WP/15/140

IMF Working Paper

Assessing Default Risks for Chinese Firms: A Lost Cause?

Daniel Law and Shaun K. Roache

INTERNATIONAL MONETARY FUND

 WP/15/140

IMF Working Paper

Monetary and Capital Markets Department

Assessing Default Risks for Chinese Firms: A Lost Cause?

Prepared by Daniel Law and Shaun K. Roache[1]

Authorized for distribution by Matthew Jones

June 2015

Abstract

Assessing default risks for Chinese firms is hard. Standard measures of risk using market indicators may be unreliable because of implicit guarantees, the large role played by less-informed investors, and other market imperfections. We test this assertion by estimating stand-alone 1-year default probabilities for non-financial firms in China using an equity-based structural model and debt costs. We find evidence that the equity measure of default risk is sensitive to a firm's balance sheet health, profitability, and ownership; specifically, default probabilities are higher for weaker, less profitable, and state-owned firms. In contrast, measures based on the cost of debt seem largely detached from fundamentals and instead determined by implicit guarantees. We conclude that for individual firms, equity-based measures, while far from perfect, provide a better measure of stand-alone default risks than borrowing costs.

JEL Classification Numbers: G12, G13, G17, G33

Author's E-Mail Address: tlaw@imf.org; sroache@imf.org

[1] We would like to thank Dale Gray, Matthew Jones, Hui Miao, Dragon Tang, and seminar participants at the Hong Kong Institute for Monetary Research Annual China Conference for their comments. The usual disclaimer applies.

CONTENTS PAGE

ABSTRACT......2

I. INTRODUCTION......3

II. MARKET-BASED DEFAULT PROBABILITIES FOR CHINESE FIRMS......4

III. CASE STUDIES......12

IV. AGGREGATE RESULTS......14

V. DETERMINANTS OF DEFAULT PROBABILITIES IN CHINA......16

VI. CONCLUSION......29

REFERENCES......30

TABLES

Table 1. Sample Summary Statistics: Balance Sheet Items......9
Table 2. Jump-Diffusion Structural Credit Model: Distribution of Estimated PDs......11
Table 3. 1-Year Default Probability to Implied Credit Rating Mapping......11
Table 4. Firm-Specific Explanatory Variables......18
Table 5. Macroeconomic Explanatory Variable......19
Table 6. Default Probabilities Pooled Regression, Q1-2006 to Q3-2014......21
Table 7. Comparison of Coefficients with Altman's Model for U.S. Firms......22
Table 8. Wald Test Results of Coefficients of State Ownership Variables......23
Table 9. Default Probabilities Pooled Regression, Q1-2006 to Q3-2014......24
Table 10. Default Probabilities Pooled Regression, Q1-2006 to Q3-2014......26
Table 11. Default Probabilities Pooled Regression, Q1-2006 to Q4-2014......28

FIGURES

Figure 1. Skewness of Stock Returns in Chinese Equity Market......7
Figure 2. Chaori Solar Ltd, Nov-2011 to Mar-2014......13
Figure 3. Vanke China Ltd, Jan-2006 to Mar-2014......13
Figure 4. Default Probability-Implied Credit Rating
Distributions, Q4-2008, Q4-2013, Q4-2014......14
Figure 5. Default Probability-Implied Credit Rating
Distributions, Q4-2008, Q4-2013, Q4-2014......15
Figure 6. Leverage and Asset Volatility by Ownership Q4-2014 vs 2008......16

I. INTRODUCTION

Many policymakers, financial institutions, and investors have an urgent need to improve their understanding of the credit risk of China's corporate sector. As China continues to open up, corporate credit exposures are growing quickly. A large suite of sophisticated methods to quantify credit risk already exists but can it be applied to Chinese firms? China's unique financial system, including a prominent role for the state as a borrower and lender, could mean that these tools will not work. A related complication is the absence of a full credit cycle in China which can help to calibrate risks. Finally, China's financial indicators—such as equity prices and borrowing costs—may be less reliable gauges of credit risk than in other countries. This could reflect implicit guarantees of state-owned enterprises (SOEs), fragmented domestic markets with different investors, capital account restrictions, and a smaller influence of global investors.

In this paper, we assess whether standard credit risk tools are useful for assessing Chinese firms. We estimate the stand-alone 1-year probability of default for a sample of about 4,500 non-financial firms using a variant of Merton's (1974) structural credit model. We allow for unexpected jumps in default risk (Zhou, 1997), the inclusion of non-listed firms (Jobst and Gray, 2013), and map to a database of actual defaults (Gray, 2009). Our definition of the "stand-alone" probability of default is consistent with that of Standard & Poor's (2010) which is "an issuer's creditworthiness in the absence of extraordinary support or burden. It incorporates direct support already committed and the influence of ongoing interactions with the issuer's group and/or government."

Our contribution is a comprehensive assessment of whether default probabilities calculated using a structural model are related to firm fundamentals. Specifically, we follow Altman, Fargher, and Kalotay (2011) (henceforth Altman et al.) and model the link between default probabilities and firm fundamentals reported in their financial accounts, other firm-specific characteristics such as ownership, and broad economic and financial conditions. We compare the results from an equity model to one using borrowing costs to measure default probability.

This is a useful exercise for four reasons. First, it helps confirm whether firm-specific and economic variables thought to influence default probabilities in developed market economies are useful for inference in China. For example, are default probabilities higher for Chinese firms with low profitability or weak balance sheets? We know that in developed markets the answer is typically "yes". Second, it can determine the extent to which firm ownership—whether the firm is private or state-owned—influences default probabilities. Are default probabilities lower for SOEs with implicit guarantees? Third, we can identify which indicators—equity markets or borrowing costs—are more reliable for assessing stand-alone credit risk. Finally, we can use this model to estimate default probabilities for firms that lack market data (which includes a large proportion of China's corporate universe) using the firm's accounts and other characteristics.

II. MARKET-BASED DEFAULT PROBABILITIES FOR CHINESE FIRMS

A. Methodology

We start from Merton's (1974) structural model of credit risk as described by Gray and Malone (2008) and Jobst and Gray (2013). Consider a firm for which the total market value of its assets is denoted by *V*. This market valuation is derived from the expected present value of the firm's free cashflows discounted by the weighted average cost of capital as shown by Damodoran (1996). The firm will default if its assets fall to a level—often defined as a "default barrier" and denoted by *DB*—which produces cashflows that are insufficient to service its debt. The specific value of *DB* in theory is the book value of the firm's total liabilities. In practice, *DB* is sometimes assumed to lie between total liabilities and current, or short-term, liabilities to reflect that longer maturity debt need not be repaid immediately (Crosby and Bohn, 2003).

Equity holders possess a junior contingent claim on the residual value of future assets. The value of equity *E* at maturity can be considered as a call option on *V* with a strike price equal to the *DB*:

$$E = max[V - DB, 0] \tag{1}$$

Risky debt holders, in contrast, will either receive the book value of the firm's liabilities *DB* or, in the case of default, the firm's remaining assets *V*. This payoff at maturity can be described equivalently as the value *DB* minus a put option in which debt holders "sell" the firm's assets at a strike price *DB*:

$$D = min[V, DB] = DB - max[DB - V, 0] \tag{2}$$

(1) and (2) are the payoffs at maturity to European options with strike prices equal to the default barrier *DB*. According to Jobst and Gray (2013), the risk-adjusted contingent claims analysis (CCA) balance sheet then defines the value of the firm as $V = D + E$. Before using these payoffs to calculate default probabilities, we follow Zhou (1997) and allow for the possibility that changes in firm value are not normally distributed so that *V* follows a jump diffusion process. The specific process for *V* under the risk-neutral measure $\mathbb{Q}$ is then:

$$\frac{dV_t}{V_t} = (\mu - \lambda v)dt + \sigma dZ + (\Pi - 1)dY \tag{3}$$

In (3), μ is the expected rate of return, υ is the expected jump, σ is the instantaneous volatility of *V* conditional on the jump not occurring, *dZ* is a Wiener process, and *dY* is a Poisson process with intensity parameter λ. The jump size Π is a log-normally distributed random variable:

$$\ln\Pi \sim N(\mu_\pi, {\sigma_\pi}^2) \tag{4}$$

The expected value of jump size can then be written as:

$$v = E[\Pi - 1] = \exp\left(\mu_\pi + \frac{{\sigma_\pi}^2}{2}\right) - 1 \tag{5}$$

We estimate the parameters for each firm in our sample using a log-likelihood function and a discrete probability density function. We solve for the jump diffusion process parameters (μ, σ, λ, μ_π, and σ_π) based on the methodology developed in Ardia, David, Arango, and Gómez (2011); specifically, if the intensity parameter λ is small then in a sufficiently short time period then V will either jump once or not at all. This allows us to assume that the jump probability ΔY during Δt is approximately equal to a Bernoulli random variable for small $\lambda\Delta t$. Denote the log change in the firm's asset value by Δx, then the density of Δx during Δt is a weighted mixture of densities given by:

$$f_{\Delta x} = (1 - \lambda\Delta t) f_{\Delta D} + \lambda\Delta t (f_{\Delta D} * f_J). \tag{6}$$

In (6), the Brownian motion part of the diffusion process is:

$$f_{\Delta D} \sim N\left(\left(\mu - \frac{\sigma^2}{2}\right)\Delta t\,, \sigma^2 \Delta t \right). \tag{7}$$

And the jump part is:

$$\left(f_{\Delta D} * f_j\right) \sim N\left(\left[\left(\mu - \frac{\sigma^2}{2}\right)\Delta t + \mu_\pi\right], \sigma^2 \Delta t + {\sigma_\pi}^2\right). \tag{8}$$

Given the empirical distribution of daily log changes in firm asset value, we maximize a log-likelihood function over the set of parameter values $\theta = \{\mu, \lambda, \sigma, \mu_\pi, \sigma_\pi\}$:

$$\log L(\theta | \Delta x_1, \ldots \Delta x_T) = \sum_{t=1}^{T} \log f_{\Delta x}\left(\Delta x_t | \theta\right) \tag{9}$$

subject to the constraint

$$\lambda \leq 252.$$

The value of λ is constrained to ensure that the probability that the asset value jumps once in Δt is less than or equal to one (i.e., $\lambda\Delta t \leq 1$ where $t = 1/252$).

