Title:

Forecasting Chinese corporate bond defaults: A comparative study of market vs accounting- based models

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Abstract

This paper provides the first empirical study on bond defaults in China market, overcoming the deficiencies of the existing methods, which suffer from lack of actual default data for back testing. With newly available bond default data, we analyzed the roles of market variables vs accounting variables under various models. While we found Merton's market-based structural model and KMV's Distance to Default exhibits languid discriminating power compared to hazard models with carefully constructed predictors, other market variables carry significant information about bond default and could help improve on models with accounting variables only. This implies that the collective intelligence of the market could somehow mitigate the distortion caused by misreported accounting information. We found model performance can be improved significantly by adding predicting variables linking individual financial measure to the broader market performance, such as relative margin, business environment proxy introduced in this paper. This study not only sheds light on the default behavior of Chinese bond market but also provides a promising approach to improve the variable selection process.

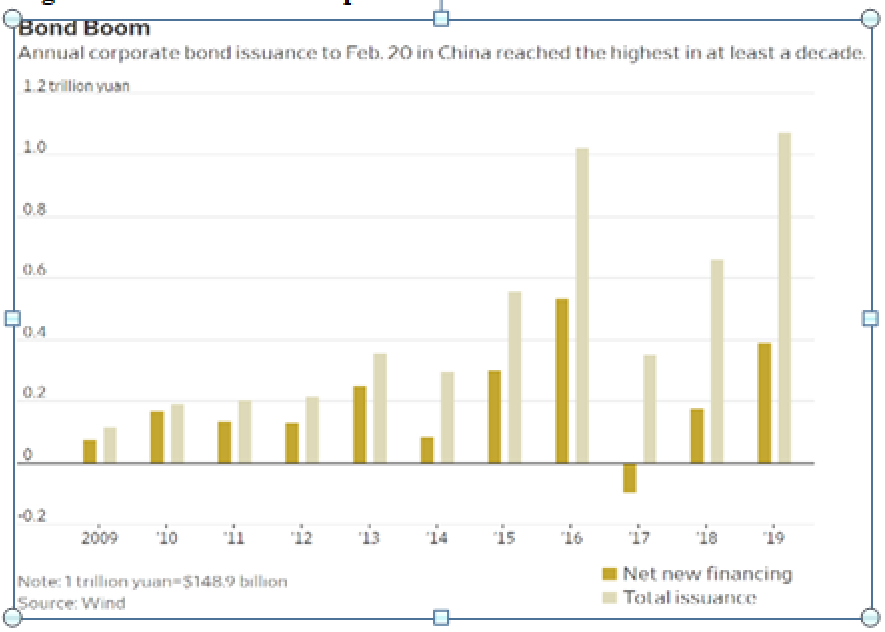
Key words: Bond default; Chinese bond default; bankruptcy forecast; hazard model; Merton model; accounting variables; Z-score; LASSO regression

JEL: B41, C58, F65, G15, G17, G32, G33

1. Introduction

China, the world's third largest bond market, has been experiencing a notable spike of defaults due to economic slowdown since late 2017. Corporate bond default cases surged to 47 in 2018 from just 10 in 2017, with a total principal amount of 110.5 billion yuan ($16.3 billion), amid a trade war with the United States (See **Fig 2** below), adding to worries about risks to the economy. Companies rushed to sell new bonds in China in 2018, as Beijing loosens financial conditions to shore up businesses in a weakening economy, by lowering reserve requirements for banks five times in little over a year, encouraging them to lend more to aid an economy that has been hit by trade tensions with the U.S. and an earlier campaign against financial risk. While China has eased monetary policy, Chinese banks are still reluctant to lend. That has pushed companies into the bond markets; As **Fig. 1a** shows, the total issuance hit record in 2018. However, the issuance boom mostly were mostly driven by state-run firms, while financially weaker private companies struggle to get funding. Only 78 out of the 657 bond issuers are private. Note that there are apparently some signs of mispriced risk. Gloomy economic outlook, wave of issuance and defaults would normally lead investors to demand a premium before buying bonds. Instead, they have lapped them up, making it cheaper for China's companies to borrow. As shown in **Fig.1b,** yield on five-year corporate bonds with a AAA domestic rating, a grade mostly held by state-run enterprises, have fallen to 3.81% from 5.40% in the past year. But the yields on AA- [1]debt have declined just 0.05 percentage point to 6.87%.

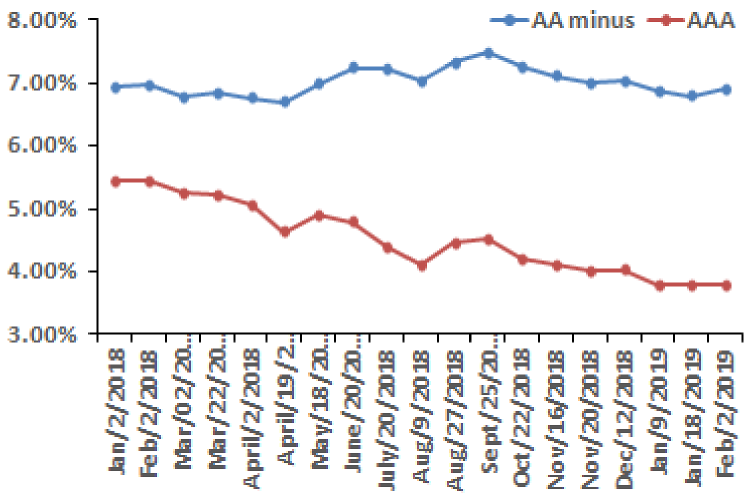
Fig 1a A Wave of New Corporate Issuance



[1] This rating is China's equivalent of junk, and debt with this status is mostly issued by private firms.

In general, there are three modeling approaches for default forecasting: i) Accounting variables based statistical model (including Altman Z score models); ii) market based models, which include "Structural model[2] "(Merton 1974) extracting credit information from equity market and Reduced Form [3] model which deduce default information from the price of traded-bond); iii) hybrid model (containing both above types of variables). For an excellent review of these models, see Campbell (2008) and Bauer (2014). Bauera, et al 2014, using UK annual data from 1979 to 2009, compared these approaches and concluded that the hazard model outperformed the other two alternatives while accounting-based Z-score has more predictive power than contingent-based approach. Agarwal (2008) reached similar conclusion using a different source of UK data.

Fig 1b Chinese Corp Bond Yield: AAA vs AAA minus



Source: Wind

Forecasting defaults in Chinese bond market, however, has been a challenge since no empirical study has been done using actual default data. This is understandable because there had been no official default event until mid-2014[4]. The absence of the default event data not only makes it hard to build a true statistical model taking all relevant risk drivers into account, but also render it impossible to validate any alternative models such as Merton's structural model or reduced form model. Almost without exception, the literature on the credit risk of public listed firms in China used some default proxies. The most widely used proxy is the Special Treatment

[2] A full description of Merton's underlying assumptions and its wide application can be found in an excellent review by Sundaresan (2013).

[3] For a good theoretical review of reduced form, see for example, Jarrow and Protter (2004). However, the bond price, which usually heavily depends on credit rating in the West, is much less a reliable indicator for risk in China. As well as questions on the lack of secondary market liquidity, another issue is the objectivity of China's domestic rating agencies, which are often state owned. In fact, more than 90% of Chinese corporate bonds are rated AA or above, and risk differentiation is not easily done form rating per se. Moreover, the high ratings are not recognized in overseas markets.

[4] It was Shanghai Chaori Solar private company

(hereafter ST)[5], a delist warning sign designated by the regulators. (see Chen, 2014; Yang ,2010; Zhang et.al, 2010; Zeng and Wang, 2013; Ren 2011). It can be shown that, however, ST is not a reliable default. For example, Cerrato et al (2106) found that the spread of default probability between ST firms and non-ST firms is larger before 2006, but it narrows afterwards. This is not consistent with empirical default fact. In addition, high default probabilities could cause a delisting but not vice versa; i.e. the default event is not the unique reason for delisting a firm. Looking at the empirical results (both 'default' and 'post-default'), ST is not significant, confirming that ST may not be directly related to actual default.

In theory, the market-based model is superior since it should timely reflect investor's collective intelligence about the firm's financial and operating status. However, this is not necessarily the case in reality given the degree of market efficiency. Of course, the effectiveness of the accounting-based model to assess the firm's credit risk hinges upon the quality of the information contained in the financial statements. It is for this reason that the superiority of one model over the other is closely related to that country's accounting system and the efficiency of its financial markets, and should be an empirical question. By comparing the outcome built on data from Taiwan (a relatively more mature and developed security market), with mainland China (a less developed market), Liu et al (2010) concluded that the underperformance of the market based model can somehow be attributed to the invalidity of efficient market assumption implicit in Merton's model. Further, the secondary market trading is usually very lethargic to say the least. This low liquidity makes it hard for investor to derive default information from trading information, rendering "reduced form" model ineffective. To our knowledge, one of most cited paper combining Merton's approach with statistical model was by Daniel Law and Shaun (2015) from IMF ("IMF paper" hereafter), which linked a set of balance sheet variables to the PD implied from the Chinese equity market using an enhanced Merton model (with jump component).

Armed with the latest bond default data, this paper is to explore the most appropriate--methodologically sound and empirically robust approach in forecasting default of Chinese corporate bond by assessing which variables are more predictive. Classic hazard models are compared to those deriving Probability of Default (PD) from equity market (i.e. Merton's approach). First, we will re-estimate several well-known default forecasting models (Shumway

[5] When a stock is marked as *ST, its trading is suspended for one accounting year.

2001, Campbell 2008, Jarrow 2004, Zmijewski 1984). Then we will test a few discrete hazard models with a set of variables characterizing Chinese issuers and the market, including Altman's Z^{China} score (re-estimated with the new data) and Merton's Distance to Default computed from the China market. In particular, we are to assess the discriminating power of "IMF" paper mentioned above so that we can directly compare a model using Merton implied PD with that using actual default as the dependent variable. For all the limitation of the data[6], we were able to obtain comparable results (in terms of coefficient sign, significance and predictive power) with classic models applied to mature market such as US. We found the IMF model, with the dependent variable being the Merton implied PD, under-performs the alternative specifications using actual default event information. On the other hand, we found while the Distance to Default under Merton's framework exhibits languid discriminating power, other market variables such as equity return and relative market cap (see RSIZE in Table A in Appendix) do carry valuable information about bond default and help improve on models with accounting variables only. Finally, we found several of our proposed models stand out as the best performing ones with quite a few predictors we constructed quite robust in boosting predictive power. These variables include: rela_margin, a variable linking individual firm profitability to the sector median, nega_margin, a proxy for business condition and Altman's Chinese Z -score re-estimated with actual default data.

