Default Probabilities and Interest Expenses of Privately Held Firms

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Abstract

In this study, we estimate term structures of default probabilities for private firms using Korean data comprising 1,440 default events from 29,894 firms between 1999 and 2011. We then study whether the reported interest expenses are reflective of the estimated default term structure. Each private firm's default likelihood is characterized by a forward intensity model employing both macro risk factors and firm-specific attributes derived from financial statements. Although private firms have no traded stock prices, we devise a way of obtaining a public-firm equivalent distance-to-default by projection which references the distance-to-defaults of public firms with comparable firm attributes. Statistical tests indicate that the fitted model provides accurate multiperiod forecasts of defaults for both financial and non-financial private firms. Our methodology can be directly applied by commercial lenders in charging appropriate interest rates upon lending decisions for different future periods.

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1 Introduction

The appropriate assessment of credit risk is not only of interest to academics, but even more important for commercial lenders who must decide both whether to lend and how much of a credit spread to charge for a given loan application. Although the academic literature has been rife with studies of credit risk assessment ever since the early works of Altman (1968), most of the works, whether structural or non-structural in nature, focus on publicly-traded firms (see Beaver (1966), Bharath & Shumway (2004), Campbell, Hilscher & Szilagyi (2008), Chava & Jarrow (2004), Hillegeist, Keating & Cram (2004), Ohlson (1980), Duffie, Saita & Wang (2007), Duan, Sun & Wang (2012), and many others).

In contrast, defaults of privately held firms mainly remain in the realm of commercial interest, and the research findings are kept proprietary. Academic research on the subject of private firm defaults is skimpy. Other than Altman (2012)'s work, there are only a few studies, mostly from the practitioners' perspective, that examine credit risk of private firms. For instance, Cangemi, Servigny & Friedman (2003) of Standard and Poor's examined the default risk of French private firms based on maximum expected utility (MEU) approach. Falkenstein, Boral & Carty (2000) of Moody's explained their non-structural approach in assessing private firms' credit risk in the US. This relative paucity of academic attention is partly due to the lack of publicly available data on privately held firms. Even if financial statement data on privately held firms were widely available, there is no market data, such as stock prices, to offer an important dimension of timely information on these firms. Studying defaults of private firms thus poses an additional challenge, because the recent advancement in credit risk models typically requires some form of market information.

In this paper, we devise a way to utilize timely market information. Specifically, we estimate a powerful market information measure, known as distance-to-default (DTD), for private firms by referring to the universe of public firms for similar characteristics.[1] Our approach can thus help assess whether using a modified version of the credit risk model that requires market data to predict defaults of private firms actually adds any value.

In addition, we adopt the newly developed doubly stochastic Poisson forward-intensity default modelling technique of Duan et al. (2012) so that we can easily and consistently estimate the term structure of default probabilities for privately held firms. By directly modelling forward intensities, one can directly relate future defaults in any particular

[1] Bharath & Shumway (2004) and many others have found that Merton (1974)'s DTD is helpful for forecasting defaults for non-financial public firms listed on the U.S. stock exchange.

time period to the current information set characterized by some market-wide common risk factors and firm-specific attributes. Using forward as opposed to spot intensities, one in effect bypasses the challenging task of modelling very high dimensional time series of covariates arising from firm-specific attributes due to the sheer number of firms in the data sample.

We study privately held firms, both financial and non-financial. Needless to say, financial firms are of great importance. Despite their relevance, the literature on corporate default/bankruptcy typically ignore financial firms, in part because financial firms are highly leveraged making them somewhat distinctly different from non-financial firms and technically speaking, reliable DTDs for financial firms is harder to obtain. Duan et al. (2012), however, demonstrated that using properly estimated DTDs in corporate default predictions can yield a universal model (i.e., financial and non-financial firms share the same default prediction model) that performs equally well for the subsamples of financial and non-financial firms in terms of the accuracy ratio.[2] In our study of Korean private firms, we add a dummy variable into the forward intensity model to distinguish the financial and non-financial subgroups to see whether they differ in default intensity above and beyond differences in their generic firm attributes. Our empirical findings suggest that the financial dummy variable is statistically significant, but putting financial and non-financial firms together in a sample does not reduce the predictive power of the model after adding the dummy variable.

In this paper, we evaluate the credit risk of Korean private firms (financial and non-financial) with the data comprising 1,440 default events from 29,894 firms between 1999 and 2011. Our data sample includes all private firms in Korea in excess of a certain size and all default events triggered by bounced checks issued by any entity with a checking account within the Korean banking system. Since our sample of private firms and default events are much larger than those in the previous studies based on large firms' publicly-traded debts, our tests are likely to be more reliable and convey more information. Our results can also be readily applied by commercial lenders whose customers are in most cases private firms and individuals.

Related to our study are Kocagil & Reyngold (2003) and Hood & Zhang (2007) of Moody's who employ binary probit models to estimate firm-level default probabilities for privately held Korean non-financial companies using the information conveyed by financial statements. From lenders' perspective, an appropriate assessment of both financial and non-financial private firms' credit risks remains a fundamental task. This practical

[2]For further details on estimating DTDs for financial firms, please refer to Duan & Wang (2012).

demand for the appropriate assessment of private firms' credit risk partly explains the degree of interest that commercial credit rating agencies have had in this issue relative to academia. In contrast to the existing literature, our study includes financial firms, and employs a more advanced and appropriate econometric model to produce term structure of default probabilities. In addition, we have incorporated an innovative implementation feature that factors in public-firm equivalent DTDs for privately held firms.

The risk premia that a private firm is required to pay on its debts of different maturities are obviously an important matter. With the default term structure in place, one can begin to answer this related question of interest. There is a large literature on pricing credit risk, and Duffie & Singleton (1999), Driessen (2005), Pan & Singleton (2008), Jarrow, Lando & Yu (2005) and Azizpour, Giesecke & Kim (2011) are some examples. In the context of our paper, a pricing model will be normative in nature, simply because there are hardly any traded credit instruments for checking the performance of a pricing model. However, we can study whether the interest expenses paid by private firms are reflective of their default likelihoods to ascertain the usefulness of the default term structure model. Based on the reported interest expenses in a fiscal year, we are able to come up with an implied interest rate of a private firm and a maturity proxy for that firm-year, and show that implied interest rates are indeed positively related to their corresponding default probabilities. Moreover, we show that the conclusion is robust to factoring in various control variables.

The remainder of the paper is organized as follows. Section 2 explains how we develop our model of credit risk and term structure estimation for private firms. Section 3 provides a detailed description of the data sources, sample construction process, and definitions of key variables. Section 4 outlines our major empirical results. Section 5 makes our concluding remarks.

2 Modeling framework

In this section, we specify the modeling framework for the estimation of the term structure of physical default probabilities for privately held firms in Korea. Our goal is two-fold. First, we estimate the term structure of physical default probabilities for privately held firms. Second, we use them to study whether the observed interest expenses by the Korean private firms properly reflect their credit risks. Hereafter, the uncertainty is modeled by a complete probability space $(\Omega, \mathcal{F}, P)$, where P is the physical (statistical) probability measure. The information flow is represented by a right-continuous and complete filtration

$\mathbb{F} = (\mathcal{F}_t)_{t\geq 0}$ satisfying the usual conditions described in Protter (2004). Expectation conditional on $\mathcal{F}_t$ is denoted by $E_t(\cdot)$.

Our default term structure model follows that of Duan et al. (2012) to rely on forward instead of spot intensities. In addition to default events, we factor in exits for reasons other than defaults/bankruptcies to avoid censoring biaes. An example of other form of exits is merger/acquisition. The i-th private firm's default is assumed to be signaled by a jump in a doubly-stochastic Poisson process, N_t^i, which is governed by a non-negative spot *default* intensity, λ_t^i. Let τ_D^i be the i-th firm's default time, which is the first time that N_t^i reaches 1. Thus, $N_t^i - \int_0^t \lambda_s^i ds$ is a martingale relative to $\mathbb{F}$ and P, and we are only interested in this process up to the stopping time τ_D^i. The default intensity process λ_t^i is also the conditional default rate in the sense that $P\left(\tau_D^i \leq t + \Delta | \mathcal{F}_t\right) \approx \lambda_t^i \Delta$ for sufficiently small $\Delta > 0$, prior to its default. We also assume that the other exit for the i-th firm in a group is governed by a separate doubly-stochastic Poisson process M_t^i. We assume that there is a non-negative spot *other exit* intensity process ϕ_t^i that satisfies $M_t^i - \int_0^t \phi_s^i ds$ such that it is also a martingale relative to $\mathbb{F}$ and P.

Note that λ_t^i and ϕ_t^i need not be two independent processes, but they must be adapted to the filtration $\mathbb{F}$. In fact, they are likely to be dependent when both are defined as functions of some common stochastic covaraties. Although intensity processes can be dependent, N_t^i and M_t^i are assumed to be independent once being conditioned on λ_t^i and ϕ_t^i. If we denote the i-th firm's *combined exit* time by τ_C^i, then by design the condition $\tau_D^i \geq \tau_C^i$ holds, and the instantaneous combined exit intensity is $\lambda_t^i + \phi_t^i$ at time t. By the standard result, the time-t conditional survival probability over the period $[t, t+\tau]$ can be given by

$$s_t^i(\tau) = E_t\left[\exp\left(-\int_t^{t+\tau}\left(\lambda_s^i + \phi_s^i\right) ds\right)\right], \tag{1}$$

and the default probability over $[t, t+\tau]$ is given by

$$p_t^i(\tau) = E_t\left[\int_t^{t+\tau} \exp\left(-\int_t^{s}\left(\lambda_u^i + \phi_u^i\right) du\right) \lambda_s^i ds\right]. \tag{2}$$

Up to this point, the model is essentially that of Duffie et al. (2007) based upon spot intensities. The Duan et al. (2012) approach that we adopt begins to deviate by introducing a *forward intensity* version of the above model as a new tool for default prediction over a range of horizons. Specifically, let $f_t^i(\tau)$ and $g_t^i(\tau)$ denote the forward *default* intensity and the forward *combined exit* intensity, respectively. It follows that

$$s_t^i(\tau) = \exp\left(-\int_0^\tau g_t^i(s)ds\right) \tag{3}$$

$$p_t^i(\tau) = \int_0^\tau \exp\left(-\int_0^s g_t^i(u)du\right) f_t^i(s)ds. \tag{4}$$

Although spot intensity has served as the main tool for modeling defaults in the literature, Duan et al. (2012) have shown the forward-intensity approach's superiority in application. To put it simply, the forward-intensity approach allows users to bypass the task of modelling the very high-dimensional stochastic covariates, for which a suitable model is hard to come by and its estimation inevitably challenging. As the name suggests, the forward-intensity model explicitly absorbs into a set of forward intensity functions the effects arising from the evolution of future spot intensities. The forward intensities corresponding to different forward starting times are functions of variables (i.e., stochastic covariates) observable at the time of making predictions. In short, predictions for various future horizons can be made without having to know the dynamics of the stochastic covariates.

In this paper, we also follow Duan et al. (2012) to adopt the following family of forward intensity functions:

$$f_t^i(\tau) = \exp\left(\alpha_0(\tau) + \sum_{j=1}^{k} \alpha_j(\tau) x_t^i(j)\right) \tag{5}$$

$$g_t^i(\tau) = f_t^i(\tau) + \exp\left(\beta_0(\tau) + \sum_{j=1}^{k} \beta_j(\tau) x_t^i(j)\right), \tag{6}$$

where $X_t^i = (x_t^i(1), x_t^i(2), \cdots, x_t^i(k))$ is the set of the stochastic covariates (common risk factors and firm specific attributes) that affect the forward intensities for the i-th firm. Please note that the forward-intensity functions are specific to the forward starting time through τ-specific coefficients. To implement the model empirically, we use a discrete-time version of the model by setting the basic time interval to one month. Thus, we in effect have a discrete-time model on the monthly basis. In the empirical section, we will describe the stochastic covariates being used.