At a daily frequency, the market value of a firm's assets V is not observable and this necessitates the use of an iterative procedure to calibrate the jump diffusion parameters and estimate firm value. Consider first the equation that calculates the price of a European call option C on the firm's assets V with a strike price equal to the default barrier DB:

$$E = C = e^{-rT} \sum_{i=0}^{\infty} \frac{e^{-\lambda T} (\lambda T)^i}{i!} \left[V e^{\mu T + i\left(\mu_\pi + \frac{{\sigma_\pi}^2}{2}\right)} N(d_1) - DB \cdot N(d_2) \right] \tag{10}$$

where

$$d_1 = \frac{ln\frac{V}{DB} + \left(\mu + \frac{\sigma^2}{2}\right)T + i(\mu_\pi + \sigma_\pi{}^2)}{\sqrt{\sigma^2 T + i\sigma_\pi{}^2}}$$

$$d_2 = d_1 - \sqrt{\sigma^2 T + i\sigma_\pi{}^2}$$

.

In (10), T is the maturity of the option, r is the risk-free interest rate, and i is the number of jumps over T. Given the equivalence between this call option and the value of equity from (1), equity value can be seen as a function of asset value. If the jump diffusion parameters are assumed to be known, we can solve for firm value V in each period with the Newton method. In practice this method does not easily converge. An alternative approach to calculating the call value is to use put-call parity where:

$$C = V - (e^{-rT}DB - P) \tag{11}$$

In (11), the call (equity) value is denoted by C, the put value is P, and the book value of liabilities (default barrier) is DB. In this expression, $e^{-rT}\,DB - P$ is the value of risky debt. Following Jobst and Gray (2013), we set the default barrier DB equal to short-term liabilities plus half of long-term liabilities. The put option premium can be calculated in the following formula:

$$P = e^{-rT} \sum_{i=0}^{\infty} \frac{e^{-\lambda T}(\lambda T)^i}{i!} \left[DB \cdot N(-d_2) - V e^{\mu T + i\left(\mu_\pi + \frac{\sigma_\pi{}^2}{2}\right)} N(-d_1) \right] \tag{12}$$

We can now solve for V using (10), (11) and (12) using jump diffusion parameters initially estimated from the empirical distribution of equity returns. We update our parameter estimates using the solution for V and then iterate this process until the estimates of V, μ, σ, λ, μ_π, and σ_π converged. We then follow Zhou (1997) and calculate the (risk-neutral and stand-alone) default probability, denoting the drift μ by r for each individual firm using:

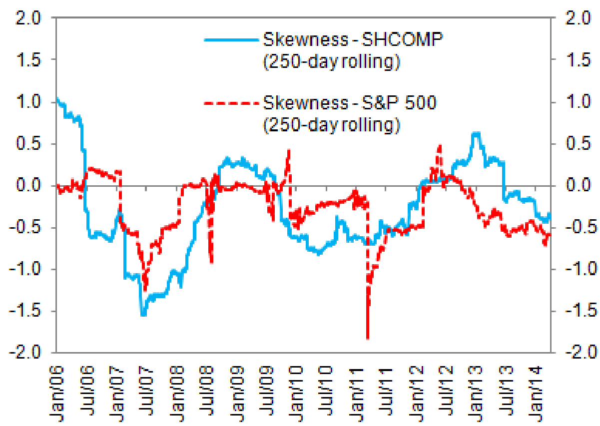
$$Pr\left\{\frac{V}{DB} \leq \xi\right\} = \sum_{i=0}^{\infty} \frac{e^{-\lambda T}(\lambda T)^i}{i!} \,.\, N\left(\frac{\ln(\xi) - \ln\left(\frac{V}{DB}\right) - \left(r - \frac{\sigma^2}{2} - \lambda v\right)T - i\mu_\pi}{\sqrt{\sigma^2 T + i\sigma_\pi{}^2}} \right) \tag{13}$$

where ξ is the default barrier which we set to 1.

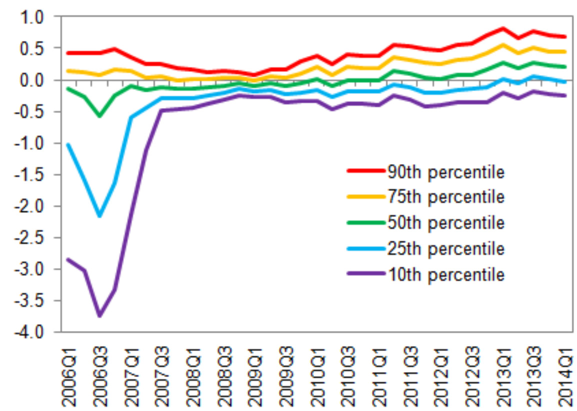
The incorporation of jump diffusion allows for a sudden change in firm value and default risk which is a common feature in most equity markets, including China (Figure 1, panel 1). Jump risk need not always be negative. Since 2010, returns for smaller firms have tended to be positively skewed (sudden price increases) (Figure 1, panel 2). (13) can incorporate sudden jumps in either direction and, as a result, we claim that it provides a better estimate for default probability than a standard Merton model.

Figure 1. Skewness of Stock Returns in Chinese Equity Market

1. Skewness of daily returns for Shanghai Composite index and S&P 500 index (with 250-day rolling window)



2. Distribution of skewness of daily returns for listed firms in China (4-quarter rolling window)



Sources: Bloomberg and authors' calculations.

Adjusting to real-world probabilities

Up to this point, we have been working with risk-neutral default probabilities which use the risk-free rate of return as the Brownian motion drift rate in (13) and theoretical distributions for firm values. Our aim is to uncover real-world (or actual) probabilities based on empirical distributions because previous research has found that these can differ significantly from risk-neutral estimates—see Chan-Lau (2006) and Sun, Munves, and Hamilton (2012). The main reason is that risk-neutral probabilities overestimate the true probability of default because they compensate investors for their unobservable aversion to bad outcomes. Theoretical distributions, meanwhile, can overestimate default risk. This is because in reality, distressed firms have strong incentives to adopt extreme measures to avoid default including, for example, the sale of non-core assets. This can mean that the default probabilities of poor credit quality firms can be overestimated.

We address these challenges by using two adjustments suggested by Gray (2009). First, to better approximate Moody's KMV EDF^{TM}s as described by Crosby and Bohn (2003), which incorporate evidence from actual default histories, the asset volatility in (3) was calculated as a positive linear function of the fitted asset volatility σ_v as written in (14a). Gray found that a linear transformation of Moody's published asset value volatility from (14a) in a structural credit model produced default probabilities very close to KMV EDF^{TM}s. For Chinese firms, we were unable to identify a clear relationship between our estimates of asset volatility and those published by Moody's. Therefore, to keep our process as transparent, we use our own estimate of asset volatility as the independent variable σ_v in (14a) which is derived using (9) and is available for all firms. In many cases, this produced default probabilities that share similar features of EDF^{TM}s. Second, to convert risk-neutral to actual default probabilities, the risk free-rate r in (13) was replaced by a drift term that is designed to capture the timevarying price of risk and is calculated as the product of the correlation between the equity price of the firm and the market and the Sharpe ratio. These adjustments, including the parameter values suggested by Gray and KMV, are shown in (14):

$$\sigma_V^* = \gamma_0 + \gamma_1 \sigma_V \tag{14a}$$

$$\mu^* = r + \rho_{A,M} SR \sigma_V \tag{14b}$$

Where: $\gamma_0 = 0.05$; $\gamma_1 = 1.37$; $\rho_{A,M} = 0.6$; and $SR = 0.75$.

In (14a), σ_V^* denotes the linear transformation of the asset volatility σ_V that is estimated in (9). In (14b), μ^* denotes the expected return, r is the risk-free rate, $\rho_{A,M}$ is the correlation, and SR is the Sharpe ratio.

Two remarks are worth making related to the application of this method for China. First, the linear transformation of the estimated asset volatility in (14a) effectively means that we are fitting default probabilities on an approximation of Moody's proprietary database of actual default rates. This database 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. For example, the 2014 World Bank's "Doing Business" survey ranked China 53rd in resolving insolvency (the United States and Canada ranked 4th and 6th, respectively), mainly due to high costs, a low recovery rate, and a low probability that the firm would emerge as a going concern. At the same time, China's actual default rates may be suppressed by public sector support, mainly for SOEs. We believe this adjustment still has merit, however, as it provides an estimate of stand-alone default probabilities based on the fundamental health of the firm rather than the intricacies of the legal system or complex political economy. If a firm is unable to pay its obligations the financial costs must be borne somewhere, and if not by bondholders then by banks or the public sector.

Second, we have to estimate the market price of risk and the Sharpe ratio. A common approach is to estimate these two variables ex-post using historical data but this is not easy in China mainly because ex-post Sharpe ratios have been close to zero or negative during 2008 to 2013, contrary to theoretical predictions (results not shown). One interpretation of this outcome is that Chinese investors have been persistently surprised by low equity market returns—in other words, they suffer from biased expectations. Of course, the risk price and Sharpe ratio in the model should correspond to investors' forward-looking rational expectations rather the past so we use the theoretically-consistent prior in our estimates in (14b).

B. Data

Sample of firms

Default probabilities were estimated for an unbalanced panel with a maximum of 4,483 non-financial firms for the period between Q1-2006 and Q4-2014. Of this panel, 2,441 were firms with listed equity on a public exchange and 2,042 firms were unlisted but had issued bonds in the onshore bond market. Our sample includes 1,020 local government financing vehicles (LGFVs) of which are listed firms. The LGFVs are identified when they issue urban investment (Changtou) bonds in the onshore bond markets. Over this period, there have been very few de-listings and any survivor bias in the sample is likely to be minimal.

Firms' balance sheet items

All balance sheet data, including total assets, total liabilities, and current and non-current liabilities were extracted from the WIND database. Listed firms report these variables shortly following the end of each calendar quarter. Non-listed firms that issue bonds are required to disclose their financial statements for the three years prior to issuance and every subsequent year, although a few firms do report quarterly. As the data are available only for the period up to their issuance, most of the firms do not have a complete time series during the sample period. The main items among current liabilities are short-term loans, notes payable, financial liabilities held for trading, accrued expenses, account payable, tax payable and interest payable. Non-current liabilities include long-term loans, bonds payable, long-term accounts payable, and deferred income tax liabilities. We included all types of liabilities in our definition of the default barrier because of their material size and their status as contingent claims on the firm. Summary statistics for selected balance sheet variables over the sample period are provided in Table 1. Non-listed firms tend to be larger on average even though an increasing number of smaller companies has issued bonds since 2008 (reducing asset size for the median firm). The total liabilities of sample firms was about RMB53 trillion as of Q4-2014, which accounted for about 45 percent of non-equity total social financing (TSF).

