Predicting Default with Firm-specific Macroeconomic Exposures

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Abstract

In this paper, we propose a new hazard model for default prediction. In the model, macroeconomic exposures are formed to be linear functions of observable firm characteristics. With this feature, the model allows not only time-varying but also firm-specific exposures on macroeconomic risk factors. Empirical tests are performed in Korean market using the default data from 1993 to 2005. Our model outperforms alternative models with regard to the power of forecasting default of firms. We also find that IT, health care and consumer companies are more exposed to changes in USD/KRW exchange rate volatility. Also, high credit quality firms are found to be more sensitive to macroeconomic effects, which is consistent with previous researches.

Keywords: hazard model; macroeconomic exposure; default prediction; credit risk

JEL classification: G17, G11

1 Introduction

It is reasonable to expect that the individual firm's default likelihood responds differently on various macroeconomic effects. For example, the financial healthiness of firms like Toyota Motors, whose businesses depend heavily on exports, are more affected by the foreign exchange rate movement than the others, and thus those firms can be more vulnerable to currency risk.

In a linear factor model, the individual sensitivity to macroeconomic effects means that the beta coefficients of the common factors are firm-specific. However, we cannot simply allow the beta coefficient to be firm-specific due to the cross-sectional nature of the survival data. Default is a rare event and it is usually not repeated for a company. Thus, even if we have multi-period information of a firm's survival status, it is not enough to conduct a time series analysis to obtain individual sensitivities. So the models for estimating default likelihood introduced so far do not provide firm-specific sensitivities on macroeconomic effects.

We use the hazard model to estimate default probability. Shumway (2001) argues that the single-period models such as static logit models are inconsistent because those models fail to consider each firm's period at risk. On the other hand, hazard models are shown to be consistent because they are basically multi-period and consider the whole life of a firm. Also, hazard models can easily incorporate dynamic nature of firms' credit healthiness by allowing time-varying explanatory variables.

The importance of macroeconomic factors on default probability has been explored in many researches (Duffie *et al.*, 2007; Bonfim, 2009). Unfortunately, the hazard models applied in credit risk so far do not capture firm-specific sensitivities to macroeconomic or other common factors because the coefficients of the explanatory variables are restricted to be common to all firms; see Shumway (2001), Chava and Jarrow (2004) and Duffie *et al.* (2007).

One way to obtain firm-specific sensitivities on common factors is to use time-series of credit spread data as in Duffee (1999) and Driessen (2005). However, this requires a well-developed and highly liquid credit market, which is not the case for many countries. Thus, we still need to look at default data directly to cover a broad range of firms and markets.

In this paper, we extend the existing hazard models to incorporate firm-specific exposures on common macroeconomic factors. In our hazard model specification, individual firm characteristics form the beta coefficients or, more specifically, the factor loadings. By allowing the factor loadings be linear functions of firm characteristics, the parameters can be identified. This is based on the assumption that the firm-specific factor loadings are explained by firm characteristics, which is in line with the classical multi-factor model by Rosenberg (1974). This assumption is partially justified by the long list of researches on the determinants of beta; see Hamada (1972), Rosenberg and McKibben (1973), Turbull (1977) and Ryan (1997) among many others.

The model is tested with Korean default data from 1993 to 2005 both in-sample and out-of-sample. Our model is shown to capture firm-specific macroeconomic exposures well. Also, it outperforms previous hazard models with regard to forecast accuracy. The proposed model allows us to investigate which firms are more exposed to macroeconomic shocks. We find that IT, health care and consumer companies are more vulnerable to foreign exchange rate volatility (FXV) changes. Also, high credit quality firms are found to be more sensitive to FXV. Of course, this empirical result is specific to Korean firms.

The factor loadings in our model are not only individual but also time-varying since the factor loadings are functions of firm-specific characteristics which is time-varying. This structure allows dynamic default correlations, and this is a topic of subsequent research in Kang, Kim and Lee (2009).

The rest of the paper is organized as follows. In section 2, we briefly introduce hazard models. Section 3 develops a new hazard model that allows firm-specific macro exposures. Section 4 describes the data and presents the empirical results. Section 5 concludes.

2 Hazard Model

In this section, we briefly review the hazard models in survival analysis; see the monographs by Cox and Oakes (1984) for details.

The default time of a firm is represented by a non-negative random variable τ. We assume that τ is a continuous random variable with a probability density function $f(t)$ and a cumulative distribution function $F(t) = \Pr[\tau \leq t]$. The probability that the firm survives until t is given by the survival function

$$S(t) = \Pr[\tau > t] = 1 - F(t) = \int_t^{\infty} f(s)\, ds. \tag{1}$$

The hazard rate is defined as

$$\lambda\left(t\right)=\lim_{dt\rightarrow0}\frac{\Pr\left[t<\tau\leq t+dt\mid\tau>t\right]}{dt}. \tag{2}$$

For a small dt, the $\lambda\left(t\right)dt$ can approximate the conditional probability that the default event occurs in the interval $\left(t,t+dt\right)$ given that it has not occurred before. From this, we can interpret the hazard rate as an instantaneous rate of default. Using the definition of the conditional probability, we have

$$\lambda\left(t\right)=\frac{\lim_{dt\rightarrow0}\Pr\left[t<\tau\leq t+dt\right]/dt}{\Pr\left[\tau>t\right]}=\frac{f\left(t\right)}{S\left(t\right)},$$

which is often used as an alternative definition of the hazard rate.

If we note that $-f\left(t\right)$ is the derivative of $S\left(t\right)$, the hazard rate can be written as

$$\lambda\left(t\right)=-\frac{d}{dt}\ln S\left(t\right). \tag{3}$$

From this and a boundary condition, $S\left(0\right)=1$, we can obtain a formula

$$S\left(t\right)=\exp\left\{-\int_{0}^{t}\lambda\left(s\right)ds\right\}. \tag{4}$$

So the hazard rate and the survival probability have effectively the same information.

