PREDICTING CONTRACTOR FAILURE USING STOCHASTIC DYNAMICS OF ECONOMIC AND FINANCIAL VARIABLES

By Jeffrey S. Russell,1 Member, ASCE, and Huaming Zhai2

ABSTRACT: This paper examines the pattern of stochastic dynamics, which includes percentage changes, trends, and volatility for economic and financial variables of failed and nonfailed contractors and uses them to predict contractor failure. Contractor failure is defined as the termination of a contractor’s operation. Monthly economic data were collected from publicly available economic reports such as the Federal Reserve Bulletin. Contractor financial data were obtained from five insurance companies. The total sample consisted of 430 financial statements representing 120 contractors (49 failed and 71 nonfailed). Statistic analysis reveals that failed contractors have a negative trend and larger volatility in the percentage changes of net worth, gross profit, and net working capital. A random coefficient method is proposed to describe the stochastic dynamics, i.e., the future position, the trend, and the volatility. A discriminant function for detecting failed contractors has been developed using stepwise regression. The discrimination function includes the following variables: (1) trend—prime interest rate; (2) future position—new construction value in-place; (3) trend—new construction value in place; (4) future position—net worth/total asset; (5) trend—gross profit/total asset; and (6) volatility—net working capital/total asset. An additional 23 contractors (10 failed, 13 nonfailed) were used to validate the developed model. The model misclassified five contractors. Example applications of the model are also provided.

INTRODUCTION

Contractor evaluation is a critical step in successfully completing a project (or, stated in another way, preventing failure). Historically, this evaluation process has relied heavily on engineering experience and judgment. Recently, however, more formal and systematic studies have resulted in an improved understanding of critical inputs to the evaluation process. This understanding, developed through statistical analysis, has been represented in the form of predictive analytical models that are static in nature. These prior studies have not investigated the interrelationships nor the stochastic dynamics between economic and contractor financial variables and contractor failure. Contractor failure is defined as the termination of a contractor’s operation. This can result in losses to owners and contractors. On the other hand, a nonfailed contractor is a contractor that is an ongoing concern.

Previous statistical models have focused on predicting bankruptcy using statistical discrimination methods. For example, Beaver (1966) studied univariate discrimination models. He found that by comparing a number of seemingly independent financial ratios that measure profitability, liquidity, and solvency, one could discriminate between failed and nonfailed firms for periods of up to five years. He also observed that there was no trend in a nonfailed firm’s ratios, although there was a marked deterioration in ratios for failed firms. His model placed emphasis on individual signals of impending problems without revealing the variables’ interactions. Altman (1968) developed a popular multivariate prediction framework, namely, the Z-score model. The Z-score model uses multiple discriminant analysis (MDA), which classifies an observation into one of the several groupings dependent on the observation’s individual characteristics. Subsequently, Altman et al. (1977) constructed a more comprehensive discriminant model entitled the ZETA model. However, for reasons of proprietary, they have not revealed the discriminant function Z. Ohlson (1980) used the maximum likelihood estimation of conditional logit model in developing the probabilistic prediction of failure. For a further overview on these models, refer to Russell and Jaselksis (1992).

The aforementioned models have several limitations, including the following:

1. Use of financial ratios only: No considerations are given to factors such as economy, operation, and management. Including financial variables alone may not capture the total relationship between the cause and effect of business failure.
2. Static models: These models ignore the time-series effects of a firm’s financial and operational performances on the risk of business failure.
3. Lack of investigation related to construction industry: These models are not related to the contractor evaluation problem found in the construction industry.

Prior research related to contractor evaluation and predictive failure models have also been described by Russell and Jaselksis (1992). Additionally, a model has been developed using discrete choice modeling to predict contract bond claims using contractor financial data (Severson et al. 1994). The model predicts the probability of experiencing a claim in the accounting period following the period in which the financial statement was prepared. Variables identified in the model are: (1) cost monitoring; (2) underbillings/sales; (3) total current liabilities/sales; (4) retained earnings/sales; and (5) net income before taxes/sales. A limitation of this model is the subjective and qualitative nature of the variable cost monitoring. In addition, this model did not consider the impact of economic condition on the risk of contractor failure.

As a natural extension to the studies by Russell and Jaselksis (1992) and Severson et al. (1994), this paper describes a stochastic model that enhances the understanding of the impact of economic conditions and a contractor’s financial profile on the risk of failure. The model predicts the probability of failure for a given construction contractor based on the stochastic dynamics of economic and financial variables.