The paper proceeds as follows: the next section describes data sources and in Section 3 where we discussed the specifications of the empirical models to be tested. Results were reported in Section 4, which covered performance comparison among models and out of-sample tests. In Section 5, we presented case studies in which we illustrated how well the models forecasted default risk for individual Chinese firms. Conclusions were drawn in Section 6, along with Caveats.

2. Sample Selection and Data Description

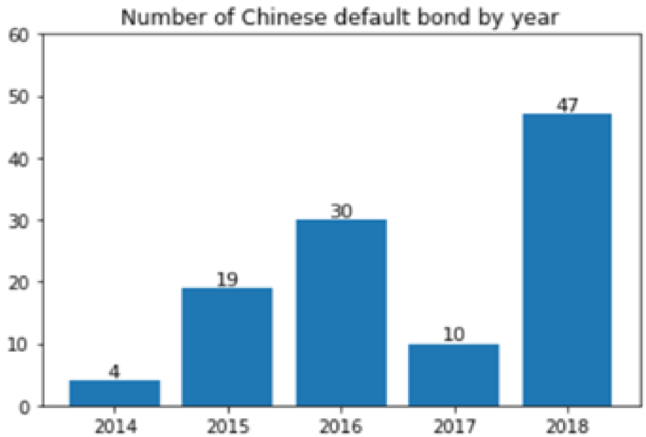
2.1 Historical default events in China: a brief description

Corresponding with the growth and increasing openness of the bond market is an upsurge in risk. Bond defaults in China have historically been quite rare. Defaults on domestically issued bonds were non-existent and the majority of bonds were issued by large state-owned enterprises

[6] The default sample size is still relatively small. In particular, among the defaulted companies, only 20 of them are listed firms as of January, 2019.

with an implicit guarantee of government support. As a result, yield spreads in the corporate bond market provided investors little information on the actual riskiness of corporate issuers. Things began to change after Chaori, a private solar panel manufacturer, became the first company to default on a domestic bond in March 2014. Over the following two years, several more firms have defaulted, postponed payments or restructured debt, including several large state-owned enterprises. There were 19 bond issuers defaulted in 2015 and a whopping 47 default 2018 (**Fig. 2**), with more likely to occur this year, according to Fitch rating. Since the very first default event in 2014, the frequency of default is getting higher and higher and the involved sectors are ever broadening (**Table 1**). Statistics shows that, while the defaults are mostly concentrated at traditionally cyclical sectors such as steel, coal, construction, there is an increasing default event in agriculture, and retail area. Different from past two years, the myth of default-proof of SOE is shattered. **Table 1** summarizes the defaults as of Dec 31 2018. It can be seen that while defaults distributes widely across various sectors, most defaults occur in traditional manufacture (mostly in steel, coal and transportation). Besides, the defaulted firms comprise most of private firms. Moreover, SOE are no longer immune to default as there are 2 central SOE and 6 local SOE, a record number ever.

Fig 2.



By stratifying the default firms by sector (**Table 2**), we found that, while the absolute number of default seem to be unevenly distributed, the default rates are roughly comparable across different sectors in terms of magnitude. Except for Finance and Public utility, which have no default, the difference of default rate is within signal digit- from the lowest Construction (0.65%) and Construction (0.65%), Manufacture 4.69% to the highest Consumer Staple/Retail of 7%.

Table 1 Bond Default Distribution by Issuer's Ownership and Sector (as of 12/2018)

Firm Type by Ownership\Sector	Transportation	Leisure /Entertainment/Travel	IT	Agricultural/Forest/Fishing	Manufacturer	Construction	Real Estate	Whole Sale &Retail	Energy (Electricity/Gas &Water)	Service/Health Care	Mining/Steel	Finance/Insurance	Others	Total
Joint Venture	1	0			2	1			1				2	7
Central SOE					2	0		1	1	0	2		1	7
Local SOE	2		0	1	1	0	0	2	2	0	1	0	3	12
Other SOE			0			0	0			0		0	0	0
Solely Foreign Owned					0	1		3					1	5
POE & LLC	6	5	3	4	12	6	3	8	7	3	3		15	72
Collective Enterprise	0				1									1
Others	1	0				0	0		0	0			5	6
Total	10	4	3	5	17	8	3	14	11	2	6	0	27	113

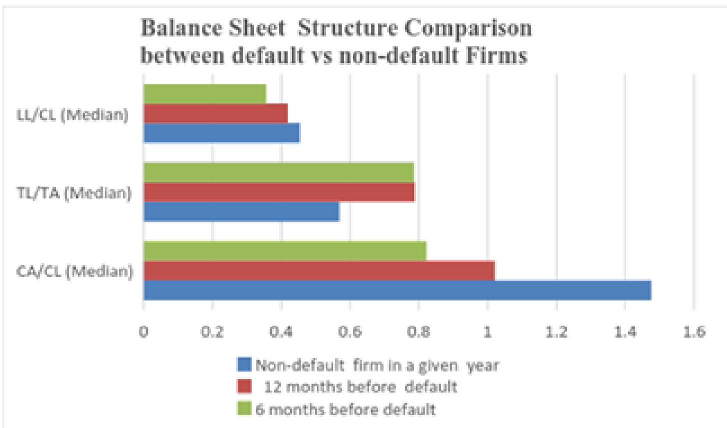
SOE: State-owned entity
POE: Private-owned entity

Table 2: Percentage of Default by Sector

Sector	Transportation	Leisure /Entertainment/Travel	IT	Agricultural/Forest/Fishing	Industry/Manufactoring	Construction	Real Estate	Whole Sale &Retail	Utility/Energy	Service/Health Care	Mining/Steel	Finance/Insurance	Others
#of Default	10	4	3	5	17	8	3	14	11	2	6	0	27
Total Sample	363	121	75	74	384	1237	464	198	386	239	139	217	3937
% of default	2.75%	3.31%	4.00%	6.76%	4.43%	0.65%	0.65%	7.07%	2.85%	0.84%	4.32%	0.00%	0.69%

2.2 Data Source and Empirical Observation

Fig 3a



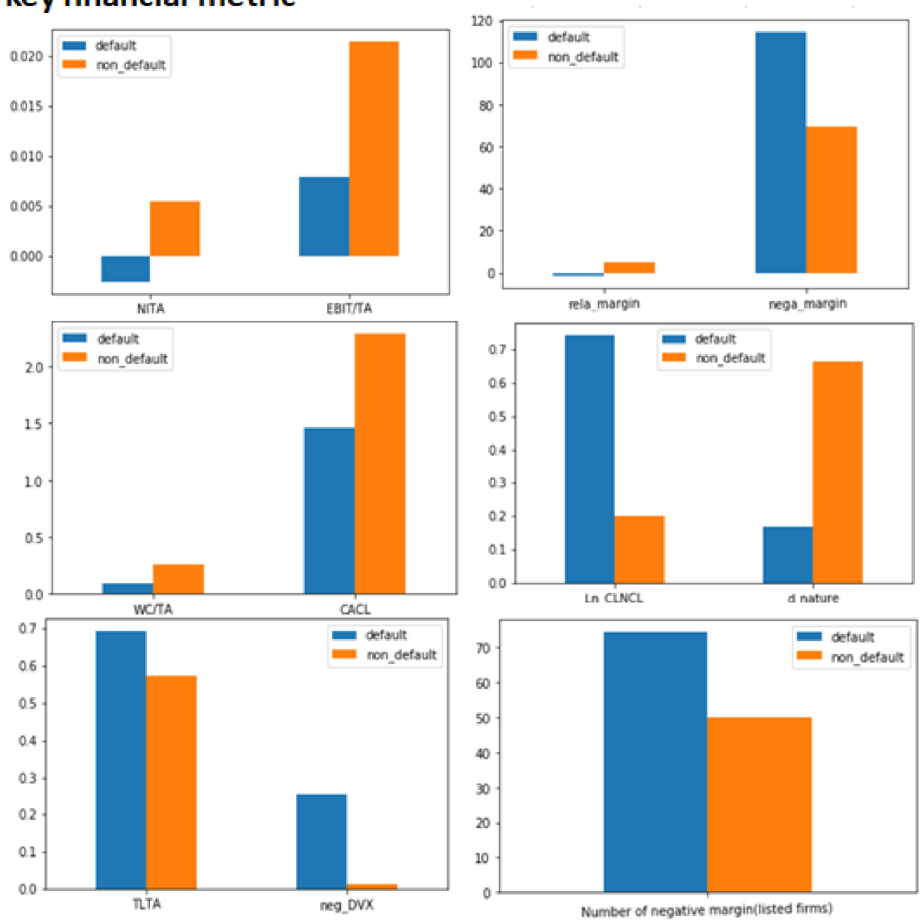
2.2.1 Default Data

We collected all the default information from the official Chinese bond website (http://www.chinabond.com.cn). The data source contains comprehensive bond transaction with timely updated default information. All balance sheet data including total assets, liability, profit margin, and EBITA were extracted from Eastern Wealth and the WIND database, both are highly regarded and widely used data source, sometimes dubbed as Chinese “Bloomberg”. Our data sample included all firms that had an outstanding public traded debt immature before Dec 31 2018, which included short-term debt, targeted instrument, government-agency-guaranteed debt, intermediate debt, transferable debt. We roughly categorized the sectors suggested by China SEC into economic cyclical and non-economic-cyclical categories. The cyclical category refers to discretionary consumption, material/commodity, industrial, and finance while the non-cyclical refers to staple consumption, energy, technology, health care/Medical and public utility. Data within two reporting quarters before bond default were excluded: a firm is therefore considered *censored* in the data set 6 months before filing. For example, for a firm that declares bankruptcy in May 2015, we used data on and prior to Nov 2014 to form prediction covariates. The basic data structure is “firm-quarter” panel. The main reason that we forecast 6 months ahead default probability instead of 12 months as in most literature was due to data limitation and peculiarity encountered as discussed above, i.e no default until 2014, with defaults clustered during 2016 and 2018. Should we use firm-year structure to predict 12- month default probability, it would not only dramatically reduce the number of samples, but also distort the causal relationship between the co-variants and the default probability.