In practice, it is convenient to directly model the hazard function. The most frequently used is the proportional hazard model by Cox (1972). It assumes the following form for the hazard rate at time t for an individual firm i with covariate x_i:

$$\lambda_i\left(t\mid x_i\right)=\lambda_0\left(t\right)\exp\left\{\beta' x_i\right\}, \tag{5}$$

where β and x_i are vectors with the same dimension. For a hypothetical firm with $x_i=0$, the hazard rate is $\lambda_0\left(t\right)$, which is called the baseline hazard rate. Then $\exp\left\{\beta' x_i\right\}$ gives the relative risk associated with the individual characteristics x_i. The covariates can be time-varying so that the hazard rate can change over time.

Survival data has censoring features. There are several cases. First, firms can survive until the end of the observation period. Second, firms can exit from the data set due to merge or reasons other than default event even during the observation period. Lastly, we have firms that experienced default event. The firms in the first two cases are said to be censored (right censoring). Also note that firms can newly enter the market during the observation period. All the firms, except those newly enter the market, are also censored because the business starting dates of those firms are not known (left censoring).

The likelihood function considers the censoring mechanism. Assume we observe firms $i = 1, 2, \cdots, n_j$ at discrete time t_j where $j = 1, 2, \cdots, T$, and default occurs only at t_j's. If a firm defaulted at t_j, its contribution to the likelihood at that time is the density of the default time, which is the product of the hazard rate and the survival function, $f(t_j) = \lambda(t_j) S(t_j)$. If a firm is alive at t_j, the likelihood of this event is simply $S(t_j)$. So the likelihood at t_j for firms $i = 1, 2, \cdots, n_j$ is

$$L_j = \prod_{i=1}^{n_j} \lambda(t_j \mid x_i(t_j))^{D_i(t_j)} S(t_j \mid x_i(t_j)) \tag{6}$$

where $D_i(t_j)$ is either 1 if firm i defaulted at t_j or 0 otherwise. The total likelihood function is then

$$L = \prod_{j=1}^{T} \prod_{i=1}^{n_j} \lambda(t_j \mid x_i(t_j))^{D_i(t_j)} S(t_j \mid x_i(t_j)), \tag{7}$$

and the log-likelihood function is

$$\ln L = \sum_{j=1}^{T} \sum_{i=1}^{n_j} \left[D_i(t_j) \ln \lambda(t_j \mid x_i(t_j)) + \ln S(t_j \mid x_i(t_j)) \right] \tag{8}$$

Note that the number of firms in each period n_j can change over time due to new entries or exits of firms.

3 Incorporating Macroeconomic Effects

Let us look at the proportional hazard function for firm i with time-varying covariates:

$$\lambda_i(t \mid x_i(t)) = \lambda_0(t) \exp\left\{\beta' x_i(t)\right\}$$

If we directly take common factors as covariates, the sensitivities to the movement of common factors, that is the beta coefficients, are equal across firms cross-sectionally. In usual multi-factor asset pricing models, the beta coefficients can be easily estimated from time-series regressions so that we can obtain firm-specific beta estimates. However, we cannot obtain individual beta estimates from default data because default is basically a zero/one event that is rare for a firm.

We now turn our attention to the beta coefficients. If we notice that the beta coefficients (β) are common to all firms and the covariates (x_i) are firm-specific, we can think differently to interpret β as common factors and the firm-specific x_i as factor loadings. Considering individual firm characteristics as factor loadings is in line with the multi-factor asset pricing model by Rosenberg (1974), which is based on the assumption that the factor loadings in multi-factor models are linear functions of firm characteristics. This assumption is partially justified by the researches on the determinants of systematic risk (beta) in equity markets; see Hamada (1972), Rosenberg and McKibben (1973), Turnbull (1977) and Ryan (1997) for example. However, these are all based on the classical capital asset pricing model (CAPM). Thus, a full justification should be done on a multi-factor framework and this requires a further research.

More specifically, we suppose a linear factor structure for the beta coefficients, which are time-varying. Let

$$x_i(t) = \begin{pmatrix} x_{i1}(t) \\ \vdots \\ x_{iL}(t) \end{pmatrix}, \beta(t) = \begin{pmatrix} \beta_1(t) \\ \vdots \\ \beta_L(t) \end{pmatrix}. \tag{9}$$

The beta coefficients are assumed to have linear factor structures

$$\beta_k(t) = b_{k0} + \sum_{j=1}^{M} b_{kj} F_j(t) \tag{10}$$

where b_{ij}'s are constants and F_j's are common factors. Then, we can see that the factor loadings for common factors are linear transformations of individual firm characteristics:

$$\begin{aligned}\beta(t)' x_i(t) &= \sum_{k=1}^{L} \beta_k(t)\, x_{ik}(t) \\ &= \sum_{k=1}^{L} \left(b_{k0} + \sum_{j=1}^{M} b_{kj} F_j(t) \right) x_{ik}(t) \\ &= \sum_{k=1}^{L} b_{k0} x_{ik}(t) + \sum_{j=1}^{M} \left(\sum_{k=1}^{L} b_{kj} x_{ik}(t) \right) F_j(t)\end{aligned} \tag{11}$$

In another form, we can write

$$\begin{aligned}\beta(t)' x_i(t) &= \sum_{k=1}^{L} b_{k0} x_{ik}(t) + \sum_{k=1}^{L} \sum_{j=1}^{M} b_{kj} x_{ik}(t)\, F_j(t) \\ &= b' y_i(t)\end{aligned} \tag{12}$$

where

$$y_i(t) = \begin{pmatrix} x_i(t) \\ x_i(t)\, F_1(t) \\ \vdots \\ x_i(t)\, F_M(t) \end{pmatrix}, b = \begin{pmatrix} b_{10} \\ b_{20} \\ \vdots \\ b_{LM} \end{pmatrix} \tag{13}$$

The hazard model becomes the Cox's proportional hazard model with new covariates $y_i(t)$:

$$\lambda_i(t \mid y_i(t)) = \lambda_0(t) \exp\left\{ b' y_i(t) \right\}. \tag{14}$$

So we can utilize the same estimation method for the linear multi-factor hazard model.