IMPACT OF ECONOMIC CONDITIONS ON CONTRACTOR FAILURE

It has been estimated by the Dun and Bradstreet (D&B) Corporation that an excess of 60% of construction contractor
failures are due to economic factors (Russell 1991). Significant economic factors contributing to failure include insufficient profits, high interest rates, loss of market, no consumer spending, and no future. The availability of construction projects is believed to be directly related to the economy. The availability of construction projects or, the lack thereof, affects the financial profile of contractors. As construction projects become more scarce, the chance of contractor failure increases. Kangari (1988), using multiple linear regression, developed a macroeconomic model to assist in determining when the failure rate will be high for construction contractors. He found that changes in the: (1) new business index (obtained from D&B); (2) federal interest bank load rate index; and (3) contract value index (obtained from the Department of Commerce’s Survey of Current Business for 1978–1987) are significant variables to predict changes in the failure rate index between the selected two years.

A contractor operates in a competitive environment. The risk of failure depends not only on the operational and financial performance, but also the dynamic changes in the economy. A contractor’s risk of failure is related to economic conditions and the financial performance of the contractor. The total size of the economy changes with uncertainty over time. The size of the construction industry and thus the construction decisions are affected by a changing economy. New contractors enter the market and join existing contractors to compete for new opportunities generated by the market demand. When the market demand shrinks, competition may result in failure of the less competitive contractors.

When promises of a contractor to creditors are not met or are honored with difficulty, financial distress occurs. In this case, the creditors may initiate legal actions to protect their positions. When a debt-leveraged contractor is in financial distress, it is possible that bankruptcy, liquidation, reorganization, or a merger may result.

A financially distressed contractor is more likely to have difficulties in obtaining credit and new business opportunities if the distress is detected by the creditors and/or project owners. The more a contractor becomes financially distressed, the more likely the business identity will fail. Under competitive conditions, as the financial distress increases the risk of failure accelerates. When a contractor is financially healthy, there is still risk of future business failure that can impact the future value of the firm. From the financial-structure viewpoint, the value of a contractor is a combination of debt and equity. A contractor’s total value changes with uncertainty over time, depending on cash flow, profitability, and work backlog, among others. The equity portion or the net worth represents the contingent claim of the contractor on the total value of the firm, i.e., the residual net value of the debt value. When the net worth is at or below zero, the contingent claim has zero value. Hence, the ownership has been transferred from the contractor to the creditors.

DESCRIPTION OF STOCHASTIC DYNAMICS: RANDOM COEFFICIENT METHOD

Intuitively, the symptoms of financial distress should be observable several years prior to failure. As discussed in the preceding section, economic conditions also impact the financial health of a contractor. The time dependencies of the economic and financial variables that reveal the distress symptoms are referred to as stochastic dynamics.

The quantification of stochastic dynamics serves two purposes: (1) It identifies construction industry benchmark measures that can characterize the financial performance of individual firm; and (2) provides signals prior to failure.

To test the differences between the failed group and the nonfailed group, two statistics are used as the indices for stochastic dynamics: (1) increment; and (2) percentage change. A parametric stochastic dynamic model is proposed to describe how the two groups behave differently. The differences are characterized by the two parameters in the model, i.e., the mean drift and volatility. Furthermore, under the constraint of small sample size, we propose a random coefficient method to characterize the stochastic dynamics of an individual contractor.

Let \( X_t \) be an observed value of a financial variable, e.g., the net worth of an existing contractor, at year \( t \). Let \( X_i \) \( i = 0, 1, 2, \ldots, n \) be an observed time series. The increment is calculated from

\[
\Delta X_t = X_{t+1} - X_t
\]

and the percentage change is calculated from

\[
\frac{\Delta X_t}{X_t} = \frac{X_{t+1} - X_t}{X_t}
\]

The percentage change is used partially because of the normality requirement when using standard statistical test procedures. In addition, the following discrete stochastic dynamic model can be used to describe the changes in the financial variables:

\[
\frac{\Delta X_t}{X_t} = \mu \Delta t + \sigma \Delta Z
\]

where \( \mu = \) drift parameter; \( \Delta t = \) increment of time; \( \sigma = \) volatility or the standard deviation of the percentage change over one time unit; and \( \Delta Z = \) normal random variable with a mean of zero and variance of \( \Delta t \).

