Assessing Default Risks for Chinese Firms: China is Not So Different After All

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Abstract

We estimate stand-alone 1-year default probabilities for a large sample of non-financial firms in China using an equity-based structural credit model. Notwithstanding China's unique financial system, we find that stand-alone default risk: is sensitive to standard metrics of corporate health, economic growth, and financial conditions, in a comparable way to other countries; and is higher for state-owned firms. In contrast, borrowing costs exhibit weaker relationships with credit metrics suggesting less efficient risk-pricing by creditors that may reflect implicit guarantees. Stress tests for a sample including non-listed firms suggest that a large proportion of liabilities would become sub-investment grade in the event a broad adverse shock. We conclude that policies that facilitate corporate restructuring, especially in state-owned enterprises, can mitigate the effects of deleveraging on financial stability.

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[1] This Working Paper should not be reported as representing the views of the IMF. The views expressed in this Working Paper are those of the authors and do not necessarily represent those of the IMF or IMF policy.

I. INTRODUCTION

The opening of China's financial system is bringing new opportunities and challenges to the policymakers, financial institutions, and investors with a stake in its progress. One challenge is to understand and quantify the credit risk of Chinese firms, exposures to which are gradually widening from domestic banks to include domestic non-banks and bondholders, and foreign financial institutions and investors. The size of these exposures is potentially large, commensurate with the scale of China's economy. The likelihood that such exposures will eventually reach globally systemic levels, if not there already, also means that policymakers and regulators outside China will need to better understand and carefully monitor these credit risks.

Of course, a large suite of robust and sophisticated methods to quantify credit risk already exists but can it be usefully applied in China? China's unique financial history and its current institutional arrangements, including a dominant role of the state in many aspects of financial activity, could mean that traditional tools will not work. A related complication is the absence of a full credit cycle in China, or at least a cycle with relevance to today's economy, which can help to calibrate risks. Earlier cases of rising defaults and asset quality deterioration reflected deep structural reforms of state-owned enterprises (SOEs) and imposed financial losses almost exclusively on large SOE banks. The situation now is more complex, with a mix of SOEs and privately-owned enterprises (POEs) as borrowers and a larger range of banks, trusts, bondholders, and non-residents as creditors. The next credit cycle may result from slower economic growth or excess leverage in particular sectors, rather than policy-directed structural reforms. 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 SOE firms, fragmented domestic markets with different investors, a relatively closed capital account, and a smaller influence of global investors.

In this paper, we assess whether standard credit risk assessment tools can be usefully applied in China. First, 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 the mapping 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."

We then follow Altman, Fargher, and Kalotay (2011) (henceforth Altman et al.) and model the link between equity market-based assessments of default probabilities and accounting-based measures, other firm-specific characteristics, and macroeconomic and financial variables. We compare the results from this model to one using borrowing costs (or effective interest rates) to calculate default probabilities. This is a useful exercise for at least four reasons. First, it helps confirm whether the same firm-specific and macroeconomic variables thought to influence default probabilities in developed market economies can be useful for inference in China. Second, it can determine the extent to which firm ownership—whether the firm is private or state-owned—influences default probabilities. This can help guide market risk pricing but also inform policymakers regarding the possible implications for corporate sector stability in the transition to a larger role for mixed-ownership firms in some sectors of the economy. 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.

We are contributing to a new but growing literature on credit risk in China. Zhang, Han, and Chan (2014) use a structural model to show that default probabilities co-move with the business cycle and are higher in sectors known to suffer from overcapacity. Chivakul and Lam (2014) find that pockets of highly leveraged firms account for a large share of total corporate debt.

II. Market-based default probabilities for Chinese firms

A. Methodology

We start from the standard Merton (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*—at which its cashflows 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. As first described by Merton (1974), the value of equity *E* can thus 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. 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, σ is the instantaneous volatility of *V* conditional on that the jump does not occur, *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 only one jump can occur. 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:

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

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

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

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 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 necessitated 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 distress barrier DB where we have denoted $\mu \equiv r$:

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

where

$$d_1 = \frac{ln\dfrac{V}{DB} + \left(r + \dfrac{\sigma^2}{2}\right)T + i(\mu_\pi + {\sigma_\pi}^2)}{\sqrt{\sigma^2 T + i{\sigma_\pi}^2}} \tag{10}$$

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

.