If we also put a multi-factor structure into the baseline hazard rate, we can have constant terms for each of the factor loadings. More specifically, if we let

$$\lambda_0(t) = \exp\left\{ a_0 + \sum_{j=1}^{M} a_j F_j(t) \right\}, \tag{15}$$

then

$$
\begin{aligned}
&\lambda_0(t)\exp\left\{\beta(t)' x_i(t)\right\} \qquad (16)\\
&= \exp\left\{a_0 + \sum_{j=1}^{M} a_j F_j(t) + \sum_{k=1}^{L} b_{k0} x_{ik}(t) + \sum_{j=1}^{M}\left(\sum_{k=1}^{L} b_{kj} x_{ik}(t)\right) F_j(t)\right\}\\
&= \exp\left\{a_0 + \sum_{k=1}^{L} b_{k0} x_{ik}(t) + \sum_{j=1}^{M}\left[a_j + \left(\sum_{k=1}^{L} b_{kj} x_{ik}(t)\right)\right] F_j(t)\right\}
\end{aligned}
$$

This is the model we consider in this paper.

4 Empirical Analysis

4.1 Data

We investigate Korean market for our empirical tests. Data is obtained from NICE D&B and NICE Investors Service. The sample space includes all the firms that have ever listed in KSE (Korea Stock Exchange) and KOSDAQ (Korean Securities Dealers Automated Quotations) from 1993 to 2005. Financial companies are excluded in the analysis. The default event is defined broadly to include bankruptcy filings, workouts, pre-packs and failure to payments.

Table 1 reports the number of non-defaulted and defaulted firms in our data. Each year, the default status of each firm is recorded as either 1 if defaulted or 0 if survived. For example, survived firms show only zeros before they are censored. On the other hand, defaulted firms show zeros before the default year when the status is recorded as one.

[Table 1]

For the macroeconomic variable, we use KRW/USD foreign exchange rate volatility (FXV) using monthly rate. Firm-specific explanatory variables for hazard rates are summarized in Table 2. Due to limited observations in Korea, we only consider one-factor model. Though not reported in the paper, we also investigated other macroeconomic variables such as GDP growth rate and KOSPI index returns, but these variables do not provide any advantage over FXV for explaining default likelihood in Korea. Nam et al. (2008) also use FXV as a macroeconomic variable to explain default likelihood of Korean firms.

[Table 2]

To reduce the influence of extreme values, we replace all observations above the 99th percentile of each variable with the 99th percentile value. The observations below the first percentile of each variable are also truncated in the same way.

4.2 Model Specification

We investigate three hazard models. We first consider the hazard model with only firm-specific explanatory variables (Model I):

$$\lambda_i\left(t \mid x_i\left(t\right), F\left(t\right)\right) = \exp\left\{a_0 + \sum_{k=1}^{L} b_{k0} x_k\left(t\right)\right\}$$

The second model (Model II) takes a macroeconomic factor (FXV) as an another explanatory variable in addition to the firm-specific variables:

$$\lambda_i\left(t \mid x_i\left(t\right), F\left(t\right)\right) = \exp\left\{a_0 + a_1 F\left(t\right) + \sum_{k=1}^{L} b_{k0} x_k\left(t\right)\right\}$$

Finally, the last model (Model III) has product terms of the macroeconomic factor and the firm-specific variables so that each firm can show individual sensitivity to the common factor:

$$\begin{aligned}
&\lambda_i\left(t \mid x_i\left(t\right), F\left(t\right)\right) \\
&= \exp\left\{a_0 + \sum_{k=1}^{L} b_{k0} x_k\left(t\right) + \left(a_1 + \sum_{k=1}^{L} b_{k1} x_{ik}\left(t\right)\right) F\left(t\right)\right\} \\
&= \exp\left\{a_0 + \sum_{k=1}^{L} b_{k0} x_k\left(t\right) + a_1 F\left(t\right) + \sum_{k=1}^{L} b_{k1} x_{ik}\left(t\right) F\left(t\right)\right\}
\end{aligned}$$

In this setup, the coefficient of the macroeconomic factor is a linear function of the firm-specific covariates.

4.3 Estimation

For estimation, we use discrete time hazard rates following Allison (1995), Shumway (2001) and Chava and Jarrow (2004). We divide our sample into two sub-samples. The parameters are estimated with the data from 1993 to 2000. Then the estimated parameter is used for out-of-sample test from 2001 to 2005. For the out-of-sample test, we use the previous year's variables to predict the default likelihood of firms. For example, for the default events in 2002, we use variables observed in 2001.

[Table 3]

Table 3 presents the estimation result. The numbers are the coefficient estimates of explanatory variables, and the corresponding chi-square statistics (χ^2) are in the parentheses.

Model I is the simple hazard model that uses only firm-specific market and accounting characteristics as explanatory variables. In this model, a firm's default probability is explained by TEGR, FCTD, CDTA, OCFTA, STA, SIGMA and METL. The result shows that SIGMA is significant at 10% level, and the others are significant at 5% and 1% levels. TEGR, OCFTA, STA and METL are shown to be negatively related to default probability, whereas FCTD, CDTA and SIGMA show positive relationship. This result is consistent with our intuition.

Model II is the hazard model with common macroeconomic exposure that has FX volatility (FXV) as an additional common explanatory variable. Here, we exclude SIGMA because it becomes insignificant after FXV is added. As expected, FXV is significant at 5% level.

Model III, which is the main focus of this paper, is the hazard model with firm-specific macroeconomic exposures, which has cross-product terms between macroeconomic factor (FXV) and firm-specific variables. The selected firm-specific variables (FCTD, OCFTA, STA and METL) are assumed to explain individual macroeconomic exposures. All the cross-product terms are statistically significant supporting this assumption. OCFTA and STA are excluded from the single terms as they become insignificant. This implies that these variables have explanatory power only as parts of macro exposures.