By comparing the drift term \( \mu \) and the volatility \( \sigma \) for nonfailed and failed contractors, the differences in the stochastic dynamics of the two groups can be determined. Furthermore, these parameters provide construction industry benchmark measures for the financial performance. The financial dynamics of an individual contractor can be evaluated against the average industry dynamics by comparing the drift and volatility for specific financial variables. The comparison of drift and the volatility will reveal some information as to an organization’s financial management.

To systematically capture the stochastic dynamics under small sample sizes (e.g., three years), a random coefficient method is proposed. Instead of using three or more consecutive observations to describe the stochastic dynamics, we can use three random coefficients to summarize the dynamic information, namely the future position, the trend, and the volatility. The term “random coefficient method” simply means a data reduction procedure that transforms an observed time series of some variable to a group of more interpretable variables named as the coefficients in order to summarize the stochastic dynamics in the observed time series. The data transformation is carried out here by fitting a simple linear regression equation, where the two linear coefficients in the regression equation along with the error term become the new random variables of interests. The intercept coefficient characterizes the short-term future position of the underlying time series, the slope characterizes the trend, and the standard error term characterizes the volatility. One must be clear that the random coefficient method is not a regression analysis, hence there is no need to require the usual probabilistic assumptions about the regression model, such as the independently identically distributed (i.i.d.) error distribution. In fact, there are many other alternatives to summarize the short-term stochastic dynamics. It can be argued that there is no stationarity guarantee on the random coefficients, since the stochastic dynamics changes over time. It is, however, impossible to use only one-year data to estimate the instantaneous stochastic dynamics.
We have to assume that the short-term stochastic dynamics can be roughly estimated by a short-term data set, say of three or four years.

Assume \( X_{-t}; t = 1, 2, \ldots, n \) are the consecutive \( n \)-years observations under a particular financial or economic variable (e.g., net worth), where subscript \(-t\) denotes \( t \) years prior to contractor failure, and the time order for a nonfailed contractor. For a failed contractor, \( t = 0 \) is the year of failure. For a nonfailed contractor, \( t = 0 \) is the year after the last year of the observed period. The stochastic dynamics of the variable is assumed linear in time. So if \( n \geq 3 \), three coefficients from a linear regression equation can be fitted, namely the intercept \( \alpha_i \), the slope of the trend \( \beta_i \), and the volatility \( \sigma_i \) for a contractor \( i \) in the following:

\[
X_{-t} = \alpha_i + \beta_i t + \epsilon_{it}
\]

where the error term \( \epsilon_{it} \) = deviation from the trend with zero mean and standard deviation \( \sigma_i \). The three random coefficients are calculated using the least-squares regression formula

\[
\text{trend: } \hat{\beta}_i = \frac{\left( \sum_{t=1}^{n} t \right) \left( \sum_{t=1}^{n} X_{-t} \right) / n - \sum_{t=1}^{n} t X_{-t}}{\sum_{t=1}^{n} t^2 - \left( \sum_{t=1}^{n} t \right)^2 / n}
\]

\[
\text{intercept: } \hat{\alpha}_i = \frac{1}{n} \sum_{t=1}^{n} X_{-t} - \hat{\beta}_i \frac{1}{n}\sum_{t=1}^{n} t^2
\]

\[
\text{volatility: } \hat{\sigma}_i = \sqrt{\frac{1}{n} \sum_{t=1}^{n} (X_{-t} - \hat{\alpha}_i - \hat{\beta}_i t)^2 / (n - 1)}
\]

The intercept \( \alpha_i \) is the future position of the variable at time \( t = 0 \), or \( X_0 \). Therefore, \( \hat{\alpha}_i \) predicts where the average value of the variable should be if the current trend continues.

This study uses the percentage change to verify that the stochastic dynamics provide significant amounts of information regarding the risk of contractor failure. The proposed random coefficient method is used to summarize the short-term stochastic dynamics of the candidate financial and economic factors. The investigation of the mathematical properties of the proposed random coefficient method is beyond the scope of this paper.

**DESCRIPTION OF DATA**

**Economic Data**

Economic data were obtained from the Federal Reserve Bulletin, U.S. Bureau of the Census, Statistical Abstract of the United States, and U.S. Department of Labor Statistics. Data were collected on 22 economic factors including:

1. Monthly and annual average prime interest rates
2. Consumer price index
3. Gross national product (GNP) measured in current dollars
4. Constant dollars
5. Deflator
6. New business incorporation
7. Total business failures
8. Failure rate
9. Number of construction contractor failures
10. Number of construction workers
11. Number of construction administrative employees
12. Total employees in construction
13. Value of new construction put in place measured in current dollars and deflator (monthly and annual average)
14. Value of construction contracts (monthly and annual average)
15. Holding of construction loans, number of corporate construction income tax forms returned, and items on corporate construction tax returns such as assets, liabilities, receipts, deductions, and net income.