2.2.2 Financial data on the balance sheet

The raw data for accounting variables were collected from the balance sheet information provided by Eastern Wealth (China). These data were processed and vetted using Python and SAS programs before being transformed to construct synthetic variables for the model estimation. Data recorded with any variable value at top or bottom 1% were excluded to eliminate outliers. The key data elements collected from the balance sheet are shown in **Table 3a-3d**. To get a smell test whether the key balance sheet variables have any predictive impact on default, we made a comparison of some the balance sheet structure between the default firms (6 month and 12 months before default) and non-default firms (in a given year) as shown in **Fig.3a**. The following observation can be made:

Fig.3b. Default-bound vs non-default firms: A comparison of key financial metric



1)The ratio of current asset over current liability was declining from 12 months prior to default to 6 months before default.

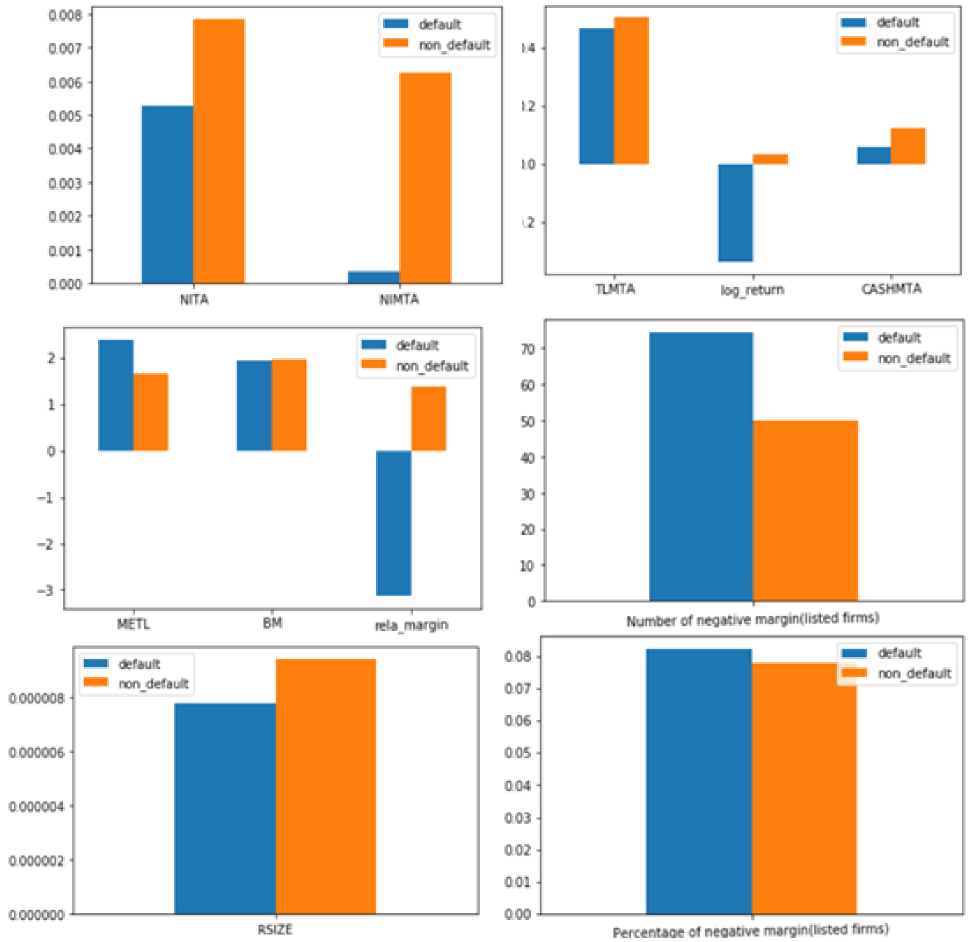
2)The ratio between long-term debt and short-term debt was shrinking too. CA/CL, EBIT/TA, NI/TA, WC/TA are all significantly higher for non-default firm (in a given year) than for default firms (6-12 month prior to default).

3) The total liability over total asset (TL/TA), Short term liability over long term liability (CL/NCL) were significantly higher for default firms than non-default firms. All the above are intuitively clear and indicate the differentiating nature of the balance sheet structure between

risky firms and relatively healthy ones.

4)The relative profit margin (i.e. rela_margin = the firm specific profit margin relative to the whole market) is appreciably lower for default-bound than for non default firms (for the full sample see Fig 3b and for listed firm sample See Fig 3c, where the relative margin at the median for the default-bound firms is even worse (negative) .

Fig.3C. Default-bound vs non-default firms: A comparison of market related variables



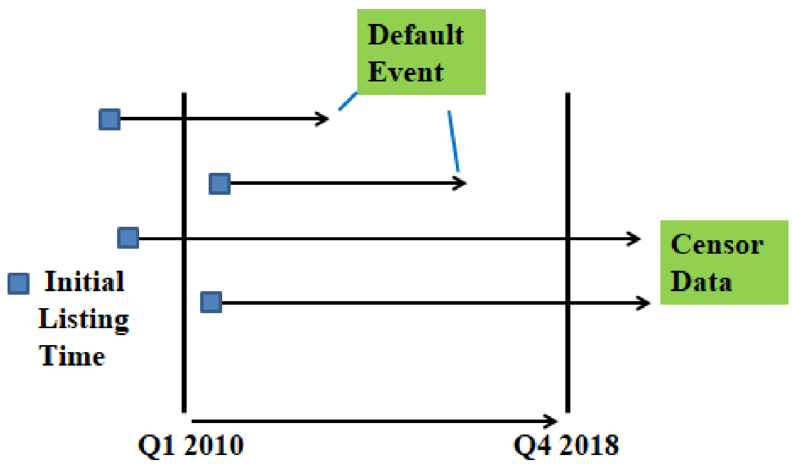
5) It is observed that on average during any given period (“quarter“), when there are bond defaults, the number and the proportion of money losing companies are both higher , compared to the periods when there is no default. This concurs with the intuition that defaults is more likely to happen when the macro business condition is less benign.

6) For listed firms it is observed that: Relative Market Size, Equity Return (log return), Relative Margin and Net Income and Cash as a percentage of market value of Total Asset, are all lower for default-bound firms than non-default firms. These information provide intuitive support for our empirical forecasting model based on balance sheet variables.

3. Empirical Methodology

This section describes our econometric model using actual bond default data. In an attempt to find the best approach to forecast the bond default, we will first estimate a few classic hazard models using the same set of variables as the original models and then we will expand into our own specification, which incorporate several constructed variables not traditionally used in literature.

Fig.4 Survival of a firm beyond time t



3.1 Model Specification

Since the seminal work of Shumway (2001), the use of hazard rate modeling technique (also called survival analysis) has become a standard methodology in firm's default prediction in developed market. The hazard rate is defined as the conditional probability that an event of interest occurs within a particular time interval (t, t+ Δt), given that it survived to the time t. Following Standard survival analysis literature (Klein and Moeschberger, 1997), we define the hazard rate or intensity rate for the bankruptcy time τ^i , a random variable, as: $\lambda^i(t) = \lim_{\Delta t \to 0} \frac{\Pr(t < \tau < t + \Delta t | \tau \ge t)}{\Delta t}$

Suppose we have collected a total sample data of N firms (i=1,…n), who listed their bond at the bond market . Our observation period starts at the beginning (t=1) until the end (t=T) of our sample period. However, the observation of any particular firm i continue from some starting time t_i (the start of its issuance of bond of first time) until sometime $T_i < T$ when the firm experiences bankruptcy (τ_i) or is censored T_i. Censoring means that the firm is observed at the time Ti but not at time $Ti+_1$, Time Ti usually is the last date in our sample period. For example, the firm could experience a merger and vanish from the data set. In this study, we ignore the reoccurrence of default i.e. when a default occurred, the observation ends, even though it would cure later before relapse. This process can be visually described by **Fig.4**. We define the discrete time condition hazard rate process as:

$$P_i^t = \Pr ob[t \le \tau_i \le \min(t+1, T_i) | \tau_i > t-1, X_{it-1,}] \quad \text{for} \quad t_i + 1 \le t < T_i$$

i.e. The probability of default time occur between time period t and the following period (before censoring time)---given the fact that the firm survives to the period t-1, with corresponding time dependent attributes where $\boldsymbol{\tau}_i$ is the discrete random variables giving the uncensored time of event occurrence . It is also the conditional probability that an event occurs at time t, giving the dynamic attributes. Following Chava and Jarrow (2004), we define:

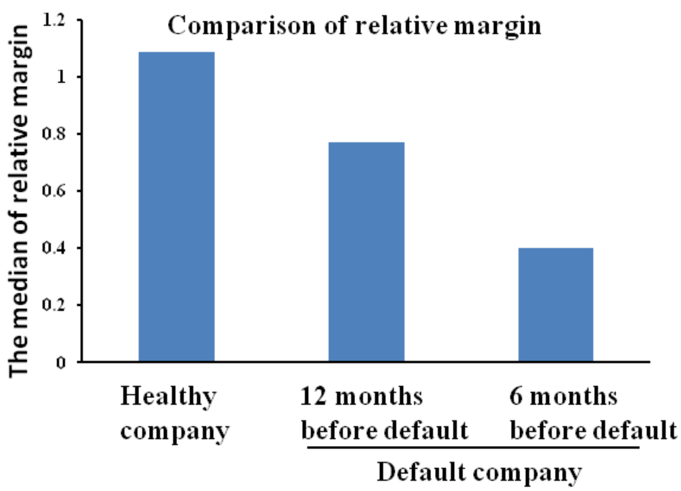
i) the point process for this bankruptcy time as $N_t^i = \{1 \ \ if \ \tau \le t; \ \ ,0 \ \ otherwise\}$

ii) the random time $Y_i = min(\boldsymbol{\tau}^i, T_i)$

We estimated this probability via logistic link function

$$\log\left[\frac{P_i^t}{1-P_i^t}\right] = [\alpha + \beta X_{i,t-1} + \gamma Z_{t-1} + \zeta D + \tau_t] + \varepsilon_{it} \qquad \text{<2>}$$

Fig.5



Where $X_{i,t-1}$ is a (k×l) vector of k variables specific to firm i and lagged one period, γ is a ($k \times 1$) vector of parameters, Z $_{t-l}$ is an l×l vector of macro variables lagged one period, ζ is an $m \times 1$ vectors of parameters, **D** is an m×l vector dummy variables, corresponding firm's ownership type, sectors ,etc. τ_t is a time effect variable, representing the vintage of the firm i. ε_{it} is assumed to be independently across firms.