4.4 Forecast Accuracy

We now compare the out-of-sample forecast accuracy of the hazard models under consideration.

[Table 4]

Table 4 presents the out-of-sample forecast accuracy of the hazard models. During the test years (2001-2005), the default probabilities are calculated each year using the parameter estimates from 1993 to 2000. Following Shumway (2001), the firms are grouped into deciles sorted by their forecasted default probabilities in descending order. The number of defaults in each decile in each year is then aggregated over the test years. We also repeat the same procedure with default probability quintiles.

We can see that the most accurate model is the hazard model with firm-specific macroeconomic exposures (Model III). Model III classifies 72.5% of defaults in the highest default probability decile (Decile 1) while Model I and II classify 67.5% and 62.5% in the first deciles, respectively. Quintile classification confirms that Model III significantly outperforms other models. From Model III, 87.5% of defaults are classified in the first quintile whereas Model I and II classify 75% and 72.5% of defaults in the same quintile.

We also calculate AUROC (area under receiver operating characteristic curve), a widely used forecast accuracy measure in categorical data analysis, to compare the performance of the hazard models. A value of 0.5 means the model has no predictive power, and the predictive power increases as AUROC becomes closer to 1; see Argesti (2007, pp.143-144) for details.

[Table 5]

Table 5 presents a summary of AUROC for each model, measured yearly from 2001 to 2005. Again, Model III shows the best performance. The mean AUROC of Model III is 0.8887 while that of Model I and II are 0.8332 and 0.8164, respectively. Also, Model III provides the most stable forecast accuracy during the whole test years; see the standard deviation and minimum reported in the table.

4.5 Firm-specific Macroeconomic Exposures

The purpose of this research is to examine firm-specific exposures on macroeconomic risks. In our model (Model III), the macroeconomic exposure is a linear function of firm characteristics including a constant. So the estimated exposure is

$$\widehat{a}_j + \sum_{k=1}^{L} \widehat{b}_{kj} x_{ik}(t)$$

where $\widehat{a}_j$ and $\widehat{b}_{kj}$ are estimates.

[Figure 2]

The model allows not only individual but also time-varying macroeconomic exposures via the time-varying firm characteristics $x(t)$. Figure 2 shows how the average exposures on macroeconomic risk change over time. It is constructed based on yearly average of macroeconomic exposure estimates of all firms in the sample. It seems that there is a structural change through the Asian financial crisis period (1998-1999). This is due to the changes in firm characteristics in Korea after the crisis.

[Figure 3]

Since our model provides firm-specific exposures, it is easy to investigate the risk exposures by industry. Figure 3 shows the changes of industry average macroeconomic exposures. We can see that IT, health care and consumer industries are more exposed to macroeconomic shock (FXV), and they also experienced larger structural changes through the Asian financial crisis. This can be verified if we look at Table 6, which reports the industry average FXV exposures over two sub-periods (1993-1998 and 1999-2005). We can see that all industries, except utilities, become more exposed to FXV after the crisis, and the change is larger for IT, health care and consumer industries.

[Table 6]

[Figure 4]

Figure 4 shows how the macro exposures differ by default probability. We divide firms by half based on default probabilities estimated from our model (Model III). Low default probability firms are those with high credit quality. In the figure, we can see that the low default probability firms are more exposed to macroeconomic effect (FXV) than the high default probability firms.

5 Conclusion

In this paper, we present a new hazard model for predicting default. The model allows firm-specific and time-varying exposures on macroeconomic risk factors as macroeconomic exposures are formed to be linear functions of observable firm characteristics. We test the model with Korean default data from 1993 to 2005 both in-sample and out-of-sample. It is shown that our model captures individual macroeconomic exposures well, and it outperforms alternative models with regard to the power of forecasting default of firms. With the proposed model, we can now investigate which firms are more exposed to macroeconomic shocks. We find that IT, health care and consumer companies are more vulnerable to changes in macroeconomic environment. Also, high credit quality firms are found to be more sensitive to macroeconomic effects.

Due to the limited default observations in our data, we have explored only one-factor hazard model in this paper. Empirical investigation of multiple factor models would be subject to rich historical default data.

With firm-specific exposures on macro factors, we can measure default correlation more accurately. In a companion paper, Kang, Kim and Lee (2009), we show that our model produces higher default correlation than previous hazard models. This is due to more realistic specification of common variables as expected in Yu (2005). Since our model provides firm-specific and time-varying coefficients, it is possible to measure firm-level default correlation. Also, conditional on firm characteristics, default correlation can change dynamically over time with macro variables. Thus, the default correlation measure from our hazard model can be a good alternative to the measures from the cohort methods (Lucas, 1995) or the copula methods (Li, 2000).

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Figure 1. Foreign exchange rate volatility (FXV) and annual default frequency.