3 Data and sample

This section describes the default and accounting data, the explanatory covariate data, their sources, and the sample construction of our data set. In addition, we explain how the public-firm equivalent DTDs are estimated, the implied interest rates are derived from reported interest expenses, and the approximate maturities are determined.

3.1 Default and accounting data sources

Our initial default dataset is created from the Korea Financial Telecommunications and Clearings Institute (KFTC) website. The KFTC keeps track of all suspensions of checking accounts triggered by bounced checks for all accounts in the Korean banking system, and it publicly discloses this information electronically. The dataset is updated every day and covers all default events by all corporations, both public and private, as well as all individuals.[3] Since our default dataset is literally comprehensive, it is free from any potential selection issues and thus may be considered superior to the existing commercial databases available in the US that offer limited coverage based on information provided by the participating banks.[4]

The data items available from this list are the first six or seven digits of the issuer identification codes, similar to Tax Identification Number (TIN) or Social Security Number (SSN) in the US, the name and address of the account holder, and the exact date of the suspension. This unique dataset provides us with a precise measure of default that does not rely on any proxies of financial distress: the eschewal of such proxies is one of the key advantages of this paper. One drawback is that the KFTC website publicly discloses default events only for the most recent two years in an effort to protect privacy.

To extend the dataset beyond the most recent two years, we resort to two major business daily newspapers in Korea, Maeil Business Newspaper and the Korea Economic Daily, which have been (and still are) reporting the same default information provided by the KFTC since even before the KFTC started distributing this information on its website. To ensure the reliability of the two business dailies, we randomly selected 30 days during the most recent two years and verified that the data provided by both business dailies are perfectly consistent with those from the KFTC website. We also compared the consistency

[3]Personal checks issued by individual households that we typically observe in the US are virtually non-existent in Korea. Entities that issue checks are typically corporations or individual entrepreneurs, allowing the KFTC to track and disclose all suspended accounts within the Korean banking system.

[4]One such example is Moody's Credit Research Database (CRD). The description in Falkenstein et al. (2000) provides a detailed account of this dataset.

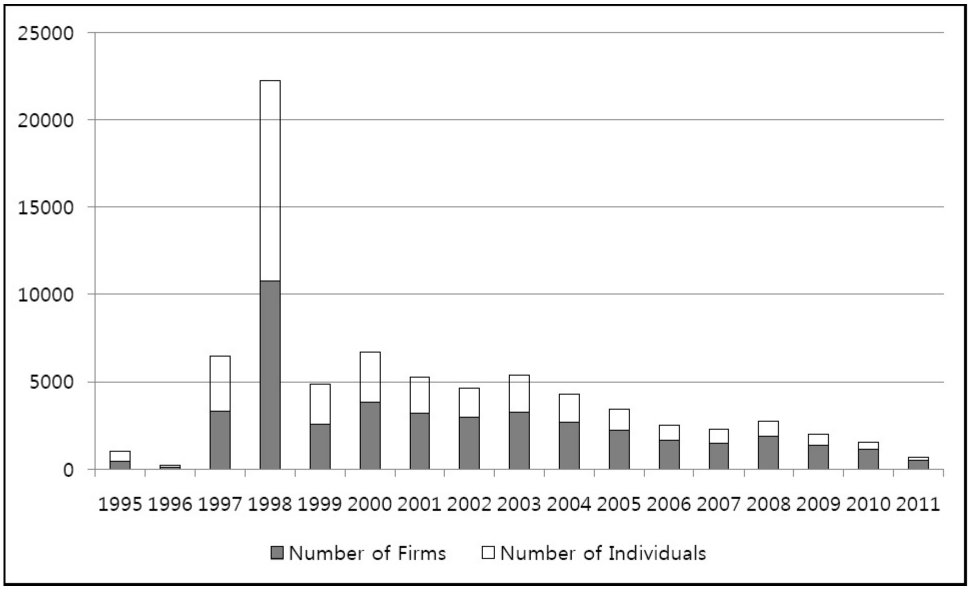

Figure 1: Number of Default Events over Time. This figure provides the number of default events in our initial default dataset. Default event is defined as the suspension of checking accounts triggered by bounced checks within the Korean banking system. Default events include all corporations, both public and private, as well as all individuals.

between the two business dailies beyond the most recent two years by randomly selecting one day from every month, and we found that they are almost perfectly consistent after 2000. Figure 1 presents the overall trend in the number of default events in Korea from 1995 to June 2011. Note that there is a sharp spike in 1998 in the aftermath of the 1997 Asian financial crisis.

Our accounting data are drawn from TS2000, compiled by the Korea Listed Companies Association (KLCA): TS2000 is comparable to the Compustat provided by Standard and Poor's. One advantage of TS2000 over Compustat is that TW2000 provides extensive coverage of private firms whose total assets exceed a certain threshold.[5] Since the financial statements are audited by external auditors, we can be reasonably comfortable that the data are accurate and credible even for private firms, making this dataset superior to those provided in typical commercial databases in terms of quality.[6] The data for private firms have been made available annually since 1999 and covers roughly 100 data items for some 30,000 unique private (closely-held) firms.

[5]Korean auditing regulations require that all corporations whose total assets are greater than KRW 10 billion (roughly USD 10 million) hire an external auditor (accounting firm) to audit their financial statements every fiscal year. This information is compiled by the Korea Listed Companies Association.

[6]For example, only 28% of the financial statements used in Falkenstein et al. (2000) are audited.

3.2 Sample construction

After we assemble our initial default dataset and extract accounting information for private firms, we merge these two datasets. Our matching is mainly performed through identification codes and addresses whenever identification codes are available. When identification codes are unavailable, we compare company names, CEO names, and addresses, and designate a match when at least two of the three variables match. Since our default dataset is mostly reliable after 2000 and accounting information for private firms is mostly available from December 1999, we naturally start our sample period from then. More precisely, our final default sample starts in 2000 and ends in June 2011 while our accounting data ranges from December 1999 to December 2010.[7] Table 1 provides summary statistics of our final sample for each year during our sample period. There are a total of 1,440 default events by the corresponding number of unique private firms during these 11.5 years. The numbers reported in Table 1 are largely comparable to those reported in Falkenstein et al. (2000) who use Moody's Credit Research Database (CRD).[8]

3.3 Covariates

To characterize the forward intensity functions specified in Section 2, we employ both (1) macro risk factors and (2) firm-specific attributes based on the financial statements. The selected covariates are used to infer the likelihood of observing defaults for private firms.

(1) Common variables: The following two macro risk factors are motivated by Duffie et al. (2007) and Duan et al. (2012).

- KOSPI (common): The trailing one-year return on the Korea Composite Stock Price Index.
- CP (common): The yield on 91-day commercial paper.

(2) Firm-specific variables: We have explored a set of candidate variables that are known to represent firm characteristics by the prior literature and research findings, such as Duan et al. (2012), Kocagil & Reyngold (2003), and Hood & Zhang (2007), among others. The last variable (maturity mismatch) is motivated by Adrian & Brunnermeier (2009).

[7] In our subsequent main analysis, we use the previous year's accounting information to map with the current year's default event. Because private firms' accounting information has been available since 1999, we do not include private firm defaults that occurred during 1999 in our final sample.

[8] In Falkenstein et al. (2000)'s sample, there are a total of 24,718 unique firms with 1,621 default events and 115,351 financial statements over the 11-year period from 1989 to 1999.

Year	Number of Firms	Number of Defaults
1999	5,956	N/A
2000	6,278	11
2001	8,749	74
2002	12,397	100
2003	12,050	135
2004	13,688	166
2005	14,873	163
2006	16,616	107
2007	21,736	142
2008	22,407	206
2009	23,654	135
2010	22,338	143
2011	19,153	58
Sum	135,396	1,440
Unique Firms	29,894	

Table 1: Sample Summary Statistics. This table provides the number of firms and number of default events in our final sample of private firms in Korea. Private firms are those whose assets are in excess of KRW 10 billion (roughly USD 10 million). Default event is defined as the suspension of checking accounts triggered by bounced checks within the Korean banking system.

- DTD (firm-specific): The estimated firm-level distance-to-default as a measure of volatility-adjusted leverage. See Section 3.4 for details of its computation.
- GP/CA (firm-specific): The ratio of the gross profit over the current asset as a measure of profitability.
- EBITDA/IE (firm-specific): The earnings before interest, taxes, depreciation and amortization divided by the interest expense as a measure of debt coverage.
- CASH/CA (firm-specific): The ratio of the cash over the current asset as a measure of liquidity.
- TA (firm-specific): The total assets adjusted by the GDP deflator reported by the Bank of Korea as a measure of size.
- MM (firm-specific): The current liability minus the cash then divided by the total liabilities as a measure of maturity mismatch.

For the common macro variables, we collect historical month end data whereas for the firm-specific attributes, we employ audited financial statements. The firm-specific

Variable	Obs.	Missing Obs.	Average	Min	Max	Stdev	Median
KOSPI	140	0	0.1362	-0.5092	1.2056	0.3024	0.1744
CP	140	0	4.7082	2.6200	7.8500	1.3458	4.6250
DTD	158411	399	1.6073	-4.7390	13.5470	1.5715	1.6369
GP/CA	158411	6159	0.7312	-1.1840	15.9546	1.6736	0.3513
EBITDA/IE	158411	23381	33.865	-209.000	2147.090	203.600	2.015
CASH/CA	158411	3241	0.1407	0.0000	0.9849	0.1933	0.0632
TA	158411	37	57852	716	1679080	171930	18045
MM	158411	3324	0.4933	-8.6147	0.9999	0.8719	0.6724

Table 2: Descriptive Statistics of Covariates. This table reports the summary statistics of the variables at monthly frequency for the period between December 1999 and March 2011. KOSPI is the trailing one-year return on the Korea Composite Stock Price Index, CP is the yields on 91-day commercial paper, DTD is the distance-to-default, GP/CA is the gross profit over the current assets, EBITDA/IE is the earnings before interest, taxes, depreciation and amortization over interest expense, CASH/CA is the cash over the current asset, TA is the total assets adjusted by the GDP deflator, and MM is the maturity mismatch measure defined as the current liability minus the cash then divided by the total liabilities.

variables start from the period end of the statement but are lagged by three month to ensure that default predictions are made on the available information at the time of prediction. Table 2 reports the monthly summary statistics of the selected variables, and Table 3 shows the correlation coefficients among the selected firm-specific attributes to check for excessive multicollinearity and potential over-fitting.

Our approach differs in several ways from that of Duan et al. (2012). First, we exclude several variables that are oavailable to listed firms, such as the ratio of a firm's market equity value to the average market equity value of the market index portfolio (SIZE) and the market-to-book asset ratio (M/B). Also, we add or modify certain input variables that are used in Duan et al. (2012) so that the variable selection is better suited for the Korean private firms in our dataset. Furthermore, we consider only the value of each variable, rather than its trend, because of the annual frequency of the financial statement data for private firms.[9]

We also use various macro variables in our estimation procedure: KOSPI (Korea Composite Stock Price Index) trailing one year returns, yields on 91-day commercial papers (CP's), and foreign exchange rate (against USD). These variables are obtained from the Risk Management Institute (RMI) at the National University of Singapore.

[9]Duan et al. (2012) consider the trend, which is computed as the current value of the variable less the one-year average of the measure, to address a momentum effect.