3.2 Variable selection

The explanatory variables selected in the above discrete hazard model can be classified into three categories: firm specific, macro level variables, and (equity) market related. Our basic criteria for including covariates in the model is parsimoniousness, i.e. to develop a set of explaining variables that provides the best differentiating power but not over fitting the data. In addition, the variables selected must be numerically stable and conducive to out- of-sample test.

3.2.1 Balance Sheet Related, Firm Specific Variables

General features include age, ownership type dummy, and sector/industry dummies (defined in 4.2.4) according to the classification of Chinese Security and Exchange Committee. Individual features include firm size, liquidity, profitability, and relative margin *etc*. *Firm size* is measured as the ratio between the firm's revenue over industry median as a measure of firm size. *Relative size* refers to the ratio between firm revenue over total revenue of all firms within the same sector. We choose the relative size because it reflects the dynamic status market share of the firm. If it loses competitiveness to its peers, this measure will reflect that and its credit risk would increase. *Liquidity* is measured by a) CACL, current asset/current Liability, b) TATL, total asset/total liability and c) CLCNL: short term debt/long term debt. *Profitability:* is measure as: a) RETA, ratio of retained earnings (RE) vs total asset. b) *Relative margin* is a key measure of firm's pricing power and strength. The lower margin, the less the pricing power of a firm. We use profit margin relative to sector median (rela_margin) to measure the competitiveness of the firm. A rough glance of **Fig.5** shows the medium of relative margin of default companies is much smaller than that in healthy companies. EBIT over total asset (EBIT/TA) and Net Income over Total Asset (NITA) are measures of return on asset. Other computed variables include: ii) Z-score, a widely used indicator to discern "unhealthy" firm from healthy ones. We computed the Chinese version of Z-score developed by Altman (2007); 2) Negative DVX [ln(1-RE/TA)], an indicator used by IMF paper, to capture the potential asymmetric effects of positive and negative retained earnings. It is the negative dummy variable.

$$= \begin{cases} 1 \ \ if \ \ \ln(1 - RE/TA) \ \ is \ \ negative \Leftrightarrow RE \ \ is \ \ positive \\ \qquad\qquad\qquad\qquad 0 \ \ otherwise \end{cases}$$

It is expected that the sign of the estimated coefficient to be negative in our setting, meaning a positive RE will reduce the probability of default. [7]

3.2.2 *Altman Z score: A Synthetic Measure of Financial Health of Firm with accounting variables*

Altman (1968)'s Z score has been proved to be an effective discriminator for corporate default risk and is still a widely used gauge for firm's financial health in US and developed countries (albeit with variations adjusted for countries). Working with several prominent researchers in China, Altman (2007) established a Chinese version of Z score and applied it to diagnose potential distress of Chinese firms. Based upon our literature search, however, it has never been empirically tested against actual default experience due to the lack of occurrence until recent years (the same reason that accounting based models were almost non-existent in academia for

[7] According to the Authors, this additional variable is to account for a peculiarity in China—retained earnings were negative for about one-fifth of sample observations. This fact was independently confirmed by us.

China market, as discussed in the Introduction). To fill this literature vacuum, we tested its validity in this paper. We first computed Altman's Z-score for Chinese firm, as a composite measure of default risk implied in the financial ratio, using Altman's original coefficients (henceforth "Altman Z^{China} ") and then we re-estimated the Z-Score (with Linear Discriminatory Analysis) using the same set of

variables (henceforth "Test- Z-score"), i.e. Total Liability/ Total Asset, : net Profit/Total asset, working Capital/Total assets, : Retained earnings /Total asset).

$$Z = -5.77 * TLTA + 3.24 * \left(\frac{WC}{TA}\right) + 1.05 * NITA + 0.2 * RETA - 3.24$$

Note that all the variables have correct and interpretable sign (the sign of RETA in the original Altman Z^{China} score is unintuitive.

3.2.3 Macro variables

It can be argued that the macroeconomic environment significantly affects the default. There are numerous candidates for the macro variables, such as change in exchange rate, GDP growth, unemployment rate, global liquidity *etc.* Given the relatively short period of time horizon since the first actual bond default, these variables are not collected across economic cycles and thus not sensitive enough to have meaningful impact on the quarterly default events in China. Therefore, in the spirit of parsimony, we constructed a proxy to characterize the general business conditions under which the bond issuers are operating: nega_margin, which is defined as the *proportion of firms with negative profit margin among all bond issuers* for the same period. The less the number, the better the credit environment. Using this proxy as macro variable can be justified by the fact that under a distressed economic condition, there would be much more firms that operate at loss. Since the sample we collected covers the bond-issuing firms quite broadly— in terms of size, geographical, ownership type and industry, we assume that the proxy is representative of the economy as whole.

3.2.4 Market Variables

For Listed companies, we constructed following variables of equity market.

1) ME/TL =Market Cap over Total Liability

This is the measure of dynamic leverage, with market cap supposedly reflecting the latest information about the investor's expectation of the firm's future free cash flow, the large the ratio, the less the leverage of the firm, which should correspond to less default risk.

2) Relative Return: log_return

It is defined as Rela_Return = R^i / R^{market}, Where R^i and R^{market} stand for quarterly log return for firm i and the overall market respectively. The “overall market” is embodied by the Index of the Shanghai Stock Exchange. This is a measure of the risky equity return (quarterly) relative to the broad market. Breig at el (2009) summarized four compelling argument why equity return and default risk are negatively correlated. To the degree the equity market is efficient, the stock price contains certain timely information about the credit quality of the issuer.

3) Relative Market Size RSIZE = Firm’s Market Cap^{i} /Market $\text{Cap}^{\text{China Market}}$

This is a measure of relative importance of the firm in terms of the market cap. In general, the larger the relative size valuated by the equity market, the less probable it will default since its asset is valued higher than its liability by the market. To the degree that a firm’s equity position is weak, its asset value is close to its debt. Therefore, we expect a negative sign of this variable.

4) Net income, Cash and Total Liability as percentage of market value of total asset:

- NIMTA = Net Income / Market Value of Total Asset
- CASHMTA= CASH/ Market Value of Total Asset,
- TLMTA = Total Liability/Market Value of Total Asset

where Market Value of Total Asset ≈ Equity Market cap + Book Value of Debt

5) Distance to Default

Essentially, DD is a measure of the difference between the asset value of the firm and the face value of its debt, normalized by the standard deviation of the firm’s asset value. To implement the structural approach, the calculation was done in the manner of Hillegeist et al. (2004) by solving a system of two nonlinear equations.

All the key variables are listed in **Appendix Table A1.**

3.3 Model Performance Measure

To gauge the performance of risk classification of the model, we rely on Pseudo-R2 and the Receiver Operating Characteristics (ROC) (also used by Chava and Jarrow (2004) as a measure of a model's ability to discriminate between bankrupt and non-bankrupt firms. AUROC is the area under the ROC curve, and a larger area indicates that the model is correctly predicting more bankrupt firm as being likely to fail. Its value ranges between 0.5, indicating no discriminatory power, and 1, implying perfect identification of bankrupt and healthy firm. In general, there is no 'golden rule' regarding the value of AUROC, however anything between 0.7 and 0.8 is acceptable, while above 0.8 is considered to be excellent (Hosmer Jr et al. 2013).

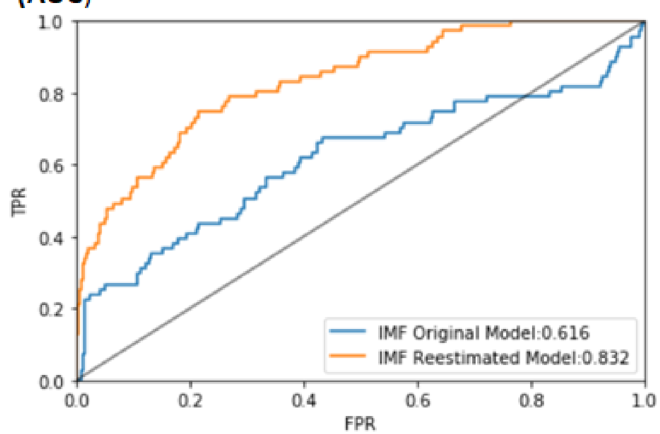
4. Results and Analysis

In this section, we provided our estimation results of the models described in 4.1. We estimated the following models using the default data available and compared their performance.

4.1. Hazard Model with Merton implied PD vs Actual Default event

Recall that the IMF's paper linked a set of balance sheet (financial ratios) to the market-implied PD (converted from risk neutral PD) as the dependent variable in a logistic formulation. To test the validity of this approach, we used the same set of variables to estimate a discrete hazard model with actual default data for listed companies. The results are shown in **Fig 6**. The results indicate that all empirical models outperform IMF Merton model in terms of predictive power of default probability. We attribute this weak performance of the model to several deficiencies of this approach applied to Chinese market. Firstly, the Chinese equity market is grossly over-valued by any measure and the unobserved "Firm value" could be significantly over estimated, resulted in low probability of default. Secondly, in adjusting the risk neutral to actual PD, the risk neutral PD were fitted on approximation of Moody's proprietary database of actual default rates. This database, however, includes only North American firms which "operate in a very different economic and legal environment to Chinese firms. Bankruptcy procedures in the United States and Canada are well defined, tested through the economic cycle, and rarely influenced by actual or prospective public sector bail-outs. These conditions do not yet hold for China. Moreover, to convert the risk free-rate was convert risk-neutral to actual default probabilities, the risk free-rate in Merton model was replaced by a drift term that was designed to capture the time-varying price of risk and was calculated as the product of the correlation between the equity price of the firm and the market and the ex-post Sharpe ratio, and this ratio, however, had been anti-intuitively

Fig.6 IMF Merton vs Actual Default Hazard Model (AUC)



close to zero or negative during 2008 to 2013. The authors thus used the "theoretically-consistent prior" but did not elaborate how this was done. Lastly, while the Merton implied Probability of Default is converted to empirical PD, there was no default data to validate whether these PD have discriminating power.