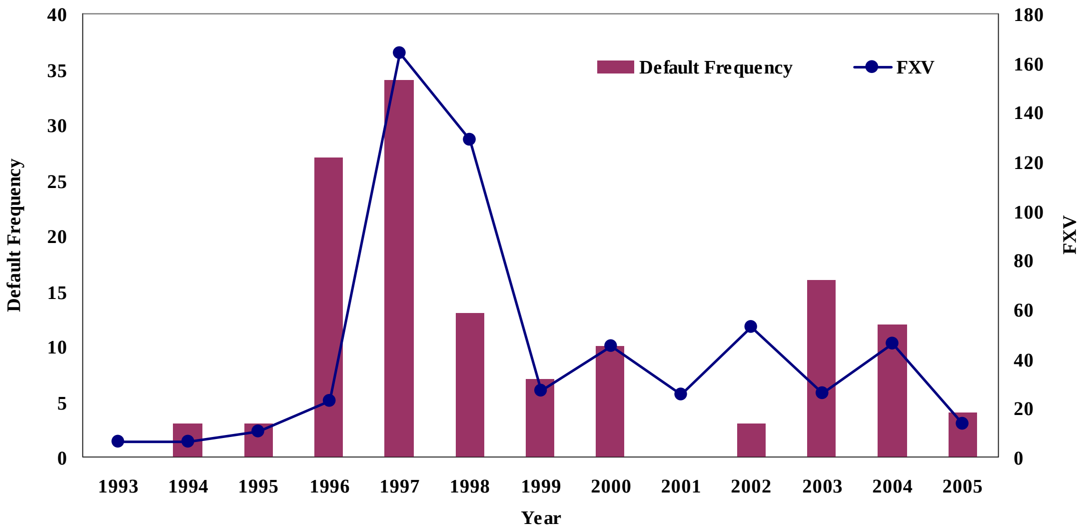


Table 1. Number of firms

	1993-2000	2001-2005	Total
Non-defaulted	1,553	1,599	1,712
Defaulted	108	46	154

Table 2. Description of explanatory variables.

Variable	Definition	Expected Sign	Mean	Median	Std. Dev	Min	Max
TEGR	total equity growth rate	-	0.4722	0.1198	1.4382	-1.4368	10.6476
FCTD	financial costs to total debt	+	0.0513	0.0489	0.0334	0.0	0.1393
CDTA	current debt to total assets	+	0.3818	0.3693	0.1898	0.0342	0.9765
STA	asset turnover ratio(sales to total assets)	-	1.1619	1.0178	0.6937	0.0883	4.2228
OCFTA	operating cash flow to total assets	-	0.028	0.0022	0.1102	-0.4097	0.3341
SIGMA	volatility of monthly stock returns	+	0.0363	0.0331	0.0184	0.0014	0.0906
METL	market equity to total liabilities	-	1.8561	0.6823	3.6569	0.024	24.9423
FXV	volatility of foreign exchange rate	+	43.7244	25.68	43.8186	6.22	164.07

Notes: The third column shows the expected sign of the coefficient of each explanatory variable.

Table 3. Estimation results.

	Model I			Model II			Model III		
Intercept	-5.6298	***	(81.72)	-5.3265	***	(83.6)	-7.3889	***	(69.91)
TEGR	-0.3732	**	(4.6)	-0.3318	*	(3.76)	-0.3947	**	(4.97)
FCTD	21.2610	***	(26.14)	20.3074	***	(24.14)	39.2093	***	(25.95)
CDTA	2.3905	***	(14.06)	2.371	***	(13.44)	2.1412	***	(11.16)
OCFTA	-3.1603	**	(6.53)	-2.7823	**	(4.94)			
STA	-1.0686	***	(11.14)	-1.2134	***	(13.65)			
SIGMA	10.8412	*	(3.56)						
METL	-1.4607	***	(11.32)	-1.4156	***	(10.64)	-3.5592	***	(16.19)
FXV				0.0041	**	(5.63)	0.0220	***	(9.19)
FCTD*FXV							-0.1902	***	(8.2)
OCFTA*FXV							-0.0284	***	(9.48)
STA*FXV							-0.0069	**	(6.48)
METL*FXV							0.0203	***	(10.33)
Model Fit	204.9	***		214.03	***		222.72	***	

Model I is the simple hazard model, Model II is the hazard model with common macroeconomic exposure, and Model III is the hazard model with firm-specific macroeconomic exposures. USD/KRW exchange rate volatility is used as a proxy of macroeconomic risk factor in Korea. The estimation is conducted using data from 1993 to 2000. The data set consists of all the firms that have ever listed in both KOSPI and KOSDAQ, excluding non-financial companies. Parameter estimates are given with chi-square statistics in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively. TEGR = total equity growth rate; FCTD = financial costs to total debt; CDTA = current debt to total assets; OCFTA = operating cash flow to total assets; STA = asset turnover ratio (sales to total assets); SIGMA = volatility of monthly stock returns; METL = market equity to total liabilities; FXV = volatility of USD/KRW foreign exchange rate; FCTD*FXV, OCFTA*FXV, STA*FXV, and METL*FXV are cross-product terms between FXV and each firm variable. The chi-square statistics of likelihood ratio test for the model fit are reported in the last row.

Table 4. Comparison of accuracy.

Decile	Model I	Model II	Model III
1	67.50	62.50	72.50
2	7.50	10.00	15.00
3	5.00	7.50	0.00
4	5.00	2.50	0.00
5	5.00	7.50	0.00
6	2.50	2.50	5.00
7	5.00	5.00	0.00
8	0.00	0.00	2.50
9	2.50	2.50	5.00
10	0.00	0.00	0.00

Quintile	Model I	Model II	Model III
1	75.00	72.50	87.50
2	10.00	10.00	0.00
3	7.50	10.00	5.00
4	5.00	5.00	2.50
5	2.50	2.50	5.00

Model I is the simple hazard model, Model II is the hazard model with common macroeconomic exposure, and Model III is the hazard model with firm-specific macroeconomic exposures. USD/KRW exchange rate volatility is used as a proxy of macroeconomic risk factor in Korea. The estimation is conducted using data from 1993 to 2000. The data set consists of all the firms that have ever listed in both KOSPI and KOSDAQ, excluding non-financial companies. The numbers represent the percentage of defaulted firms classified into each of the deciles in the year when they failed.

Table 5. Area Under the ROC curve.(AUROC)

Model	Mean	Median	Std. Dev	Min	Max
Model I	0.8332	0.8793	0.0990	0.6922	0.9171
Model II	0.8164	0.8675	0.0980	0.6745	0.9061
Model III	0.8887	0.8874	0.0512	0.8230	0.9601

Figure 2. FXV exposure changes over time, where the exposures are averaged across all firms cross-sectionally.