Table 1. Sample Summary Statistics: Balance Sheet Items
(Billions of yuan unless otherwise specified)

	Q4 2014 1/		Q3 2008 1/	
	Median	Std. Dev.	Median	Std. Dev.
Listed non-financial firms				
Total assets	2.83	68.97	2.05	40.35
Total liabilities	1.16	39.82	1.06	18.27
Current liabilities	0.92	28.03	0.83	12.82
Non-current liabilities	0.11	13.57	0.09	5.98
Market cap	3.85	32.93	1.86	70.33
Number of firms	2,411		1,390	
Non-listed non-financial firms				
Total assets	7.55	185.07	9.32	120.48
Total liabilities	4.34	111.56	5.00	56.68
Current liabilities	2.37	47.35	3.17	30.90
Non-current liabilities	1.07	75.68	1.53	29.60
Number of firms	1,586		675	

Source: WIND database and authors' calculations.
1/ End-2013 and End-2008 for non-listed firms.

Estimating the market value of assets

Estimates for unobservable asset values and asset volatilities for each listed firm were based on the quarter-end levels and rolling 250-day standard deviations of the log changes in equity market capitalizations, respectively, with data sourced from Bloomberg. For dual-listed shares, the market capitalization is calculated as the sum of all listings for each firm converted into yuan at the prevailing exchange rate, including H shares traded in Hong Kong SAR.

To extend our analysis to non-listed firms, we followed Jobst and Gray (2013) who used peer group matching in their contingent claims analysis of two non-listed banks in the United Kingdom (IMF, 2011). As a first step, we grouped non-listed firms according to the sub-industry classification provided in the WIND database (the most detailed level available). An alternative was the classification adopted by the China Securities Regulatory Commission (CSRC) but this differed between listed and non-listed firms. In the second step, we minimize the squared distance (*DS*) for each non-listed firm *i* and all the listed firms $j = 1\ldots N$ in the same sub-industry over a vector of dispersion-standardized characteristic variables including size (the book value of assets or *BV*) and leverage (debt-to-equity or *D/E*) over the sample period:

$$\min_j DS_i(j) = \sqrt{\sum_{t=0}^{T}\left[\frac{1}{\sigma_{BV}^2}\left(BV_{it} - BV_{jt}\right)^2 + \frac{1}{\sigma_{D/E}^2}\left(D/E_{it} - D/E_{jt}\right)^2\right]} \qquad (15)$$

The procedure (15) thus equally weights relative firm size and leverage when minimizing distance. We then solve for the non-listed firms' market values of assets and jump diffusion parameters using the same process described above but using the book value of equity multiplied by the median price-to-book ratio of the same sector as listed firms.

C. Default Probability Under-Prediction

It is well known that structural credit models tend to under-predict default probabilities, particularly at short horizons of about one year and for investment grade debt (Leland, 2006). Notwithstanding our incorporation of jump-risk into the basic model of section II and the linear transformation (14a) to better reflect actual default rates, we still arrive at default probabilities that appear unreasonably low. This statement assumes that China's actual default rates would have been materially above zero in the absence of third-party financial support that appears to have suppressed the frequency of credit events, at least as measured by the bond market. As Table 2 shows, the default probability of the upper quartile firm (i.e., the firm with a default probability at the 75th percentile of the full sample) at the end of Q1 2014 was just 0.1 percent. Alternatively, mapping the default probabilities of the sample into credit ratings suggests that 89 percent of firms were investment grade at the end of Q1-2014.

Table 2. Jump-Diffusion Structural Credit Model: Distribution of Estimated DPs (Q1-2014)

	Default Probability	Cumulative Number of Firms
10th percentile	$1.7X10^{-20}$	400
25th percentile	$4.3X10^{-9}$	1,000
50th percentile	0.0006	1,999
75th percentile	0.1	2,998
90th percentile	0.6	3,597
Max	46.9	3,997

Source: Authors' calculations.

This is unlikely to just be a China-specific issue as it is a finding in studies of credit risk in advanced economies (Huang and Huang, 2012). Under-prediction may reflect, in part, technical shortcomings of the jump diffusion calibration, including its limited ability to capture volatility clustering (Kou, 2008).

D. Default Probability-Implied Credit Ratings

We follow Hui, Wong, Lo and Huang (2005) and complement the reporting of estimated default probabilities with implied credit ratings. Hui et al. (2005) found a close fit between a least squares fit of credit model-generated default probability term structures and published ratings. Our mapping does not correct for downward bias in the same way as Hui et al and is designed only to provide an alternative means of reporting. We assign an implied credit rating by mapping the estimated 1-year default probability to the actual default rates by published credit rating as provided by Standard & Poor's (2014). The range of default probabilities for each credit rating is determined by the mid-point of the averages of two adjacent ratings over the interval (0,1) (Table 3).

Table 3. 1-Year Default Probability to Implied Credit Rating Mapping

Implied Credit Rating	Issuer-Weighted Long-Term Average	Lower Limit	Upper Limit
AAA	0.00	0.00	0.01
AA	0.02	0.01	0.05
A	0.07	0.05	0.14
BBB	0.21	0.14	0.51
BB	0.80	0.51	2.46
B	4.11	2.46	15.49
CCC/C	26.87	15.49	100.00

Source: S&P (2014) and authors' calculations.

III. CASE STUDIES

Before discussing some of the results at the aggregate level, we will present in this section some case studies to give a sense of how the model performs for specific firms.

A. Shanghai Chaori Solar Energy Science and Technology Ltd

Our first case is the first (and as yet only) default in China's domestic bond market. Shanghai Chaori Solar Energy Science and Technology Ltd (Chaori) manufactures solar energy products for both export and domestic residential installation. Immediately after the Global Financial Crisis (GFC), which was preceded by a spike in oil prices, solar was seen as a growth industry that could potentially benefit from government support. (For example, the U.S. solar power market grew by 67 percent in 2010 to record the fastest growth of any energy sector.) This helped privately-owned Chaori to raise 2.38 billion yuan in its November 2010 IPO. Supply outpaced demand, however, and the solar industry has been plagued by overcapacity problems for some time. It was likely no surprise that many of its firms started to see profitability deteriorate as the post-GFC surge in economic activity moderated. Chaori started reporting large and persistent losses and sharply increasing leverage in late 2012.

The model first identified Chaori's rising default risk in July 2013 when the 1-year default probability (DP) picked up from near zero to over 10 percent as the stock price began to fall. Thereafter, the DP dipped to the 3-5 percent range before spiking up to over 25 percent by the end of 2013. The corresponding changes in implied credit ratings would be from AAA-AA to B and finally to CCC. As Figure 2 shows, a declining distance-to-default explains a large part of the rise in DPs, as our estimate of the market value of assets declined through 2013. At the same time, the expected volatility of asset values and "jump risk"—seen by a downward skew in the estimated distribution of asset values—both increased. In March 2014, Chaori was unable to meet a coupon payment on the 5-year 1 billion yuan bond it had issued in May 2012.

B. Vanke China Ltd

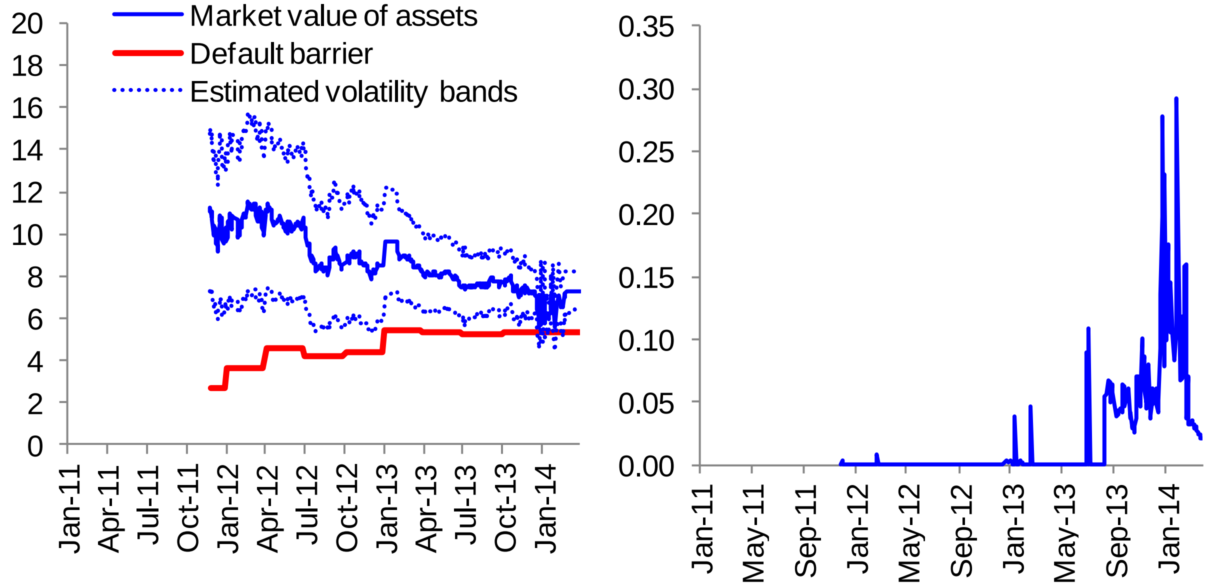
Vanke China Ltd is one of the largest property developers in the country. The privately-owned firm was founded in 1984, commenced real estate activities in 1988, and became the second listed company on the Shenzhen Stock Exchange in 1991. Vanke specializes in residential sales and enjoyed rapid growth in turnover as China's property market boomed through late 2013. While still regarded as one of the strongest firms in the sector—as evidenced by investment grade credit ratings by the three largest global agencies—Vanke's leverage has increased and its debt servicing capacity has eroded over recent years. The firm is clearly exposed to the property market cycle.

The model shows that the estimated 1-year DP increased significantly during 2008 as the market value of assets declined and asset volatility increased. Following the recovery of 2009 and through early 2013, the DP has stayed low as rising asset values and low volatility offset a large rise in the firm's liabilities. As the property market has slowed since early 2013, a gradual decline in asset values has combined with rising asset volatility to lift the DP to between 2-4 percent.