Data were collected from 1975–93.

**Contractor Financial Data**

Contractor financial data were obtained from five insurance companies that underwrite construction contract surety bonds. Some data are from the Severson et al. (1994) study. The total sample consisted of 430 financial statements representing 120 contractors (49 failed and 71 nonfailed). For each contractor, at least three consecutive years of financial information was provided, including: (1) Audited financial statements, with schedules of contracts in progress and completed contracts; (2) percentage-of-completion income recognition; and (3) whether the firm had a formal cost monitoring system (yes, no).

Similar to the Severson et al. (1994) study, the contractors were categorized by construction type. Three categories of construction type were used: (1) Building construction; (2) heavy construction; and (3) special trade construction. The construction types are defined in the Standard Industrial Classification Manual (1987). The sample contained approximately an equal number of contractors for each respective construction type. The failed and nonfailed contractors were equally distributed over the three construction types.

**STATISTICAL TESTS ON STOCHASTIC DYNAMICS OF FINANCIAL VARIABLES**

The hypothesis that the stochastic dynamics of financial variables can signal financial failure needs to be verified statistically. From many candidate financial variables, three are selected for the purpose of verification: (1) Net worth (NW) that represents the equity; (2) gross profit (GP), which represents the financial productivity; and (3) net working capital (NWC), which represents the short-term financial capacity of a contractor. The writers have hypothesized that nonfailed contractors have different stochastic dynamics (drift and volatility) in these three measures when compared to failed contractors.

Figs. 1, 2, and 3 are histograms of percentage changes for both failed and nonfailed contractors. For the failed contractors, we assumed that the percentage changes are stationary over time so only one histogram is plotted. For the failed contractors, the percentage changes of one and two years prior to failure are plotted separately to illustrate the different dynamic characteristics over time. The three sets of plots have similar patterns and are described as follows:

1. For the nonfailed contractors, the average of the percentage changes (\( \mu \)) is slightly positive, indicating that the group’s financial performance increases over time. For the failed group, the average percentage is becoming more negative when approaching the year of failure. This indicates their financial performance becomes poorer as they become more distressed.
2. For the nonfailed contractors, the volatility of percentage changes (\( \sigma \)) is smaller than that of the failed group, possibly indicating that financially healthy contractors have adequate financial management capability. For the failed group, the volatility increases when approaching the year of failure, indicating that the financially distressed contractors lose control of their financial performance.
3. For the nonfailed contractors, the percentage change approximately follows a normal distribution, i.e., a bell-shaped curve.
where \( s \) = pooled standard deviation; \( n_i \) = sample size for group \( i \); \( a \) = coefficient of significant; and \( v \) = degree of freedom. But due to unequal variances, the foregoing procedure cannot be applied directly. We used a modified version of the test, which assumed unequal variances. Further, since the sample sizes for each group were large, i.e., 49 and 71, the standard normal score \( z \) was used to derive the critical value of the test. The modified multiple comparison procedure is then

\[
|\bar{y}_i - \bar{y}_j| \geq z_{ov} \sqrt{s^2/n_i + s^2/n_j}
\]

(8b)

where \( z_{ov} \) = standard normal score for a two-sided test with the significant coefficient \( \alpha \).

The problem with multiple comparisons, such as in the foregoing procedures, is that if the number of groups \( g \) is large, there are a total of \( g(g - 1)/2 \) such comparisons. We can expect

\[
d = \alpha g(g - 1)/2
\]

differences to appear significant even if there are no real differences. The probability of finding at least one significant difference or the experiment-wise error would be \( 1 - (1 - \alpha)^d \). With three groups, \( g = 3 \), and \( \alpha = 0.01 \), then \( d = 3 \) and the unwanted experiment-wise error would be \( 1 - (0.99)^3 = 0.029 \). An approximate procedure for controlling the experiment-wise error rate at \( \alpha \) can be obtained by using the Bonferroni method. If the \( \alpha \) level of 5% is given, the Bonferroni approach uses a modified coefficient of significance.
are significantly different from those of the nonfailed group and the group of two years to failure. Therefore, if large negative percentage changes in the financial performance variables are observed, they can be interpreted as a warning signal of potential contractor failure.

