Industry Effect, Credit Contagion and Bankruptcy Prediction

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Abstract

In this paper, we examine the effect of intra-industry credit contagion using three different kinds of intra-industry measures in our empirical study. We apply the competitive strategic measure (CSM) of Sundaram et al. (1996) to capture the strategic interaction faced by firms. We also consider the measure of industry-wide financial distress and the measure of equity correlations. We use the forward intensity approach proposed by Duan et al. (2010) to examine if these industry measures can affect default intensity. Our empirical results suggest that intra-industry contagion effect may be characterized by the level of industry-wide financial distress or equity correlations among firms.

Keywords: Credit Contagion, Intra-Industry Interaction, Strategic Competition, Industry-Wide Financial Distress, Bankruptcy Prediction

1. Introduction

The recent global financial crisis has impacted the financial markets around the world, and raises the importance of the forecast of credit events. Credit contagion has been considered as a possible major cause of why the corporate defaults cluster in the global financial crisis. Although it is well-documented in literature that asset returns become more correlated during financial crisis, debate is still ongoing about the explanation of the increasing comovement in asset returns – Can the heightened correlation during crisis be explained by the more correlated fundamentals? Or alternatively, can correlation increase beyond the explain ability of fundamentals, the condition that Bekaert, Harvey, ang Ng (2005) refer to as contagion? In prior literature of credit contagion, researchers indicated that industry characteristics can affect the bankruptcy probabilities and how credit risks propagate. However, the prevailing reduce-form models rarely consider this important factor. Therefore, in this study, we attempt to approach this issue by investigating the impact of industry effects on bankruptcy prediction and credit contagion.

Credit risk modeling can be classified into two categories: structural-form and reduce-form approaches. Structural-form models, pioneered by Merton (1974), assume that valuation of any corporate security can be modelled as a contingent claim on the underlying value of the firm. These models implicitly assume that firm value has contained sufficient information for the probability of bankruptcy. However, Bharath and Shumway (2008) indicated that this is unlikely to be the case. Furthermore, recent research in reduced-form model has greatly improved the accuracy of default forecasting by incorporating macroeconomic and other firm-specific variables. Therefore, in this study, we perform our empirical analysis by the reduced-form approach.

The early reduce-form models for bankruptcy prediction employ approaches like discriminant analysis (Altman 1968) or binary response models such as logit and probit regresstion (Ohlson 1980; Zmijewski 1984). Shumway (2001) argued that these models are inconsistent because their single-period static features do not adjust period for risk. Hazard model proposed by Shumway (2001) can incorporate time-varying covariates that change with time, and this model is later adopted by Chava and Jarrow (2004), Hillegeist et al. (2004) and many others. More recently, Duffie et al. (2007) proposed a doubly stochastic Poisson intensity approach, which is capable of specifying the time-series dynamics of the explanatory covariates and is able to estimate likelihood of default over several future time periods.

The doubly-stochastic assumption implies that the exit of one firm has no direct impact on the likelihood of default of the other firms. The default times are correlated only as their exit intensities are correlated through covariates. Unlike the prior models, Lando and Nielsen (2010) consider the direct effect of one firm’s bankruptcy to the remaining firms, and they suggested using Hawkes process to model this direct impact of propagation of firms’ default intensities. Nonetheless, their empirical results found no significant contagion effect. In contrast, Wang (2010) did find evidence of credit contagion and showed that contagion could be captured by the economic-wide and sector-wide distress measures. In addition, Wang (2010) also argued that the specification of Lando and Nielsen (2010) may have multicollinearity problem so that their results of contagion is not significant.

In addition, Duffie et al. (2007) proposed a doubly stochastic Poisson intensity approach to jointly model default and other types of firm exits such as mergers and acquisitions in which state variables governing Poisson intensities are assumed to follow a specific time-series dynamic. However, every single firm-specific state variable, such as distance to default, requires estimation and the high-dimensional time dynamics of the state variables is extremely computationally intensive. For the purpose of multiperiod default prediction, firm-based study can be expensive. More recently, Duan et al. (2010) proposed a reduced-form approach based on a forward intensity construction which is also capable of estimating a firm's default probabilities several periods ahead. Similar to Duffie et al. (2007), their construction takes into account both defaults/bankruptcies and other types of firm exits. In addition, this method can also estimate forward default probabilities and cumulative default probabilities for longer than one future period. The advantage of the forward intensity approach is that it can estimate term structure of default probabilities solely using the known data at the time of performing prediction, and can circumvent the difficult task of specifying time dynamics for covariates. The forward intensity approach can be implemented by maximum pseudo-likelihood estimation. In particular, the pseudo-likelihood function can be decomposed into independent components, making it less numerically intensive in estimation.

In credit contagion literature, Jorion and Zhang (2007) and Lang and Stultz (1992) have documented significant intra-industry contagion effect of bankruptcies by event study. Most of the reduced-form models, however, do not consider the industry effect. Only a few exceptions like Chava and Jarrow (2004) has incorporated industry effects. Chava and Jarrow (2004) revealed the importance of including industry effects into hazard rate estimation. Nonetheless, they merely consider industries as dummy variables and their interaction terms with accounting variables, which can only demonstrate the industry differences as well as the importance levels of accounting variables for different industries. If default intensities are different across industries with otherwise identical firm-specific characteristics, it is then of interest to introduce industry related variables, in addition to commonly considered macroeconomic condition and firm-specific characteristics in the reduced-form models. Therefore, in this study, we attempt to explore the possible credit contagion through the perspective of intra industry relationship between firms.

In our paper, we focus on the effect of intra-industry interactions on default probabilities, and use the measures of intra-industry interactions to explain the intra-industry contagion effect. We estimate the default probability using the forward intensity approach by Duan et al. (2010), and we consider three different kinds of intra-industry measures in this paper. First, the Competitive Strategy Measure (CSM) is one of the measures that we use, which is a measure of strategic competition developed by Sundaram et al. (1996). Sundaram et al. (1996) argued that profits of individual firm and overall industry profits depend on how firms interact with each other. Accordingly, firms can increase value by behaving strategically by committing to actions that will elicit favorable responses from the rivals in the industry. The definition of strategic competition is that firms face strategic competition when their marginal profit is influenced by competitors' action. Therefore, the strategic competition may affect consequences of financial policies and investment choices. It is of interest to examine whether the strategic competition can affect the default probabilities of firms. The second measure of intra-industry interaction is financial distance, since not all the bankruptcy events in an industry are of equally importance for the remaining survival companies. Financial distance can be captured by the equity correlation between firms in the same industry. By event study method, Jorion and Zhang (2007) have shown that equity correlations significantly influence CDS contagion. Another study by Chen (2010) also modeled the contagion effect by using a function of equity correlations. The last intra-industry measure is the average of firm's distance to default in the same industry. Wang (2010) used it to capture the industry-wide distress, and he argued that the contagion effects are much less significant when he add this measure to his model. Furthermore, we also include the market-driven variables of Shumway (2001) and Bharath and Shumway as controls in our empirical analysis. The detail will be described in section 4.

In Section 2, we briefly review the forward intensity model proposed by Duan (2010). Our data and variables are described in Section 3. We present our empirical results in Section 4, and make the conclusion in Section 5.

2. Methodology

In this section, we briefly review the forward intensity approach proposed by Duan et al. (2010). Under the assumptions of doubly stochastic Poisson process, the occurrence of default and other exits follow Poisson process with stochastic intensities, and the intensities are the functions of state variables. The reasons of other exits are mergers, acquisitions, and any reason of the disappearance of firms except default.

As the definition in Duan et al. (2010), the spot combine exit intensities for the period $(t, t+\tau)$ is

$$\psi_{it}(\tau) = -\frac{\ln(1-F_{it}(\tau))}{\tau} = -\frac{\ln E_t[\exp(-\int_t^{t+\tau}(\lambda_{is}+\phi_{is})ds)]}{\tau} \qquad (1)$$

where λ_{it} and ϕ_{it} are the default intensities and other exit intensities for the firm i, , $F_{it}(\tau)$ is the time-t conditional distribution function of the combined exit time evaluated at $t+\tau$, so the the survival probability for $(t, t+\tau)$ is $\exp(-\psi_{it}(\tau)\tau)$.