Figure 2. Chaori Solar Ltd, Nov-2011 to Mar-2014

1. Firm Value and the Default Barrier (billions of yuan)

2. Estimated 1-Year Default Probability (decimals)

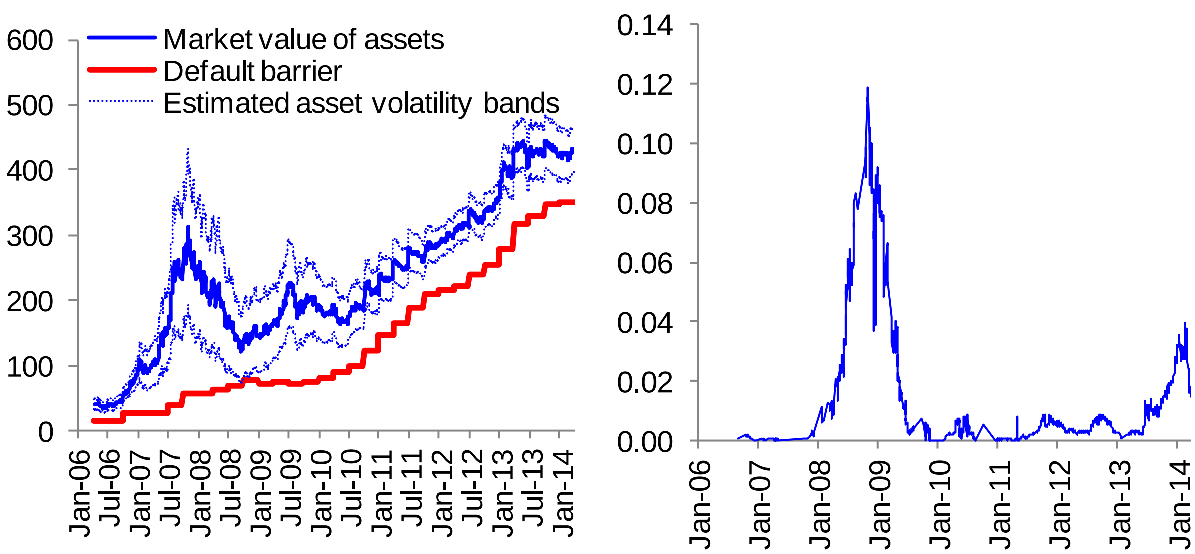


Sources: Wind; Bloomberg; and authors' calculations.

Figure 3. Vanke China Ltd, Jan-2006 to Mar-2014

1. Firm Value and the Default Barrier (billions of yuan)

2. Estimated Probability of Default



Sources: Wind; Bloomberg; and authors' calculations.

IV. Aggregate Results

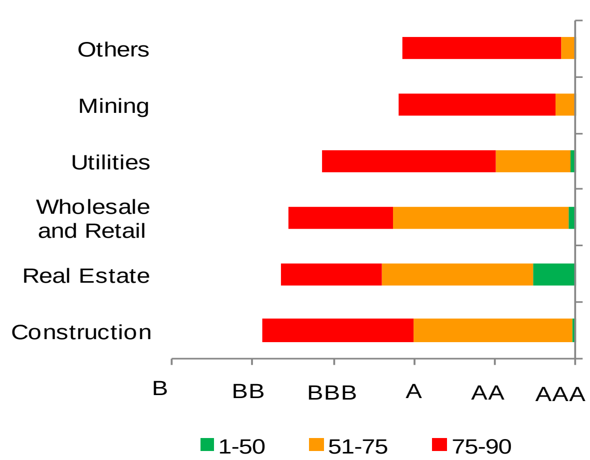
In this section, we present an aggregated summary of the results from the model described in section I and focus on how default probabilities for a large sample of Chinese firms has changed between Q1-2006 and Q4-2014. For each quarter, we use the methodology described by (1)-(14) to estimate 1-year default probabilities for all firms and then describe the resulting distribution for the full sample and along different dimensions, including sectors, listing status, and ownership structure.

The distribution of default probabilities shifted significantly higher during the GFC but has remained quite stable and low since 2012. Notwithstanding increased liabilities across most firms, rising asset values and remarkably low equity price volatilities since 2012 have helped keep default probabilities low.

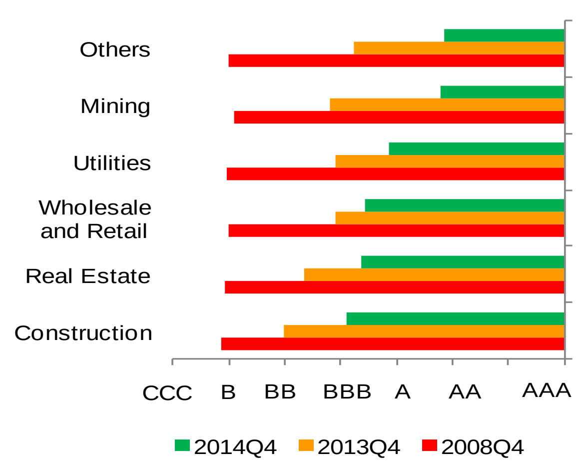
Figure 4 panel 1 shows the distribution of mapped credit ratings for selected sectors. We show two segments of the distribution where credit default risks are higher than for the median firm. The greater the degree of concentration of firms with weak ratings, the further to the left of the scale each segment will start. For example, from the median to the 75th percentile firm, implied credit ratings for construction, real estate, retail and wholesale, and utilities compares unfavorably to the rest of the sample. For these sectors, this segment of the distribution is mostly sub-investment grade. Figure 4 panel 2 compares the 90th percentile firms in each sector at the end of Q4-2014, Q4-2013, and the quarter which saw default risks reach their maximum for most firms, Q4-2008. This provides one measure of the "weak tail" of the distribution. Rising equity market valuations have lowered default risks over the last year but construction, real estate, and retail and wholesale continue to stand out as most vulnerable.

Figure 4. Default Probability-Implied Credit Rating Distributions, Q4-2008, Q4-2013, Q4-2014

1. Distributions by Sector, Q4-2014



2. 90th Percentile Firms by Sector



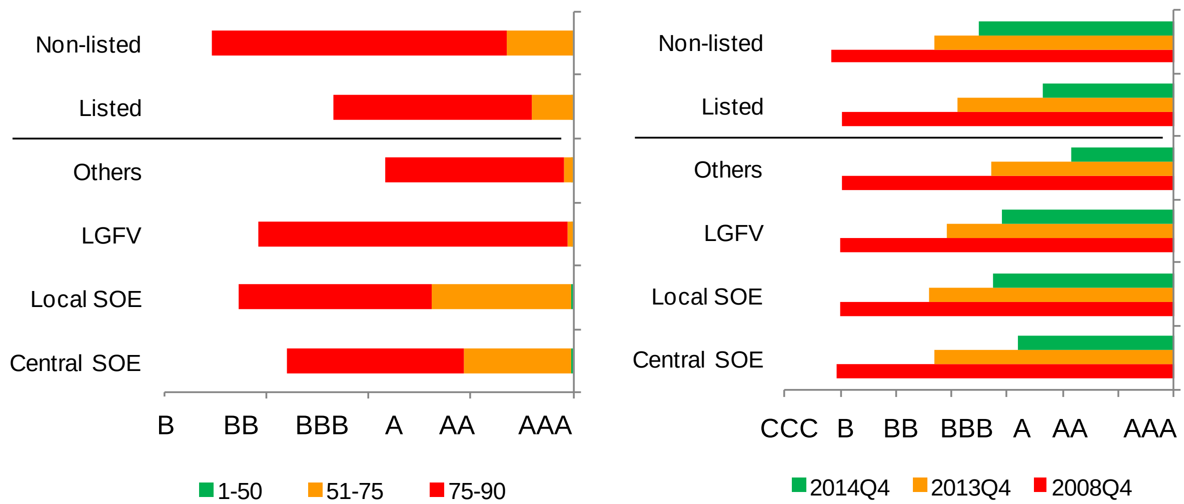
Sources: Wind; Bloomberg; and authors' calculations.

At the end of Q4-2014, the distribution of default risk is similar for listed and non-listed firms (Figure 5). Our main finding is that unconditional stand-alone default risk appears to be much higher for SOEs—particularly locally-owned SOEs—compared to LGFVs and privately-owned firms. For example, the range of implied credit ratings for local SOE firms between the 75th and 90th percentile are close to A-BB. In contrast, the range for LGFVs is almost all investment grade from AAA to BB.

Figure 5. Default Probability-Implied Credit Rating Distributions, Q4-2008, Q4-2013, Q4-2014

1. Listing Status and Ownership, Q4-2014

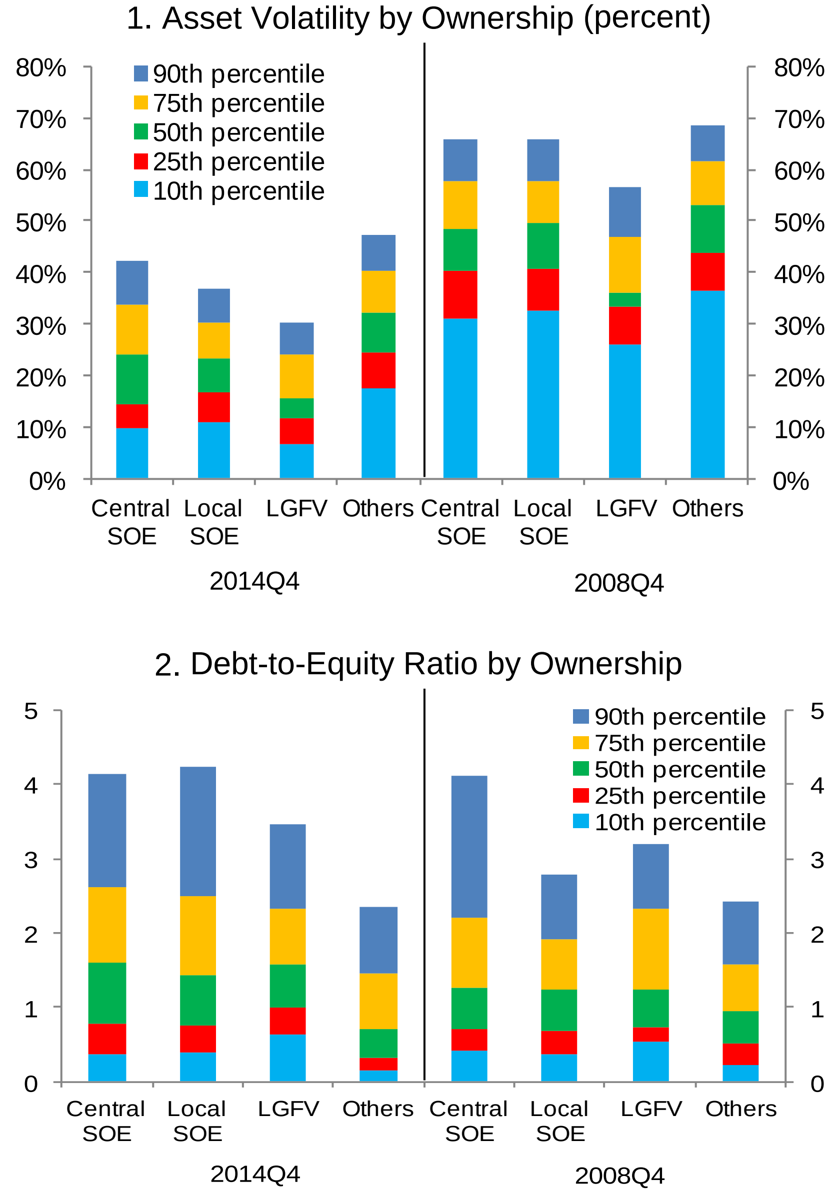
2. 90th Percentile Firms by Listing/ Ownership



Sources: Wind; Bloomberg; and authors' calculations.