Pairwise F-tests were used to verify whether the volatilities of nonfailed and failed contractors were statistically significant. An F-test statistic can be easily constructed by using the sample standard deviations (STD Dev) in Table 1. For example, regarding the percentage change in net worth, the nonfailed group had a volatility of 0.145, and the two year to failure had a volatility of 0.29. Then the F statistic is 0.29/0.145², which yields 4. The degrees of freedom for the F-test are 49 and 71. The F-test declared a significant difference in volatilities between the two groups with p-value = 0.0001. All the F-tests on volatilities resulted in statistical significance. Using the Bonferroni approach again, we concluded that volatility should be considered in discriminating contractor failure.

The following can be concluded about the stochastic dynamics of the financial variables:

1. Nonfailed contractors have different stochastic dynamics in equity value (NW), financial productivity (GP), and short-term financial capacity (NWC) compared to failed contractors.
2. The impact of financial dynamics on the risk of contractor failure is the most significant one to two years prior to the failure.
3. For nonfailed contractors, the percentage changes of NW, GP, and NWC are normally distributed.

MODEL DEVELOPMENT

Method

Figs. 1, 2, and 3 presented the trends for failed contractors over a two-year period. To capture the trends and volatility effectively, the random coefficient method introduced earlier is used.

From the original data set, 133 sets of random parameters are generated. If a nonfailed contractor has more than five years of data, the data were split into subsets with three or four points in each subset. Each of the split subsets is treated as an independent identity. The rationale of the splitting procedure is that the random parameters generated from more than five years data may not efficiently capture the dynamic impact of the economic and financial conditions on the failure risk.

After randomization, 110 random parameter sets were used to fit the contractor failure prediction function. The remaining 23 sets were used to validate the prediction function. Stepwise regression was used, considering more than 100 candidate variables.

TABLE 2. Multiple Comparisons on Drift of Percentage Changes

<table>
<thead>
<tr>
<th>Comparison (1)</th>
<th>Net worth (2)</th>
<th>Gross profit (3)</th>
<th>Net working capital (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu_{\text{NW}} ) versus ( \mu_{\text{GP}} )</td>
<td>0.099</td>
<td>0.232</td>
<td>0.412</td>
</tr>
<tr>
<td>( \mu_{\text{NW}} ) versus ( \mu_{\text{GP}} )</td>
<td>0.100*</td>
<td>0.234*</td>
<td>0.416*</td>
</tr>
<tr>
<td>( \mu_{\text{NW}} ) versus ( \mu_{\text{GP}} )</td>
<td>0.119*</td>
<td>0.279*</td>
<td>0.495*</td>
</tr>
</tbody>
</table>

Note: \( \mu_{\text{NW}} \) is drift of the nonfailed group; \( \mu_{\text{GP}} \) is drift of the failed group one year prior to failure; and \( \mu_{\text{GP}} \) is drift of the failed group two years prior to failure.

*Significant at 95%.
Contractor Failure Prediction Function

A contractor failure prediction function consists of the following:

\[ Y = 2.569 + 0.079X_1 - 0.000004579X_2 + 0.000008813X_3 \]
\[ - 0.965X_4 - 1.009X_5 + 2.244X_6 \]

where \( Y \) = failure detection score. If \( Y \) is close to 0, the contractor is classified as nonfailed. If \( Y \) is close to 1, the contractor is classified as failed. The prediction function represents the significant variables related to the risk of failure:

- \( X_1 \): Slope-prime interest rate (slope-interest)
- \( X_2 \): Intercept-new construction value in-place (int-VinP)
- \( X_3 \): Slope-new construction value in-place (slope-VinP)
- \( X_4 \): Intercept-net worth/total assets (int-NW/TAST)
- \( X_5 \): Slope-gross profit/total assets (slope-GP/TAST)
- \( X_6 \): Standard deviation-net working capital/total assets (STD-NWC/TAST)

Table 3 summarizes the regression results and indicates the statistical significance of each variable. The \( R^2 \) of the model is 54.7% with degree of freedom 103, indicating the statistical significance of the model.

Fig. 4 suggests that the failure detection scores calculated from the prediction function follow a normal (bell-shaped) distribution. The Kolmogorov-Smirnov test was conducted to test the normality of the distribution of discriminant scores. The test did not reject the normality of the distribution.