	GP/CA	EBITDA/IE	DTD	CASH/CA	TA	MM
GP/CA	1.0000	0.0079	-0.0210	0.2097	-0.0189	0.0123
EBITDA/IE	0.0079	1.0000	0.2041	0.0737	0.0233	-0.0630
DTD	-0.0210	0.2041	1.0000	0.1739	0.0113	-0.3802
CASH/CA	0.2097	0.0737	0.1739	1.0000	-0.0062	-0.4232
TA	-0.0189	0.0233	0.0113	-0.0062	1.0000	0.0007
MM	0.0123	-0.0630	-0.3802	-0.4232	0.0007	1.0000

Table 3: Correlation Matrix for Firm-specific Attributes. This table reports the estimated correlation coefficients for the selected firm-specific attributes for the period between December 1999 and March 2011. DTD is the distance-to-default, GP/CA is the gross profit over the current asset, EBITDA/IE is the earnings before interest, taxes, depreciation and amortization over the interest expense, CASH/CA is the cash over the current asset, TA is the total assets adjusted by the GDP deflator, and MM is the maturity mismatch measure defined as the current liability minus the cash then divided by the total liabilities.

3.4 Public-firm equivalent distance-to-default

One of the key variables that we use in the subsequent analysis is firm-level DTDs estimated at different points of time. Firms that exhibit large DTD estimates are expected to be more resilient and less likely to default. This measure, originally developed by Merton (1974), needs firm's asset value and volatility. Modern techniques exist for the estimation of these unknown quantities, but these techniques require knowing firm's equity market capitalization. Obviously, privately held firms by definition do not have traded stocks for one to assess their equity market capitalizations. For this, we devise a way to estimate DTDs for private firms indirectly by projecting onto the universe of public firms. We first obtain monthly DTD estimates for public firms in Korea.[10] Then, we regress these monthly DTD estimates on monthly macro variables and on firm characteristics that have been identified in the previous literature as determinants of default probabilities.[11] We run 12 separate regressions and obtain 12 different sets of coefficients based on the number of months since the most recent fiscal year end to reflect the age of the information in the reported annual financial statements. We run these regressions separately for financial firms and non-financial firms.

The results of these regressions are reported in Table 4. Using the coefficient estimates in Table 4 and private firms' characteristics with at least a three-month lag, we obtain DTD estimates for private firms. In the subsequent analysis, we use the estimates of

[10] Monthly DTD estimates for all public firms in Korea and many other economies are calculated and provided on a regular basis by the Risk Management Institute of the National University of Singapore. The DTD data are freely retrievable at its web site.

[11] Firm characteristics are as of the most recent fiscal year end.

coefficients from 0, 3, 6, and 9 months after the most recent fiscal year end.

3.5 Implied interest rate and proxy maturity

Two other firm-level variables employed in our subsequent analysis are the implied interest rate and the proxy maturity of debt for private firms. The implied interest rate is defined as the interest expense for a given fiscal period scaled by the outstanding interest bearing debt as of the previous fiscal year end (i.e., short term borrowing, current portion of long term debt, bonds, and long term borrowing). Admittedly, it is a crude measure of the true interest rate that the firm is facing, but a similar approach is commonly used in the accounting literature to back out the overall cost of debt capital even for publicly traded firms (e.g., Pittman & Foretin (2004)). Our estimates nevertheless reflect the general interest rate trend observed in the Korean debt market.

Maturity information for outstanding debt is generally unavailable in financial statements. To obtain an estimate of maturity for each firm-year, we make the following assumptions. The short-term borrowing and the current portion of the long-term debt are assumed to mature within six months. Most of the corporate bonds issued in Korea have an average initial maturity of three years, so we assume that the outstanding bonds mature within 1.5 years. For the long term borrowing, we resort to a Bank of Korea report that provides a detailed analysis of the maturity structure of bank loans.[12] According to this document, the proportion of bank loans to the corporate sector that mature within one year is 77%, and the average maturity is 16 months. Based on these numbers, we infer that the average maturity for long term debts is 4.12 years.[13] Then for any given firm-year, we take the weighted average of these assumed maturities for different debt classes where the weight is the relative proportion of a debt class corresponding to the assumed maturity in that firm-year.

4 Empirical analysis

This section presents an empirical analysis of the model calibration, the parameter estimates, the forecasting accuracy of the fitted model, and how the interest expenses are related to the estimated default term structures.

[12]See Jeong & Cha (2006) for reference.

[13]The average maturity for long term debt, say x, satisfies the following equation; $0.77 \times 0.5 + 0.23 \times x = 1.333$ (or 16 months).

4.1 Calibrating the forward intensity model

Calibration of the forward intensity model can be performed by maximizing a so-called overlapped pseudo-likelihood function. Statistical inference can utilize the model's large sample properties, even though the objective function does not satisfy the standard assumptions on likelihood functions.[14] We fit the model to our dataset of monthly frequency.

The model's implementation is based on the assumption that firms' default activities are conditionally independent given the common factors and firm-specific attributes, which are not affected by any firm's default or other exit. Suppose that there are N firms in our dataset, and our sample period is $[0, T]$, which is discretized into $T/\Delta t$ periods. Under this assumption, we can decompose the pseudo-likelihood function into horizon-specific pseudo-likelihood functions as in Duan et al. (2012). Naturally, the horizon (τ) must be smaller than T to the extent that there are enough observations to determine the forward-intensity function of horizon τ.

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

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

for $s = 0, \Delta t, 2\Delta t, \cdots, \tau - \Delta t$, where

$$\begin{aligned}
\mathcal{L}^i_{\alpha(s),k} &= 1_{\left\{t_0^i \le k\Delta t, \tau_C^i > (k+1)\Delta t + s\right\}} \exp\left[-f^i_{k\Delta t}(s)\Delta t\right] \\
&+ 1_{\left\{t_0^i \le k\Delta t, \tau_D^i = \tau_C^i = (k+1)\Delta t + s\right\}} \left(1 - \exp\left[-f^i_{k\Delta t}(s)\Delta t\right]\right) \\
&+ 1_{\left\{t_0^i \le k\Delta t, \tau_D^i \ne \tau_C^i, \tau_C^i = (k+1)\Delta t + s\right\}} \exp\left[-f^i_{k\Delta t}(s)\Delta t\right] \\
&+ 1_{\left\{t_0^i > k\Delta t\right\}} + 1_{\left\{\tau_C^i < (k+1)\Delta t + s\right\}},
\end{aligned}$$

and

$$\begin{aligned}
\mathcal{L}^i_{\beta(s),k} &= 1_{\left\{t_0^i \le k\Delta t, \tau_C^i > (k+1)\Delta t + s\right\}} \exp\left[-h^i_{k\Delta t}(s)\Delta t\right] \\
&+ 1_{\left\{t_0^i \le k\Delta t, \tau_D^i = \tau_C^i = (k+1)\Delta t + s\right\}} \left(1 - \exp\left[-h^i_{k\Delta t}(s)\Delta t\right]\right) \\
&+ 1_{\left\{t_0^i \le k\Delta t, \tau_D^i \ne \tau_C^i, \tau_C^i = (k+1)\Delta t + s\right\}} \exp\left[-h^i_{k\Delta t}(s)\Delta t\right] \\
&+ 1_{\left\{t_0^i > k\Delta t\right\}} + 1_{\left\{\tau_C^i < (k+1)\Delta t + s\right\}},
\end{aligned}$$

[14] See Appendix A in Duan et al. (2012) for details.

where $h_t^i(\tau) = g_t^i(\tau) - f_t^i(\tau)$.

These horizon-specific pseudo-likelihood functions can be separately maximized using numerical optimization methods, because the original pseudo-likelihood function to be maximized is conveniently the product of the horizon-specific pseudo-likelihood functions. This decomposability allows the entire calibration procedure to be separated into completely unrelated sub-modules. Considering the large sample size of our dataset, this property certainly increases the computational efficiency.[15]

4.2 Parameter estimates

We are now in the position to discuss the statistical implication of the selected covariates in the forward-intensity model. Tables 5-6 report the maximum pseudo-likelihood estimates for $\alpha(\tau)$ and $\beta(\tau)$ in equations (5)-(6) with different prediction horizons, denoted by τ, ranging from 0 month to 35 months.

The fitted forward default intensities tend to increase with the yields on 91-day commercial paper for prediction horizons shorter than 26 months, whereas the coefficients lose their significance for longer horizons. This observation is consistent with the fact that higher interest rates force firms to carry heavier burden to cover interest expenses; however, such an effect seems to fade in the long run. Admittedly, this phenomenon runs counter to the results obtained by Duffie et al. (2007) in that lower short-term interest rates were used as a policy instrument to boost the economy during recessions. For Korean private firms, we find that the former effect outweighs the latter, offsetting each other for longer prediction horizons, along with business cycles.[16]

Controlling for other covariates, the forward default intensities are estimated to increase in the trailing one-year return of the KOSPI for all prediction horizons considered. While this observation is certainly counterintuitive from a univariate reasoning perspective, Duffie et al. (2007) and Duan et al. (2012) also report the same result for the effect of the one-year S&P500 index return on the default intensities of the US public firms. This relationship could be explained by the fact that the KOSPI return is a lagging business indicator because of its trailing nature in relation to business cycles.

It turns out that a private firm's profitability signaled by the GP/CA ratio plays a

[15] The numerical experiments in our analysis were performed based on code written in MATLAB. We are grateful to Tao Wang for providing the sample codes to implement the pseudo-likelihood estimation of the forward intensity model. Details are available upon request.

[16] In the analysis performed by Duan et al. (2012) on the US public firms, the forward default intensities are estimated again to decrease with the three-month Treasury bill rate when the prediction horizon is shorter than one year but to increase for longer horizons.

significant role in the prediction of defaults. This measure was originally proposed by Hood & Zhang (2007) for predicting private company defaults in Korea. Holding other covariates fixed, the estimated forward default intensities in our analysis are decreasing with the ratio of the gross profit over the current asset for almost all prediction horizons.

Similarly, a firm's debt coverage measured by the EBITDA/IE ratio is estimated to significantly decrease the forward default intensities across different prediction horizons. The inclusion of this covariate is also motivated by Hood & Zhang (2007). The negative sign of the coefficients is consistent with a simple univariate reasoning.

We also confirm that the DTD measure, which can be interpreted as a volatility-adjusted measure of leverage, is one of the most crucial attributes in distinguishing distressed firms from others. Although we use a proxy for private firms' DTDs because we are unable to observe their stock prices, the result shows that a smaller value of a firm's DTD foreshadows a higher default likelihood with a strong statistical significance. To the best of our knowledge, this is the first study that proposes a way to use public-firm equivalent DTDs to gauge the default probabilities of privately held firms. Our finding of its statistical significance in default prediction is consistent with those public-firm studies as reported in Bharath & Shumway (2004), Duffie et al. (2007), Duan et al. (2012), and many others.

We find a significantly negative relationship between the fitted forward default intensities and the CASH/CA ratio after controlling for other covariates. This result is consistent with a univariate reasoning, because this attribute is assumed to represent the degree of a firm's liquidity to meet its financial obligations in the near term. Note that Duan et al. (2012) reports a similar estimation result with the CASH/TA ratio, which is found to be less indicative in our dataset.

The estimated forward default intensity is, ceteris paribus, significantly decreasing with the firm's size measured by its inflation-adjusted value of total assets (normalized by the Korean GDP deflator) for all horizons. Similar results have been reported in the prior research such as Kocagil & Reyngold (2003), Hood & Zhang (2007), Duffie et al. (2007), and Duan et al. (2012), among others.

A firm's maturity mismatch profile is measured by the current liability minus the cash then divided by the total liabilities. It reflects the tendency of a business to mismatch its balance sheet in the sense that liabilities exceed assets in the short run and that medium- and long-term assets dominate the corresponding obligations. Our estimation results report that the estimated coefficients for this attribute are significantly positive in the forward default intensity model for all prediction horizons. In particular, the maturity mismatch profile makes a strong contribution to the characterization of short-term default likelihood.