4.2. Testing classic default forecasting models using bond default data of China

To see if the classical empirical models in the literature, which have been well tested in the

Table 7 Shumway's' Hazard model on US firms vs Our re-estimates using China Data

Model/Coefficient (p-value)	**WC/TA**	**RE/TA**	**EBIT/TA**	**ME/TL**	**Sale/TA**	**Ln(age)**	**Intercept**
Shumway(2001), Table 2/Panel B., p117	-0.732 -(0.577)	-0.818 -(0.312)	-0.8946** -(0.001)	-0.1712** -(0.012)	0.158 -(0.446)	0.015 -(0.967)	-3.226** -(0.001)
Re-estimates using latest default data(Table 9 below) (henceforth "PJW")	-4.1566 (0.006)	-9.5814 (0.007)	-22.1791 (0.167)	0.3305 (0.001)	-1.3144 (0.349)	1.252 (0.278)	-8.5281 (0.014)
	Both having correct sign but PW model is more plausible from p-value perspective	Both having correct sign but PJW model is more plausible from p-value perspective	Both having correct sign but Shumway model is more plausible from p-value perspective	Both are significant but PJW has wrong sign	Both are insignificant while PJW has wrong sign	Both model are insignificant	

developed market such as US, are still applicable in China market, we re-estimated some of the well-cited forecasting models, such as Shumay (2001) and Zmijewski (1984). In general, our results are similar to those studies in US markets. As in the literature, the default probability is associated with small firm size, low net income to total assets, low current asset to current liability, and low working capital to total assets. Of all the default-forecasting studies, Shumway (2001) is a milestone. Shumway's main contribution was to estimate a hazard model, which enabled him to use all available information to determine each firm's bankruptcy risk at each point in time". This improves the static logit model (before his seminal paper) in that it includes all firm-years as observations instead of only one firm-year for each firm. Specifically, the author uses a dataset of non-financial firms that began trading between 1962 and 1992 on either NYSE or AMEX. The resulting dataset contains 300 bankruptcies among 3,182 firms and 39,745 firm-years. The dependent variable is set to 1 when the firm goes bankrupt and to 0 otherwise. We re-estimated Shumway's model with the data set described in 2.2. The comparison of Shumway's' Hazard model on US firms vs our estimates using China's data are shown in **Table 7,** where it can be seen that our estimates have the same (correct) sign and are statistically significant at 1% for ME/TL and EBIT/TA, as well as the intercept For WC/TA; both have the same correct sign but our model looks slightly more plausible judging from p-value perspective . For the rest two variables Sale/TA and Ln (age1), none of two estimates is both correctly signed and significant.

In the Zmijewski's paper (1984), three most common determinants, net income to total assets, total debt to total assets, and current assets to current liabilities were included. Higher leverage (TL/TA) and lower return on assets (NI/TA) are associated with a higher probability of default, while the relationship between liquidity (CA/CL) and default risk is not statistically significant (as re-estimated by Shumway 2001, Panel A, Table IV). By comparison, our results (**Table 10b**), show that, when all the above variables were included in the model, both the liquidity and return on assets have the correct sign and significant; but the leverage (TL/TA) does not have the intuitively interpretable sign. We reasoned that since TL/TA is associated with long term debt/short term debt, high TL/TA firms are more likely to have higher ratio of long term debt [8] , which could serve as some degree of mitigation for liquidity stress and default. Econometrically, this implies there is some co-linearity between TL/TA and CA/CL[9]. This can also be seen from the results summarized in **Table 10b,** where both NI/TA and CA/CL have expected sign and are significant when TL/TA is taken out of the model specification.

Role of State Own firm

Given the data, it is interesting to note that State Own Entity (SOE) is less prone to default as indicated by the negative sign of d_Nature, whose value is set to 1 if the firm is a State-Owned. Note that this result contradicts to the IMF paper, where coefficients for both local and central SOE have statistically significant positive sign (Table 9 in IMF paper), implying that being a SOE is more likely to default. We believe our results are more plausible for the following

[8] Based upon the balance sheet data from WIND, it was found that the correlation between TL/TA and Long term debt/Short term debt is statistically 0.2208 (p=0.0002);. And the median ratio of long term debt/Short term debt is 0.35 for defaulted firms (one year before default) as compared to 0.45 for non defaulted firm.

[9] The Pearson correlation between TL/TA and CA/CL was found to be statistically significant -0.16.

reasons. First, the leverage ratios for state-owned firms are low, a fact that was empirically tested by Wang (2013) from Tsinghua University[10]. Secondly, an SOE usually enjoys funding advantage over private firms, particularly when it comes to restructuring if in distress. Therefore, an all-out default was usually avoided. Further, In China, SOE bonds are widely deemed as fully guaranteed by the government and the issuers are usually bailed out when in financial distress. Therefore, the SOE bonds could be issued at lower yields versus private company bonds. Those bonds were allowed to default by regulator in 2015 to relieve the government from the role of the government, especially local government, treats SOEs differently. Some SOEs have a closer relationship with local government than others. Local government is inclined to bail out those enterprises that it deems important, such as those that contribute more employment and tax revenue.

Our findings are consistent with some literature on default in emerging market. For example, in a similar study on corporate default of Jordan, Zeitun and Tian (2007) suggested that government ownership was significantly negatively related to the firm's probability of default.[11] In IMF paper, however, it implied that local SOEs are more prone to default. We thus conclude that some results from the IMF paper are not convincing, nor are they consistent with the actual default data so far. We believe, this result is likely generated by distorted market parameter. One is magnified volatility. Large blocks of stock in state-owned enterprises do not trade as they are held by government entities. It is the restricted shares that reduced the liquidity of SOE and thus contributed to heightened volatility of equity market, which in turn would magnify the asset volatility. Higher volatility will reduce the model calculated “Distance to Default”, resulted in higher default probability derived for SOE[12]. The other is uncertainty in Liability Estimation.

[10] The university is often dubbed as “China’s MIT”.

[11] Their paper “Does ownership affect a firm's performance and default risk in Jordan? “ was extracted from http://ro.uow.edu.au/cgi/viewcontent.cgi?article=2516&context=commpapers

[12] This can be seen from the basic version of Merton’s Model :

Prob (Default) = $\Phi(-DD)$

Where $\Phi(.)$ denote the cumulative standard normal distribution, and DD denotes “distance to default”, defined as:

$DD_t = \dfrac{\ln V_t + (r-\sigma^2/2)(T-t) - \ln L}{\sigma\sqrt{T-t}}$,where V_t is the (unobserved) firm value, σ_v is the volatility of firm’s asset value, which follows a geometric Brown process, L is the total liability of the firm. See for example, p29, “Credit Risk Modeling Using Excel and VBA , Gunter Loffler, Peter N Posch, 2014

One of the key parameters of Merton model is the book value of liability as the barrier of default. The true liability is hard to gauge for state owned firms since they usually can get soft funding and even "debt forgiveness" due to their relationship with the government. The two combined could lead to wrong conclusion applying Merton's model to China's equity market to establish a causal relationship between the ownership structure and the derived PD. There are several key explanatory variables that are supposedly contributing to the default.

The Role of Market Variables

Theoretically, it is expected that the informed investor will discount the default risk by lowing the stock price so that the return from investing the equity underperform the market; The firm with higher leverage (associated with *lower* equity value) should be more likely in distress and thus prone to default. In addition, if all the market variables included in this estimation incorporate all the default signals contained in the quarterly accounting reports, then the forecast should outperform the accounting based. To test this concept, as was done similarly in Shumway (2001) and Jarrow (2004), we estimated the model with specification that excludes the accounting variables and the results are shown in **Table 10a**. The simple model with only Distance to Default has the lowest differentiating power in terms of AUC (0.52) and AIC (highest) with insignificant coefficient, albeit with correct sign (i.e negative)---even the simple model with univariate of Log_Return performs much better, fetching a 0.76 AUC (than model DD performs worse than the Adding other market variables including relative log-Return improves the model performance , albeit slightly. The model with labeled ("DD & Return") is a simple model incorporating only the log equity return and DD but shows decent predictive power (with AUC being 79%, beating other alternatives in the table. Model 2 and Model 3 contains not only all the available market related variables , but also the business condition indicator (i.e., nega_margin) and relative profitability measure , i.e. relative margin; both outperform Model 1 which does not incorporate these two additional variables (In fact Model one has the second lowest AUC). It is observed, however, the relative equity value (MV/BV, ME/TA) is neither insignificant nor correctly signed (Model 2, which exclude Distance To Default , has expected negative sign of MV/BV but insignificant). This indicate that the relative value placed on the firm’s equity by stockholder is not a good discriminatory for default risk. Recall that in Fig 3b, it was shown that the average market-to-book ratio default-bound firm is almost the same as non-default firm. Apparently, there is an overvaluation of the equity market which underestimates of default risk by equity holders. Interestingly, this result coincides with Campbell (2008) a well cited paper, which studies US market. Campbell (2008) noted that that “the average market-to-book ratio is slightly higher for bankruptcy “and the variable is insignificant, with the wrong sign (Table IV, p2913); In Law and Roache (2015) in its comprehensive study on China firm default, using the Merton’ implied PD as the dependent variable, found that the Market/Book ratio significant *but* had a wrong sign. In a recent study by Cerrato et al (2016) on default for listed Chinese firm, it was reported that market-to-book is a significant predictor with the expected sign (Table 5); however, some other key explanatory variable, such as NI is neither significant nor have correct sign and the overall out of sample fitting is poor (AUC =0.67) . In general, default firms often experience losses and these depreciate the book value of their equity; thereby the market-to-book ratio rises up. On the other hand, investors’ s informed default risk may could weigh on the equity value and the market-to-book ratio. The ending result is depends upon which side dominate. In China’s market, it is well likely that investors were kept in the dark until the last minute.

As is well known, the quality of financial disclosure for many Chinese companies are notoriously poor. Even the for the listed companies and/or bond issuers, the financial statement is not up to the standard of West. Under these circumstances, the collective intelligence of equity market might somehow help remedy the deficiencies of accounting variables in signaling default risk. We will demonstrate this point in a more concrete way in a case study at the end.

Table 10a Simple Hazard Models with market variables only

This table exhibits the estimation results and predictive power for several selected models that incorporate only market-related variables, one of being the Distance to Default, an indicator for default risk, calculated under Merton’s structural model framework. This table is to test the differentiating power of the market variables alone without the auxiliary of any accounting variables. These models were estimated with the sub sample of listed companies, which included a relatively small number of defaults (18 in total). The p-values were reported in parenthesis. * denotes significance at 5%, ** denote significance at 1%. The overall out of sample predictive power of each model is gauged by AUC and AIC listed in the last two rows of the table.