Assume ψ_{it} is differentiable, the forward exit intensity is

$$g_{it}(\tau) \equiv \frac{F'_{it}(\tau)}{1-F_{it}(\tau)} = \psi_{it}(\tau) + \psi'_{it}(\tau)\tau \qquad (2)$$

, hence $\psi_{it}(\tau)\tau = \int_0^\tau g_{it}(s)ds$.

The forward default intensity is

$$f_{it}(\tau) \equiv e^{\psi_{it}(\tau)\tau} \lim_{\Delta t \to 0} \frac{P_t(t+\tau < \tau_{Di} = \tau_{ci} \leq t+\tau+\Delta t)}{\Delta t}$$

$$= e^{\psi_{it}(\tau)\tau} \lim_{\Delta t \to 0} \frac{E_t[\int_{t+\tau}^{t+\tau+\Delta t} \exp(-\int_t^s(\lambda_{iu}+\phi_{iu})du)\lambda_{is}ds]}{\Delta t} \qquad (3)$$

where τ_{Di} and τ_{ci} are the default time and exit time due to any reason of firm i , and the default probability for $(t, t+\tau)$ becomes $\int_0^\tau e^{-\psi_{it}(s)s} f_{it}(s)ds$.

Suppose the variables that affect forward intensities for firm i are $(X_{it,1}, X_{it,2}, \ldots\ldots X_{it,k})$ and $f_{it}(\tau)$ and $g_{it}(\tau)$ are non-negative functions of $(X_{it,1}, X_{it,2}, \ldots\ldots X_{it,k})$. For convenience, Duan et al. (2010) let

$$f_{it}(\tau) = \exp\left(\alpha_0(\tau) + \alpha_1(\tau)X_{it,1} + \alpha_2(\tau)X_{it,2}, \ldots\ldots + \alpha_k(\tau)X_{it,k}\right) \qquad (4)$$

$$g_{it}(\tau) = f_{it}(\tau) + \exp\left(\beta_0(\tau) + \beta_1(\tau)X_{it,1} + \beta_2(\tau)X_{it,2}, \ldots\ldots + \beta_k(\tau)X_{it,k}\right) \qquad (5)$$

Finally, we can estimate the forward default probabilities and cumulative default probabilities by estimating the parameters of $f_{it}(\tau)$ and $g_{it}(\tau)$. The estimation can be implemented by maximum pseudo-likelihood estimation.

Suppose the sample period is (0, T), and it is divided into $\frac{T}{\Delta t}$ periods. Let N be the total number of companies, and t_{0i} is firm i's first month in the sample, τ is the intended prediction horizon. If a firm defaults, then $\tau_{Di} = \tau_{Ci}$, otherwise $\tau_{Di} < \tau_{Ci}$. The likelihood function can be expressed as

$$\mathcal{L}_{\tau}(\alpha, \beta; \tau_D, \tau_C, X) = \prod_{j=0}^{T/\Delta t-1} \prod_{i=1}^{N} P_{\tau,i,j}(\alpha, \beta)$$

where the $P_{\tau,i,j}(\alpha, \beta)$ is

$$\begin{aligned}
P_{\tau,i,j}(\alpha, \beta) \equiv\ & 1_{\{t_{0i} \le j\Delta t, \tau_{Ci} > j\Delta t+\tau\}} \exp\left\{- \sum_{k=0}^{\tau/\Delta t-1} g_{i,j\Delta t}(k \Delta t) \Delta t\right\} \\
& + 1_{\{t_{0i} \le j\Delta t, \tau_{Ci} = \tau_{Di} \le j\Delta t+\tau\}} \exp\left\{- \sum_{k=0}^{\tau_{Di}/\Delta t-j-2} g_{i,j\Delta t}(k \Delta t) \Delta t\right\} \\
& \times (1 - \exp\{-f_{i,j\Delta t}(\tau_{Di} - (j+1) \Delta t) \Delta t\}) \\
& + 1_{\{t_{0i} \le j\Delta t, \tau_{Di} > \tau_{Ci}, \tau_{Ci} \le j\Delta t+\tau\}} \exp\left\{- \sum_{k=0}^{\tau_{Di}/\Delta t-j-2} g_{i,j\Delta t}(k \Delta t) \Delta t\right\} \\
& \times \left(\exp\left\{-f_{i,j\Delta t}(\tau_{Ci} - (j+1) \Delta t) \Delta t\right\} - \exp\left\{-g_{i,j\Delta t}(\tau_{Ci} - (j+1) \Delta t) \Delta t\right\}\right) \\
& + 1_{\{t_{0i} > j\Delta t\}} + 1_{\{\tau_{Ci} \le j\Delta t\}} \qquad (6)
\end{aligned}$$

It is composed of probability of survival and probability of exit. If the firm does not appear in the sample period, then $P_{\tau,i,j}$ will be transformed to 0 in the log-likelihood function.

The likelihood function can be divided into two parts. Our purpose is estimating α and β. It can be implemented by maximizing the two parts separately. The two parts are

$$\mathcal{L}_{\tau}^{\alpha}(\alpha; \tau_D, \tau_C, X) = \prod_{j=0}^{T/\Delta t-1} \prod_{i=1}^{N} \mathcal{L}_{\tau,i,j}^{\alpha} \qquad (7)$$

$$\mathcal{L}_{\tau}^{\beta}(\beta; \tau_D, \tau_C, X) = \prod_{j=0}^{T/\Delta t-1} \prod_{i=1}^{N} \mathcal{L}_{\tau,i,j}^{\beta} \qquad (8)$$

$$\text{where } \mathcal{L}_{\tau,i,j}^{\alpha} = 1_{\{t_{0i} \le j\Delta t, \tau_{Ci} > j\Delta t+\tau\}} \exp\left\{- \sum_{k=0}^{\tau_{Di}/\Delta t-j-1} f_{i,j\Delta t}(k \Delta t) \Delta t\right\}$$

$$+1_{\{t_{0i}\le j\Delta t, \tau_{Ci}=\tau_{Di}\le j\Delta t+\tau\}} \exp\left\{-\sum_{k=0}^{\tau_{Di}/_{\Delta t}-j-2} f_{i,j\Delta t}(k\,\Delta\,t)\,\Delta\,t\right\}$$

$$\times\,(1-\exp\{-f_{i,j\Delta t}(\tau_{Di}-(j+1)\,\Delta\,t)\,\Delta\,t\})$$

$$+1_{\{t_{0i}\le j\Delta t, \tau_{Di}>\tau_{Ci}, \tau_{Ci}\le j\Delta t+\tau\}} \exp\left\{-\sum_{k=0}^{\tau_{Di}/_{\Delta t}-j-2} f_{i,j\Delta t}(k\,\Delta\,t)\,\Delta\,t\right\}$$

$$\times\exp\{-f_{i,j\Delta t}(\tau_{Di}-(j+1)\,\Delta\,t)\,\Delta\,t\}$$

$$+1_{\{t_{0i}>j\Delta t\}}+1_{\{\tau_{Ci}\le j\Delta t\}} \tag{9}$$

$$\mathcal{L}^{\beta}_{\tau,i,j} = 1_{\{t_{0i}\le j\Delta t, \tau_{Ci}>j\Delta t+\tau\}} \exp\left\{-\sum_{k=0}^{\tau_{Di}/_{\Delta t}-j-1} h_{i,j\Delta t}(k\,\Delta\,t)\,\Delta\,t\right\}$$