During Q4-2014, default probabilities were depressed by lower asset volatilities (Figure 6, panel 1). The weak tails the distribution of both central and local SOEs have lower volatilities than other privately-owned firms, offsetting generally higher leverage among these firms (Figure 6, panel 2). The leverage of local SOEs and LGFVs has continued to rise while that of other firms has been more stable. Lower default probabilities for LGFVs may be attributable to lower asset volatility and leverage.

Figure 6. Leverage and Asset Volatility by Ownership Q4-2014 vs 2008



Sources: Wind; Bloomberg; and authors' calculations.

V. Determinants of Default Probabilities in China

In this section, we establish an empirical link between market-based assessments of default probabilities and a set of potential explanatory variables including firm-specific accounting ratios and economic and financial conditions. Our aim is to understand whether market-based measures of default probability are affected by factors that, intuitively, should influence credit risk. In other words, are we justified in using standard methods of credit risk assessment in China or is China different?

A. Previous Literature

To allow for comparisons with earlier literature, we follow Altman et al. (2011) who quantified these linkages using a logit model for a large sample of firms in the United States over a sample period covering 1978 to 2007. The dependent variable in their model is the risk-neutral default probability estimated from a structural credit model using equity market capitalizations, equity price volatilities, and a distress barrier of short-term liabilities plus one-half of long-term liabilities. Their explanatory variables are largely taken from Altman's (1968) seminal Z-score paper and include one-quarter lagged firm-specific indicators of profitability, leverage and liquidity. Firm size and age are also included. They find, on the basis of pooled regressions, that these accounting-based measures explain about 40 percent of the total in-sample variation in market-based default probabilities. All of the Z-score variables are correctly signed and statistically significant. Zhang, Han, and Chan (2014) adopt a similar approach for China and find that a set of Altman Z-score variables accounted for about half of the estimated variation in default probabilities.

Much of the previous research linking default probabilities to fundamental factors use actual default rates with the dependent variable taking a value of 1 in the event of "default" and zero otherwise. This is not a useful approach for China given the paucity of data related to confirmed credit events but this literature can provide some perspective for the results that we present in this paper. In almost all cases, the choice of firm-specific explanatory variables includes various measures of profitability, interest coverage, leverage, and liquidity. Growth and firm size and age are often also included. Jacobson, Lindé, and Rozbach (2013) exploit a large dataset on the payment behavior of Swedish firms between 1990-2009 and classify a firm as having default status conditional on the occurrence of any one of five events, including declaration of bankruptcy or suspension of payments (including debt service or other obligations). Macroeconomic variables include an estimate of the output gap, annual inflation, the nominal policy interest rate, and the de-trended real effective exchange rate, They find that firm-specific variables are important determinants of relative default likelihood but macroeconomic variables exert much greater influence on average economy-wide default risk, as might be expected. Bonfim (2009) considered a large sample of Portuguese firms using annual data over1996-2002 and estimated a random-effects probit model in which the firm defaults if it becomes overdue on a bank loan payment. She finds that firm-specific explanatory variables (lagged by one year) are important determinants of default probability. She also finds that economic sectors and macroeconomic variables such as GDP growth, interest rates, and loan growth contributed to default risk in terms of systematic shocks but tend to exert less influence than firm-specific factors. Benito, Delgado, and Pagés (2004) reached a similar conclusion for Spanish firms.

B. Methodology and Data

Specification and estimation

We use a standard logit pooled regression specification which can be written as:

$$y_{it} = \alpha + \boldsymbol{\beta}'\boldsymbol{X}_{it-1} + \boldsymbol{\gamma}'\boldsymbol{Z}_{t-1} + \boldsymbol{\zeta}'\boldsymbol{D} + \lambda_t + \varepsilon_{it}$$

Where $PD_{it} = \frac{1}{1+e^{y_{it}}}$

(16)

And from (13)

$$PD_{it} \equiv Pr\left\{\frac{V_{it}}{DB_{it}} \leq \xi\right\}$$

In (16) for each time *t* and firm *i*, α is a common intercept, $\boldsymbol{\beta}$ is a (*k* x 1) vector of parameters, $\boldsymbol{X}_{it-1}$ is a (*k* x *1*) vector of *k* variables specific to firm *i* and lagged one period, $\boldsymbol{\gamma}$ is an (*l* x 1) vector of parameters, $\boldsymbol{Z}_{t-1}$ is an (*l* x *1*) vector of macroeconomic variables lagged one period, $\boldsymbol{\zeta}$ is an (*m* x 1) vector of parameters, $\boldsymbol{D}$ is an (m x 1) vector of dummy variables, and λ_t is a time effect. The residual terms ε_{it} are assumed to be independent across firms after controlling for common factors. The firm specific variables were winsorized at the 1st and 99th percentiles to remove the effect of extreme outliers. We estimated (16) using OLS with robust standard errors. Our sample includes an unbalanced panel of 2,409 listed firms for which firm-specific equity market data were available.

Firm-specific explanatory variables

Our choice of firm-specific explanatory variables denoted by $\boldsymbol{X}_{it-1}$ in (16) directly follows Altman et al. (2011) and is shown in Table 4. The first four variables are taken from the well-known Z-score model of default risk described in Altman (1968) and are augmented with indicators of size and age. Table 6 also shows our expectations for the signs on the coefficients included in the parameter vector $\boldsymbol{\beta}$ in (16). We would expect that default probability should be decreasing with profitability, liquidity, and firm age and increasing with leverage and the proportion of short-term liabilities. The summary statistics are calculated after winsorization at the 1st and 99th percentiles, respectively. On the basis of standard panel unit root tests (results not shown), we found strong evidence that these series are stationary.

Table 4. Firm-Specific Explanatory Variables

Description	Variable	Median	Standard Deviation	Expected Sign
Profitability: ratio of earnings before interest and taxes to total assets	$\ln\left(1 - \frac{EBIT_{it-1}}{TA_{it-1}}\right)$	-0.06	0.08	–
Profitability: ratio of retained earnings to total assets	$\ln\left(1 - \frac{RE_{it-1}}{TA_{it-1}}\right)$	-0.14	0.27	–
Leverage: ratio of total assets to total liabilities	$\left(1 + \ln\frac{TA_{it-1}}{TL_{it-1}}\right)$	1.73	0.66	+

Table 4. Firm-Specific Explanatory Variables

Description	Variable	Median	Standard Deviation	Expected Sign
Liquidity: ratio of working capital to total assets	$\frac{WC_{it-1}}{TA_{it-1}}$	-0.16	0.31	–
Debt maturity structure: ratio of current liabilities to non-current liabilities	$\ln\left(\frac{CL_{it-1}}{NCL_{it-1}}\right)$	2.30	30.36	–
Relative size: ratio of total assets to median of total assets of all sample firms	$\frac{TA_{it-1}}{Median\ TA_{t-1}}$	0.57	8.87	+/–
Age: number of months since listing	Age_{it}	112.37	68.54	+

Economic and financial conditions explanatory variables

Our choice of macroeconomic explanatory variables denoted by $\boldsymbol{Z}_{\mathbf{t-1}}$ in (16) includes a survey of manufacturing activity, broad money growth, and the real lending rate (Table 5). As the weighted average lending rate is available only from 2008Q4, the 1-year average lending rate is used during Q1-2006 to Q3-2008 (discontinued from Q4-2008).

Table 5. Macroeconomic Explanatory Variable

Description	Variable	Expected Sign
Economic outlook: Official manufacturing PMI	$\ln(PMI_{it-1})$	+
Monetary conditions: M2 year-on-year growth deflated by CPI inflation	$Real\ M2\ growth_{it-1}$	+
Monetary conditions: Average lending rate deflated by CPI inflation	$Real\ lending\ rate_{it-1}$	–
Market valuation: Price-to-book ratio of Shanghai Composite index	PBV_{it-1}	+

Industry, period-effect, and ownership dummy variables

We follow Bonfim (2009) and include quarterly (time-effect) and sector dummies as denoted by ***D*** in (16), the latter using the China Securities Regulatory Commission (CSRC) industry classification. We also include a set of dummies denoting whether the firm is centrally state owned, locally state owned, an LGFV, or privately owned. Previous research suggests that ownership may be important for stand-alone default risk—for example, Zhang et al (2014) argue that a state ownership stake in a firm of 50 percent or more is associated with higher default likelihood. Our underlying assumption is that the payoffs from the equity of Chinese firms are not implicitly guaranteed. This should mean that an equity market-based estimate of default risk reflects more the impact of state ownership on the probability that the firm is unable to service its obligations from its own resources rather than the probability of public sector financial support.

C. Results

The results from a range of specifications based on (16) are shown in Table 6.

Firm-specific explanatory variables

The effect of the firm-specific variables denoted by $\boldsymbol{\beta}$ in (16) is largely in line with our expectations and similar to, or somewhat larger than, those from the study of U.S. firms by Altman et al. (2011). This is shown in Table 7 for the most basic specification (1) which excludes industry and seasonal dummies to allow a like-for-like comparison. The estimated coefficients on both profitability indicators, ln(1-EBIT/TA) and ln(1-RE/TA), were correctly signed (negative), statistically significant, and robust across specifications. In other words, rising profitability lowers default risk, all else equal.