Table 10a Hazard Model with Market Variables Only

Variables	naïve_dd	log_return	dd&return	dd/return/margin	dd/return/rela_margin	model 1	model 2	model 3
Intercept	-6.727	-7.2959	-7.2629	-6.275	-6.988	-6.149	-7.2806	-12.9188
	0	0	0	0	0	0.043	0.023	0.005
naive_dd	-0.0018		-0.0011	-0.001	-0.0011	-0.0004		0.0003
	0.681		0.728	0.755	0.709	0.906		0.921
CASHMTA						-15.412	-13.89	-15.30
						0.02	0.03	0.02
Lnage						-0.067	0.1162	1.9219
						0.943	0.908	0.194
BM (=MV/BV)						0.038	-0.2365	0.018
						0.808	0.3	0.937
NIMTA						-133.1	-110.79	-12.77
						0	0	0.817
TLMTA						2.0162	1.9452	2.9153
						0.24	0.26	0.128
META						0.311	0.4234	0.7973
						0.373	0.231	0.203
log_return		-3.753	-3.7236	-3.4902	-3.4094		-2.9616	-3.4848
		0	0	0	0		0	0
nega_margin				-2.5208				-2.066
				0.652				0.715
rela_margin				-0.2849	-0.2483			-0.2408
				0.008	0.033			0.194
AUC	0.52	0.76	0.79	0.71	0.72	0.62	0.71	0.73
AIC	283.22	257.4	224.15	259.34	260.07	274.91	259.98	258.66

That the Distance To Default under Merton's framework exhibits very poor discriminating capability does not means market variables are not useful at all. In fact, given the limited sample size, the properly selected market variables could save the day for accounting variables. This can be seen from **Table 10b**, if only the sample of listed companies are used to train the model with the balance sheet /accounting variables (e.g Z**mijewski or Shumway)** the predictive power of the model is very weak, with a paltry AUC of 0.55, implying the model almost no better than a random classifier. However, when several market variables such as log_return (i.e. firm's quarterly return relative to the whole market) and NIMTA, the performance is significantly improved.

Table 10b Classic Hazard Models Trained with Sample of only Listed Companies

This table reports the predictive power and coefficients estimated from the sub sample of listed companies for several classic hazard models predicting defaults in developed market such as US. The sub -sample included a relatively small number of defaults (18). For each model, we first estimated the original version and then expanded the model by incorporating some new variables related to the equity market. The predictive power of the expanded model was compared with the original one's. This is to demonstrate that while Distance to Default (under Merton's framework) provides little predictive power, certain equity market related variables do contain additional information about default risk when the accounting variables are s rendered powerless by the relatively small data sample of listed companies. * denotes significance at 5%, ** denote significance at 1%.

Table 10b Classic Models Trained with Sub Sample of Listed Companies

Variables	zmijewski	zmijewski_mkt	shumway	shumway_mkt	IMF	IMF_mkt
Intercept	-7.3329	-6.7058*	-4.8904	-4.9752	-0.314	-1.2042
	(0.011)	(0.027)	(0.076)	(0.086)	(0.936)	(0.769)
log_return		-2.7964**		-3.0354		-3.4996
		(0.000)		(0.000)		(0.000)
CASHMTA		-15.2868**		-14.8407		-11.8913
		(0.013)		(0.014)		(0.051)
Naïve_DD						
NIMTA		-102.6028**				
		(0.000)				
Lnage	-0.4107	-0.1126	-0.0342	0.1798	-0.5288	-0.1709
	(0.616)	(0.907)	(0.971)	(0.852)	(0.620)	(0.873)
TLTA	3.6725	2.7492				
	(0.056)	(0.144)				
CACL	-0.0983	-0.0699				
	(0.785)	(0.844)				
NITA	-64.0792					
	(0.001)					
WC/TA			-1.8423	-1.1407	-0.822	0.3465
			(0.113)	(0.340)	(0.512)	(0.778)
S/TA			-1.8815	-1.1594		
			(0.185)	(0.361)		
EBIT/TA			-17.824	-14.9953		
			(0.247)	(0.317)		
RE/TA			-7.5202	-6.6392		
			(0.004)	(0.071)		
Ln_1-EBIT/TA					-43.88	-47.82
					(0.004)	(0.001)
Ln_1-RE/TA					-4.126	-6.748
					(0.308)	(0.026)

neg_DVX					4.1017	4.4702
					(0.000)	(0.000)
LnTATL					-3.989	-4.2483
					(0.008)	(0.009)
Ln_CLNCL					-0.138	-0.0917
					(0.323)	(0.562)
firm_size					-0.163	-0.0934
					(0.071)	(0.247)
AUC	0.52	0.73	0.55	0.76	0.75	0.83
AIC	275.65	236.69	267.2	227.98	235	218.78

Table 11 Classic Hazard Model Trained with the full sample

This table reports the estimation results (and out of sample performance) for several classic models (including one, i.e. IMF model developed specifically for China market). These models were re-estimated with the full data sample. For each model, we first estimated the original version using accounting variables only and then expanded the model by incorporating two additional variables we deem informative in predicting bond default: one is relative_margin, a measure of firm's profitability of the firm relative to the overall market, the other is quarterly business condition index, measured by the proportion of firm that lose money in the quarter. The predictive power of the expanded model was compared with the original one's. This is to demonstrate that while Distance to Default (under Merton's framework) provides, certain variables related equity market do contain additional information in predicting bond default when the accounting variables are powerless rendered by the small data sample limited to listed companies. * denotes significance at 5%, ** denote significance at 1%.

Table 11 Hazard Model Estimated with Full Sample Using Accounting and Macro Variables

Variables	zmijewski	zmijewski_with macro and relative margin variable	shumway	shumway_with macro & relative margin	IMF's China Default Model	IMF_with macro variable	IMF Model Variation 1	IMF Model Variation 2	Our proposed Best Performing Model
Intercept	-10.45	-8.78	-6.91	-6.87	-0.91	-2.68	-2.05	-2.94	-7.28
	0.00	0.00	0.00	0.00	0.57	0.11	0.18	0.06	0.00
d_nature		-2.29		-2.21		-2.14		-2.35	-2.32
		0.00		0.00		0.00		0.00	0.00
firm_size		0.00		0.00	-0.01	0.00	-0.01	0.00	
		0.67		0.96	0.40	0.85	0.57	0.86	
nega_margin		4.27		1.41		3.03		2.56	5.22
		0.03		0.46		0.14		0.21	0.01
rela_margin		-0.46		-0.57		-0.69		-0.45	-0.46

		0.00		0.00		0.00		0.00	0.00
Lnage	0.56	0.45	0.62	0.43	0.31	0.36	0.30	0.37	
	0.09	0.21	0.07	0.24	0.37	0.34	0.39	0.32	
TLTA	-18.27	4.32							1.07
	0.00	0.00							0.42
CACL	5.92	-0.14							
	0.02	0.37							
NITA	-0.37	8.04							-149.17
	0.05	0.28							0.00
WC/TA			-3.60	-2.82	-1.94	-1.76	-2.01	-2.40	-1.58
			0.00	0.00	0.01	0.03	0.00	0.00	0.04
S/TA			0.51	0.24					
			0.02	0.40					
EBIT/TA			-21.00	-6.30			-16.03	-7.94	
			0.00	0.05			0.00	0.04	
RE/TA			2.53	6.99			11.08	10.64	
			0.18	0.01			0.00	0.00	
Ln_1-EBIT/TA					-1.21	-45.34			-180.79
					0.89	0.00			0.00
Ln_1-RE/TA					-10.52	-10.71			
					0.00	0.00			
neg_DVX					3.74	4.05	3.52	3.76	2.97
					0.00	0.00	0.00	0.00	0.00
LnTATL					-4.76	-3.33	-3.63	-2.57	
					0.00	0.00	0.00	0.00	
Ln_CLNCL					0.26	0.06	0.31	0.001	
					0.06	0.68	0.02	0.98	
AUC	0.69	0.82	0.65	0.81	0.80	0.87	0.78	0.86	0.91
AIC	910.87	800.29	925.65	800.52	831.31	705.27	838.56	739.06	659.25

Table 11 reports the hazard model:

i) For the original zmijewski model , the TL/TA and CA/CL exhibit wrong sign but the expanded version (with relative_margin and business condition indicator added) remedied the issue, and improved the model performance (AUC increased from 0.69 to 0.82), with the cost of NITA being wrongly signed , albeit not significant

ii) For both the original Shumway model and expanded version, Working Capital and Ebit as percentage of total Asset (WC/TA, EBIT/TA) are correctly signed and significant but Sale/Total Asset (S/TA) and Retained Earning/Total Asset (RE/TA) are not. The expanded version, though, significantly enhanced the model performance (with AUC increased from 0.65 to 0.81)

iii) Re-estimated original IMF model using actual default rather than using Merton model implied PD as independent variable exhibit quite good out of sample performance (with AUC being above 0.80), all but two log transformed variable (1-EBIT/TA) and (1-RE/TA) have incorrect sign. This problem is remedied once the log transformation is removed in the variance versions;

iv) The negativity (flag neg_DVX) for retained earning has correct sign and significant. When a company records a profit, the amount of the profit, less any dividends paid to stockholders, is recorded in retained earnings, which is an equity account. When a company records a loss, this too is recorded in retained earnings. If the amount of the loss exceeds the amount of profit previously recorded in the retained earnings account as beginning retained earnings, then a company is said to have negative retained earnings. Negative retained earnings can arise for a profitable company if it distributes dividends that are, in aggregate, greater than the total amount of its earnings since the foundation of the company. It is observed that the number of firms with negative retained earnings is disproportionally high (23% for firms lurching towards default vs 3% of all sample population. Negative retained earnings appear as a debit balance in the retained earnings account, rather than the credit balance that normally appears for a profitable corporation. On the company's balance sheet, negative retained earnings are usually described in a separate line item as an "Accumulated Deficit." Indeed, the variable used to flag the negativity of the retained earnings, neg_DVX shows correct sign and is significant.

v) Both the relative profitability proxy (rela_margin) and the business condition proxy (nega_margin) are significant and correctly signed cross all model specifications, so is the ownership nature flag: d_nature.