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 but 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:

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

We can now solve for V using (10), (11) and (12) using jump diffusion parameters initially estimated using 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 for each individual firm using:

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

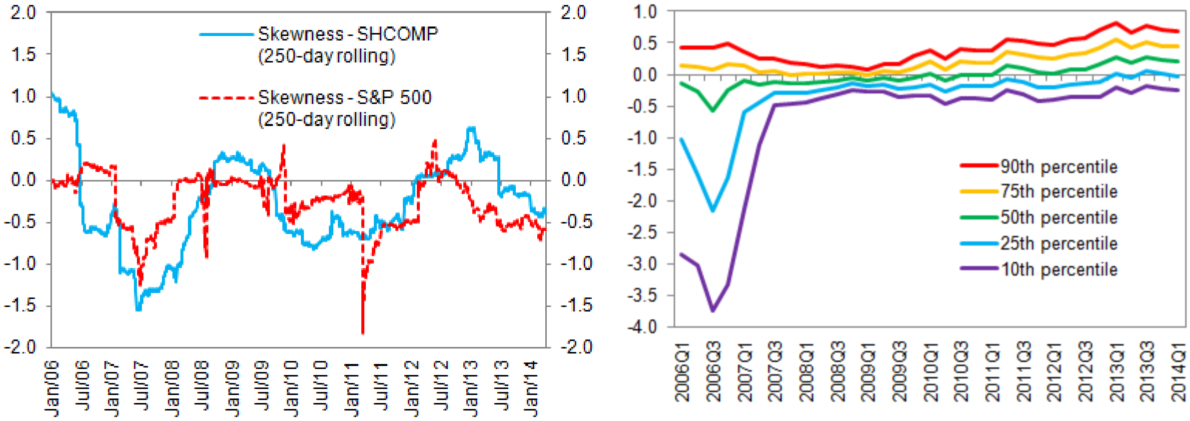
where ξ is the default barrier which we set to 1.

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, provide 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 drift rate in (10)-(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 because they compensate for investors' unobservable aversion to bad outcomes. Other reasons include incentives for management at distressed firms to adopt whatever steps necessary to avoid default including, for example, the sale of non-core assets. This can mean that the default probabilities of poor credit quality firms are underestimated.

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 as possible, 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 (expected return) term that is designed to capture the time-varying 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 estimated 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 a 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 of 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 since 2008, 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 Q1-2014. 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. 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 at 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 distress 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 RMB56 trillion as of Q1-2014, which accounted for about 48 percent of non-equity total social financing (TSF).

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

	Q1 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 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, 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:

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

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

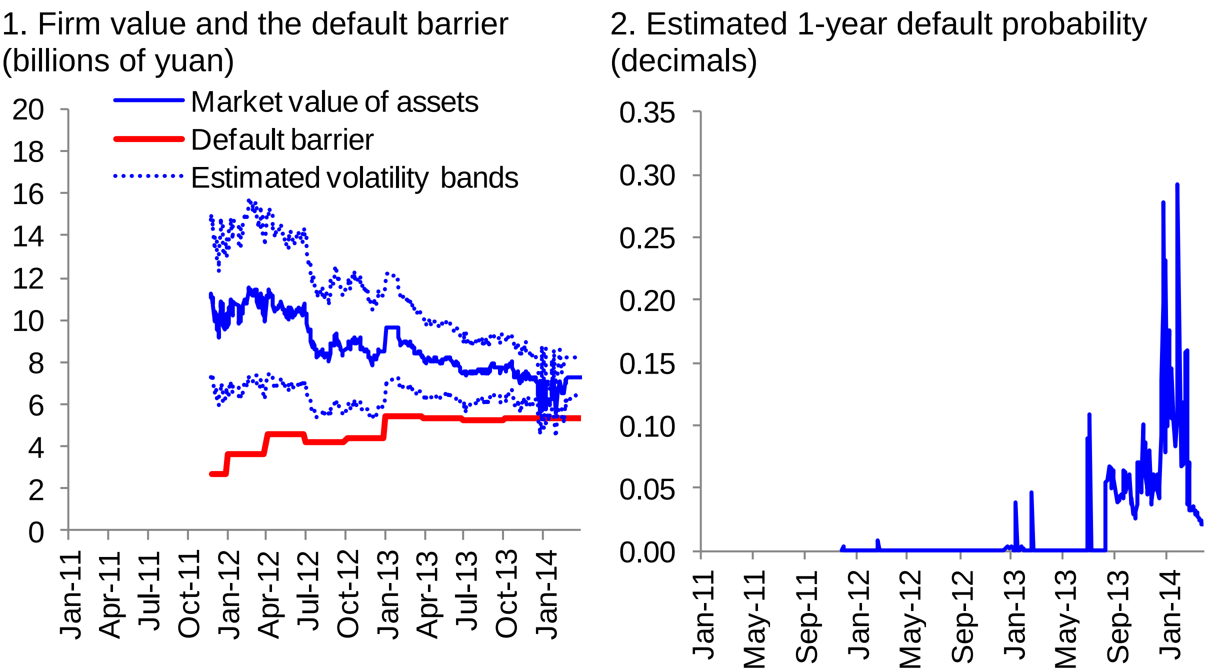
Before discussing some of the results at the aggregate level, we will present in this section some case studies to give a sense of how the model performs for specific firms.