Interpretation of Model

The result of the prediction function can be interpreted in the following:

1. The failure risk increases when the prime interest rate increases. This is expected because higher interests rates imply a higher cost of capital and possibly a higher level of current debt. Increase in the debt level implies that the contractor is more likely to fail to pay debt promises.

2. The failure risk depends on the future volume and change in the output of the construction market (VinP). The positive parameter to the slope of VinP appears to contradict intuition. A possible explanation is that the slope of the value of new construction in-place is strongly correlated with an increase in competition. Fig. 5 reveals that the value in-place moves jointly with the adjusted contract rate (1977-based) with an approximate two-year lag. The adjusted contract rate represents the market demand or input. When market demand increases, more new firms enter the market to compete with the existing firms, and existing firms may expand their operations due to an increase in opportunities. More sunk costs are incurred and usually additional loans are secured for both new and existing firms. But when the market demand for construction decreases, the industry continues to fulfill the contracts made in the prior two years. The total volume of available projects shrinks. Consequently, existing firms experience more intensive competition for future contract. Firms that are highly leveraged, poorly managed, and financially weak may become less competitive and subsequently forced out of the market.

3. The higher the net worth/total assets and the gross profit/total assets ratios over a given period, the less the risk of failure in that period. These two ratios reflect equity positions and the financial productivity of a contractor.

4. The more volatile the net working capital/total assets ratio for a given period, the higher the failure risk in the next period. Volatility in NWC/TAST may imply the quality of financial management and control of a contractor. It is highly correlated with the volatility of equity and financial productivity when the debt level is stable. The trigger of failure may be when the net-worth position becomes zero or negative. Even if on average a contractor has a nonnegative net-worth position and gross-profit level, due to the lack of financial management and control, the volatility in equity level and productivity can be large. The chance of failure for contractors with larger volatility is higher than for those contractors who have

![FIG. 4. Histograms of Failure Detection Scores](image-url)
the same mean net worth and productivity levels but better quality in financial management and control (e.g., with less volatility in NWC/TAST).

Optimization of Failure Detection Procedure

A primary application of the developed contractor failure prediction function is to discriminate failed from nonfailed contractors. Given specific economic conditions and recent financial data for a contractor, a failure detection score \( Y \) can be computed. A decision has to be made based on the detection score (failed or nonfailed). Specifically, a cut-off value, say \( c \), has to be selected. If \( Y \) is greater than \( c \), the contractor is classified as failed. Otherwise, the contractor is classified as nonfailed.

Selection of the cut-off value \( c \) is a critical aspect of the modeling process. The cut-off value is dependent on the distributions of failure detection scores associated with failed and nonfailed contractors. It also depends on the costs of different misclassifications. An optimized selection of the cut-off value is presented in the following.

Assume the failure detection scores calculated from the contractor failure prediction function are normally distributed:

\[
Y_{\text{failed}} \sim N(\mu_F, \sigma^2_F) \quad \text{and} \quad Y_{\text{nonfailed}} \sim N(\mu_n, \sigma^2_n)
\]

where \( \mu_F \) and \( \sigma_F \) = mean and standard deviation for the population of failed contractors, and \( \mu_n \) and \( \sigma_n \) = for nonfailed contractors. This assumption is verified by previous hypothesis tests on normality. The means and variances of the distributions can be estimated by using sample values.

Let the loss function for selecting the cut-off value be illustrated in Fig. 6 where \( C_{01} \) is the cost of misclassification error when the actual is nonfailed and the prediction is a failure, and \( C_{10} \) is the cost of misclassification when the reality is failed. The loss function can be determined based on the risk attitude of the decision maker.

It is important to notice that the two error costs \( C_{01} \) and \( C_{10} \) are not necessarily identical. A decision maker may lose more money when falsely selecting a failed contractor instead of nonfailed contractor. A conservative selection strategy may, on the other hand, reject contractors that are, in fact, not a high risk to failure.

Let \( p \) and \( q \) be equal to the corresponding misclassification errors. Then

\[
p = 1 - \Phi \left( \frac{c - \mu_n}{\sigma_n} \right)
\]

and

\[
q = \Phi \left( \frac{c - \mu_F}{\sigma_F} \right)
\]

where \( c \) = cut-off value; and \( \Phi() \) = standard normal probability function. Following a statistical convention, \( p \) and \( q \) are the type I and type II errors, respectively.