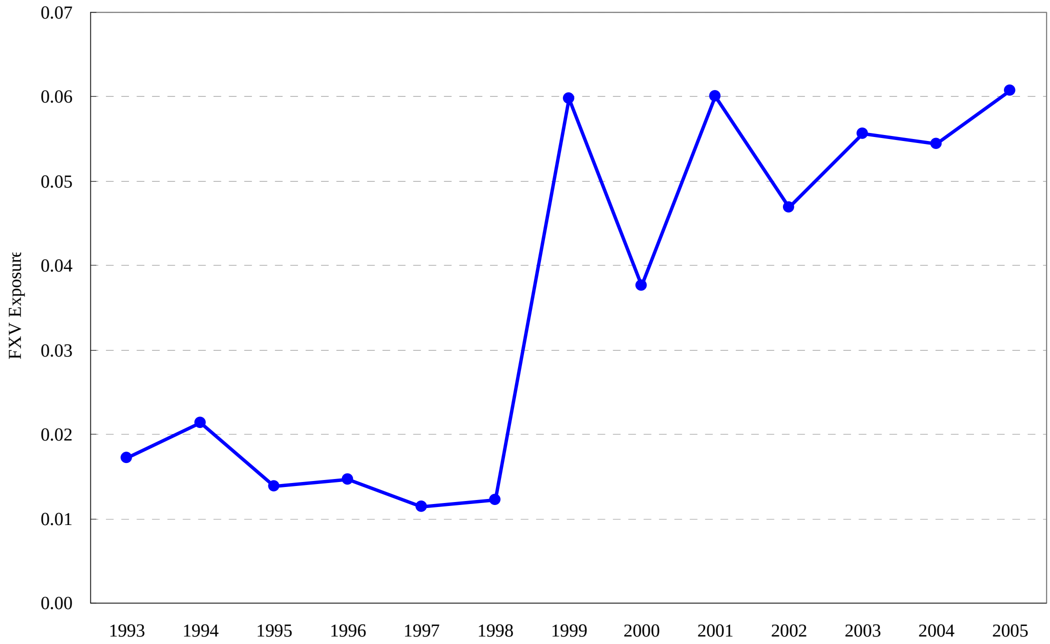


Figure 3. FXV exposure changes by industry.

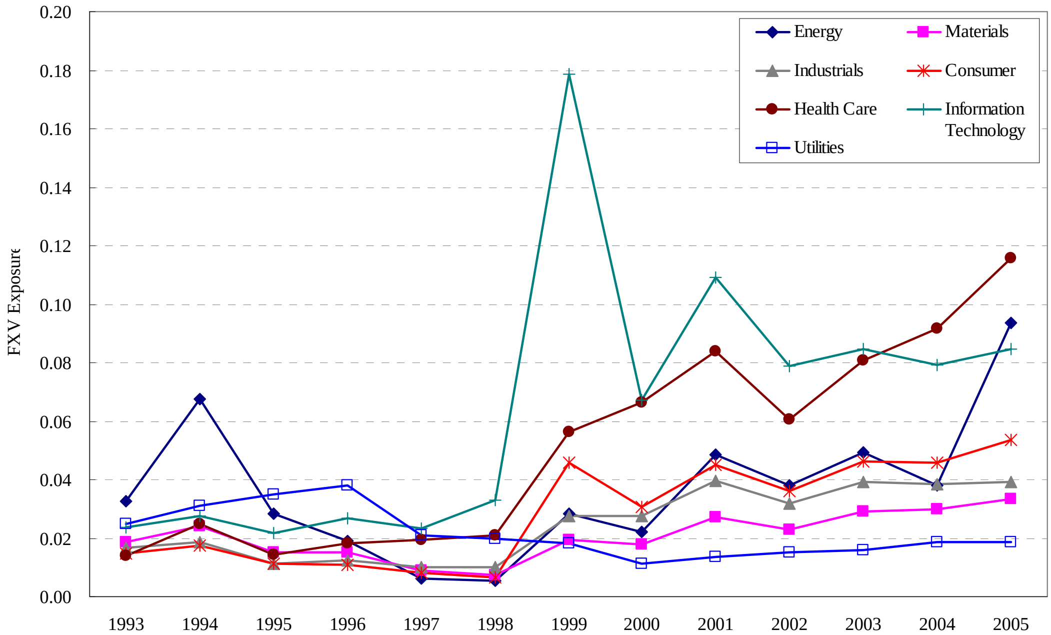
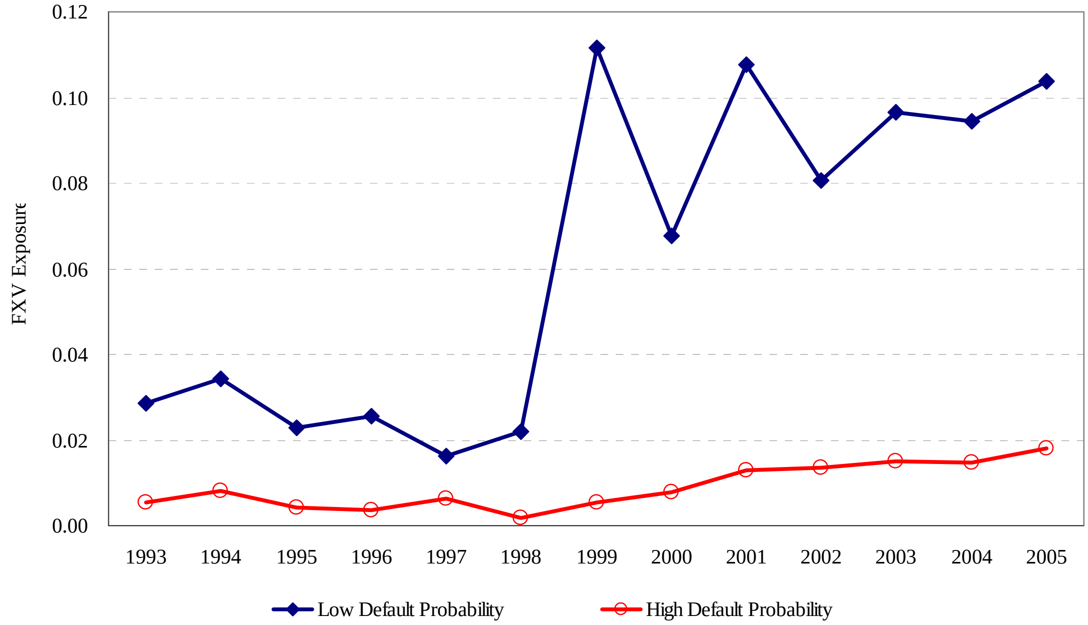


Table 6. Average FXV exposures by industry and sub-period.