$$+1_{\{t_{0i}\le j\Delta t, \tau_{Ci}=\tau_{Di}\le j\Delta t+\tau\}} \exp\left\{-\sum_{k=0}^{\tau_{Di}/_{\Delta t}-j-2} h_{i,j\Delta t}(k\,\Delta\,t)\,\Delta\,t\right\}$$

$$+1_{\{t_{0i}\le j\Delta t, \tau_{Di}>\tau_{Ci}, \tau_{Ci}\le j\Delta t+\tau\}} \exp\left\{-\sum_{k=0}^{\tau_{Di}/_{\Delta t}-j-2} h_{i,j\Delta t}(k\,\Delta\,t)\,\Delta\,t\right\}$$

$$\times\,(1-\exp\{-h_{i,j\Delta t}(\tau_{Di}-(j+1)\,\Delta\,t)\,\Delta\,t\})$$

$$+1_{\{t_{0i}>j\Delta t\}}+1_{\{\tau_{Ci}\le j\Delta t\}} \tag{10}$$

and $h_{i,j\Delta t}(\tau) = g_{i,j\Delta t}(\tau) - f_{i,j\Delta t}(\tau)$

$$= \exp\left(\beta_0(\tau)+\beta_1(\tau)X_{it,1},\ldots\ldots\ldots+\beta_k(\tau)X_{it,k}\right) \tag{11}$$

Furthermore, equation (7) and (8) also can be decomposed to separate components for different α(s) and β(s). The likelihood functions for specific horizon are as follows:

$$\mathcal{L}_{\alpha(s)} = \prod_{j=0}^{(T-s)/_{\Delta t}-1}\prod_{i=1}^{N}\mathcal{L}_{\alpha(s),i,j} \tag{12}$$

$$\mathcal{L}_{\beta(s)} = \prod_{j=0}^{(T-s)/_{\Delta t}-1}\prod_{i=1}^{N}\mathcal{L}_{\beta(s),i,j} \tag{13}$$

where $$\mathcal{L}_{\alpha(s),i,j} = 1_{\{t_{0i}\le j\Delta t,\tau_{Ci}>(j+1)\Delta t+s\}} \exp\{-f_{i,j\Delta t}(s)\Delta t\}$$
$$+1_{\{t_{0i}\le j\Delta t,\tau_{Ci}=\tau_{Di}=(j+1)\Delta t+s\}}(1-\exp\{-f_{i,j\Delta t}(s)\Delta t\})$$
$$+1_{\{t_{0i}\le j\Delta t,\tau_{Di}\ne\tau_{Ci},\tau_{Ci}=(j+1)\Delta t+s\}} \exp\{-f_{i,j\Delta t}(s)\Delta t\}$$
$$+1_{\{t_{0i}>j\Delta t\}} + 1_{\{\tau_{Ci}<(j+1)\Delta t+s\}} \quad (14)$$
$$\mathcal{L}_{\beta(s),i,j} = 1_{\{t_{0i}\le j\Delta t,\tau_{Ci}>(j+1)\Delta t+s\}} \exp\{-h_{i,j\Delta t}(s)\Delta t\}$$
$$+1_{\{t_{0i}\le j\Delta t,\tau_{Ci}=\tau_{Di}=(j+1)\Delta t+s\}}$$
$$+1_{\{t_{0i}\le j\Delta t,\tau_{Di}\ne\tau_{Ci},\tau_{Ci}=(j+1)\Delta t+s\}}(1-\exp\{-h_{i,j\Delta t}(s)\Delta t\})$$
$$+1_{\{t_{0i}>j\Delta t\}} + 1_{\{\tau_{Ci}<(j+1)\Delta t+s\}} \quad (15)$$

We estimate the α(s) and β(s) by maximizing the equation (14) and equation (15).

3. Data and Covariates

3.1 Data

In our empirical study, we mainly identify Chapter 11 filings from www.bankruptcydata.com. In addition to the bankruptcy related data, the timing of other type of exits such as mergers and acquisitions are identified from CRSP delisting code. The equity prices are collected from CRSP and the financial statement information is retrieved from Compustat. Since the sample size of bankruptcy filings are relatively small, our sampling period is from January 1985 to December 2010. The quarterly accounting information is from 1984 to 2010 because some firms under financial distress stop filing financial reports a long time before they are delisted from the stock exchanges. For prediction purpose, if the accounting variable is missing, we substitute it with the most recent or closest observation prior to it. As commonly adopted in literature, we lag all the accounting information by three month to ensure the accounting data are observable for investors.

There are 1,371,245 firm-month observations in our sample. In this paper, firms are classified as the same industry if they have the same first three digits of SIC code. We exclude financial and utility companies, because they are strictly regulated by government.

In this paper, we adopt two definitions of bankruptcy as the following.

Definition I: Based on the broad definition of bankruptcy by Brockman and Turtle (2003), firms are classified as bankruptcy if they are delisted because of bankruptcy, liquidation or poor performance. Specifically, a firm is considered as broad definition of bankruptcy if it is given a CRSP delisting code of 400 to 499, or 550 to 599. Under this definition, there are 5,093 defaulted firms in our sample.

Definition II: Firms that file Chapter 11 or firms with CRSP delisting code between 400 and 490. Under the definition II, the total number of bankruptcy firms is 1,276.

3.2 Covariates

We estimate the forward intensities using three market-driven variables of Shumway (2010), distance to default of Duffie et al. (2007), and three intra-industry measures as the following.

(I) Firm-Specific Covariates

(1) Relative size: It is the logarithm of the ratio of each firm's equity value to the total value of NYSE and AMEX.

(2) Excess return: The excess return for firm in month *t* is the return of firm in month *t-1* minus the NYSE/AMEX index return in month *t-1*.The monthly return of firm is sum of the daily returns.

(3) Idiosyncratic risk: We compute the idiosyncratic risk by regressing each firm's monthly returns on the monthly returns of NYSE/AMEX. Idiosyncratic risk is the standard error of the residual, and we use it as the measure of firm’s specific risk.

(4) Distance to Default (DTD): The distance to default (DTD) is derived from the Merton model (1974), which can be regarded as the firm’s volatility adjusted leverage measure. The details of how to calculate DTD is presented in the Appendix. Following Duffie et al. (2007), we measure the short-term debt as the maximum of debt in current liabilities and total current liabilities, and we define the debt value of firms by short term debt plus half of long term debt.

(II) Industry Related Variables

(1) Contagion Effect of Financial Distance to Default Firms (FDDcont)

By event study, Jorion and Zhang (2007) have shown that equity correlations between firms and bankruptcy firms significantly influence CDS contagion. Recently, Chen (2010) used the equity return correlations to model the intra-industry contagion effect (competition effect). The financial distance is a function of the equity return correlation of the survival and defaulted firms. In spirit of Chen (2010), we construct a variable considering the effect of firms that defaulted during the past 12 months. Let *t* denote the elapsed time since firm *j* defaulted. $\mathrm{Corr}_{t,i,j}$ denotes the equity return correlation between firm i and defaulted firm *j*, given that firm *i* and firm *j* belong to the same industry. $\mathrm{Corr}_{t,i,j}$ is calculated by the daily stock returns during the past 12 months. We specify a time-weighted function of equity correlation as follows.

The aggregate financial distance to defaulted firms (AFDD) for firm *i* is

$$\mathrm{AFDD_i} = \sum_{t=-12}^{0} \mathrm{W_t} \sum_{j} \mathrm{Corr}_{t,i,j} \tag{17}$$

where $\mathrm{W_t} = \frac{13+t}{13}$ $\quad t = -12, -11, \ldots\ldots.., -1, 0$

To construct this intra-industry contagion variable, we also incorporate the size of bankruptcy firms. Intuitively, the impact of bankruptcy of larger firm shall be bigger than that of small firm. The impact shall decrease when time pass by. Accordingly, we define the FDDcont as each firm's AFDD times the relative size of bankruptcy firms. The FDDcont can be expressed as

$$\mathrm{FDDcont} = \mathrm{AFDD} \times \log\left(\sum_{t=-12}^{0} \mathrm{W_t}\, \frac{\text{sum of defaulted firms}'\text{value in the industry}}{\text{sum of all firms}'\text{value in the industry}}\right) \tag{18}$$

where $\text{t is the elasped time since firms defalut}$ and $\mathrm{W_t} = \frac{13+t}{13}$.