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% 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.

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



Sources: Wind; Bloomberg; and authors' calculations.

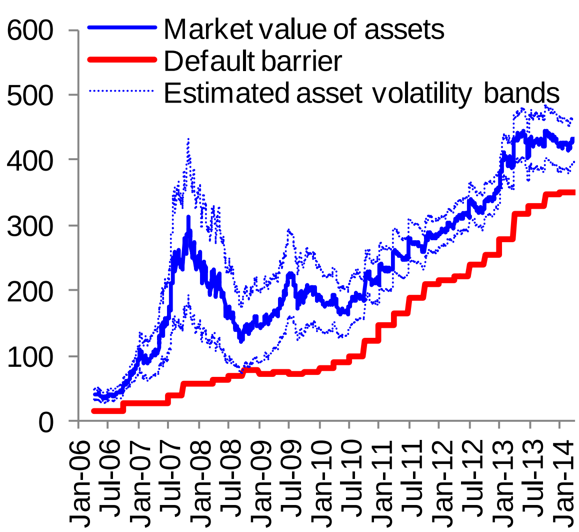
B. Vanke China Ltd

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.

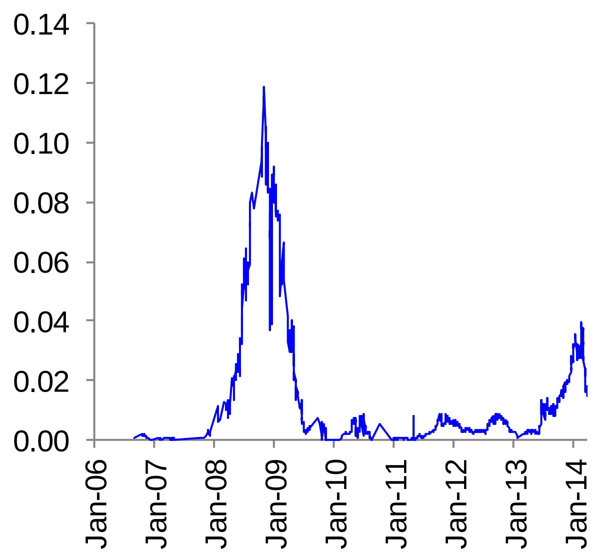
The model shows that the estimated 1-year DP increased significantly during 2008 as the market value of assets declined and asset volatility increased. Following the recovery of 2009 and through early 2013, the DP has stayed low as rising asset values and low volatility offset a large rise in the firm's 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 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 and Stress Testing

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 Q1-2014. 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.

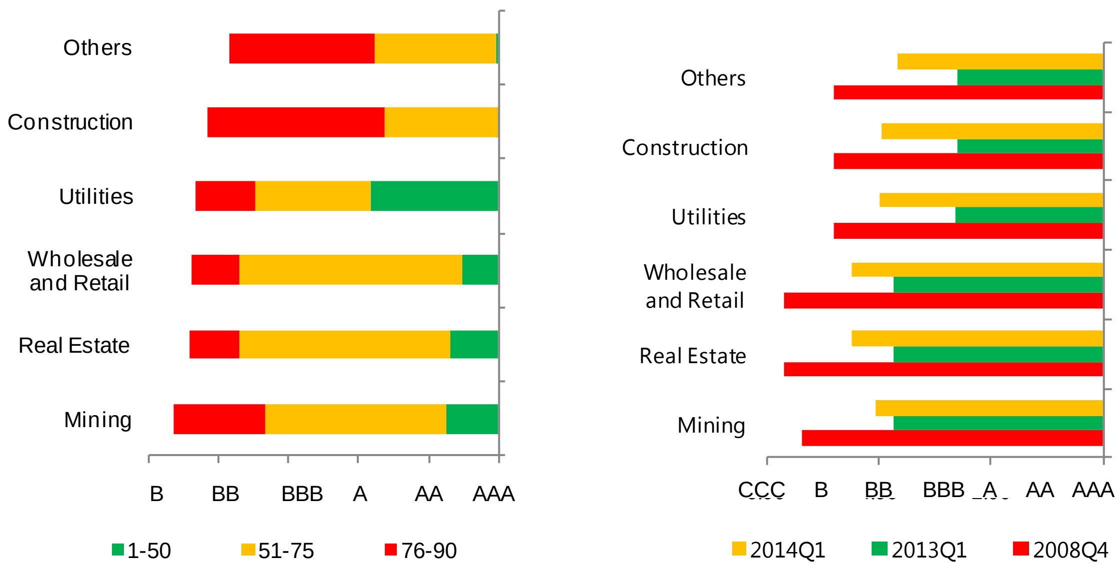
A. Aggregate results by sectors, listing status and ownership

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 real estate, mining, 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 Q1-2014, Q1-2013, 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 and shows that while lower than 2008, default risk appears to have risen over the last year as the economy has slowed and the property market cooled. Once again, mining, real estate, and retail and wholesale stand out as most vulnerable.