Industry	1993-1998	1999-2005
Energy	0.0200	0.0455
Materials	0.0141	0.0260
Industrials	0.0128	0.0353
Consumer	0.0109	0.0437
Health Care	0.0187	0.0818
Information Technology	0.0269	0.0898
Utilities	0.0267	0.0159

Figure 4. FXV exposure changes by high and low default probability groups.



Appendix. Summary statistics of FXV exposures by industry and year.

Industry	Year	Mean	Std. Dev	Min	Q1	Median	Q3	Max
	1993	0.0328	0.0282	0.0104	0.0104	0.0235	0.0645	0.0645
	1994	0.0675	0.0860	0.0087	0.0087	0.0277	0.1662	0.1662
	1995	0.0283	0.0304	0.0047	0.0047	0.0176	0.0626	0.0626
	1996	0.0192	0.0189	0.0015	0.0027	0.0141	0.0391	0.0496
	1997	0.0060	0.0112	-0.0086	0.0006	0.0058	0.0075	0.0282
	1998	0.0054	0.0133	-0.0122	-0.0044	0.0037	0.0114	0.0301
Energy	1999	0.0285	0.0609	-0.0015	0.0018	0.0037	0.0140	0.1661
	2000	0.0222	0.0215	0.0036	0.0085	0.0203	0.0243	0.0677
	2001	0.0486	0.0537	0.0044	0.0073	0.0281	0.1121	0.1378
	2002	0.0382	0.0417	0.0101	0.0128	0.0170	0.0756	0.1172
	2003	0.0493	0.0669	0.0070	0.0137	0.0201	0.0716	0.1930
	2004	0.0380	0.0379	0.0022	0.0151	0.0241	0.0482	0.1167
	2005	0.0936	0.1764	0.0023	0.0202	0.0213	0.0529	0.4918
	1993	0.0187	0.0204	-0.0046	0.0074	0.0135	0.0212	0.1358
	1994	0.0242	0.0257	-0.0041	0.0103	0.0173	0.0289	0.1987
	1995	0.0151	0.0146	-0.0070	0.0049	0.0123	0.0193	0.0811
	1996	0.0151	0.0201	-0.0106	0.0040	0.0098	0.0205	0.1592
	1997	0.0089	0.0136	-0.0177	0.0017	0.0064	0.0133	0.1026
	1998	0.0076	0.0161	-0.0202	-0.0027	0.0043	0.0118	0.0993
Materials	1999	0.0195	0.0299	-0.0130	0.0040	0.0107	0.0249	0.2130
	2000	0.0179	0.0218	-0.0082	0.0044	0.0121	0.0224	0.1457
	2001	0.0270	0.0364	-0.0045	0.0083	0.0176	0.0324	0.3161
	2002	0.0229	0.0219	-0.0104	0.0092	0.0180	0.0297	0.1649
	2003	0.0291	0.0308	-0.0109	0.0108	0.0195	0.0338	0.2069
	2004	0.0299	0.0418	-0.0060	0.0109	0.0180	0.0340	0.5133
	2005	0.0333	0.0434	-0.0032	0.0139	0.0212	0.0384	0.5211
	1993	0.0168	0.0189	-0.0155	0.0059	0.0115	0.0237	0.1209
	1994	0.0184	0.0181	-0.0202	0.0066	0.0138	0.0268	0.0937
	1995	0.0113	0.0130	-0.0240	0.0041	0.0088	0.0175	0.0528
	1996	0.0126	0.0217	-0.0277	0.0036	0.0068	0.0159	0.2018
	1997	0.0101	0.0288	-0.0267	0.0012	0.0055	0.0126	0.3336
	1998	0.0101	0.0285	-0.0351	-0.0007	0.0056	0.0122	0.2476
Industrials	1999	0.0274	0.0507	-0.0285	0.0055	0.0134	0.0292	0.3400
	2000	0.0276	0.0572	-0.0328	0.0052	0.0138	0.0287	0.5223
	2001	0.0398	0.0589	-0.0320	0.0092	0.0221	0.0452	0.3511
	2002	0.0317	0.0428	-0.0192	0.0102	0.0176	0.0395	0.3510
	2003	0.0393	0.0567	-0.0094	0.0119	0.0208	0.0429	0.3747
	2004	0.0386	0.0582	-0.0176	0.0127	0.0197	0.0404	0.4781
	2005	0.0391	0.0419	-0.0221	0.0158	0.0237	0.0432	0.3103
	1993	0.0149	0.0167	-0.0112	0.0042	0.0101	0.0215	0.0900
	1994	0.0176	0.0166	-0.0115	0.0073	0.0136	0.0219	0.0844
	1995	0.0112	0.0120	-0.0131	0.0038	0.0081	0.0156	0.0692
	1996	0.0109	0.0122	-0.0117	0.0036	0.0080	0.0158	0.0766
	1997	0.0081	0.0123	-0.0165	0.0007	0.0051	0.0123	0.0758
	1998	0.0066	0.0176	-0.0210	-0.0024	0.0024	0.0103	0.1417
Consumer	1999	0.0458	0.1032	-0.0140	0.0037	0.0108	0.0280	0.5156
	2000	0.0305	0.0556	-0.0180	0.0060	0.0149	0.0278	0.4326
	2001	0.0451	0.0725	-0.0132	0.0100	0.0221	0.0459	0.5264
	2002	0.0363	0.0514	-0.0177	0.0116	0.0213	0.0376	0.3868
	2003	0.0462	0.0631	-0.0006	0.0138	0.0240	0.0485	0.5124
	2004	0.0460	0.0729	-0.0068	0.0125	0.0234	0.0476	0.5272
	2005	0.0536	0.0790	-0.0040	0.0160	0.0274	0.0578	0.5262