The quantity \( q \) can also be viewed as a definition of the risk of contractor failure. The higher the value \( c \), the more likely the contractor will be classified as failed.

The total loss function for selecting the cut-off is obtained

\[
TC(c) = pC_{01} + qC_{10}
\]

The first-order condition is

\[
\frac{\sigma^2_n C_{01} (c - \mu_n)}{\sigma^2_F C_{10} (c - \mu_F)} = \exp \left[ \frac{1}{2\sigma^2_n} (c - \mu_n)^2 - \frac{1}{2\sigma^2_F} (c - \mu_F)^2 \right]
\]

Then the cut-off value \( c \) can be solved numerically from (13) under the constraint that
\[ \mu_c < c < \mu_f \]  
(14)

For the sake of illustration, the variances have been assumed identical and the losses of misclassification are the same, i.e.

\[ \sigma^2_c = \sigma^2_f = \sigma^2, \quad C_{00} = C_{10} \]  
(15)

the cut-off value is solved as

\[ c = \frac{\mu_c + \mu_f}{2} \]  
(16)

The sample mean and variance of failure detection scores are 0.152 and 0.056 for nonfailed, and 0.699 and 0.058 for failed contractors. Therefore, the distribution parameters of the failed and nonfailed populations can be estimated as

\[ \mu_n = 0.152; \quad \sigma_n^2 = 0.056; \quad \mu_f = 0.699; \quad \sigma_f^2 = 0.058 \]  
(17a-d)

The sample variances are essentially identical. Thus, the overall rate of misclassification is estimated to be 15.5% \[(11 + 6)/(73 + 37)\]. This implies that 84.5% of the sampled contractors are correctly classified.

The standard deviation is calculated to be

\[ \sqrt{\frac{\sigma_n^2 + \sigma_f^2}{2}} = \sqrt{\frac{0.056 + 0.058}{2}} = 0.080 \]  
(18)

Thus, the cut-off value is solved as

\[ c = \frac{\mu_c + \mu_f}{2} = \frac{0.152 + 0.699}{2} = 0.4255 \]

The cut-off value is calculated to be

\[ c = \frac{0.152 + 0.699}{2} = 0.4255 \]

\[ c = \frac{0.152 + 0.699}{2} = 0.4255 \]

Thus, the cut-off value is solved as

\[ c = \frac{0.152 + 0.699}{2} = 0.4255 \]

The sample mean and variance of failure detection scores are 0.152 and 0.056 for nonfailed, and 0.699 and 0.058 for failed contractors. Therefore, the distribution parameters of the failed and nonfailed populations can be estimated as

\[ \mu_n = 0.152; \quad \sigma_n^2 = 0.056; \quad \mu_f = 0.699; \quad \sigma_f^2 = 0.058 \]  
(17a-d)

The sample variances are essentially identical. Thus, the overall rate of misclassification is estimated to be 15.5% \[(11 + 6)/(73 + 37)\]. This implies that 84.5% of the sampled contractors are correctly classified based on three-year data.

**Model Validation**

Twenty-three contractors were used to validate the developed model. Fig. 8 presents the discriminant results. Among the 10 failed contractors, two were misclassified. Among the 13 nonfailed contractors, three were misclassified. The total rate of misclassification was 22% \[(5/23)\]. Considering the random effect from the small sample size, this rate is consistent with the total misclassification rate of 15.5% using the original data.

**EXAMPLE APPLICATION OF MODEL**

To illustrate how to use the contractor failure prediction model, consider the contractors presented in Table 4. One of the contractors experienced financial failure during 1994, while the other was a nonfailure. For both cases, five years of economic and financial data were collected. The macroeconomic conditions were similar in terms of interest rates and values of new construction in-place. The financial profiles between the two contractors were different. The failed contractor had larger total assets and a higher debt ratio. The financial performance variables, namely net worth, gross profit, and net working capital appeared to have more variation.