Our forward default intensity model contains a financial dummy variable that takes a value of 1 if the firm is a financial private firm, and 0 otherwise. The estimated coefficients are found to be negative and statistically significant. The implication is that a financial firm is exposed to a smaller default risk than an otherwise identical non-financial firm.

4.3 Forecasting accuracy analysis

This section presents our testing results after performing a prediction accuracy analysis based on the cumulative accuracy profile of the fitted model. The cumulative accuracy profile, along with the accuracy ratio as its summary statistic, is in practice the most popular validation technique to evaluate the prediction power of any default risk ranking system.

For completeness, we briefly review the concept of the cumulative accuracy profile.[17] First, we compute the cumulative default probabilities implied by our fitted forward intensity model at a conditioning time point and rank each of the private firms in our dataset from the riskiest to safest according to the estimated cumulative default probabilities. Then, for a given fraction x of the total number of private firms ordered by their respective risk scores (i.e., default probabilities), we generate a curve by calculating the percentage of the defaulters whose risk score is equal to or smaller than the maximum score of each fraction x, ranging from 0 to 1. At the same time, we construct the same type of curve with a hypothetically perfect rating model, which generates a curve that increases linearly and then holds constant at one if the fraction x is equal to or larger than the proportion of firms that default over the risk horizon. Finally, we consider a random model without any prediction power, which generates a linear curve from 0 to 1 with a slope of 45°. The accuracy ratio is defined as the ratio of the area between the curve of the model being tested and that of the random model over the area between the curve of the perfect model and that of the random model. The better the prediction power of a tested model, the larger the value of its accuracy ratio with the ideal value being one.

We conduct an out-of-sample analysis in the time dimension using a moving-window approach. Specifically, we re-estimate the model at each month-end from January 2004 with all the data available up to that time and compute the out-of-sample accuracy

[17] A detailed explanation of the cumulative accuracy profile can be found in Sobehart, Keenan & Stein (2000) and Vassalou & Xing (2004).

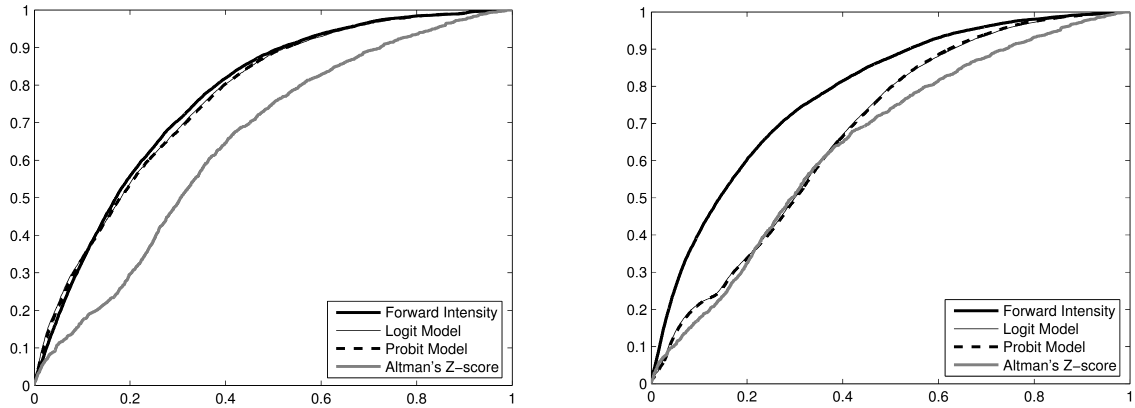

Figure 2: Out-of-sample Cumulative Accuracy Profiles. This figure shows the out-of-sample cumulative accuracy profiles based on all private firms in our dataset from Dec 1999 to Jun 2011 for different modeling approaches for one-year (left panel) and three-year (right panel) prediction ahead. The fitted logit and probit models share the same risk factors with the forward intensity model.

ratio over different future periods. Figure 2 plots the out-of-sample cumulative accuracy profiles of the fitted forward intensity model and other alternative models for one-year (left panel) and three-year (right panel) prediction horizons for the full sample, where the fitted logit and probit models share the same risk factors with the forward intensity model.[18] It is worth noting that the forward-intensity model differs from Altman (2012)'s Z-score model both in the statistical method and the set of explanatory variables. In the comparison with the binary response models, the forward-intensity model only differ in the econometric method not the explanatory variables.

For the one-year ahead prediction, we can see that the fitted forward intensity model with an accuracy ratio of 0.5432 outperforms the alternatives models: Altman (2012)'s Z-score model for private firms has an accuracy ratio of 0.3, and the two binary response models (logit and probit regressions) with the same set of explanatory variables as in the forward-intensity model exhibit accuracy ratios of 0.5335 and 0.5321, respectively. The fitted forward intensity model still maintains its superiority over the alternative models for longer horizons. For three-year prediction ahead, the fitted forward intensity model achieves an accuracy ratio of 0.5709, while the prediction accuracy ratios for the binary response models (logit model: 0.3659, probit model: 0.3639) significantly deteriorate with the same explanatory variables. Table 7 summarizes the out-of-sample accuracy ratios of the fitted forward intensity model and the alternative models for different prediction

[18]When we estimate the binary response models, we deal with other exits as non-default cases.

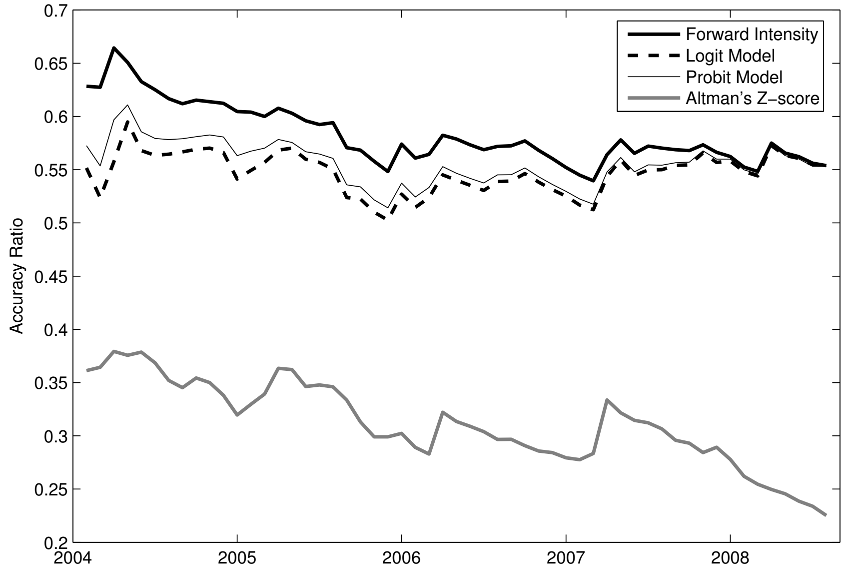

Figure 3: Out-of-sample Accuracy Ratios. This figure shows the time-series behavior of the out-of-sample accuracy ratios based on all private firms in our dataset from Jan 2004 to Jun 2011 for different modeling approaches for three-year prediction ahead. The fitted logit and probit models share the same risk factors with the forward intensity model.

horizons. The result shows that the prediction power of the fitted forward intensity model does not deteriorate for longer horizons relative to other modeling approaches.

Figure 3 shows the time-series behavior of the out-of-sample prediction power for the fitted forward intensity model and alternative models for over next three years. This behavior confirms that the fitted forward intensity model tends to outperform the other alternative models out-of-sample, especially for longer horizons. Overall, considering the lack of available data for private firms, the prediction power of the forward intensity model is impressive, not to mention its ability to perform dynamic estimation over multiple future periods, which is applicable to the next step as described in the following section.

4.4 Relationship between interest expense and default risk

Having estimated the term structure of default probabilities for our sample of private firms based on the forward intensity model, the next natural question is to ask how creditors might use this information to come up with appropriate default risk premia to charge private borrowers. Ideally, one could develop a formal pricing model that explicitly factors in the estimated term structure of default probabilities. However, such an approach is subject to at least two caveats. First, developing a formal pricing model inevitably requires further assumptions regarding key parameters (e.g., relationship between forward intensities and interest rates). Second and perhaps more importantly, the debt instruments used by our sample firms are mostly private in nature and do not have market prices for these non-traded instruments. Thus, we have no information to test the validity of the pricing model.

Instead of resorting to a 'normative' approach to develop a model that we cannot test directly, we take a more direct 'positive' approach and ask whether the reported interest expenses of our sample private firms actually reflect the credit risk captured by the estimated default term structure. Specifically, we regress the implied interest rate defined as interest expense scaled by interest bearing debt[19] on the fitted default probability, controlling for other potential factors. Default probability is calculated from the fitted forward intensities by applying equation (4) for a particular maturity τ. We consider its annualized value, $\frac{1}{\tau}p_t^i(\tau)$, making it directly compatible with the annualized implied interest rate.

Even if our default probability estimate is a sufficient statistic that has adequately captured all factors relevant to physical default, the risk premium that a firm pays will still depend on the recovery rate when its default occurs and the market risk premium prevailing at the time of debt pricing. Naturally, we should consider other factors that may be relevant to the implied interest rate across firms and over time. Specifically, we include the risk-free interest rate, the term spread, and the industry dummies. We have also considered other variables, including the regional dummies and the year dummies, but regional dummies do not show any impact on implied interest rates while year dummies have confounding effects with the macro level interest rates.

The risk-free interest rate is estimated for each maturity τ using the cubic spline interpolation from the yields of 91-day certificate of deposit and Korean Governments Bonds for multiple maturities of 1, 3 and 5 years, obtained from the Economics Statistics System (ECOS) of the Bank of Korea. The term spread is defined as the yield differential between the 5-year Korean Government Bonds and the 91-day certificate of deposit.

All variables (except for dummy variables) are winsorized at the first and 99th percentiles to ensure that the results are not unduly influenced by outliers. We also exclude all firm-years where the interest expense is zero or the estimated maturity hits either the minimum or the maximum of the empirical distribution.[20] Table 8 provides sum-

[19] The detailed definition is provided in section 3.5.

[20] According to the estimation procedure in section 3.5, the minimum possible maturity is 0.5 while the maximum possible maturity is 4.12 years.

mary statistics for all the variables after the winsorization (Panel A) and the results of regressing implied interest rates on a number of explanatory variables (Panel B).

The numbers in Panel A of Table 8 indicate that our sample private firms pay roughly 6 to 7% per annum on their debt instruments, which seems to be plausible. Annualized default probabilities are somewhere around 0.5% on average, while the average estimated maturity is slightly less than 2 years. The risk-free rate is just above 4% on average, while the term spread is roughly around 1% point on average. The fact that the minimum term spread is negative suggests that there is sometimes a reversal in yield curve in the Korean debt market.

Panel B of Table 8 summarizes the regression results where the implied interest rate is the dependent variables and the independent variables are the fitted default probability, estimated time to maturity, risk-free interest rate, term spread, and industry dummy variables. The results clearly indicate that the fitted default probability is a strong predictor of the implied interest rate across different regression specifications. The estimates are not only statistically significant, but also economically substantial. For example, a one standard deviation increase in default probability leads to 0.56 to 0.65% point increase in interest rates for our sample private firms after controlling for other variables. These numbers suggest that our forward intensity model is a useful tool in predicting interest rates facing the private firms in Korea, and that creditors indeed factor in default probabilities in setting interest charges.

The relationship between the implied interest rate and the risk free rate is well represented by the positive sign of the coefficient. Since the risk free rate reveals the overall level of time value of money in the economy, it is hardly surprising that borrowing rates of private firms are positively tied to the level of risk-free rate.