Industry	Year	Mean	Std. Dev	Min	Q1	Median	Q3	Max
Health Care	1993	0.0140	0.0122	-0.0019	0.0054	0.0120	0.0183	0.0623
	1994	0.0248	0.0185	0.0018	0.0139	0.0181	0.0378	0.0769
	1995	0.0144	0.0130	-0.0027	0.0055	0.0111	0.0211	0.0516
	1996	0.0182	0.0169	-0.0012	0.0087	0.0139	0.0222	0.0818
	1997	0.0195	0.0282	-0.0042	0.0052	0.0099	0.0211	0.1194
	1998	0.0211	0.0496	-0.0076	0.0026	0.0088	0.0156	0.2861
	1999	0.0563	0.1041	-0.0046	0.0051	0.0172	0.0481	0.4958
	2000	0.0663	0.1100	-0.0026	0.0122	0.0363	0.0569	0.5289
	2001	0.0837	0.1273	-0.0011	0.0239	0.0418	0.0676	0.5290
	2002	0.0606	0.0897	-0.0005	0.0172	0.0350	0.0708	0.5300
	2003	0.0807	0.1151	0.0021	0.0242	0.0381	0.0734	0.5241
	2004	0.0916	0.1247	0.0086	0.0257	0.0449	0.0859	0.5277
	2005	0.1158	0.1338	0.0098	0.0318	0.0585	0.1448	0.5271
Information Technology	1993	0.0239	0.0209	-0.0005	0.0133	0.0166	0.0294	0.0883
	1994	0.0277	0.0198	0.0021	0.0145	0.0222	0.0335	0.0883
	1995	0.0218	0.0282	-0.0048	0.0107	0.0159	0.0208	0.1680
	1996	0.0270	0.0361	-0.0090	0.0089	0.0151	0.0290	0.2266
	1997	0.0234	0.0425	-0.0170	0.0054	0.0120	0.0248	0.2783
	1998	0.0330	0.0859	-0.0113	0.0028	0.0109	0.0260	0.5229
	1999	0.1787	0.1863	-0.0019	0.0334	0.0926	0.2917	0.5244
	2000	0.0671	0.0848	-0.0154	0.0195	0.0374	0.0821	0.5266
	2001	0.1091	0.1333	-0.0008	0.0280	0.0548	0.1249	0.5302
	2002	0.0787	0.1081	-0.0017	0.0198	0.0371	0.0920	0.5313
	2003	0.0848	0.1160	-0.0034	0.0200	0.0371	0.0969	0.5349
	2004	0.0794	0.1101	-0.0073	0.0180	0.0345	0.0907	0.5295
	2005	0.0847	0.1074	-0.0087	0.0253	0.0423	0.0984	0.5353
Utilities	1993	0.0249	0.0084	0.0168	0.0168	0.0244	0.0336	0.0336
	1994	0.0310	0.0068	0.0241	0.0252	0.0315	0.0368	0.0368
	1995	0.0351	0.0108	0.0190	0.0259	0.0381	0.0410	0.0485
	1996	0.0379	0.0240	0.0150	0.0173	0.0273	0.0514	0.0835
	1997	0.0208	0.0187	0.0038	0.0058	0.0145	0.0235	0.0578
	1998	0.0197	0.0289	-0.0188	0.0011	0.0151	0.0234	0.0873
	1999	0.0181	0.0153	-0.0041	0.0106	0.0136	0.0204	0.0585
	2000	0.0113	0.0113	-0.0071	0.0088	0.0118	0.0176	0.0327
	2001	0.0136	0.0098	-0.0047	0.0111	0.0131	0.0158	0.0315
	2002	0.0153	0.0080	0.0041	0.0095	0.0137	0.0182	0.0334
	2003	0.0160	0.0091	0.0045	0.0091	0.0156	0.0196	0.0351
	2004	0.0186	0.0082	0.0085	0.0146	0.0166	0.0189	0.0369
	2005	0.0186	0.0088	0.0081	0.0138	0.0164	0.0193	0.0368
Total	1993	0.0172	0.0186	-0.0155	0.0061	0.0122	0.0220	0.1358
	1994	0.0213	0.0213	-0.0202	0.0086	0.0162	0.0273	0.1987
	1995	0.0138	0.0156	-0.0240	0.0046	0.0104	0.0189	0.1680
	1996	0.0147	0.0207	-0.0277	0.0043	0.0097	0.0193	0.2266
	1997	0.0114	0.0239	-0.0267	0.0016	0.0067	0.0137	0.3336
	1998	0.0122	0.0389	-0.0351	-0.0015	0.0051	0.0138	0.5229
	1999	0.0599	0.1182	-0.0285	0.0055	0.0147	0.0437	0.5244
	2000	0.0377	0.0661	-0.0328	0.0079	0.0181	0.0387	0.5289
	2001	0.0601	0.0956	-0.0320	0.0125	0.0280	0.0601	0.5302
	2002	0.0469	0.0745	-0.0192	0.0125	0.0232	0.0459	0.5313
	2003	0.0557	0.0850	-0.0109	0.0146	0.0257	0.0540	0.5349
	2004	0.0545	0.0860	-0.0176	0.0137	0.0254	0.0531	0.5295
	2005	0.0607	0.0875	-0.0221	0.0177	0.0298	0.0633	0.5353