(2) Contagion Effect of Competitive Strategy Measure (CSM)

We use the competitive strategy measure (CSM) to capture the strategic interactions faced by firms, which was developed by Sundaram et al (1996). Strategic competition can be classified as strategic complement and strategic substitute. The firm faces strategic complement when its marginal profit increases with an increase in the rival's output. If the firm's marginal profit decreases with an increase in the rival's output, the firm is classified as strategic substitute. Following Sundaram et al. (1996), the rival is defined as all other firms in the given industry. The CSM is the correlation of firm's marginal profit and the change in the rival's output. The proxy of marginal profit is the ratio of change in net income to the change in sales. The rival's output is defined as the sum of all competitors' sales. The CSM for firm *i* can be expressed as

$$\mathrm{CSM_i} = \mathrm{corr}\left(\frac{\Delta \text{net income}_i}{\Delta \text{sales}_i}, \Delta \text{sales}_r\right) \quad (16)$$

If the CSM is less than -0.05, firm *i* is classified as strategic substitute; If the CSM is greater than 0.05, firm *i* is classified as strategic complement.

In order to keep as many bankruptcy samples as possible, we modify some conditions of computing CSM. First, Sundaram et al. (1996) defined the competitors as all other firms that have the same four digits SIC code. Under this definition, many firms do not have any competitors. Thus, we define the competitors as all other firms that have the same first three digits of SIC code. Second, Sundaram et al. (1996) used 40 quarters of net income and sales data to compute CSM, while we relax it to 12 quarters of data since many defaulted firm's lives are less than 10 years. The 12 quarters of data include the quarters prior to and the quarter of estimation. If the firms have any missing values within the past three years, we use the most recent 12 quarters of data within the past five years. We only compute CSM if firms have data for at least 12 quarters within the past five years.

We next build the intra-industry contagion variable SScont and SCcont. The SS (SC) is a dummy variable for strategic substitute (strategic complement); it takes 1 when firms is classified as strategic substitute (strategic complement) and zero otherwise. Note that CSM is calculated using quarterly data, thus the CSM are the same within three months for each firm. Similar to FDDcont, the SScont and SCcont also take into account the size of defaulted firms.

$$\mathrm{SScont} = \mathrm{SS} \times \log\left(\sum_{t=-12}^{0} \mathrm{W_t} \frac{\text{sum of defaulted firms}'\text{value in the industry}}{\text{sum of all firms}'\text{value in the industry}}\right) \quad (19)$$

$$\mathrm{SCcont} = \mathrm{SC} \times \log\left(\sum_{t=-12}^{0} \mathrm{W_t} \frac{\text{sum of defaulted firms}'\text{value in the industry}}{\text{sum of all firms}'\text{value in the industry}}\right) \quad (20)$$

where $\text{t is the elasped time since firms defalut}$ and $\mathrm{W_t} = \frac{13+t}{13}$.

(3) $\mathrm{DTD_{industry}}$: It is the arithmetic average of all the companies' DTD in the given Industry. Wang (2010) measures the industry-wide distress with this variable. To mitigate collinearity problem, we follow Wang (2010) to replace the DTD with $\mathrm{DTD_{diff}}$ when we include $\mathrm{DTD_{industry}}$ in the model. $\mathrm{DTD_{diff}}$ is DTD minus $\mathrm{DTD_{industry}}$.

To eliminate the potential effect of outliers, we follow Shumway (2001) to winsorize the market-driven variables at 1% and 99% level in our empirical tests. In order to understand which industry-wide variable has better explanatory power, we construct three models for different intra-industry measures, each including all the four market-driven variables. Note that many firms have lives for less than three years. It means we are unable to calculate CSM of these firms. We exclude these firms when we examine the effect of strategic competition, and the number of samples of CSM model is less than other two models.

4. Empirical Result

Before we estimate the forward intensities, we divide the sample into the estimation group and the prediction group. The estimation group contains all the data over the period 1985 to 2007, and the monthly-samples from 2008 to 2010 are classified as prediction group. We estimate the parameters of forward intensities using only the data in estimation group, and apply the coefficients obtained to perform the out-of-sample prediction accuracy analyses.

4.1 Parameter Estimates

In this section, we estimate the $\alpha(\tau)$ and $\beta(\tau)$ for various τ ranging from 0 to 5 months. We test three models for different measures of intra-industry effect under two definitions of bankruptcy. First, we report the correlation matrix of variable in Table 1. The estimated results are shown in Tables 2 to 7. We focus on how these variables can affect default probabilities, which are reflected in the estimates of $\alpha(\tau)$s. The reason of the other exits may be too complicated, thus it is not of interest in this study to examine the significance of β(s).

[INSERT TABLES 1-4 HERE].

In Table 2, one can find that the FDDcont significantly influences the default intensities. The default probability is higher when the firm has higher equity return correlation to bankruptcy firms. The positive coefficients of FDDcont indicate that the financial correlations affect the default correlations. The significance of FDDcont also suggests that the impacts of defaults of large firms are bigger than those of small firms, as expected.

On the contrary, in Table 3, there is no significant difference between firms that face strategic competitions or not. The estimated coefficients of SCcont and SScont are not statistically significant when τ is greater than two months. It appears that the measure of strategic competition cannot explain the industry-wide contagion effect. It may be due to the fact that the sample size is much smaller due to the 12 quarters requirement to compute CSM. For each quarter, we calculate the CSM when firms have at least 12 quarterly data during the past 5 years.

In Table 4, we also find that forward default intensities decrease with the increase in $\mathrm{DTD}_{\mathrm{industry}}$. This is consistent with the findings of Wang (2010). The negative estimated coefficients of $\mathrm{DTD}_{\mathrm{industry}}$ mean that default probabilities of firms increase under the industry-wide financial distress. The default probabilities are high when all the firms have high default risk in the industry. That may potentially explain clustered defaults of firms in the given industry.

For each model, all the four market-driven variables are statistically significant for different τs, and their signs are consistent to previous literature. Firms that have large size, low idiosyncratic risk, and high excess return have lower default probabilities. Using forward intensity approach, our results regarding the significance of market variables are consistent with Shumway (2001), Bharath and Shumway (2008) and Duffie et al. (2007). More importantly, our results also indicate that the FDDcont and $\mathrm{DTD}_{\mathrm{industry}}$ siginificantly influence default intensities, and they are useful variables in explaining the industry-wide contagion effect.

For the estimates of bankruptcy definition II in Tables 5 to 7, most of the results are very similar to those in Tables 2 to 4 in terms of statistical significance. We also estimated the parameters of the model that only include market-driven variables. The results are similar to Tables 2 to 4. To conserve space, we do not present the results. We estimate these coefficients in order to test whether the predictive performance is better incorporating intra-industry measures to the existing market-driven variables.

[INSERT TABLES 5-7 HERE].

4.2 Out-of-sample Prediction Accuracy

In this section, we report the bankruptcy prediction performance adding intra-industry measure using the ROC curves and accuracy ratios. We focus the analysis on FDDcont and $\mathrm{DTD}_{\mathrm{industry}}$ due to the lack of significance of CSM. To compare the out-of-sample prediction performance, one needs to estimate the cumulative default probability before plotting ROC curves. According to Duan et al. (2010), The cumulative default probability at time *t* for the future period $(t, \ t+\tau)$ is

$$P_t(\, t < \ \tau_{Di} = \ \tau_{ci} \leq t + \tau)$$

$$= \sum_{j=1}^{\tau/\Delta t} e^{-\psi_{it}((j-1)\Delta t)(j-1)\Delta t}\left(1 - e^{-f_{it}((j-1)\Delta t)\Delta t}\right) \quad (18)$$

We apply the estimated coefficients obtained from estimation group (1985-2007) to prediction group (2008-2010) to compute the cumulative default probabilities of each firm-month sample. We report the ROC curves and accuracy ratios for 1-month- and 6-month- ahead bankruptcy prediction, in Figures 1 and 2, respectively. All models in the AR test include 4 firm-specific market variables. We term the benchmark model Shumway model, which contains only 4 firm-specific variables; $\mathrm{DTD}_{\mathrm{industry}}$ and Financial Distance models add the industry measures $\mathrm{DTD}_{\mathrm{industry}}$ and Financial Distance, respectively.