The effect of retained earnings, an indicator of past profitability, was much higher in our model than Altman et al. (2011). This may reflect our inclusion of an additional coefficient to account for a peculiarity in China—retained earnings were negative for about one-fifth of sample observations. As Table 6 shows, the median level and standard deviation of this variable is not large and its total effect is, on average, small.

The estimated coefficient on firm leverage, 1+ln(TA/TL), is correctly signed (positive), statistically significant, and robust across specifications. For the hypothetical A-rated firm, In common with Altman et al. (2011), we find that the estimated coefficients on indicators of liquidity, debt structure, size, and age are either statistically insignificant, economically insignificant, or not robust to different specifications.

To assess the economic significance of these coefficients, we calculate the estimated marginal impact of these firm-specific variables on default probabilities. For example, for an A-rated firm with a 1-year estimated default probability of 0.07 percent, a fall in the asset-to-liabilities ratio from 5 to 4 (consistent with 25 percent increase in liabilities) would increase the default probability to 0.19 percent. For the same firm, a decline in profitability measured as a 10ppts fall in the EBIT-assets ratio would increase the default probability to 0.09 percent.

Table 6. Default Probabilities Pooled Regression, Q1-2006 to Q3-2014

	Dependent variable: logit function of probability of default (specifications 1-9)								
	1	2	3	4	5	6	7	8	9
Constant	-4.46**	-1.62**	-4.98**	-70.48**	-128.59**	-1.73**	-5.02**	-70.17**	-128.70**
	(-14.55)	(-3.71)	(-9.75)	(-15.21)	(-27.74)	(-3.97)	(-9.84)	(-15.15)	(-27.77)
ln(1-EBIT/TA)	-3.43**	-3.71**	-9.91**	-3.89**	-5.30**	-3.70**	-9.88**	-3.92**	-5.30**
	(-3.50)	(-3.77)	(-9.90)	(-3.91)	(-5.34)	(-3.76)	(-9.88)	(-3.94)	(-5.35)
WC/TA	0.75**	0.89**	-1.05**	1.05**	-0.12	1.10**	-0.88**	1.24**	0.06
	(2.55)	(2.59)	(-3.07)	(3.02)	(-0.35)	(3.19)	(-2.60)	(3.60)	(0.17)
ln(1-RE/TA)	-8.78**	-8.37**	-2.90**	-8.47**	-6.42**	-8.57**	-2.94**	-8.64**	-6.53**
	(-11.72)	(-11.11)	(-3.82)	(-11.16)	(-8.49)	(-11.39)	(-3.87)	(-11.40)	(-8.64)
Negative DV X	19.47**	18.23**	12.56**	18.45**	16.16**	18.54**	12.66**	18.73**	16.35**
ln(1-RE/TA)	(22.36)	(20.70)	(14.33)	(20.86)	(18.34)	(21.13)	(14.46)	(21.23)	(18.60)
1+ln(TA/TL)	9.77**	9.33**	9.54**	9.30**	9.41**	9.29**	9.49**	9.26**	9.37**
	(62.53)	(55.15)	(58.46)	(55.00)	(56.33)	(54.90)	(58.19)	(54.74)	(56.07)
Size	-0.02**	-0.01**	-0.03**	-0.01**	-0.02**	-0.01	-0.02**	0.00	-0.01**
	(-6.48)	(-4.19)	(-7.55)	(-3.35)	(-5.29)	(-1.89)	(-5.83)	(-1.08)	(-3.27)
ln(CL/NCL)	-0.0086**	-0.0105**	-0.0022	-0.0086**	-0.0073**	-0.0099**	-0.0018	-0.0080**	-0.0067**
	(-3.0500)	(-3.7000)	(-0.8100)	(-3.0400)	(-2.6100)	(-3.5000)	(-0.6500)	(-2.8200)	(-2.4200)
Age	0.0037**	0.0079**	-0.0020	0.0083**	0.0041**	0.0066**	-0.0027**	0.0069**	0.0030**
	(3.6700)	(7.4500)	(-1.8600)	(7.7400)	(3.8100)	(6.3000)	(-2.5300)	(6.6000)	(2.8900)
LGFV dummy		-2.94**	-2.16**	-2.92**	-2.58**				
		(-7.88)	(-5.88)	(-7.78)	(-6.96)				
Local SOE		-1.87**	-1.10**	-1.85**	-1.53**				
dummy		(-13.33)	(-8.07)	(-13.20)	(-11.03)				
Central SOE		-1.23**	-0.37**	-1.22**	-0.85**				
dummy		(-6.87)	(-2.14)	(-6.82)	(-4.82)				
Estimated SOE						-3.42**	-1.99**	-3.39**	-2.82**
shareholding						(-12.38)	(-7.42)	(-12.31)	(-10.33)
ln(PMI)				17.11**	33.80**			17.01**	33.82**
				(14.80)	(28.77)			(14.71)	(28.80)
Real money				-11.01**	7.23**			-11.31**	7.12**
supply growth				(-7.82)	(4.83)			(-8.03)	(4.75)
Real lending				67.36**	-36.16**			68.63**	-35.77**
rate				(12.24)	(-5.70)			(12.47)	(-5.63)
PBV ratio					-2.63**				-2.64**
					(-38.12)				(-38.35)
Dummies									
Industry	N	Y	Y	Y	Y	Y	Y	Y	Y
Seasonal	N	Y	Y	Y	Y	Y	Y	Y	Y
Quarterly	N	N	Y	N	N	N	Y	N	N
No. of obs.	58,258	58,258	58,258	58,258	58,258	58,258	58,258	58,258	58,258
R-squared	0.168	0.174	0.225	0.177	0.193	0.173	0.225	0.176	0.192

Source: Authors' estimates.

1/ ** represents statistically significance at 5 percent level. T-statistics in parentheses.

Table 7. Comparison of Coefficients with Altman's Model for U.S. Firms

Explanatory Variables	Specification 1 Coefficients	Altman et al. (2011) Coefficients
$\ln\left(1-\frac{EBIT_{it-1}}{TA_{it-1}}\right)$	-3.43** (-3.50)	-4.25** (-55.9)
$\frac{WC_{it-1}}{TA_{it-1}}$	0.75** (2.55)	0.78** (49.8)
$\ln\left(1-\frac{RE_{it-1}}{TA_{it-1}}\right)$	-8.78** (-11.72)	-0.81** (-129)
$\left(1+\ln\frac{TA_{it-1}}{TL_{it-1}}\right)$	9.77** (56.66)	2.11** (304)
$Size_{it-1}$	-0.02 (-6.48)	0.58** (299)
$\ln\left(\frac{CL_{it-1}}{NCL_{it-1}}\right)$	-0.0086** (-0.6900)	-0.13** (-62.6)
Age_{it}	0.0037** (3.67)	0.0015** (74.8)

Note: Newey and West (1987) corrected t-statistics are in parentheses.

Ownership

State ownership appears to increase the probability of default, all else equal. It is worth reiterating that we are measuring the *stand-alone probability*, excluding the likelihood of state financial support, from the perspective of an equity investor. The estimated coefficients on dummy variables denoting whether the firm is a centrally-owned or locally-owned SOE or an LGFV were negative (positive relation with default probability), statistically significant, and robust to different specifications. Some caution should be used when considering the coefficient for LGFVs as most of these firms are non-listed and not included in the regression sample.

To provide some quantitative context, again consider an A-rated privately-owned firm with a default probability of 0.07 percent. Using the results from specification 5 in Table 6, for the same set of firm-specific and macroeconomic variables, the default probability of a central SOE would be 0.06ppt higher, which would be equivalent to a rating one notch lower at A-minus. For a local SOE, the default probability would rise by 0.1ppt, which would imply a rating two notches lower at BBB. Finally, for an LGFV the default probability would rise by 0.17ppt or an implied rating close to BBB-minus.

The estimated coefficient on a variable that measures the proportional stake held by the public sector was also negative and statistically significant. Using the results from specification 5, the estimated coefficient implies that for an A-rated firm, the default probability would rise by 0.02ppt for every 10ppt increase in public ownership. We were able to reject the null hypothesis that ownership variables have no impact on default probability at the usual levels of confidence (Table 8).

Table 8. Wald Test Results of Coefficients of State Ownership Variables

Specification with All Macro Variables		Specification with All Macro Variables	
Constraints on parameter vector **ζ**	Chi-squared	Constraints	Chi-squared
(1) $\zeta_{\text{Central SOE}} = 0$	23.20**	(1) $\beta_{\text{SOE shareholding}}=0$	106.79**
(2) $\zeta_{\text{Local SOE}} = 0$	121.59**		
(3) $\zeta_{\text{LGFV}} = 0$	48.44**		
Wald test statistic	46.86**	Wald test statistic	106.79**

** represents statistically significant at 5 percent level.

Separately, we estimated the model for the sample of state-owned enterprises (SOEs) and local government financing vehicles (LGFVs) (Table 9). While coefficients on firm specific variables remained significant with expected signs, the results reiterated that central SOEs have lower default probabilities than those for local SOEs, which were lower than LGFVs. The differences of ratings are similar to specification 5 in Table 8.