Table 12 Best Performing Hazard Models

This table takes our best -model variables for listed firm sub-sample and full sample and report their statistical significance and predictive power. The dependent variable is bond official default. The explanatory variables are selected by an optimal process via Lasso regression. The *P*-value is reported in parentheses. * denotes significance at 5%, ** denote significance at 1%.

Table 12 Best Performing Models Selected by Lasso Regression Process

	M1: Hybrid_model trained with listed sample	M2: trained with full sample	M3: trained with listed sample	M4: trained with full sample	M5: with re-estimated Z included	M6: with Altman Z^{China} included
Intercept	-14.8723**	-7.28*	-8.22**	-6.7107	-2.5719	-4.699
	0	0	0	0	0.078	0.001
WC/TA	-4.4139	-1.577	-1.9634	-1.7438		
	0.022	0.041	0.214	0.015		
rela_margin	-0.5734	-0.455	-0.2595	-0.4124	-0.221	-0.21
	0.003	0	0.029	0	0.00012	0.00015
EBIT/TA			7.2082	-9.22		
			0.653	0.257		
Ln_1-EBIT/TA	-285.037	-180.8				
	0	0				
TLMTA	5.3068		0.6837			
	0.005		0.645			
NIMTA	-308.8708		-23.0674			
	0		0.758			
CASHMTA	-16.1289		-13.1437			
	0.029		0.065			
log_return	-3.8939		-3.3969			
	0		0			
ln_rela_size	-0.6076		-0.3747		0.0025	-0.1904
	0.011		0.064		0.983	0.091
neg_DVX		2.9728		2.6944		
		0		0		
d_nature		-2.317		-2.6292	-2.2128	-2.487
		0		0	0.0002	0.00036
nega_margin		5.2187		3.0829	0.0085	0.01
		0.01		0.145	0.00017	0.0027
TLTA		1.0748		3.2245		
		0.422		0.008		
NITA		-149.2		27.409		
		0		0.033		
lange1					-0.1134	-0.1194
					0.493	0.464

Lage					0.2788	0.4098
					0.493	0.246
Re-estimated Z					-0.6793	
					0.0003	
Altman Z^{China}						-1.79
						0.001
AUC	0.856	0.91	0.75	0.84	0.87	0.838

Following Hardle (2103), we employed a unified regularization approach (LASSO) , with logit as an underlying model, which simultaneously selects the default predictors and optimizes all the parameters within the model. The LASSO is a regularization technique for simultaneous estimation and variable selection, now widely used for model selection in machine learning algorithm and has been recently introduced into corporate bankruptcy forecast (See Tian, etc. 2015 for an excellent discussion about the advantage of using LASSO regression to improve in-sample and out of sample performance). K-fold cross validation was used to validate these models.

The coefficients of the selected variables are reported in Table 12. These models are characterized by i) Good out-of-sample performance measured by AUC (most of the greater than 80%.) ii) Almost all coefficients are significant with at most one exception iii) Correctly signs of the coefficients. The first two models have the best out-of- sample predictive power; All but one coefficient (ln (1-EBIT/TA), are correctly signed and statistically significant. Further it can be seen from table 12 that: 1) Working Capital as percentage of total asset, WC/TA, Relative profitability measure (relative_margin) and log return are all significant and have correct sign across all the best models. In particular, both Altman's original Chinese Z score and our re-estimated Z score (using the same variables). Models trained with the sub sample of listed companies underperform those trained with the full sample in terms of out of sample predictive power measure by AUC. This is understandable since there has been relatively smaller number of the listed companies that experienced bond default and the estimation results may not be robust. As we demonstrated in **Table 10b**, however, market variables do add information value to predictive power on top of accounting variables given the fact that a model incorporating only accounting variables but trained with the sub sample of listed companies would perform much worse.

3. *Role of firm size*

With regard to the role of firm size, our results are not totally in line with other studies, such as Ohlson's (1980), whose results showed that corporate default is associated with small firm size. In our case, the firm size measured by revenue has either wrong size or insignificant (Table 11).

Liquidity

In the seminal paper of Shumway (2001) and paper of Zmijewski (1984) as well, both TL/TA and CA/CL were included. While the expected signs of the coefficients were obtained (positive for TL/TA and negative for CA/CL), one of the coefficients (i.e. CA/CL) was not significant (Shumway 2001, Table II, Panel A).

Age

Our estimation results show that older firms measured by age (defined in Section data and Variable selection) have higher propensity to default, as evidenced by the fact that the sign of Ln (Age) are positive and statistically significant across all specifications. This result is in line with Shumway (2001) hazard model estimate (Table II, Panel B) and Jarrow (2004) re-estimated Zmijewski (1984) and Altman (1968) z-score variable set using US data from 1962-99. We noted that the result on this variate is also in line with the IMF model, the only model that contains statistically significant coefficient for the age is Model 5; and the sign is positive as reflected as pooled regression on market implied PD in IMF paper, Table 11, Model# 5. The sign and significance remain robust even if the regression is done with or without SOE firms excluded.

4.3 Test Altman's Chinese version Z-Score

In addition to the firm-specific and macro variables we proposed, we include the Z score, with coefficient being taken from the equation <4.3> in Altman (2007), as a synthetic indicator of firm's financial heath, replacing the key financial ratios used to compute the Z score. Out test results (Table 12) show that the Altman's Z^{China}-score hold statistically significant predictive power (p-value <0.001) and have expected sign (negative, which implies higher score will lower the default probability). We also test the model specification where Z score is jointly used with other variables not being a Z score component and found they are significant with expected sign. Specifically, firm's relative size (ln(rela_size), relative margin (rela_margin), proportion of money losing firm in the whole sample ("nega_margin") as the macro business environment measure, are all having statistically significant and economically intuitive sign, i.e. negative implies their reverse impact on the default probability while positive (.e.g. the coefficient for "nega_margin") indicates the opposite (the higher the proportion of negative margin firm will make all firm more likely to default, *ceteris paribus*. The other two firm specific variable AGE (ln (age1) and SOE OWNERSHIP dummy ("d_nature") are also significant, with expected sign, implying: the likelihood of default increases with firm age and the State owned firm is less likely to default. The out of sample performance, measured by ROC is quite good as 85. 4% (**Fig.7b**). We conclude that Altman's Chinese version Z-score, along with other variables proposed by us, contributes meaningful predicting power.

Fig. 7a Hazard Model with Z score only (Uni-variant Logit)

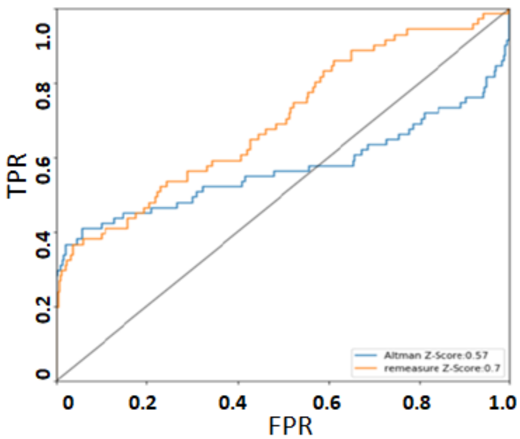
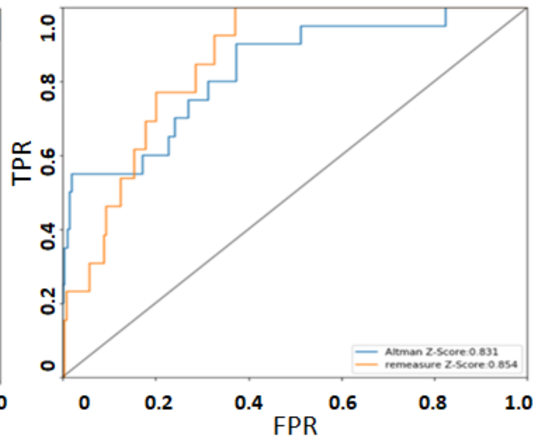


Fig 7b Hazard Model with Z & other Predictors (Model M5 & M6 in **Table 12)**



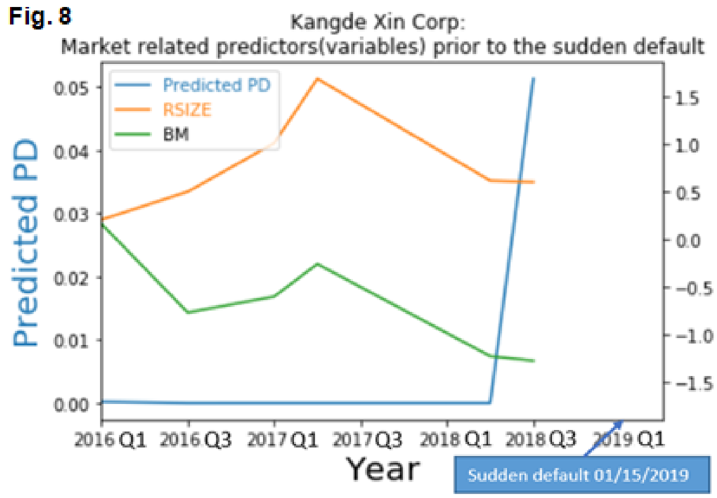
4.4. Out of sample test

To test the out of sample performance of the models, we performed k-fold cross-validation, which is to test the model's ability to predict new data not used in estimating it, in order to flag problems like overfitting or selection bias[13]. In this procedure, we first divide the *training* dataset into 5 folds. For a given hyperparameter setting, each of the 5 folds takes turns being the hold-out validation set; our hazard model is trained on the rest of the 4 folds and measured on the held-out fold. The overall performance is taken to be the average of the performance on all 5 folds. Repeat this procedure for all of the hyperparameter settings that need to be evaluated, then pick the hyperparameters that resulted in the highest 5-fold average. here is a bias-variance trade-off associated with the choice of k. Given our limited default data set, we choose k = 5 for overall dataset, k=3 for listed firms, as this parameter empirically yield test error rate estimates that suffer neither from excessively high bias nor from very high variance. Although we cannot test model performance from k=10, we randomly split overall data and run k-fold cross-validation more than 3 times. All our performance measure (AUC) reported in Table 10-12 are the average results generated from this out of sample test.