[INSERT FIGURES 1-2 HERE].

[INSERT TABLES 8-9 HERE].

In Figure 1, comparing the effect of industry variables, $\mathrm{DTD}_{\mathrm{industry}}$ model (AR = 0.8627) is the best performing model, followed by Financial Distance model (AR = 0.8579), and Shumway model with only four firm-specific variables (AR = 0.8261). It is apparent that considering industry variables can enhance out-of-sample prediction accuracy. The differences of AR ratios are statistically significant in Table 8. We found that the predictive performance is substantially enhanced after adding $\mathrm{DTD}_{\mathrm{industry}}$ or financial distance to the Shumway model. Similar results are also obtained from the 6-month prediction analysis in Figure 2 and Table 9. In sum, the out-of-sample prediction analyses indicate that $\mathrm{DTD}_{\mathrm{industry}}$ and financial distance are useful when one needs to forecast firms' default probabilities. The introduction of industry-wide variables do improve the performance of bankruptcy prediction.

5. Conclusion

We use three different kinds of measures to capture the intra-industry contagion effects, and examine how these measures affect default probabilities. The empirical evidence shows that a firm's default probability significantly increases when the level of industry-wide distress is higher. It also appears that the default probability of a firm is higher when the returns of the firm are more positively related to defaulted firms. The lack of significance of strategic competition may be due to the limitation when computing CSM since it requires a long history of accounting data. Nonetheless, it leads to loss of a large proportion of the sample firms. It is evident that the out-of-sample predictive performance is substantially enhanced when we add contagion variable of financial distance or $\mathrm{DTD}_{\mathrm{industry}}$ into the model. Overall, our results suggest that intra-industry contagion effect may be characterized by the level of industry-wide financial distress or the equity correlations among firms.

Reference

Acharya, V.. V., S. T. Bharath, and A. Srinivasan, 2007, Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries, Journal of Financial Economics 85, 787-821.
University Working Paper.

Bekaert, G., C. R. Harvey, and A. Ng, 2005, Market Integration and Contagion. The Journal of Business 78(1), 39–69.

Bharath, S. T., and T. Shumway, 2008, Forecasting default with the Merton distance to default model, Review of Financial Studies 21, 1339-1369.

Chava, Sudheer, and Robert A. Jarrow, 2004, Bankruptcy prediction with industry effects, Review of Finance 8, 537-569.

Das, S. R., D. Duffie, N. Kapadia, and L. Saita, 2007, Common failings: How corporate defaults are correlated, Journal of Finance 62, 93-117.

Duan, J. C., 2000, Correction: "Maximum likelihood estimation using price data of the derivative contract", Mathematical Finance 10, 461-462.

Duan, J. C., J. Sun and T. Wang, 2010, Multiperiod corporate default prediction - A forward intensity approach, National University of Singapore Working Paper.

Duffie, D., L. Saita, and K. Wang, 2007, Multi-period corporate default prediction with stochastic covariates, Journal of Financial Economics 83, 635-665.

Hillegeist, S. A., E. K. Keating, D. P. Cram, and K. G. Lundstedt, 2004, Assessing the probability of bankruptcy, Review of Accounting Studies 9, 5-34.

Jorion, P., and G. Y. Zhang, 2007, Good and bad credit contagion: Evidence from credit default swaps, Journal of Financial Economics 84, 860-883.

Lando, D., and M. S. Nielsen, 2010, Correlation in corporate defaults: Contagion or conditional independence, Journal of Financial Intermediation 19 (2010) 355–372.

Lang, L. and R. Stulz, 1992, “Contagion and Competitive Intra-Industry Effects of Bankruptcy Announcements,” Journal of Financial Economics 8, 45-60.

Merton, Robert C., 1974, On the pricing of corporate debt: The risk structure of interest rates, Journal of Finance 29, 449-470.

Ohlson, J. A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, Journal of Accounting Research 18, 109-131.

Shumway, T., 2001, Forecasting bankruptcy more accurately: A simple hazard model, Journal of Business 74, 101-124.

Sundaram, A., John, T., John, K., 1996. An empirical analysis of strategic competition and firm values: The case of R&D competition. Journal of Financial Economics 40, 459–486.

Wang, T., 2010, Determinants of corporate default: Systematic distress, sectoral distress and credit contagion, National University of Singapore Working Paper.

Zmijewski, M. E., 1984, Methodological issues related to the estimation of financial distress prediction models, Journal of Accounting Research 22, 59–82.

Appendix

Merton (1974) assumes that the total value of a firm follow geometric Brownian motion, $dV = \mu V dt + \sigma_V V dB$. The second assumption is that the firm is financed by equity and single discount bond maturing in *T* period. Under these assumptions, the equity value of the firm is a call option on the firm's asset value. The equity value of the firm can be expressed as

$$E = V_t N(d_1) - e^{-rT} D N(d_1 - \sigma_V \sqrt{T - t})$$

where $r =$ risk free rate

$D =$ the debt value of the firm

$$d_1 = \frac{\ln\left(V_t/D\right) + \left(r + \sigma_V{}^2/2\right)(T-t)}{\sigma_V \sqrt{T-t}}$$

$V =$ firm value

$N(\cdot) =$ the cumulative distribution function of standard normal variable

The distance to default is $\mathbf{DTD} = \frac{\ln\left(V/D\right) + \left(\mu - \sigma_V{}^2/2\right)T}{\sigma_V \sqrt{T}}$

, and the firm's bankruptcy probability at time t is $N(-DTD_t)$

Before calculating the DTD, one needs to measure the debt value and the volatility of total firm value. We follow Duffie et al (2007) to set the short-term debt as the maximum of debt in current liabilities and total current liabilities. The debt value is computed as short-term debt plus one half of the long-term debt and other liabilities.

Following Bharath and Shumway (2008), we obtain V and σ_V by solve the following equations through iterated procedure.

$$\sigma_E = \frac{V}{E} N(d_1) \sigma_V$$

$$E = V N(d_1) - e^{-rT} D N(d_1 - \sigma_V \sqrt{T})$$

Table 1

Panel A. The correlation matrix of Financial Distance model and $\mathbf{DTD_{industry}}$ model

	Relative size	Excess return	Idiosyncratic risk	FDcont	DTD	DTD_{diff}	$DTD_{industry}$
Relative size	1	0.17318	-0.41040	-0.01045	0.51575	0.44942	0.18677
Excess return	0.17318	1	0.21122	0.00087	0.32858	0.31397	0.07669
Idiosyncratic risk	-0.41040	0.21122	1	-0.43654	-0.43654	-0.29285	-0.29206
FDcont	-0.01045	0.00087	-0.14824	1	0.08053	-0.02209	0.17035
DTD	0.51575	0.32858	-0.43654	0.08053	1	0.81256	0.45216
DTD_{diff}	0.44942	0.31397	-0.29285	-0.02209	0.81256	1	-0.15248
$DTD_{industry}$	0.18677	0.07669	-0.29206	0.17035	0.45216	-0.15248	1

