404	.85	.8023	1.85	.9678	2.85	.9973
−2.10	.0179	−1.10	.1337	−.10	.4502	.90	.8159	1.90	.9713	2.90	.9931
−2.05	.0202	−1.05	.1469	−.05	.4301	.95	.8289	1.95	.9744	2.95	.9984