Table 9. Default Probabilities Pooled Regression for state-owned enterprises and local government financing vehicles, Q1-2006 to Q3-2014

	Dependent variable: logit function of probability of default (specifications 1-12)											
	1	2	3	4	5	6	7	8	9	10	11	12
Constant	-6.74**	-4.14**	-4.09**	-3.85**	-52.95**	-101.43**	-4.63**	-2.31**	-2.26**	-1.86**	-51.02**	-99.52**
	(-12.26)	(-5.94)	(-5.78)	(-4.63)	(-8.81)	(-16.67)	(-9.07)	(-3.66)	(-3.52)	(-2.39)	(-8.50)	(-16.40)
ln(1-EBIT/TA)	-4.76**	-4.74**	-4.76**	-10.01**	-4.76**	-5.98**	-4.38**	-4.50**	-4.51**	-9.81**	-4.52**	-5.76**
	(-3.57)	(-3.51)	(-3.52)	(-7.25)	(-3.48)	(-4.36)	(-3.30)	(-3.34)	(-3.35)	(-7.13)	(-3.31)	(-4.22)
WC/TA	-1.61**	-0.60	-0.62	-2.27**	-0.38	-1.35**	-1.24**	-0.28	-0.29	-1.95**	-0.05	-1.03**
	(-4.18)	(-1.30)	(-1.32)	(-4.93)	(-0.81)	(-2.91)	(-3.24)	(-0.60)	(-0.62)	(-4.26)	(-0.11)	(-2.23)
ln(1-RE/TA)	-10.61**	-10.39**	-10.40**	-5.99**	-11.07**	-8.99**	-10.63**	-10.35**	-10.37**	-5.97**	-11.02**	-8.97**
	(-10.58)	(-10.27)	(-10.28)	(-5.87)	(-10.88)	(-8.85)	(-10.57)	(-10.22)	(-10.23)	(-5.85)	(-10.81)	(-8.83)
Negative DV X ln(1-RE/TA)	21.34**	21.24**	21.25**	16.75**	21.99**	19.80**	21.46**	21.23**	21.24**	16.73**	21.97**	19.79**
	(17.17)	(16.99)	(16.99)	(13.54)	(17.54)	(15.90)	(17.25)	(16.98)	(16.98)	(13.51)	(17.52)	(15.89)
1+ln(TA/TL)	9.26**	8.74**	8.75**	9.33**	8.65**	9.01**	9.20**	8.68**	8.68**	9.26**	8.59**	8.95**
	(38.39)	(33.77)	(33.79)	(37.28)	(33.34)	(35.24)	(38.08)	(33.49)	(33.51)	(37.00)	(33.07)	(34.97)
Size	-0.01**	-0.01**	-0.01**	-0.02**	-0.01**	-0.01**	0.00	0.00	0.00	-0.01**	0.00	-0.01**
	(-3.02)	(-2.52)	(-2.56)	(-5.42)	(-2.02)	(-3.61)	(-1.38)	(-0.94)	(-0.97)	(-3.82)	(-0.44)	(-1.98)
ln(CL/NCL)	-0.0085	-0.0095**	-0.0094**	-0.0028	-0.0094	-0.0066	-0.0074	-0.0088	-0.0087	-0.0020	-0.0086	-0.0058
	(-1.8000)	(-1.9800)	(-1.9700)	(-0.6100)	(-1.9500)	(-1.4000)	(-1.5600)	(-1.8300)	(-1.8100)	(-0.4300)	(-1.7900)	(-1.2300)
Age	0.0089**	0.0101**	0.0100**	-0.0018	0.0119**	0.0058**	0.0081**	0.0095**	0.0094**	-0.0026	0.0112**	0.0051**
	(6.3700)	(7.0700)	(7.0300)	(-1.1800)	(8.1800)	(3.9800)	(5.7800)	(6.5900)	(6.5500)	(-1.7400)	(7.6700)	(3.4300)
Local SOE dummy	1.40**	1.20**	1.20**	1.19**	1.21**	1.19**						
	(4.21)	(3.19)	(3.20)	(3.26)	(3.22)	(3.20)						
Central SOE dummy	2.20**	1.92**	1.92**	1.91**	1.94**	1.91**						
	(6.28)	(4.98)	(4.99)	(5.07)	(5.03)	(4.99)						
Estimated SOE shareholding							-0.90	-0.90	-0.90	-1.35**	-0.87	-1.18**
							(-1.74)	(-1.73)	(-1.73)	(-2.67)	(-1.67)	(-2.29)
ln(PMI)					11.91**	25.97**					11.89**	25.98**
					(7.98)	(16.90)					(7.96)	(16.91)
Real money supply growth					3.08	17.80**					2.95	17.70**
					(1.71)	(9.35)					(1.63)	(9.29)
Real lending rate					26.62**	-62.78**					27.20**	-62.41**
					(3.78)	(-7.73)					(3.86)	(-7.68)
PBV ratio						-2.27**						-2.27**
						(-25.22)						(-25.26)
Dummies												
Industry	N	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y
Seasonal	N	N	Y	Y	Y	Y	N	N	Y	Y	Y	Y
Quarterly	N	N	N	Y	N	N	N	N	N	Y	N	N
No. of obs.	29,435	29,435	29,435	29,435	29,435	29,435	29,435	29,435	29,435	29,435	29,435	29,435
R-squared	12.4%	12.8%	12.9%	17.8%	13.1%	14.8%	12.3%	12.8%	12.8%	17.7%	13.1%	14.7%

Source: Authors' estimates.

1/ ** represents statistically significance at 5 percent level. T-statistics in parentheses.

Economic and financial conditions

The estimated coefficients on the economic and financial conditions variables—denoted by $\boldsymbol{\gamma}$ in (16)—while correctly signed and statistically significant in some specifications—are much less robust than the firm-specific fundamentals. The inclusion of the market price-to-book ratio as an indicator of "market sentiment" had a large effect on the estimates for some of these variables. Most robust was the finding that a rise in the PMI index of manufacturing activity lowered the probability of default, all else equal. These results are consistent with Bonfim (2009) and Jacobson et al. (2013). To put the estimates into context, consider an A-rated firm with a 1-year default probability of 0.07 percent (Table 3). Using the results from specification 5 in Table 8, for a two standard deviation (2pt) decline in the PMI, this firm's default probability would rise by about 0.09ppt, which pushes the rating two notches lower to BBB. The impact of the aggregate financial variables is less robust and highly sensitive to the inclusion of market sentiment indicators, such as the PBV ratio.

Overall model fit and robustness

In line with the previous literature, we find that firm-specific variables contribute more to in-sample predictive power default probabilities than macroeconomic variables. Measures of model fit, including adjusted R-squared, improve only marginally with macroeconomic variables, notwithstanding the statistical significance of their marginal effects. The adjusted R-squared of the estimations ranged from 16-23 percent and while this range is lower than for the study of U.S. firms by Altman et al. (2011) it is not unusually low for this literature and is close to the numbers reported by Benito et al. (2004) and Bonfim (2009).

We find that firm-specific variables still contribute more to in-sample predictive power of default probabilities than macroeconomic variables even if the sample excludes central and local state-owned enterprises and local government financing vehicles. The predictive power of monetary conditions becomes less significant for a sample excluding SOEs and LGFVs which may suggest that these firms are more sensitive to monetary policies, perhaps because of their easier access to credit.

At the same time, it suggests that other important variables may be missing from the model, including unobservable market sentiment (which we may have captured imperfectly using the PBV ratio) and adverse shocks to the market value of assets, which are stemming from the information asymmetry between investors. Estimates from panel regressions that include fixed-effects (not shown) are quantitatively similar to the results in Table 6—the size of significant firm-specific and macroeconomic variables are somewhat lower and higher, respectively. The adjusted R-squared rises to about 33 percent.

Table 10. Default Probabilities Pooled Regression excluding state-owned firms, Q1-2006 to Q3-2014

	Dependent variable: logit function of probability of default (specifications 1-6)					
	1	2	3	4	5	6
Constant	-3.59**	-2.28**	-1.70**	-1.81**	-100.85**	-168.88**
	(-8.42)	(-3.73)	(-2.70)	(-2.02)	(-14.22)	(-24.16)
ln(1-EBIT/TA)	-3.82**	-3.82**	-3.92**	-10.61**	-4.77**	-6.00**
	(-2.66)	(-2.66)	(-2.73)	(-7.29)	(-3.29)	(-4.16)
WC/TA	1.88**	2.44**	2.39**	0.36	2.47**	1.14**
	(4.12)	(4.83)	(4.73)	(0.71)	(4.88)	(2.24)
ln(1-RE/TA)	-7.33**	-6.98**	-6.98**	-0.49	-6.54**	-4.53**
	(-6.43)	(-6.10)	(-6.11)	(-0.43)	(-5.68)	(-3.95)
Negative DV X ln(1-RE/TA)	16.76**	16.42**	16.43**	9.56**	16.11**	13.67**
	(12.99)	(12.67)	(12.69)	(7.39)	(12.37)	(10.52)
1+ln(TA/TL)	9.58**	9.27**	9.29**	9.30**	9.22**	9.22**
	(44.48)	(40.24)	(40.33)	(41.83)	(40.08)	(40.49)
Size	-0.14**	-0.13**	-0.13**	-0.15**	-0.12**	-0.13**
	(-9.60)	(-8.92)	(-8.89)	(-9.13)	(-8.62)	(-8.94)
ln(CL/NCL)	-0.0118**	-0.0121**	-0.0117**	-0.0014	-0.0078**	-0.0072**
	(-3.3700)	(-3.4300)	(-3.3100)	(-0.4000)	(-2.2100)	(-2.0600)
Age	0.0083**	0.0082**	0.0081**	0.0008	0.0083**	0.0057**
	(5.4500)	(5.0600)	(5.0000)	(0.5300)	(5.1100)	(3.5100)
ln(PMI)					24.91**	44.40**
					(14.08)	(25.10)
Real money supply growth					-25.39**	-3.39
					(-11.69)	(-1.45)
Real lending rate					107.13**	-10.51
					(12.59)	(-1.07)
PBV ratio						-3.08**
						(-28.25)
Dummies						
Industry	N	Y	Y	Y	Y	Y
Seasonal	N	N	Y	Y	Y	Y
Quarterly	N	N	N	Y	N	N
No. of obs.	28,823	28,823	28,823	28,823	28,823	28,823
R-squared	17.7%	17.9%	18.0%	23.9%	18.5%	20.1%

Source: Authors' estimates.
1/ ** represents statistically significance at 5 percent level. T-statistics in parentheses.

Borrowing costs as dependent variable

A reasonable objection to our approach might be that market-based default probabilities are estimated using models that rely on assumptions, especially related to the distribution of asset values. Might not a better approach rely on observable indicators of default risk, such as bond spreads or borrowing costs? We tested this assertion using (16) and a borrowing rate-based indicator of the probability of default as the dependent variable. This firm-specific borrowing rate variable is calculated as the gross interest expense divided by total interest-bearing liabilities using balance sheet data from WIND. We then converted this borrowing rate into a default probability by assuming a zero recovery rate (an assumption that affects mainly the constant term in the regression). If borrowing rates contain useful information for credit risk, we should expect to find correctly-signed and statistically significant coefficients on the firm-specific variables.

We estimated variants of (16) for an identical but smaller sample of firms using the borrowing rate- and market based-default probabilities. The availability of effective borrowing costs reduced our sample to 1,969 firms. The results are shown in Table 11. We find that the estimated coefficients in the borrowing rate specifications are either "incorrectly" signed, smaller in size, or statistically insignificant. For example, profitability appears to have little effect and higher leverage implies a lower default probability, all else equal. In contrast to the results above, public ownership tends to lower the probability of default, all else equal.