Panel B. The correlation matrix of CSM model

	Relative size	Excess return	Idiosyncratic risk	SScont	SCcont	DTD
Relative size	1	0.13181	-0.39073	-0.01055	-0.02646	0.52624
Excess return	0.13181	1	0.26639	-0.00401	-0.00689	0.29304
Idiosyncratic risk	-0.39073	0.26639	1	0.01730	0.02382	-0.45069
SScont	-0.01055	-0.00401	0.01730	1	-0.69509	-0.03179
SCcont	-0.02646	-0.00689	0.02382	-0.69509	1	-0.03835
DTD	0.52624	0.29304	-0.45069	-0.03179	-0.03835	1

Table 2

The estimation results of Financial Distance model (Bankruptcy Definition I)

Maximum likelihood estimations for α(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.876***	-0.8101***	-0.7347***	-0.6829***	-0.6376***	-0.6007***
	(0.01962)	(0.0189)	(0.01766)	(0.01706)	(0.01621)	(0.01565)
Excess return	-0.7029***	-0.7199***	-0.7199***	-0.7251***	-0.7165***	-0.6729***
	(0.03193)	(0.03168)	(0.03127)	(0.031)	(0.03029)	(0.03015)
Idiosyncratic risk	4.00908***	4.2875***	4.28482***	4.22043***	4.13234***	4.07414***
	(0.14057)	(0.13975)	(0.13995)	(0.14132)	(0.14056)	(0.1418)
DTD	-0.2739***	-0.2655***	-0.2533***	-0.2321***	-0.2262***	-0.2153***
	(0.023)	(0.02195)	(0.02055)	(0.01974)	(0.01827)	(0.01729)
FDcont	0.01461***	0.01783***	0.01595***	0.01791***	0.01702***	0.02037***
	(0.0049)	(0.00506)	(0.00487)	(0.00507)	(0.00506)	(0.00533)

Maximum likelihood estimations for β(s) of the model

T	0	1	2	3	4	5
Relative size	-0.0072	0.01403*	0.02253***	0.01742**	0.01249	0.00984
	(0.0083)	(0.00828)	(0.0082)	(0.00814)	(0.0081)	(0.00805)
Excess return	0.75509***	0.67175***	0.549***	0.40602***	0.25376***	0.16325***
	(0.02826)	(0.02795)	(0.0283)	(0.02841)	(0.02917)	(0.02918)
Idiosyncratic risk	-0.6665***	-0.0098	0.11266	-0.1368	-0.386**	-0.7341***
	(0.1754)	(0.17044)	(0.17083)	(0.17361)	(0.18114)	(0.18626)
DTD	0.02295***	0.01456***	-0.0036	-0.0186***	-0.0295***	-0.0414***
	(0.00531)	(0.00536)	(0.00549)	(0.00564)	(0.00581)	(0.00593)
FDcont	-0.0324***	-0.0289***	-0.0269***	-0.0271***	-0.0263***	-0.0269***
	(0.00422)	(0.00413)	(0.00419)	(0.00402)	(0.00407)	(0.00404)

One, two and three asterisks (*) represent significance at the 1%, 5% and 10% level; the number in brackets are standard errors of estimated coefficients.

Table 3

The estimation results of CSM model (Bankruptcy Definition I)

Maximum likelihood estimations for α(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.9243***	-0.9178***	-0.7694***	-0.7493***	-0.7196***	-0.616***
	(0.035269)	(0.036724)	(0.032836)	(0.031113)	(0.029504)	(0.027046)
Excess return	-0.542***	-0.5666***	-0.8754***	-0.5749***	-0.5704***	-0.7211***
	(0.072069)	(0.073248)	(0.06863)	(0.0687)	(0.065228)	(0.060712)
Idiosyncratic risk	1.86517***	2.31113***	5.07013***	2.07944***	2.18216***	4.70787***
	(0.378954)	(0.381823)	(0.3128)	(0.350587)	(0.340281)	(0.288818)
DTD	-0.2477***	-0.2403***	-0.1938***	-0.315***	-0.312***	-0.2445***
	(0.03724)	(0.038681)	(0.034826)	(0.033802)	(0.032252)	(0.029489)
SCcont	0.02312***	-0.0025	0.00799	0.01031	0.00323	0.01104
	(0.00772)	(0.008821)	(0.008177)	(0.00824)	(0.007963)	(0.007661)
SScont	0.02581***	-0.0015	0.00792	0.00863	0.00116	0.00472
	(0.007666)	(0.008842)	(0.008145)	(0.007999)	(0.007715)	(0.007398)

Maximum likelihood estimations for β(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.0368***	-0.0242**	-0.0183*	-0.0197*	-0.0212**	-0.0234**
	(0.011171)	(0.011144)	(0.010979)	(0.010884)	(0.010717)	(0.010711)
Excess return	0.88752***	0.84481***	0.70618***	0.54853***	0.32094***	0.17644***
	(0.037279)	(0.038129)	(0.039514)	(0.039543)	(0.041665)	(0.041835)
Idiosyncratic risk	-0.0128	0.19122	0.24274	0.09131	0.00526	-0.1102
	(0.267312)	(0.271273)	(0.272525)	(0.264007)	(0.269693)	(0.272187)
DTD	0.06603***	0.05307***	0.03593***	0.02484***	0.01206	0.0018
	(0.007408)	(0.007387)	(0.007535)	(0.007586)	(0.007687)	(0.007798)
SCcont	-0.0029	-0.0068	-0.0093*	-0.0106**	-0.0158***	-0.0134**
	(0.005081)	(0.005145)	(0.005176)	(0.005192)	(0.005267)	(0.005241)
SScont	0.00271	0.0002	-0.0008	-0.002	-0.0068	-0.0038
	(0.005092)	(0.005182)	(0.005238)	(0.005292)	(0.005362)	(0.005337)

One, two and three asterisks (*) represent significance at the 1%, 5% and 10% level; the number in brackets are standard errors of estimated coefficients.

Table 4

The estimation results of $\mathbf{DTD_{industry}}$ model (Bankruptcy Definition I)

Maximum likelihood estimations for α(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.8768***	-0.8134***	-0.7382***	-0.6876***	-0.6432***	-0.6075***
	(0.01964)	(0.01894)	(0.01767)	(0.01707)	(0.01618)	(0.01561)
Excess return	-0.6909***	-0.7077***	-0.7091***	-0.7138***	-0.7063***	-0.6613***
	(0.03195)	(0.03168)	(0.031250	(0.03096)	(0.03028)	(0.03007)
Idiosyncratic risk	3.96797***	4.22713***	4.22423***	4.148***	4.05656***	3.98216***
	(0.13944)	(0.13846)	(0.13864)	(0.13999)	(0.13933)	(0.14061)
$DTD_{industry}$	-0.2363***	-0.2347***	-0.2305***	-0.2136***	-0.2158***	-0.2079***
	(0.02295)	(0.02199)	(0.02076)	(0.02002)	(0.01892)	(0.01821)
DTD_{diff}	-0.2905***	-0.2778***	-0.2617***	-0.238***	-0.2283***	-0.2156***
	(0.02409)	(0.02297)	(0.02149)	(0.02069)	(0.01908)	(0.01803)

Maximum likelihood estimations for β(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.0046	0.0171	0.02683***	0.02285***	0.01871**	0.01667**
	(0.00816)	(0.00815)	(0.00811)	(0.00809)	(0.00808)	(0.00804)
Excess return	0.74395***	0.66169***	0.53992***	0.39678***	0.24455***	0.15405***
	(0.0284)	(0.02812)	(0.02853)	(0.02868)	(0.02946)	(0.02944)
Idiosyncratic risk	-0.5553***	0.09788	0.23064	0.00181	-0.2315	-0.5614***
	(0.17566)	(0.17066)	(0.17139)	(0.17415)	(0.18114)	(0.18574)
$DTD_{industry}$	-0.0173*	-0.0136	-0.0157	-0.0214**	-0.0233	-0.0313***
	(0.00975)	(0.00965)	(0.00961)	(0.00966)	(0.00964**)	(0.00967)
DTD_{diff}	0.03278***	0.02101***	-0.002	-0.02***	-0.0337***	-0.0471***
	(0.0057)	(0.00579)	(0.00594)	(0.00609)	(0.0063)	(0.00643)

One, two and three asterisks (*) represent significance at the 1%, 5% and 10% level; the number in brackets are standard errors of estimated coefficients.