A somewhat odd finding is the reported negative (statistically significant) coefficients on both firm-level maturity and macro level term spread, which appears at first to be counter-intuitive. In a standard context, interest rate (default-free or defaultable) tends to go up as as the time to maturity increases, known as the normal yield curve. Our seemingly abnormal finding may be explained to some extent, however, by the lending practices of banks in Korea. That is, if a firm has a low credit standing, the lender may shorten the time to maturity while charging a higher interest rate. In short, poorly-rated firms are usually eligible only for short-term high-yield loans, whereas their highly-rated counterparts are more likely granted longer-term borrowings and required to pay lower interest charges.

Our interpretation of the negative coefficient on term spread is as follows. In periods of substantial liquidity dry-up, demand for funds tends to be more focused on short term, which could push up short-term interest rates. In fact, we do observe such inverted term structure during 1997 Asian financial crisis and also during the recent global financial crisis in our data series. Thus, the negative coefficient could well pick up the effect of such inverted term structure.

Overall, the results in this subsection suggest that default probabilities obtained through the forward intensity model explains the observed interest rates charged to private firms in Korea. This implies that utilizing forward intensity to model credit behaviors can meaningfully contribute to credit risk management for privately held firms in Korea as well as for their creditors.

5 Conclusion

This paper proposes a methodology for estimating default term structure for private firms. To the best of our knowledge, this is the first study to investigate the dynamic behavior of default risk for private firms over different future horizons. From the commercial lenders' perspective, the proposed framework can be readily applied in practice to help make credit decisions related to privately held firms.

We adopt a forward-intensity model to characterize multiperiod default likelihoods using two macro risk factors, six firm-specific attributes, and one dummy variable to distinguish financial from non-financial firms. The forward-intensity model is calibrated via maximizing an overlapped pseudo-likelihood. Our out-of-sample test results indicate that the prediction power of the fitted forward-intensity model is superior to other alternative models considered, especially for longer prediction horizons.

With the default term structure in place, we are able to examine whether the interest expenses of the Korean private firms are positively related to their default risks. Our findings are consistent with the notion that default risk is priced in credit contracts and gets manifested in higher interest expenses. A better understanding of the lending practice in granting private firm loans in Korea helps advance toward more efficient credit markets for this vital segment of the Korean economy.

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Panel A: Non-Financial Firms

	Number of Months Since the Most Recent Fiscal Year End											
	0	1	2	3	4	5	6	7	8	9	10	11
ln(1+(Currrent Asset/Currrent Liability))	0.317***	0.309***	0.302***	0.571***	0.616***	0.598***	0.368***	0.254***	0.261***	0.241***	0.204***	0.199***
	(8.283)	(8.326)	(8.147)	(15.226)	(16.669)	(16.002)	(9.660)	(6.411)	(6.720)	(6.185)	(5.152)	(5.009)
Net Income / Total Assets	-0.646***	-0.477***	-0.448***	-0.116	0.089	-0.087	-0.294***	-0.351***	-0.478***	-0.436***	-0.423***	-0.675***
	(-6.999)	(-5.327)	(-5.003)	(-1.275)	(0.985)	(-0.929)	(-2.995)	(-3.479)	(-4.838)	(-4.397)	(-4.204)	(-6.658)
Book Equity / Total Liabilities	0.053***	0.065***	0.064***	0.012**	0.009*	0.013**	0.051***	0.067***	0.070***	0.077***	0.080***	0.078***
	(10.199)	(12.908)	(12.830)	(2.430)	(1.713)	(2.484)	(9.767)	(12.398)	(13.181)	(14.487)	(14.803)	(14.381)
Total Liabilities / Total Assets	-2.209***	-2.170***	-2.133***	-2.002***	-1.873***	-1.883***	-1.994***	-1.909***	-1.954***	-1.971***	-1.918***	-2.128***
	(-31.119)	(-31.568)	(-30.997)	(-28.623)	(-26.867)	(-25.879)	(-26.718)	(-25.080)	(-26.244)	(-26.416)	(-25.455)	(-28.148)
Sales / Total Assets	-0.034	0.005	-0.004	0.100***	0.139***	0.128***	0.061**	0.053**	0.064***	0.055**	0.048**	0.081***
	(-1.426)	(0.201)	(-0.152)	(4.255)	(5.989)	(5.457)	(2.546)	(2.172)	(2.682)	(2.293)	(1.975)	(3.312)
Log (Total Assets)	0.142***	0.128***	0.117***	0.059***	0.027***	0.029***	0.084***	0.088***	0.099***	0.139***	0.136***	0.147***
	(14.215)	(13.277)	(12.067)	(5.986)	(2.834)	(2.952)	(8.459)	(8.678)	(9.913)	(13.910)	(13.441)	(14.391)
Interest Expense / Operating Income	-1.659***	-1.440***	-1.504***	-1.310***	-1.178***	-1.165***	-1.156***	-1.147***	-1.132***	-1.181***	-1.210***	-1.275***
	(-36.154)	(-32.399)	(-33.828)	(-28.974)	(-26.377)	(-25.485)	(-24.609)	(-23.658)	(-23.762)	(-24.699)	(-24.957)	(-26.135)
KOSPI trailing 1year return	1.605***	1.288***	1.125***	1.118***	0.962***	0.741***	0.747***	1.299***	0.885***	0.953***	1.547***	1.315***
	(38.578)	(26.974)	(25.665)	(27.447)	(20.507)	(15.200)	(20.139)	(37.172)	(27.268)	(26.574)	(34.655)	(28.581)
CP 91 days	0.013***	0.011***	0.007**	-0.011***	-0.051***	-0.063***	-0.077***	-0.088***	-0.083***	-0.076***	-0.075***	-0.038***
	(3.138)	(2.936)	(2.150)	(-3.168)	(-10.842)	(-13.505)	(-15.984)	(-16.108)	(-16.733)	(-15.559)	(-13.186)	(-7.766)
FX rate (KRW/USD)	-0.003***	-0.003***	-0.003***	-0.003***	-0.004***	-0.004***	-0.004***	-0.005***	-0.005***	-0.005***	-0.005***	-0.004***
	(-39.639)	(-36.807)	(-38.142)	(-37.596)	(-38.645)	(-40.331)	(-44.012)	(-45.139)	(-43.380)	(-52.189)	(-43.414)	(-42.848)
Constant	5.273***	5.034***	4.904***	5.634***	6.550***	7.079***	7.299***	8.038***	7.609***	7.677***	6.964***	5.876***
	(31.800)	(30.895)	(31.511)	(34.103)	(37.806)	(39.766)	(40.351)	(41.044)	(39.868)	(41.673)	(35.903)	(33.046)
R^2	0.457	0.431	0.437	0.405	0.402	0.388	0.373	0.398	0.375	0.408	0.424	0.409
N	16,431	16,428	16,431	16,599	16,587	16,487	17,468	16,144	16,150	16,352	16,311	16,300

Table 4a: Coefficient Estimates for Public Non-Financial Firms' Distance to Default (DTD). This table presents the OLS coefficient estimates where the dependent variable is monthly distance to default estimates between January 1993 to June 2011 for publicly traded non-financial firms in Korea based on the Merton (1974) model. Firm characteristics are as of the most recent fiscal year end. We estimate 12 separate regressions based on the number of months since the most recent fiscal year end. The t-statistics are shown in parentheses.

Panel B: Financial Firms												
	Number of Months Since the Most Recent Fiscal Year End											
	0	1	2	3	4	5	6	7	8	9	10	11
Book Equity / Total Liabilities	0.092***	0.100***	0.103***	0.106***	0.071***	0.078***	0.092***	0.078***	0.079***	0.081***	0.083***	0.087***
	(8.483)	(9.402)	(9.700)	(9.251)	(6.201)	(6.881)	(7.875)	(6.742)	(6.696)	(6.772)	(7.202)	(7.582)
Total Liabilities / Total Assets	-3.037***	-2.939***	-2.868***	-1.437***	-1.362***	-1.327***	-2.161***	-2.283***	-2.314***	-2.531***	-2.636***	-2.703***
	(-11.780)	(-11.648)	(-11.332)	(-5.252)	(-5.006)	(-4.986)	(-7.789)	(-8.665)	(-8.584)	(-9.235)	(-9.896)	(-10.120)
Sales / Total Assets	1.220***	1.219***	1.208***	1.227***	1.135***	1.075***	1.209***	1.098***	1.219***	1.325***	1.320***	1.207***
	(8.036)	(8.201)	(8.083)	(7.591)	(7.038)	(6.848)	(7.590)	(7.423)	(8.036)	(8.572)	(8.679)	(7.939)
Log (Total Assets)	0.187***	0.153***	0.159***	-0.023	-0.097***	-0.107***	-0.049	0.038	0.047	0.087***	0.075**	0.091***
	(6.310)	(5.297)	(5.471)	(-0.721)	(-3.056)	(-3.462)	(-1.529)	(1.263)	(1.510)	(2.737)	(2.419)	(2.944)
KOSPI trailing 1year return	1.507***	1.690***	1.346***	0.912***	1.168***	0.919***	0.991***	1.599***	1.252***	1.685***	1.794***	1.497***
	(10.460)	(10.682)	(9.120)	(7.214)	(8.961)	(7.581)	(7.515)	(11.083)	(8.477)	(10.922)	(9.942)	(8.688)
CP 91 days	-0.052***	-0.091***	-0.082***	-0.123***	-0.154***	-0.147***	-0.124***	-0.114***	-0.100***	-0.056***	-0.050***	-0.054***
	(-5.027)	(-6.372)	(-6.184)	(-8.285)	(-8.366)	(-8.755)	(-7.579)	(-6.807)	(-6.868)	(-4.411)	(-3.887)	(-4.676)
FX rate (KRW/USD)	-0.002***	-0.003***	-0.003***	-0.004***	-0.005***	-0.004***	-0.004***	-0.004***	-0.003***	-0.003***	-0.002***	-0.002***
	(-8.669)	(-10.304)	(-11.936)	(-12.629)	(-11.943)	(-11.718)	(-11.597)	(-11.141)	(-11.098)	(-10.736)	(-7.753)	(-8.086)
Constant	3.247***	4.552***	4.778***	7.381***	8.855***	8.780***	8.062***	6.679***	6.048***	4.906***	4.278***	4.017***
	(6.414)	(8.480)	(9.258)	(12.640)	(13.659)	(14.131)	(13.301)	(11.100)	(10.961)	(9.386)	(8.014)	(8.072)
R^2	0.468	0.503	0.500	0.427	0.405	0.403	0.432	0.450	0.427	0.444	0.422	0.421
N	972	971	972	984	952	950	1015	979	979	981	980	980

Table 4b: Coefficient Estimates for Public Financial Firms' Distance to Default (DTD). This table presents the OLS coefficient estimates where the dependent variable is monthly distance to default estimates between January 1993 to June 2011 for publicly traded financial firms in Korea based on the Merton (1974) model. Firm characteristics are as of the most recent fiscal year end. We estimate 12 separate regressions based on the number of months since the most recent fiscal year end. The t-statistics are shown in parentheses.