We conclude from these results that equity market-based default probabilities are more effective indicators of stand-alone default risk than borrowing costs in China. We conjecture that this reflects the contribution of implicit guarantees provided by the state to SOEs and LGFVs. These guarantees likely benefit creditors, including banks, non-bank lenders (such as trusts), and bond holders. Equity holders, in contrast, do not benefit from such implicit guarantees and appear to expect that, in the event of a firm struggling to meet its obligations, third-party support will do little to boost the value of an equity stake. Of course, by maintaining the firm as a going concern, such bailouts ensure that the implicit call option on asset values held by equity holders retains some value, but the effect on the value of equity is likely to be much lower than that for debt. This is particularly true if bailouts takes the form of increasing public ownership and a dilution of existing equity holders.

Table 11. Default Probabilities Pooled Regression, Q1-2006 to Q4-2014

	Dependent variable: logit function of probability of default							
	Borrowing rate-based probability of default				Market-based probability of default			
	1	2	3	4	5	6	7	8
Constant	4.84**	5.05**	5.01**	5.02**	-3.26**	-3.67**	-3.52**	-3.43**
	(79.99)	(59.26)	(58.18)	(58.51)	(-5.17)	(-4.09)	(-3.89)	(-3.81)
Firm specific variables								
ln(1-EBIT/TA)	-0.08	-0.01	-0.02	-0.02	-3.60**	-7.73**	-7.76**	-7.72**
	(-0.55)	(-0.09)	(-0.13)	(-0.11)	(-2.17)	(-4.45)	(-4.46)	(-4.44)
WC/TA	0.69**	0.75**	0.76**	0.76**	0.91	-0.26	-0.44	-0.33
	(12.91)	(13.50)	(13.74)	(13.70)	(1.53)	(-0.40)	(-0.67)	(-0.51)
ln(1-RE/TA)	-0.91**	-0.84**	-0.84**	-0.84**	-8.47**	-4.24**	-4.26**	-4.25**
	(-6.99)	(-6.35)	(-6.33)	(-6.34)	(-5.62)	(-2.74)	(-2.74)	(-2.74)
Negative DV X ln(1-RE/TA)	-0.10	-0.18	-0.14	-0.14	18.97**	13.94**	13.76**	13.72**
	(-0.67)	(-1.15)	(-0.90)	(-0.91)	(11.16)	(7.97)	(7.82)	(7.82)
1+ln(TA/TL)	-0.57**	-0.64**	-0.64**	-0.64**	8.46**	8.32**	8.36**	8.30**
	(-16.57)	(-18.29)	(-18.21)	(-18.20)	(23.88)	(23.05)	(23.13)	(22.99)
Size	0.01**	0.01**	0.01**	0.01**	-0.01	-0.02**	-0.02**	-0.01**
	(7.89)	(9.06)	(8.52)	(7.87)	(-1.84)	(-3.02)	(-3.33)	(-2.23)
ln(CL/NCL)	-0.0025**	-0.0021**	-0.0020**	-0.0020**	-0.0057	-0.0040	-0.0048	-0.0046
	(-4.6900)	(-3.9600)	(-3.7500)	(-3.7700)	(-1.0500)	(-0.7500)	(-0.9000)	(-0.8600)
Age	-0.0012**	-0.0014**	-0.0015**	-0.0015**	0.0054**	-0.0022	-0.0012	-0.0014
	(-6.9200)	(-7.9400)	(-8.8600)	(-8.6600)	(2.8900)	(-1.0800)	(-0.5700)	(-0.6800)
LGFV dummy			0.21**				-1.42**	
			(3.86)				(-2.20)	
Local SOE dummy			0.09**				-0.60**	
			(4.25)				(-2.41)	
Central SOE dummy			0.07**				0.17	
			(2.65)				(0.54)	
Estimated SOE shareholding				0.21**				-1.30**
				(4.98)				(-2.65)
Dummies								
Industry	N	Y	Y	Y	N	Y	Y	Y
Seasonal	N	Y	Y	Y	N	Y	Y	Y
Quarterly	N	Y	N	N	N	Y	N	N
No. of obs.	15,580	15,580	15,580	15,580	15,580	15,580	15,580	15,580
R-squared	0.078	0.158	0.160	0.160	0.096	0.143	0.144	0.144

Source: Authors' estimates.
1/ ** represents statistically significance at 5 percent level. T-statistics in parentheses.

VI. Conclusion

Efforts to assess default risks for Chinese firms can sometimes feel like a lost cause. At least in the bond market, actual defaults are sufficiently rare as to provide no guidance. We find credit spreads and borrowing costs to be largely unaffected by firm fundamentals—indeed, creditors appear to be more focused on implicit guarantees than underlying credit quality. An alternative but common approach until now has been to rely on descriptive statistics from the firm-specific fundamentals as reported in financial accounts. Unfortunately, this method has at least two shortcomings: it tells us little about the probability of default and it is backward looking.

Can we do better? Our preliminary answer is "yes," especially at the individual stock level. Notwithstanding caution regarding the use of highly volatile Chinese equity market prices as an input, we conclude that structural credit models that estimate the stand-alone 1-year probability of default can be usefully applied in China. We find that these default probabilities have provided signals of increased financial stress for some firms, including the first onshore corporate bond default. We also find that these probabilities respond in intuitively and quantitatively sensible ways to changes in a firm's fundamentals, including profitability and balance sheet strength. One caveat is that macroeconomic and financial conditions appear to have less impact than might be expected; for example, investor speculation about "policy stimulus" can offset the impact of an actual deterioration in broad economic and financial conditions. In some sense, this forward-looking aspect of the model should be welcomed even though there is always the possibility that equity valuations overshoot.

References

Altman, Edward, 1968, “Financial Ratios, Discriminant Analysis, and the Prediction of Corporate Bankruptcy,” *Journal of Finance*, Vol. 23, pp. 189-209.

______________, Neil Fargher and Egon Kalotay, 2011, “A Simple Empirical Model of Equity-Implied Probabilities of Default” *Journal of Fixed Income*, Vol. 20 (3), pp. 71-85.

______________, and Edith Hotchkiss, 2006, “Corporate Financial Distress and Bankruptcy” John Wiley and Sons, New York, 3rd edition.

Ardia, David, David, Juan, Arango, Ospina, and Gómez, Norman Diego Giraldo, 2011, “Jump-Diffusion Calibration Using Differential Evolution,” *Wilmott*, pp. 76–79.

Benito, Andrew, Javier Delgado and Martínez Pagés, 2004, "A synthetic indicator of financial pressure for Spanish firms", *Banco de España Working Paper*, No.411.

Bonfim, Diana, 2009, “Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics”, *Journal of Banking & Finance*, Vol. 33, pp. 281–299.

Chan-Lau, Jorge A., 2006, “Market-Based Estimation of Default Probabilities and Its Application to Financial Market Surveillance,” *IMF Working Paper* No. 06/104.

Chen, Yan and Guanglei Chu, 2014, “Estimation of Default Risk Based on KMV Model – An Empirical Study for Chinese Real Estate Companies,” *Journal of Financial Risk Management*, Vol. 3, pp. 40-49.

Crosby, Peter, and Jeff Bohn, 2003, *Modeling Default Risk*, Moody’s KMV Company.

Damodoran, Aswath, 1996, *Investment Valuation*, John Wiley & Sons, New York.

Gray, Dale, 2009, “Understanding Moody’s KMV (MKMV) Application of Contingent Claims Analysis (CCA) for Financial Institutions and Corporates and Use in Stress Testing,” *unpublished transcript*.

____________ and Samuel Malone, 2008, *Macrofinancial Risk Analysis*, Wiley Finance, UK.

Huang, Jing-Zhi and Ming Huang, 2012, “How Much of the Corporate-Treasury Yield Spread Is Due to Credit Risk?” *Review of Asset Price Studies*, Vol. 2 (2), pp. 153-202.

Hui, Cho-Hoi, Wong, Tak-Chuen, Lo, Chi-Fai, and Huang, Ming-Xi, 2005, “Benchmarking Model of Default Probabilities of Listed Companies,” *Journal of Fixed Income*, Vol. 15, No. 2, pp. 76-86.

International Monetary Fund, 2011, "United Kingdom: Stress Testing the Banking Sector Technical Note," Country Report No. 11/222 (Washington, D.C.: International Monetary Fund).

Jacobson, Tor, Jesper Lindé and Kasper Roszbach, 2013, "Firm Default And Aggregate Fluctuations," *Journal of the European Economic Association*, European Economic Association, Vol. 11 Issue.4, pp. 945-972.

Jobst, Andreas A. and Dale Gray, 2013, "Systemic Contingent Claims Analysis – Estimating Market-Implied Systemic Risk," *IMF Working Paper* 13/54.

Kou, S.G, 2008, "Jump-Diffusion Models for Asset Pricing in Financial Engineering," Chapter 2 in *Handbooks in Operational Research and Management Science*, Eds. J.R. Birge and V. Linetsky, Vol. 15, Elsevier.

Leland, Hayne E., 2006, "Predictions of Default Probabilities in Structural Models of Debt," in *The Credit Market Handbook - Advanced Modeling Issues*, Ed. H. Gifford Fong, John Wiley & Sons, Inc., Hoboken, New Jersey.

Merton, Robert C., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance*, Vol.29, pp. 449-470.

Newey, W., and K. West, 1987, "A Simple, Positive Semidefinite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, Vol. 55, pp. 703-708.

Sun, Zhao, David Munves and David T. Hamilton, 2012, "Public Firm Expected Default Frequency (EDF™) Credit Measures: Methodology, Performance, and Model Extensions", *Moody's Analytics – Capital Market Research*.

Standard & Poor's Rating Services, 2014, *Default, Transition, and Recovery: 2013 Annual Global Corporate Default Study And Rating Transitions*.

Standard & Poor's Rating Services, 2010, *General Criteria: Stand-Alone Credit Profiles: One Component Of A Rating*, (October).

Zhou, Chunsheng, 1997, "A Jump-Diffusion Approach to Modeling Credit Risk and Valuing Defaultable Securities," *Finance and Economics Discussion Series* 1997-15, Board of Governors of the Federal Reserve System.

Zhang, Wenlang, Gaofeng Han and Steven Chan, 2014, "How Strong are the Linkages between Real Estate and Other Sectors in China?," *HKIMR Working Paper*, No. 11.