Table 5

The estimation results of Financial Distance model (Bankruptcy Definition II)

Maximum likelihood estimations for α(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.1978***	-0.1246***	-0.0844***	-0.0816***	-0.0613***	-0.0427***
	0.040746	0.388322	0.02573	0.023823	0.022154	0.020667
Excess return	-0.9097***	-0.8228***	-0.6696***	-0.7181***	-0.7295***	-0.5998**
	0.120917	0.095639	0.082983	0.079663	0.073838	0.070753
Idiosyncratic risk	4.45584***	3.99154***	3.52081***	3.26598***	3.22369***	3.19576***
	0.464596	0.391858	0.353904	0.344652	0.319277	0.312125
DTD	-0.7417***	-0.8149***	-0.7995***	-0.748***	-0.7008***	-0.6819***
	0.085607	0.063824	0.049516	0.047429	0.04107	0.036034
FD	0.15775***	0.17595***	0.12925***	0.1035***	0.06432**	0.03549***
	0.041994	0.030952	0.032281	0.030481	0.026802	0.02362

Maximum likelihood estimations for β(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.1417***	-0.132***	-0.1346***	-0.1417***	-0.1476***	-0.1533***
	0.007442	0.007455	0.007363	0.007278	0.007192	0.007138
Excess return	0.25666***	0.18339***	0.0615***	-0.0598***	-0.1783***	-0.2396***
	0.023697	0.023299	0.023002	0.022799	0.022738	0.022544
Idiosyncratic risk	2.59985***	3.10881***	3.18727***	2.96497***	2.74286***	2.462***
	0.130328	0.126192	0.122764	0.121656	0.123333	0.125449
DTD	0.03875***	0.03488***	0.02119***	0.009*	0.00065	-0.009*
	0.004513	0.004516	0.004588	0.004621	0.004708	0.004772
FD	-0.0096	0.00249	0.00723	0.00422	0.00642	0.00296
	0.010251	0.010107	0.009986	0.009253	0.009452	0.009519

One, two and three asterisks (*) represent significance at the 1%, 5% and 10% level; the number in brackets are standard errors of estimated coefficients.

Table 6

The estimation results of CSM model (Bankruptcy Definition II)

Maximum likelihood estimations for α(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.2801***	-0.1928***	-0.1503***	-0.1211***	-0.0884***	-0.1014***
	(0.057297)	(0.059268)	(0.049635)	(0.043614)	(0.039814)	(0.037174)
Excess return	-0.7698***	-0.7524***	-0.6375***	-0.6138***	-0.7084**	-0.549***
	(0.203771)	(0.206491)	(0.190549)	(0.165746)	(0.15118)	(0.144169)
Idiosyncratic risk	1.54752**	1.09206	0.98004	0.76048	0.80209	0.83217
	(0.910981)	(0.942415)	(0.915143)	(0.806099)	(0.787922)	(0.739203)
DTD	-0.7834***	-0.7955***	-0.794***	-0.8359***	-0.7654***	-0.7053***
	(0.153093)	(0.141086)	(0.115473)	(0.085689)	(0.077912)	(0.06931)
SCcont	0.08161***	0.03785*	0.01844	0.01533	0.01762	0.02041
	(0.015686)	(0.020086)	(0.018304)	(0.017498)	(0.017073)	(0.016843)
SScont	0.07374***	0.0419**	0.02218	0.01283	0.00741	0.0124
	(0.015651)	(0.020302)	(0.019343)	(0.017769)	(0.017033)	(0.016255)

Maximum likelihood estimations for β(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.1874***	-0.1806***	-0.1856***	-0.1882***	-0.1987***	-0.1955***
	(0.01486)	(0.014889)	(0.014795)	(0.014796)	(0.014675)	(0.014579)
Excess return	0.37652***	0.37051***	0.19891***	0.06035	-0.1241**	-0.1731***
	(0.050962)	(0.050562)	(0.051117)	(0.050591)	(0.051292)	(0.051017)
Idiosyncratic risk	0.42353	0.629*	0.66953**	0.4693	0.45281	0.27725
	(0.334683)	(0.33297)	(0.32551)	(0.32339)	(0.330535)	(0.328396)
DTD	0.02844***	0.01504	0.00077	-0.0167	-0.0203*	-0.0381***
	(0.011037)	(0.011178)	(0.01135)	(0.011534)	(0.011656)	(0.012111)
SCcont	-0.0147**	-0.0182***	-0.0188***	-0.0192***	-0.0183***	-0.0195***
	(0.006146)	(0.006211)	(0.006198)	(0.006196)	(0.006154)	(0.006117)
SScont	-0.0115*	-0.0144*	-0.0146**	-0.0158**	-0.0144**	-0.0144**
	(0.006179)	(0.006278)	(0.006209)	(0.006192)	(0.006146)	(0.006133)

One, two and three asterisks (*) represent significance at the 1%, 5% and 10% level; the number in brackets are standard errors of estimated coefficients.

Table 7

The estimation results of $\mathrm{DTD}_{\mathrm{industry}}$ model (Bankruptcy Definition II)

Maximum likelihood estimations for α(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.2073***	-0.1355***	-0.0931***	-0.0893***	-0.0664***	-0.0465**
	(0.039795)	(0.029819)	(0.025661)	(0.023859)	(0.022309)	(0.02084)
Excess return	-0.8823***	-0.7961***	-0.6484***	-0.7001***	-0.7164***	-0.5918***
	(0.120331)	(0.095225)	(0.082694)	(0.079513)	(0.073848)	(0.070664)
Idiosyncratic risk	4.29239***	3.79162***	3.3436***	3.10337***	3.10927***	3.11487***
	(0.455909)	(0.386644)	(0.348209)	(0.339883)	(0.316992)	(0.307778)
$\mathrm{DTD}_{\mathrm{industry}}$	-0.6782***	-0.7556***	-0.755***	-0.714***	-0.6764***	-0.6716***
	(0.084717)	(0.063431)	(0.050686)	(0.04895)	(0.043424)	(0.039496)
$\mathrm{DTD}_{\mathrm{diff}}$	-0.7654***	-0.834***	-0.8122***	-0.7574***	-0.7077***	-0.684***
	(0.085877)	(0.063885)	(0.049416)	(0.047664)	(0.041393)	(0.036351)

Maximum likelihood estimations for β(s) of the model

τ	0	1	2	3	4	5
Relative size	-0.1412***	-0.1314***	-0.1334***	-0.1398***	-0.1457***	-0.1509***
	(0.00742)	(0.007439)	(0.007356)	(0.007272)	(0.007196)	(0.007147)
Excess return	0.25566***	0.18418***	0.06343***	-0.0576**	-0.1758***	-0.2373***
	(0.023657)	(0.023251)	(0.02297)	(0.022777)	(0.022708)	(0.022504)
Idiosyncratic risk	2.61204***	3.11906***	3.20546***	2.99887***	2.77739***	2.5088***
	(0.12991)	(0.125412)	(0.122019)	(0.120762)	(0.122105)	(0.124053)
$\mathrm{DTD}_{\mathrm{industry}}$	0.03764***	0.04075***	0.03375***	0.02619***	0.01885***	0.01115*
	(0.006719)	(0.006508)	(0.006427)	(0.006355)	(0.006362)	(0.006368)
$\mathrm{DTD}_{\mathrm{diff}}$	0.0389***	0.03281***	0.01672***	0.0026	-0.0061	-0.0166***
	(0.004869)	(0.004847)	(0.00488)	(0.004898)	(0.004977)	(0.005025)

One, two and three asterisks (*) represent significance at the 1%, 5% and 10% level; the number in brackets are standard errors of estimated coefficients.