5. Case Studies

With the general results discussed above, we are presenting here some case studies to provide a concrete demonstration how the model performs for individual firms and to highlight the difference between our proposed approach and the previously dominant methodology represented by the IMF paper. We compared the time series of PD estimated by different models and check how well the forecasts were borne out by actual default events. All the cases are out-of-sample firms.

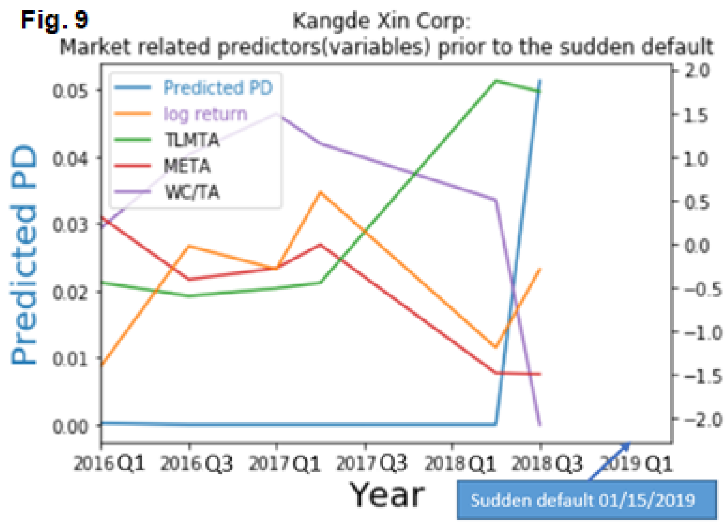
Fig. 8



[13] In the *k*-fold cross-validation, the original sample is randomly partitioned into *k* equal sized subsamples. Of the *k* subsamples, a single subsample is retained as the validation data for testing the model, and the remaining *k* − 1 subsamples are used as training data. The cross-validation process is then repeated *k* times, with each of the *k* subsamples used exactly once as the validation data. The *k* results can then be averaged to produce a single estimation. The advantage of this method over repeated random sub-sampling (see below) is that all observations are used for both training and validation, and each observation is used for validation exactly once.

5.1. The sudden default of Kangde Xin Composite Material Group Co. (01/15 2019 default)

Kangde Xin Composite Material Group Co (KDX) based in the Eastern province of Jiangsu, failed to pay a 1 billion yuan ($148 million) local note due Jan. 15 due to a liquidity crunch, according to the company. Yet as of end-September, it reportedly had 15.4 billion yuan in cash and equivalents, more than double the amount of its short-term debt, according to regulatory filings. KDX confirmed to Fitch shortly before their commercial paper due dates that their holdings of realizable cash were sufficient to meet obligations," Fitch said. But that's not how it turned out. The default out of the blue call into question the actual availability and amounts of reported cash balances. As is shown in **Fig.8**, the company has been apparently doing OK before Q2 2017, with both its relative market cap (RSIZE) and market value over book Value (BM) steadily climbing since mid 2016, peaking in Mid 2017, from where they descended in tandem until Q2 2018 when model predicted PD surge to an alarming level—implying almost certain default. To test if the risk of such sudden default be captured by our model, we employ one of our best models, M1 in Table 12 to see if there is any warning sign generated sufficiently earlier before default by our model. Its stock is in a down trend since mid of 2017. As is shown in **Fig.9**, the model presciently signaled two quarters (Q2 2018) prior to the sudden default, that the default risk has sharply increased as the predicted PD spiked abruptly ever since. It can be seen that the firm's market cap started to decline since 3Q 2017 (after it reported lower than expected profit margin) (**Fig.9**). It can be seen that the jump of the forecasted PD is in fact driven by the move of some key predictors prior to default. It is revealing, for example, to observe that Working Capital, as percentage of total asset (i.e. WC/TA), dropped precipitously several quarters prior to default while Total Liability over the Total asset (TLMTA) had been ascending rapidly during the same period of time. The relative equity return (log_return) is also in descending trend a few quarters prior to default.



Where RSIZE= Firm's Market Cap/Overall Bond Issuers Market Cap; BM= Equity Market Value/ Equity Book Value

In sum, the multi-variate hazard model built with all the available actual default data is discerning enough to be able to send out alert signal well ahead of the bond (sudden) default by the issuer. To a certain degree, it can overcome the un-reliabilities of some individual data element–in this case, the reported large cash before default. The predicted PD series, however, exhibit a sudden jump rather than a gradual shift. This is most likely due to the fact that the model was trained using the sample of listed firms, which include a relatively small number of labeled observations (i.e. default).

6. Conclusion and Caveats

Conclusion

To find a better ways to predict China bond default using the actual default data, we made empirical investigation into alternative models, assessing the roles of both market based variables and accounting variables. While we found Merton's market based structural model (for all its theoretical appeal) and KMV's Distance to Default exhibits languid discriminating power compared to hazard models with carefully constructed predictors, out-of-sample tests demonstrate other market variables such as relative return and relative market cap carry significant information about bond default and could improve on models using accounting variables only. This implies that the collective intelligence of the market could somehow mitigate the situation when certain accounting information were misreported. Merton 's model only considers firm specific risk factors under the efficiency assumption. In reality uncertainty equity price is a result of combined effect of firm-specific factor and market-related factors. This explains why model performance can be improved significantly by adding predicting variables linking individual financial measure to the broader market performance, such as relative margin, business environment proxy and relative market cap that we introduced in this paper. Therefore, it would be an overstatement to say that China equity market is too effete and too inefficient to be helpful in predicting default risk is an over statement. Market variables can serve as a counter balance against misreported accounting information. Specifically, in the absence of Relative Return and Relative Size (RSIZE) as part of the predictors--which are both statistically significant and correctly signed, the forecast would not have been as good as we've seen.

This paper makes several contributions to the literatures on bond default forecasting for emerging market such as China. First, to our best knowledge, this is the first empirical study using the latest actual default data (up to First Quarter 2019); Secondly, we re-estimated several classic default forecast models and compared the results with those on developed market such as US & UK. The predictive power of accounting-based model and Merton's market–based models were investigated for an emerging market such as China. Thirdly, our variable selection process (including LASSO regression) enables us to identify several robust and significant predictors that were never tested before, including as rela_margin, nega_margin (See **Table A1** in the Appendix) and the re-estimated Altman Z^{China} coefficients with the new data.

Our analysis not only shed light on the default behavior and predictability of China bond market but also provides a promising approach to improve the variable selection process. We believe our exercise will benefit future studies since China 's bond market will continue to expand and more market mechanism will be adopted given that pushing more firms to issue bonds fits the government's long-term goal of increasing the share of direct financing from capital markets.

Caveats

We recognize some limitations of this paper. First, while the sample size of defaults firm is large enough to conduct the meaningful empirical work, defaults are still relatively rare events compared to total sample size. Therefore, some risks of sample bias exist. Secondly, we did not consider correlated defaults or re-occurring defaults in our model. In reality, there are cases that firms default multiple times after restructuring and default events could be correlated to each other. A frailty model should be considered in these situations. Thirdly, we are predicting two reporting seasons ahead. A longer period of forecasting will be more challenging and entail more model uncertainty. Fourthly, there are quite a few institutional factors that could affect the default such as "Too Connected to Fail"---Chinese corporations are deeply enmeshed in a dense network of government institutions through equity ownership, personnel rotations. But we were unable to find a proxy to measure these characteristics.

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Figure captions

Fig 1a A Wave of New Corporate Issuance

This figure shows the recent surge in China corporate bond issuance,

Fig 1b Mispriced Risk: More Issuance, Lower Yield

This figure shows the dropping yield of both highly rated and "junk" bond while defaults and issuance hit record high during worsening economy —a sign of mispriced risk.

Fig.2. **The default surge of Chinese corporate bond**

This figure shows dramatic increase of default year over year since the first default in 2014.

Fig.3. **Comparison of Balance Sheet Structure of to be default and non –default firms**

This figure shows the clearly discernible difference of key balance features between non-default firm and default ones 6- 12 month before default, i.e. debt structure, liquidity and leverage.

Fig.4 An illustration of data admission and censoring process

This figure illustrates the observing window of our study, in which an obligor could either default or censored without further tracking (i.e. no reoccurrence of default be considered.

Fig.5. Comparison of relative margin between default companies and healthy companies

This figure highlights the difference of relative margin between healthy firm and to be-default firms (12 or 6 months prior to default), demonstrating it is a telltale predictor of default.

Fig. 6 Comparison of performance between original IMF model and re-estimated one

This figure illustrates the improved results of hazard model estimated using the actual default data but with same set of variables from IMF paper

Fig. 7a, 7b Re-estimating Z-score

These figures show the performances of model with Z-score only (7b) and model with Z-score along with other variables (7b), Altman Z^{China} and re-estimated Z score were compared

Fig. 8. Trend of predicted PD and relative market cap

The figure shows the trend of relative market cap and the sudden spike of PD prior the default.

Fig. 9. Key variables driving the spike of predicted PD

This figure shows that the movements of multiple predictors (log return, WC/TA, TLMTA, META) were revealing sign of default.

Appendix: Table A1 Definition of Key Variables

Altman Z^{china}	Z = 0.517-0.460*TLTA+9.320*NITA+0.388*WCTA+1.158*RETA	Log_return	average log return in 2 months
BM	market value of equity/book value of equity	META	market value of equity/total asset
CACL	Current asset/current liability	METL	Market Cap/Total liability
CASHMTA	cash/ market value of total asset	METL	Market Cap/total liability
D_nature	Dummy for State Ownership; SOE=1	Neg_DVX	dummy for negativity of retained earning
Default	Dummy; Default=1	NITA	Net income/total asset
EBITA	Ebita/total asset	Re-estimated Z	Z=3.24*WCTA+1.05*NITA+0.2*RETA-5.77*TLTA+3.24
Firm_size	Revenue/Median Revenue of Sector	rela_margin	Profit Margin/median margin of same sector
Ln_1-EBITA	ln(1-(EBIT/total asset))	RETA	Retained earning/total asset
Ln_1-RETA	ln(1-(retained earnings)/Total Asset	RSIZE	Firm Market Cap/Total Market Capof listed firms
lnage	Age since established	STA	Sales/total assets
lnage1	Age since debt issued	TLMTA	total liability/ market value of total asset
LnCLNCL	ln(current liability/non-current liability)	TLTA	Total liability/total asset
LnTATL	ln(total asset/total liability)	WCTA	Working capital/total Assest asset