Panel A: Maximum pseudo-likelihood estimates for $\alpha(\tau)$ (1-12 months)												
	$\alpha(0)$	$\alpha(1)$	$\alpha(2)$	$\alpha(3)$	$\alpha(4)$	$\alpha(5)$	$\alpha(6)$	$\alpha(7)$	$\alpha(8)$	$\alpha(9)$	$\alpha(10)$	$\alpha(11)$
Intercept	-4.7052***	-4.6803***	-4.7002***	-4.6899***	-4.6562***	-4.6477***	-4.661***	-4.5824***	-4.5525***	-4.5846***	-4.5619***	-4.5783***
	(-32.0042)	(-32.4083)	(-32.8846)	(-32.6432)	(-32.5641)	(-32.5633)	(-31.6442)	(-30.9489)	(-29.2585)	(-29.0501)	(-27.9955)	(-27.3393)
CP	0.1261***	0.1276***	0.1276***	0.1259***	0.1275***	0.1284***	0.1233***	0.1093***	0.1107***	0.1198***	0.1169***	0.1196***
	(6.2532)	(6.4729)	(6.5822)	(6.5636)	(6.5890)	(6.5344)	(6.1197)	(5.3586)	(5.3350)	(5.5594)	(5.2540)	(5.1610)
KOSPI	0.9180***	0.8728***	0.9169***	0.8686***	0.8957***	0.9674***	1.0115***	0.9870***	0.9256***	0.9369***	0.8939***	0.9288***
	(8.9850)	(8.5559)	(8.8617)	(8.5975)	(8.9119)	(9.4701)	(9.6556)	(9.5075)	(9.1043)	(9.1066)	(8.4682)	(8.4959)
GP/CA	-0.1604***	-0.1621***	-0.1406***	-0.1507***	-0.1551***	-0.1581***	-0.1810***	-0.1646***	-0.1701***	-0.1623***	-0.1623***	-0.1491***
	(-3.4796)	(-3.4034)	(-3.0634)	(-3.0633)	(-3.0048)	(-2.9865)	(-3.072)	(-2.8908)	(-2.8543)	(-2.7334)	(-2.6661)	(-2.593)
EBITDA/IE	-0.0013***	-0.0015***	-0.0015***	-0.0015***	-0.0016***	-0.0016***	-0.0016***	-0.0015***	-0.0016***	-0.0017***	-0.0022***	-0.0027***
	(-3.3244)	(-3.400)	(-3.4686)	(-3.4896)	(-3.4511)	(-3.4102)	(-3.2881)	(-3.2333)	(-3.1857)	(-3.141)	(-3.9519)	(-6.6654)
DTD	-0.3975***	-0.3793***	-0.3751***	-0.3651***	-0.3635***	-0.3617***	-0.3715***	-0.3693***	-0.367***	-0.3602***	-0.3519***	-0.3581***
	(-24.2408)	(-22.8098)	(-22.3024)	(-21.3323)	(-20.9568)	(-20.482)	(-20.5441)	(-20.0741)	(-20.1543)	(-19.7984)	(-19.0402)	(-19.3209)
CASH/CA	-4.5345***	-4.5012***	-4.3204***	-4.1955***	-4.1996***	-4.3236***	-3.9668***	-3.9826***	-3.9191***	-3.8508***	-3.9183***	-3.798***
	(-8.9482)	(-9.0779)	(-9.0721)	(-8.9623)	(-9.4041)	(-9.4851)	(-8.9944)	(-9.0463)	(-8.9807)	(-9.0509)	(-9.3023)	(-9.1518)
TA	-0.3405***	-0.3443***	-0.3264***	-0.3084***	-0.3181***	-0.3058***	-0.2961***	-0.2903***	-0.2986***	-0.3095***	-0.3126***	-0.3163***
	(-4.4497)	(-4.4198)	(-4.3814)	(-3.7177)	(-3.7281)	(-3.675)	(-3.5545)	(-3.3768)	(-3.3547)	(-3.3129)	(-3.2159)	(-3.1774)
MM	0.6328***	0.6005***	0.602***	0.5962***	0.5521***	0.5336***	0.5749***	0.549***	0.5102***	0.496***	0.4992***	0.4909***
	(5.0806)	(4.856)	(4.882)	(4.7998)	(4.4457)	(4.262)	(4.4794)	(4.2607)	(3.6291)	(3.5704)	(3.5381)	(3.448)
Dummy	-0.8378***	-0.847***	-0.8246***	-0.7967***	-0.8069***	-0.7935***	-0.8226***	-0.8688***	-0.8598***	-0.8913***	-0.9047***	-0.888***
	(-8.2234)	(-8.1863)	(-7.9835)	(-7.6698)	(-7.6322)	(-7.4632)	(-7.5625)	(-7.6943)	(-7.5104)	(-7.5788)	(-7.5511)	(-7.3674)

Table 5a: Maximum pseudo-likelihood estimates for $\alpha(\tau)$. This table reports the maximum pseudo-likelihood estimates of $\alpha(\tau)$ for 1-12 months horizons. KOSPI is the trailing one-year retun on the Korea Composite Stock Price Index, CP is the yields on 91 day commercial papers, DTD is the distance-to-default, GP/CA is the gross profit over the current assets, EBITDA/IE is the earnings before interest, taxes, depreciation and amortization over interest expense, CASH/CA is cash over total asset, TA is the total asset adjusted by the GDP deflator, MM is the maturity mismatch measure defined as current liability less cash over total liabilities, and Dummy is a financial dummy variable which takes 1 if it is a financial firm and 0 otherwise. The t-statistics are shown in parentheses.

Panel B: Maximum pseudo-likelihood estimates for $\alpha(\tau)$ (13-24 months)												
	$\alpha(12)$	$\alpha(13)$	$\alpha(14)$	$\alpha(15)$	$\alpha(16)$	$\alpha(17)$	$\alpha(18)$	$\alpha(19)$	$\alpha(20)$	$\alpha(21)$	$\alpha(22)$	$\alpha(23)$
Intercept	-4.6127***	-4.6447***	-4.5963***	-4.4992***	-4.5721***	-4.5983***	-4.5358***	-4.4339***	-4.4512***	-4.3318***	-4.3802***	-4.2961***
	(-27.3317)	(-26.5985)	(-25.6735)	(-24.9437)	(-24.9744)	(-24.5637)	(-23.7994)	(-22.3481)	(-22.1494)	(-21.1334)	(-20.6379)	(-19.9781)
CP	0.1289***	0.129***	0.1273***	0.1071***	0.1206***	0.1217***	0.113***	0.1101***	0.0981***	0.0729***	0.0743***	0.0571**
	(5.4565)	(5.326)	(5.0856)	(4.3027)	(4.7952)	(4.8561)	(4.3874)	(4.2395)	(3.6852)	(2.7819)	(2.7581)	(2.1022)
KOSPI	0.953***	0.9707***	0.9746***	0.8717***	0.9411***	0.8946***	0.8291***	0.8031***	0.844***	0.76***	0.8284***	0.7995***
	(8.6837)	(8.676)	(8.6356)	(7.7195)	(8.3028)	(7.783)	(6.8929)	(6.8036)	(6.9815)	(6.2894)	(6.8587)	(6.6012)
GP/CA	-0.1469**	-0.1479**	-0.1741***	-0.1815***	-0.1668***	-0.174**	-0.2214***	-0.2186**	-0.2161**	-0.2405***	-0.2300**	-0.2299**
	(-2.5373)	(-2.4913)	(-2.7371)	(-2.7477)	(-2.6438)	(-2.5227)	(-2.8116)	(-2.5445)	(-2.4919)	(-2.5848)	(-2.4999)	(-2.4614)
EBITDA/IE	-0.0028***	-0.003***	-0.0022***	-0.0022***	-0.0022**	-0.0023**	-0.0021**	-0.0025**	-0.0023**	-0.0022**	-0.0021**	-0.0022**
	(-6.6709)	(-6.678)	(-2.683)	(-2.6267)	(-2.5463)	(-2.4934)	(-2.5118)	(-2.4983)	(-2.3573)	(-2.3219)	(-2.2201)	(-2.1648)
DTD	-0.3588***	-0.353***	-0.3485***	-0.3521***	-0.3672***	-0.3621***	-0.3495***	-0.3526***	-0.3521***	-0.3446***	-0.3565***	-0.3604***
	(-19.3441)	(-18.4287)	(-17.8017)	(-17.8741)	(-18.4515)	(-17.6784)	(-16.4717)	(-16.4614)	(-16.2224)	(-15.6113)	(-15.7752)	(-15.6679)
CASH/CA	-3.5781***	-3.2745***	-3.2302***	-3.0208***	-3.0264***	-3.0397***	-3.0953***	-3.0763***	-2.8168***	-2.8957***	-2.8217***	-2.7479***
	(-8.7159)	(-7.7931)	(-7.6418)	(-7.3038)	(-7.2059)	(-7.1258)	(-7.2061)	(-7.1071)	(-6.4757)	(-6.4578)	(-6.2373)	(-6.0982)
TA	-0.3321***	-0.3529***	-0.3589***	-0.4087***	-0.3987***	-0.404***	-0.422***	-0.4111***	-0.418***	-0.4407***	-0.4552***	-0.4514**
	(-3.169)	(-3.13)	(-3.1065)	(-3.0648)	(-3.0016)	(-2.9457)	(-2.878)	(-2.8238)	(-2.7353)	(-2.6436)	(-2.5959)	(-2.5523)
MM	0.4694***	0.4945***	0.44***	0.4567***	0.4709***	0.5113***	0.5077***	0.3805**	0.4632***	0.4891***	0.5216***	0.5228***
	(3.4098)	(3.5159)	(3.1441)	(3.1942)	(3.219)	(3.3991)	(3.322)	(2.1698)	(2.7312)	(2.7948)	(2.8592)	(2.7907)
Dummy	-0.8554***	-0.8246***	-0.7906***	-0.778***	-0.808***	-0.817***	-0.8346***	-0.8306***	-0.8802***	-0.9286***	-0.9402***	-0.9273***
	(-7.0967)	(-6.7797)	(-6.4967)	(-6.3095)	(-6.3781)	(-6.3102)	(-6.2541)	(-6.1271)	(-6.2405)	(-6.2892)	(-6.1952)	(-6.0448)

Table 5b: Maximum pseudo-likelihood estimates for $\alpha(\tau)$. This table reports the maximum pseudo-likelihood estimates of $\alpha(\tau)$ for 13-24 months horizons. KOSPI is the trailing one-year return on the Korea Composite Stock Price Index, CP is the yields on 91 day commercial papers, DTD is the distance-to-default, GP/CA is the gross profit over the current assets, EBITDA/IE is the earnings before interest, taxes, depreciation and amortization over interest expense, CASH/CA is cash over total asset, TA is the total asset adjusted by the GDP deflator, MM is the maturity mismatch measure defined as current liability less cash over total liabilities, and Dummy is a financial dummy variable which takes 1 if it is a financial firm and 0 otherwise. The t-statistics are shown in parentheses.