Figure 1

The ROC curves for 1-month bankruptcy prediction

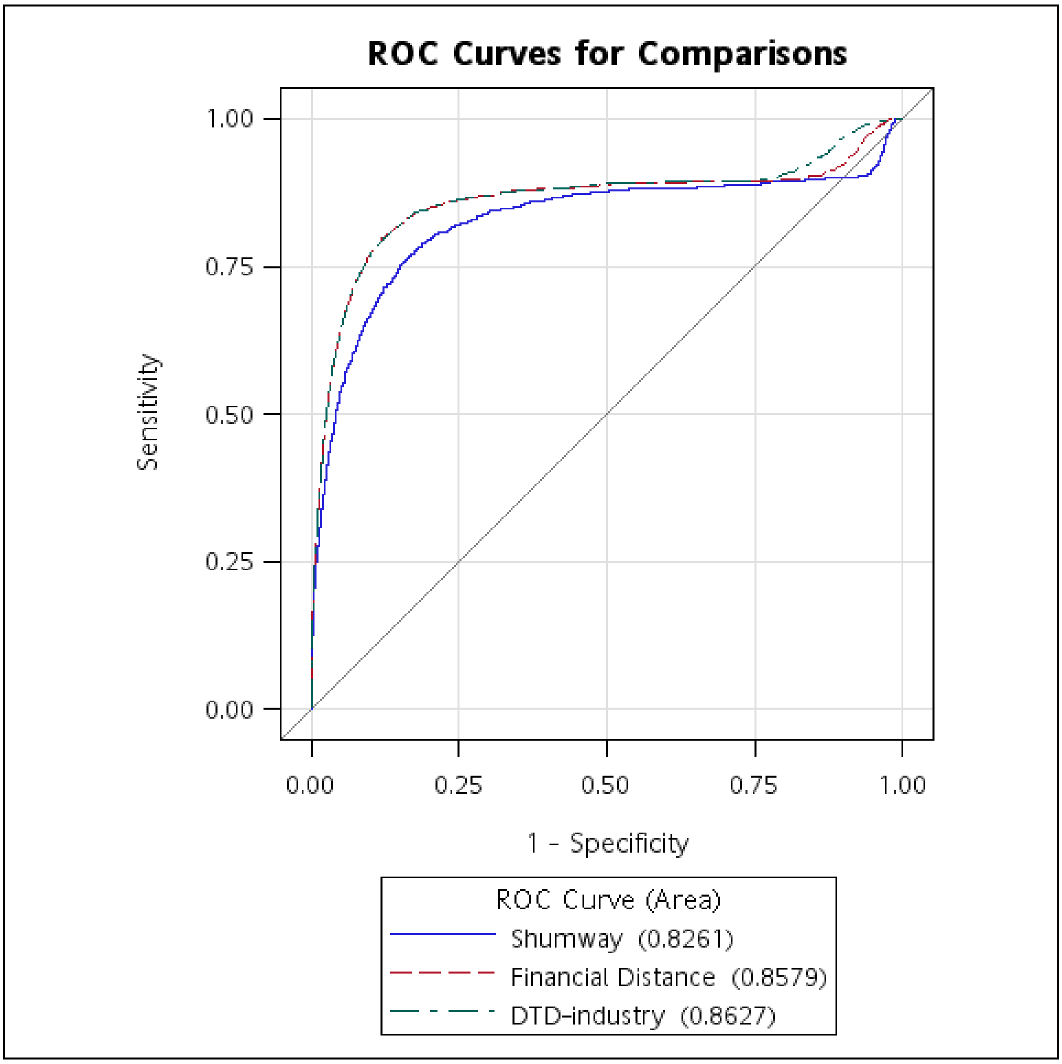

Table8

The AR ratio test result for 1-month bankruptcy prediction

	Estimate	P-value
$DTD_{industry}$- Shumway	0.0366	<0.001
Financial Distance - Shumway	0.0318	<0.001

Figure 2

The ROC curves for 6-month bankruptcy prediction

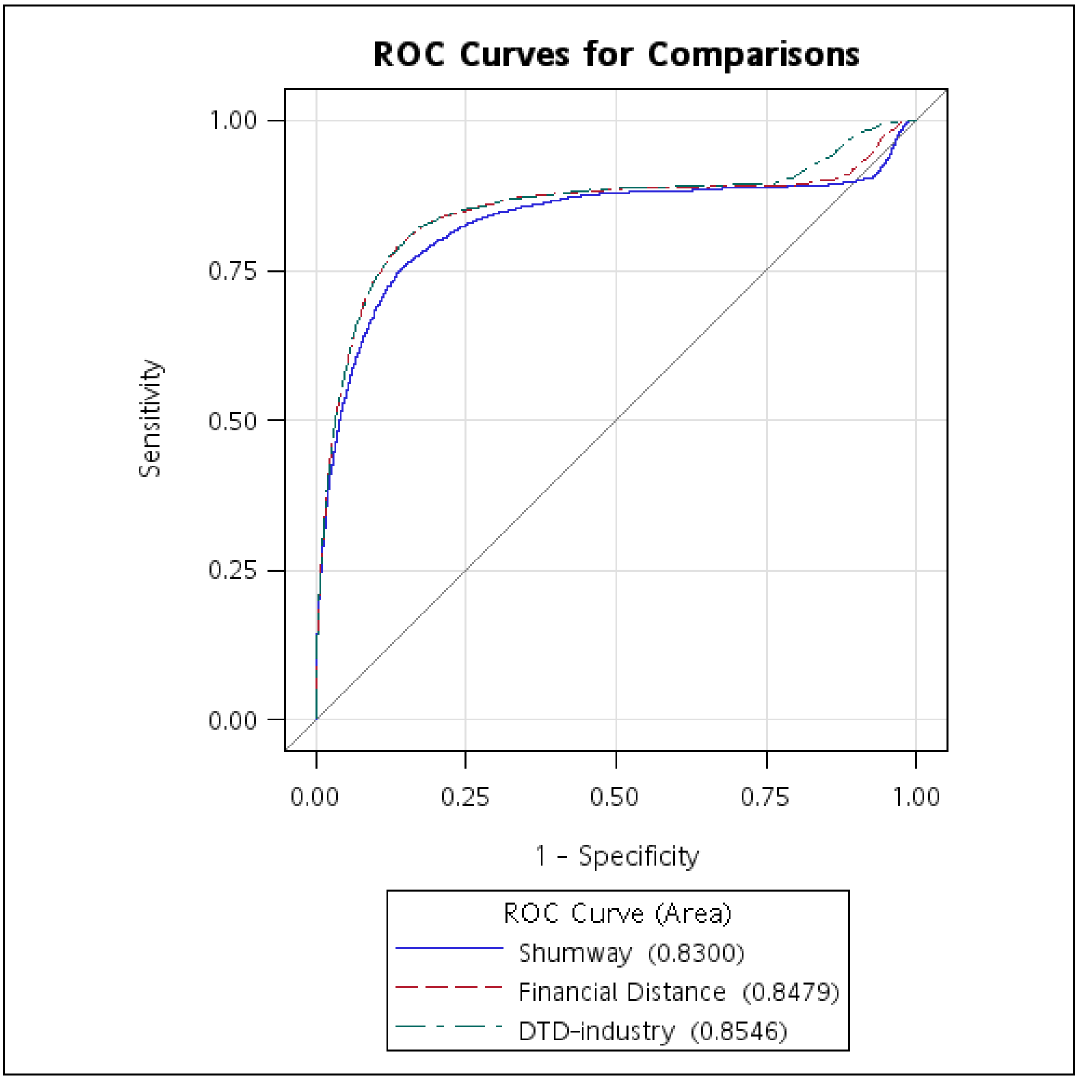

Table9

The AR ratio test result for 6-month bankruptcy prediction

	Estimate	P-value
$DTD_{industry}$- Shumway	0.0245	<0.001
Financial Distance - Shumway	0.0178	<0.001