For both cases, the economic and financial data were split into three time windows of three years. For example, the data from 1989 to 1991 were used to calculate three random coefficients, i.e., intercepts, slopes, and volatility to predict whether the contractors would fail in 1992. Then the data from 1990 to 1992 were processed in a similar fashion to predict whether failure would occur in 1993. And then the data from 1991 to 1993 were considered for the 1994 prediction. So for five-year data, three prediction scores for the years 1992, 1993, and 1994 were computed. Table 5 presents the random coefficients needed for using the prediction function along with the computed failure detection scores.
As shown in Table 5, the failed contractor had a lower equity position (int-NW/TAST), consistently decreasing financial productivity (slope-GP/TAST), and a relatively poorer ability to manage their short-term financial capacity (STD-NWC/TAST). The failure detection scores for the failed contractor are significantly higher when compared to the nonfailed counterpart. For the failed contractor in 1994, the failure detection score is 0.670, greater than the cut-off value 0.4255. Hence the model classified the contractor in a failure category. On the other hand, the nonfailed contractor had a consistent financial performance. The failure detection scores for the nonfailed contractor indicate a small likelihood of failure in the near future.

The risk of failure, \( q \), can also be assessed based on the calculated failure detection score. Given a detection score \( Y \), the risk of failure can be calculated by

\[
q = \Phi \left( \frac{Y - \mu_Y}{\sigma_Y} \right) = \Phi \left( Z < \frac{Y - \mu_Y}{\sigma_Y} \right) = \Phi \left( Z < \frac{Y - 0.699}{0.241} \right)
\]

where \( Z \) = standard normal score. Column 9 in Table 5 shows the risks of failure for different years. The results are consistent with the actual events. Specifically, the risk of failure in 1994 for the failed contractor is 45.2%.

LIMITATIONS AND PRACTICAL APPLICATIONS

Although the validation of the model indicates desirable consistency and robustness when applied to data other than those used to develop the model, there are limitations related to the model. The parameters in the model may need periodical adjustment due to changes in economic conditions and market trends.

To fully understand the impact of the market condition, further investigation on construction market mechanism and competition is needed. For example, a measure of available projects may be more appropriate as a predictor than the value of new construction in-place.

Data availability can be an obstacle in using the model. The prime interest rates and values of new construction in-place can be obtained from the Federal Reserve Bulletin monthly report. The timing in which the information is received has an impact on the robustness of the model. There may be some seasonality effects that can make a difference on the failure detection score and predicted risk of failure. In this study, it only assumes that the monthly data are available at the end of the year the user of the model wants to assess the risk of failure for the coming year. As a practical matter, however, the difficulty of timing and availability of information is not unique to this study.

There is still a great potential for improving the predictability of the developed model. Factors such as available contracts, quality of cost monitoring, geographical and industrial characteristics, among others should be quantified and included in the model.

The model is intended to assist professionals evaluating candidate contractors prior to extending credit. It can be used not only by project owners and surety underwriters as part of contractor prequalification or bonding process, but also by contractors, lending institutions, vendors, and material suppliers.

The failure detection function introduced in the model follows a normal distribution for both failed and nonfailed populations. This finding provides a foundation for developing a quality control system that can be used for the continuous monitoring of a contractor’s financial performance. For example, when the risk of failure exceeds a given value or the failure detection score is two standard deviation above the average nonfailed contractor, a review of the financial and operational management should be performed.

The developed model also provides directions for reducing the risk of failure. For example, a contractor can reduce its volatility in net working capital by improving the financial management. The contractor may need to reduce the amount of debt when work becomes less available. Financial productivity (i.e., profitability) should be continuously improved. A market predictor should be developed to prevent false expansion when the potential exists for a market to shrink. A “what-if” study can be conducted when a contractor wants to expand its operation by increasing its debt leverage.

CONCLUSION

Stochastic dynamics of financial and economic variables such as percentage changes and future position, change, and volatility can be used to discriminate between failed and nonfailed contractors. The failure detection function reveals that the economic and market conditions have a significant impact on the risk of contractor failure. The impact is reflected by increases in prime interest rate and the dynamics of new construction value in-place. Further research on the construction market mechanism is necessary to reveal how the market affects the failure risk of a contractor. The financial strength and capacity, particularly the equity position and financial productivity, are crucial to the survival of a contractor. In addition, the quality of financial management and control of a contractor, measured by the volatility in net working capital/total assets, should be monitored. In general, when the volatility in the financial performance variables increases, the risk of contractor failure increases. The model resulting from this study has consistent predictability based on a three-year window of data. The data necessary to use the model can be obtained from economic reports and a contractor’s financial statements.

ACKNOWLEDGMENTS

The writers wish to thank the surety industry professionals who participated in this study. Without their knowledge, expertise, and willingness, this research investigation would not have been possible. The first writer also thanks the National Science Foundation for Grant No. MSM-9058092, Presidential Young Investigator Award, for its financial support of this effort.

APPENDIX. REFERENCES