Panel C: Maximum pseudo-likelihood estimates for $\alpha(\tau)$ (25-36 months)												
	$\alpha(24)$	$\alpha(25)$	$\alpha(26)$	$\alpha(27)$	$\alpha(28)$	$\alpha(29)$	$\alpha(30)$	$\alpha(31)$	$\alpha(32)$	$\alpha(33)$	$\alpha(34)$	$\alpha(35)$
Intercept	-4.3611***	-4.3325***	-4.2967***	-4.2531***	-4.1833***	-3.9162***	-3.6572***	-3.5988***	-3.7122***	-3.7908***	-3.9431***	-3.8995***
	(-19.0957)	(-18.4641)	(-17.8915)	(-17.2725)	(-16.1779)	(-14.5594)	(-12.4568)	(-13.4913)	(-13.5087)	(-11.7449)	(-12.2504)	(-12.1979)
CP	0.0638**	0.0611**	0.045	0.0398	0.0269	-0.0076	-0.0623	-0.0839**	-0.0643	-0.0206	0.0147	0.012
	(2.1655)	(1.9796)	(1.4188)	(1.2086)	(0.7485)	(-0.1959)	(-1.4364)	(-2.0184)	(-1.5199)	(-0.4565)	(0.3162)	(0.2577)
KOSPI	0.842***	0.8072***	0.7425***	0.751***	0.8235***	0.8168***	0.6292***	0.518***	0.4842***	0.6205***	0.7038***	0.6664***
	(7.0293)	(6.6046)	(5.9677)	(5.8666)	(6.096)	(5.473)	(3.8121)	(3.2361)	(2.9856)	(3.6928)	(4.2631)	(3.9021)
GP/CA	-0.2366**	-0.2332**	-0.2232**	-0.2713**	-0.2772**	-0.3472***	-0.3457***	-0.3683***	-0.3124**	-0.3388**	-0.3393**	-0.3577**
	(-2.4492)	(-2.3359)	(-2.2418)	(-2.5538)	(-2.4996)	(-3.0234)	(-2.9325)	(-3.1961)	(-2.4528)	(-2.4812)	(-2.4943)	(-2.4617)
EBITDA/IE	-0.0021**	-0.0022**	-0.0034***	-0.0032***	-0.003***	-0.0028***	-0.0029***	-0.0027***	-0.0031***	-0.0031***	-0.0031***	-0.0027***
	(-2.1213)	(-2.0658)	(-4.7193)	(-4.5778)	(-4.5143)	(-4.4676)	(-4.3866)	(-4.2133)	(-6.2895)	(-6.2634)	(-6.1238)	(-5.4057)
DTD	-0.3562***	-0.3498***	-0.332***	-0.33***	-0.3405***	-0.3401***	-0.337***	-0.3422***	-0.3411***	-0.3491***	-0.353***	-0.3524***
	(-15.3173)	(-14.8072)	(-13.6757)	(-13.4905)	(-13.6366)	(-13.1731)	(-12.878)	(-12.5689)	(-12.4101)	(-12.4763)	(-12.5326)	(-12.3904)
CASH/CA	-2.7618***	-2.9792***	-2.8295***	-2.9125***	-2.8024***	-2.8999***	-2.9937***	-2.9366***	-3.0911***	-2.9257***	-2.777***	-2.7825***
	(-6.0734)	(-6.5727)	(-6.3599)	(-6.203)	(-6.0161)	(-6.0359)	(-6.0433)	(-5.899)	(-6.3092)	(-6.2072)	(-6.0623)	(-6.0352)
TA	-0.4442**	-0.4415**	-0.4637**	-0.4157**	-0.4085**	-0.4025**	-0.3743**	-0.3702**	-0.3502*	-0.3304*	-0.3235*	-0.3189*
	(-2.4846)	(-2.4448)	(-2.3821)	(-2.1228)	(-2.0774)	(-2.0417)	(-1.9751)	(-1.9646)	(-1.9238)	(-1.9063)	(-1.8944)	(-1.8739)
MM	0.5548***	0.5466***	0.5724***	0.5581***	0.5391**	0.4362**	0.4823**	0.5567***	0.54***	0.3077	0.258	0.2131
	(2.8482)	(2.7315)	(2.7743)	(2.6758)	(2.5365)	(2.0713)	(2.1906)	(3.0915)	(2.9312)	(1.151)	(0.996)	(0.8412)
Dummy	-0.925***	-0.9224***	-0.9414***	-0.9371***	-0.9506***	-0.9416***	-0.9333***	-0.9352***	-0.9174***	-1.0177***	-1.0246***	-0.9794***
	(-5.8982)	(-5.76)	(-5.6873)	(-5.5816)	(-5.5185)	(-5.3877)	(-5.2665)	(-5.1358)	(-4.9524)	(-5.1777)	(-5.1329)	(-4.9007)

Table 5c: Maximum pseudo-likelihood estimates for $\alpha(\tau)$. This table reports the maximum pseudo-likelihood estimates of $\alpha(\tau)$ for 25-36 months horizons. KOSPI is the trailing one-year return on the Korea Composite Stock Price Index, CP is the yields on 91 day commercial papers, DTD is the distance-to-default, GP/CA is the gross profit over the current assets, EBITDA/IE is the earnings before interest, taxes, depreciation and amortization over interest expense, CASH/CA is cash over total asset, TA is the total asset adjusted by the GDP deflator, MM is the maturity mismatch measure defined as current liability less cash over total liabilities, and Dummy is a financial dummy variable which takes 1 if it is a financial firm and 0 otherwise. The t-statistics are shown in parentheses.

Panel A: Maximum pseudo-likelihood estimates for $\beta(\tau)$ (1-12 months)												
	$\beta(0)$	$\beta(1)$	$\beta(2)$	$\beta(3)$	$\beta(4)$	$\beta(5)$	$\beta(6)$	$\beta(7)$	$\beta(8)$	$\beta(9)$	$\beta(10)$	$\beta(11)$
Intercept	-1.1405***	-1.0579***	-1.4595***	-2.5556***	-2.2038***	-2.0445***	-1.3721***	-0.8462***	-0.6784***	-0.5176***	-0.4458***	-0.4693***
	(-25.4999)	(-23.7954)	(-34.2789)	(-58.4599)	(-50.175)	(-44.3876)	(-29.8604)	(-18.61)	(-14.5169)	(-11.1255)	(-9.6301)	(-9.6713)
CP	-0.273***	-0.2829***	-0.1671***	0.0743***	0.0049	-0.0264***	-0.1548***	-0.2725***	-0.306***	-0.3397***	-0.3325***	-0.3148***
	(-31.0461)	(-35.4742)	(-22.0644)	(8.8562)	(0.5575)	(-2.8379)	(-17.4495)	(-32.3011)	(-34.9916)	(-38.9306)	(-38.7732)	(-35.4079)
KOSPI	1.456***	1.5082***	1.3395***	2.1431***	1.7254***	1.7563***	0.7065***	0.1099***	-0.0443	-0.5435***	-0.5475***	-0.244***
	(29.634)	(29.3978)	(33.1383)	(50.3937)	(44.5526)	(43.7479)	(22.5039)	(3.5063)	(-1.2411)	(-15.5986)	(-15.0132)	(-5.844)
GP/CA	-0.014**	-0.0153**	-0.0154**	-0.0168***	-0.0159**	-0.0163**	-0.0154**	-0.0149**	-0.0152**	-0.0149**	-0.016**	-0.017**
	(-2.3258)	(-2.486)	(-2.4604)	(-2.6591)	(-2.4283)	(-2.4504)	(-2.2559)	(-2.1347)	(-2.1225)	(-2.0415)	(-2.1909)	(-2.2819)
EBITDA/IE	-0.0005***	-0.0005***	-0.0005***	-0.0004***	-0.0005***	-0.0005***	-0.0006***	-0.0007***	-0.0007***	-0.0008***	-0.0007***	-0.0007***
	(-4.9424)	(-4.7876)	(-4.7368)	(-3.9773)	(-4.6389)	(-4.6244)	(-5.326)	(-5.7852)	(-5.8779)	(-6.1401)	(-5.6979)	(-5.4684)
DTD	-0.3217***	-0.3252***	-0.3299***	-0.387***	-0.3443***	-0.3491***	-0.2871***	-0.2397***	-0.2296***	-0.194***	-0.2506***	-0.2801***
	(-40.151)	(-40.3601)	(-40.155)	(-46.9244)	(-42.4438)	(-42.7783)	(-34.201)	(-28.1901)	(-26.6414)	(-22.1007)	(-27.4125)	(-30.1689)
CASH/CA	-0.1085**	-0.1086**	-0.0902*	-0.0499	-0.0599	-0.0611	-0.0771	-0.0892	-0.0894	-0.0898	-0.0751	-0.0673
	(-2.0401)	(-2.0156)	(-1.6498)	(-0.895)	(-1.0543)	(-1.0641)	(-1.3284)	(-1.5166)	(-1.4955)	(-1.4718)	(-1.2368)	(-1.0805)
TA	-0.4669***	-0.5908***	-0.5917***	-0.5704***	-0.5587***	-0.5691***	-0.597***	-0.6153***	-0.6277***	-0.6411***	-0.639***	-0.6483***
	(-6.6089)	(-6.7339)	(-6.7186)	(-6.6551)	(-6.6349)	(-6.6449)	(-6.698)	(-6.7174)	(-6.7296)	(-6.7396)	(-6.7282)	(-6.7192)
MM	-0.2271***	-0.2278***	-0.228***	-0.2583***	-0.2317***	-0.2343***	-0.1972***	-0.1683***	-0.1616***	-0.1388***	-0.1734***	-0.1907***
	(-20.8378)	(-20.7272)	(-20.5)	(-23.1008)	(-20.3482)	(-20.3291)	(-16.7314)	(-13.8893)	(-13.1295)	(-11.006)	(-13.6208)	(-14.7681)
Dummy	0.3949***	0.4114***	0.4405***	0.4609***	0.4832***	0.4849***	0.5099***	0.5267***	0.5366***	0.5623***	0.5403***	0.5392***
	(15.8857)	(16.3082)	(17.5305)	(18.2829)	(18.9846)	(18.821)	(19.8042)	(20.1515)	(20.3627)	(21.2519)	(20.0606)	(19.6637)

Table 6a: Maximum pseudo-likelihood estimates for $\beta(\tau)$. This table reports the maximum pseudo-likelihood estimates of $\beta(\tau)$ for 1-12 months horizons. KOSPI is the trailing one-year return on the Korea Composite Stock Price Index, CP is the yields on 91 day commercial papers, DTD is the distance-to-default, GP/CA is the gross profit over the current assets, EBITDA/IE is the earnings before interest, taxes, depreciation and amortization over interest expense, CASH/CA is cash over total asset, TA is the total asset adjusted by the GDP deflator, MM is the maturity mismatch measure defined as current liability minus cash then over total liabilities, and Dummy is a financial dummy variable which takes 1 if it is a financial firm and 0 otherwise. The t-statistics are shown in parentheses.

Panel B: Maximum pseudo-likelihood estimates for $\beta(\tau)$ (13-24 months)												
	$\beta(12)$	$\beta(13)$	$\beta(14)$	$\beta(15)$	$\beta(16)$	$\beta(17)$	$\beta(18)$	$\beta(19)$	$\beta(20)$	$\beta(21)$	$\beta(22)$	$\beta(23)$
Intercept	-0.501***	0.0468	-0.8806***	-3.4456***	-3.7132***	-3.7799***	-3.0613***	-2.3784***	-2.3162***	-2.1937***	-2.2173***	-2.3345***
	(-10.3382)	(1.0071)	(-20.153)	(-75.0747)	(-72.7522)	(-69.8759)	(-58.81)	(-47.6547)	(-45.4342)	(-42.5528)	(-39.7991)	(-39.0426)
CP	-0.2967***	-0.4728***	-0.2367***	0.3089***	0.3398***	0.3603***	0.2299***	0.0435***	0.0388***	0.0212**	0.0435***	0.0781***
	(-34.8161)	(-53.04)	(-31.7433)	(41.4453)	(41.2398)	(40.3532)	(25.2313)	(5.328)	(4.5281)	(2.3503)	(4.5172)	(7.5045)
KOSPI	-0.1725***	-0.8195***	-0.4959***	0.3921***	0.0188	0.2217***	0.247***	-0.554***	-0.3914***	-0.263***	0.2505***	0.6346***
	(-3.5345)	(-14.4505)	(-10.7433)	(8.6588)	(0.459)	(5.2032)	(7.1703)	(-14.4544)	(-9.4087)	(-7.5897)	(7.227)	(15.6589)
GP/CA	-0.0178**	-0.0534***	-0.0553***	-0.0569***	-0.0568***	-0.0582***	-0.0599***	-0.0595***	-0.0608***	-0.0621***	-0.0637***	-0.0657***
	(-2.3225)	(-5.4743)	(-5.6268)	(-5.801)	(-5.5099)	(-5.5815)	(-5.6737)	(-5.1713)	(-5.2373)	(-5.2995)	(-5.4508)	(-5.5818)
EBITDA/IE	-0.0007***	-0.0003***	-0.0002***	-0.0001	-0.0003***	-0.0002***	-0.0002***	-0.0006***	-0.0006***	-0.0006***	-0.0005***	-0.0004***
	(-5.3722)	(-3.6044)	(-2.9116)	(-1.3124)	(-3.124)	(-2.8708)	(-2.8933)	(-5.8056)	(-5.6798)	(-5.5866)	(-4.9751)	(-4.5129)
DTD	-0.2926***	-0.2776***	-0.3191***	-0.387***	-0.2848***	-0.3044***	-0.317***	-0.1065***	-0.1222***	-0.1352***	-0.1942***	-0.2343***
	(-30.8163)	(-29.9763)	(-35.5313)	(-43.791)	(-33.2009)	(-35.7387)	(-37.2536)	(-11.9505)	(-13.7318)	(-15.5561)	(-21.4588)	(-25.7937)
CASH/CA	-0.0595	-0.2332***	-0.2016***	-0.1279*	-0.1508**	-0.1487**	-0.1619**	-0.2306***	-0.2312***	-0.2326***	-0.2288***	-0.2214***
	(-0.9463)	(-3.5094)	(-3.0097)	(-1.8871)	(-2.1577)	(-2.0992)	(-2.2615)	(-3.0697)	(-3.0496)	(-3.0365)	(-2.9644)	(-2.8369)
TA	-0.6592***	-0.409***	-0.3977***	-0.3656***	-0.3417***	-0.3467***	-0.3567***	-0.3751***	-0.3782***	-0.3814***	-0.3815***	-0.3806***
	(-6.7161)	(-6.2902)	(-6.2963)	(-6.3097)	(-6.3308)	(-6.335)	(-6.3408)	(-6.3091)	(-6.3163)	(-6.3237)	(-6.3118)	(-6.3243)
MM	-0.1972***	-0.159***	-0.1812***	-0.2151***	-0.1533***	-0.1647***	-0.1728***	-0.0435***	-0.0531***	-0.0609***	-0.0967***	-0.1203***
	(-14.984)	(-10.6259)	(-12.288)	(-14.9565)	(-10.2085)	(-10.9032)	(-11.3363)	(-2.5805)	(-3.1514)	(-3.6084)	(-5.765)	(-7.2025)
Dummy	0.5492***	0.4116***	0.4451***	0.501***	0.5667***	0.5691***	0.5591***	0.6509***	0.6524***	0.6547***	0.6345***	0.6323***
	(19.7576)	(14.0594)	(15.3218)	(17.5688)	(19.9197)	(19.6835)	(19.0017)	(21.9302)	(21.7641)	(21.6119)	(20.6651)	(20.3087)

Table 6b: Maximum pseudo-likelihood estimates for $\beta(\tau)$. This table reports the maximum pseudo-likelihood estimates of $\beta(\tau)$ for 13-24 months horizons. KOSPI is the trailing one-year return on the Korea Composite Stock Price Index, CP is the yields on 91 day commercial papers, DTD is the distance-to-default, GP/CA is the gross profit over the current assets, EBITDA/IE is the earnings before interest, taxes, depreciation and amortization over interest expense, CASH/CA is cash over total asset, TA is the total asset adjusted by the GDP deflator, MM is the maturity mismatch measure defined as current liability minus cash then over total liabilities, and Dummy is a financial dummy variable which takes 1 if it is a financial firm and 0 otherwise. The t-statistics are shown in parentheses.

Panel C: Maximum pseudo-likelihood estimates for $\beta(\tau)$ (25-36 months)												
	$\beta(24)$	$\beta(25)$	$\beta(26)$	$\beta(27)$	$\beta(28)$	$\beta(29)$	$\beta(30)$	$\beta(31)$	$\beta(32)$	$\beta(33)$	$\beta(34)$	$\beta(35)$
Intercept	-2.1752***	-1.0691***	-2.3482***	-5.1584***	-4.6523***	-4.6276***	-3.856***	-2.7348***	-3.1743***	-3.0624***	-3.1186***	-3.159***
	(-35.358)	(-16.3731)	(-31.2885)	(-60.9104)	(-55.8166)	(-49.988)	(-41.9633)	(-30.3788)	(-38.4847)	(-39.5067)	(-39.2805)	(-41.7403)
CP	0.0529***	-0.2719***	0.0096	0.5471***	0.4219***	0.4263***	0.2908***	0.0587***	0.1487***	0.1382***	0.1713***	0.1872***
	(4.9020)	(-22.5626)	(0.738)	(39.5487)	(30.9581)	(27.6461)	(18.9047)	(3.8497)	(10.7984)	(10.4153)	(12.3744)	(14.3309)
KOSPI	0.6648***	0.0438	0.2952***	1.4204***	0.7837***	1.3829***	1.3148***	0.4176***	0.9874***	0.5813***	0.8939***	0.5746***
	(13.6427)	(0.7515)	(5.454)	(25.8766)	(15.8058)	(23.9815)	(25.0025)	(7.4539)	(15.8382)	(13.1576)	(21.9084)	(10.1867)
GP/CA	-0.0673***	-0.0608***	-0.0611***	-0.0607***	-0.0591***	-0.0616***	-0.0638***	-0.0632***	-0.0649***	-0.0657***	-0.0683***	-0.0692***
	(-5.6297)	(-4.4578)	(-4.5006)	(-4.5431)	(-4.1849)	(-4.3695)	(-4.4707)	(-4.2017)	(-4.3178)	(-4.2902)	(-4.4817)	(-4.4449)
EBITDA/IE	-0.0004***	-0.0004***	-0.0004***	-0.0002**	-0.0005***	-0.0004***	-0.0004***	-0.0006***	-0.0005***	-0.0006***	-0.0004***	-0.0005***
	(-4.4329)	(-3.8422)	(-3.3982)	(-2.3331)	(-4.1579)	(-3.6772)	(-3.6036)	(-4.7909)	(-4.4572)	(-4.5396)	(-3.8714)	(-3.9897)
DTD	-0.2439***	-0.2124***	-0.2522***	-0.3134***	-0.162***	-0.2197***	-0.2371***	-0.1155***	-0.1571***	-0.1416***	-0.2145***	-0.1955***
	(-26.153)	(-18.0251)	(-21.7214)	(-27.7746)	(-14.3778)	(-20.4436)	(-21.4604)	(-10.5469)	(-14.5117)	(-13.0021)	(-19.4345)	(-17.2036)
CASH/CA	-0.2227***	-0.275***	-0.2582***	-0.2211**	-0.28***	-0.2765***	-0.2817***	-0.3327***	-0.3309***	-0.3358***	-0.3202***	-0.3275***
	(-2.8137)	(-3.1422)	(-2.9528)	(-2.5423)	(-3.111)	(-3.0672)	(-3.1004)	(-3.541)	(-3.5183)	(-3.5367)	(-3.3803)	(-3.4163)
TA	-0.3841***	-0.2842***	-0.2823***	-0.2805***	-0.2658***	-0.2666***	-0.2684***	-0.2696***	-0.2724***	-0.2756***	-0.2768***	-0.2806***
	(-6.3325)	(-5.5289)	(-5.5635)	(-5.5574)	(-5.59)	(-5.6166)	(-5.641)	(-5.6105)	(-5.6259)	(-5.6284)	(-5.668)	(-5.6684)
MM	-0.1254***	-0.123***	-0.146***	-0.1815***	-0.0913***	-0.1255***	-0.1351***	-0.0619***	-0.0873***	-0.0777***	-0.1215***	-0.11***
	(-7.4004)	(-6.5664)	(-7.8843)	(-9.9695)	(-4.6747)	(-6.6351)	(-7.1415)	(-3.0764)	(-4.4139)	(-3.8633)	(-6.1586)	(-5.4702)
Dummy	0.6393***	0.5653***	0.58***	0.5822***	0.6513***	0.6311***	0.6293***	0.6839***	0.6766***	0.6995***	0.6846***	0.7132***
	(20.2002)	(15.6497)	(16.0476)	(15.9574)	(17.7278)	(17.047)	(16.8608)	(18.1698)	(17.8028)	(18.2112)	(17.6059)	(18.0844)

Table 6c: Maximum pseudo-likelihood estimates for $\beta(\tau)$. This table reports the maximum pseudo-likelihood estimates of $\beta(\tau)$ for 25-36 months horizons. KOSPI is the trailing one-year return on the Korea Composite Stock Price Index, CP is the yields on 91 day commercial papers, DTD is the distance-to-default, GP/CA is the gross profit over the current assets, EBITDA/IE is the earnings before interest, taxes, depreciation and amortization over interest expense, CASH/CA is cash over total asset, TA is the total asset adjusted by the GDP deflator, MM is the maturity mismatch measure defined as current liability minus cash then over total liabilities, and Dummy is a financial dummy variable which takes 1 if it is a financial firm and 0 otherwise. The t-statistics are shown in parentheses.

	1 year	2 years	3 years
Altman's Z-score	0.3000	0.3066	0.3062
Logit Model	0.5335	0.4792	0.3659
Probit Model	0.5321	0.4820	0.3639
Forward Intensity Model	0.5432	0.5472	0.5709

Table 7: Out-of-sample Accuracy Ratios. This table reports the out-sample accuracy ratios based on all private firms in our dataset from Dec 1999 to Jun 2011 for different modeling approaches for the prediction horizons of 1 year, 2 years and 3 years, respectively. The fitted logit and probit models share the same risk factors with the forward intensity model.

Panel A: Summary Statistics					
	Mean	Std. Dev	Min	Median	Max
Implied interest rate	0.0686	0.0377	0.0042	0.0633	0.2614
Default probability	0.0062	0.0063	0.0000	0.0044	0.0357
Maturity (years)	1.9443	1.0406	0.5155	1.7514	4.0886
Risk-free rate	0.0423	0.0091	0.0283	0.0416	0.0600
Term spread	0.0073	0.0084	-0.0038	0.0122	0.0194

Panel B: Regressions					
	Dependent variable: Implied interest rate				
	Model 1	Model 2	Model 3	Model 4	Model 5
Const.	0.0480*** (18.353)	0.0590*** (22.087)	0.0495*** (18.631)	0.0489*** (17.516)	0.0511*** (18.096)
Default probability	1.0239*** (36.036)		0.9862*** (32.062)	0.9432*** (32.005)	0.8827*** (27.844)
Maturity		-0.0029*** (-16.575)	-0.0006*** (-3.198)		-0.0009*** (-5.169)
Risk-free rate				0.0510** (2.375)	0.0587*** (2.726)
Term spread				-0.4197*** (-18.112)	-0.4253*** (-18.339)
Industry Dummy	Yes	Yes	Yes	Yes	Yes
Obs.	44187	44187	44187	44187	44187
R^2	0.0412	0.0191	0.0414	0.0509	0.0514

Table 8: Regression of the interest expenses of privately held firms on their estimated default probabilities. This table reports the results of implied interest rate regressions. The implied interest rate is defined as the interest expense for a given fiscal period scaled by the outstanding interest bearing debt as of the previous fiscal year end. Maturity is the weighted average of the assumed maturities for each debt class where the weights are the relative proportions of each debt class of the estimated maturity for that firm year. Default probability is the annualized value of equation (4) obtained from the fitted forward intensities. Risk-free rate is estimated for each maturity using the cubic spline interpolation from the yields of 91-day certificate of deposit and Korean Governments Bonds for multiple maturities of 1, 3 and 5 years. Term spread is defined as the yield differential between the 5-year Korean Government Bonds and the 91-day certificate of deposit. All observations are winsorized at the first and 99th percentiles. Panel A reports summary statistics for the sample used in the regressions and Panel B reports the regression results. The corresponding t-statistics are presented in parentheses. (*** significant at 1% level, ** significant at 5% level, * significant at 10% level)