Figure 4. Default probability-implied credit rating distributions, Q4-2008, Q1-2013, Q1-2014

1. Distributions by sector, Q1-2014 2. 90th percentile firms by sector

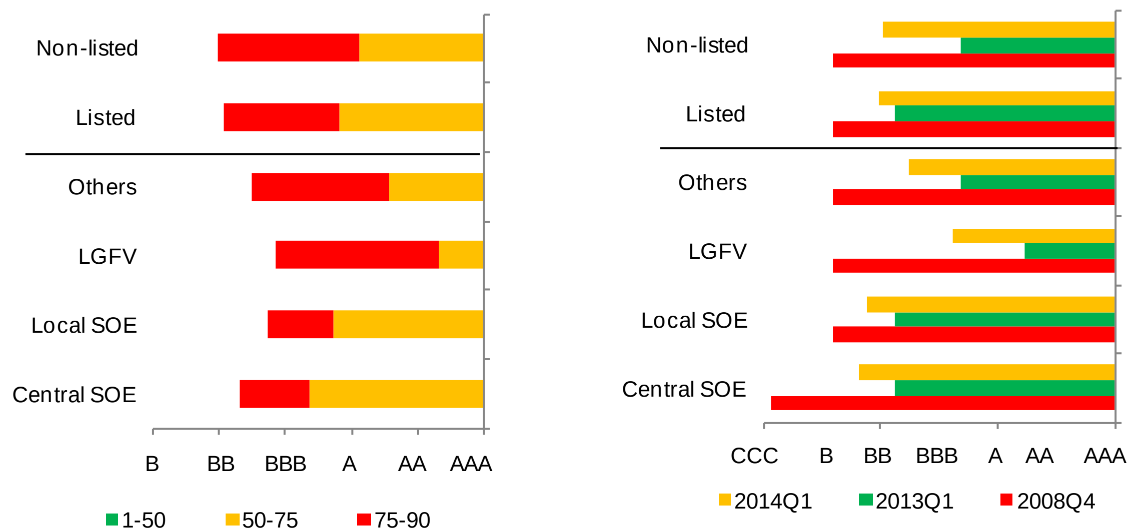


Sources: Wind; Bloomberg; and authors' calculations.

At the end of Q1-2014, 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 centrally-owned SOEs—compared to LGFVs and privately-owned firms. For example, the range of implied credit ratings for central SOE firms between the 75th and 90th percentile are close to BBB-BB. In contrast, the range for LGFVs is almost all investment grade from AA to BBB.

Figure 5. Default probability-implied credit rating distributions, Q4-2008, Q1-2013, Q1-2014

1. Listing status and ownership, Q1-2014 2. 90th percentile firms by listing/ ownership

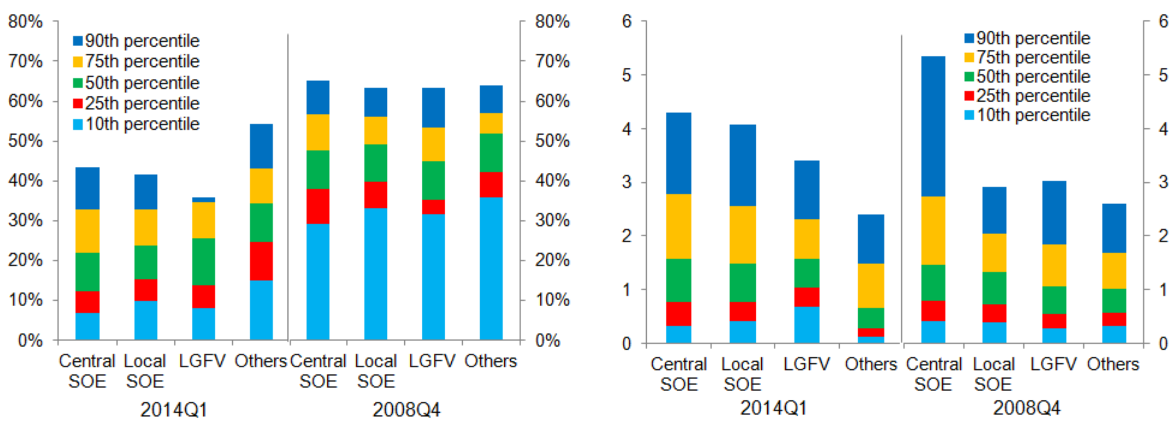


Sources: Wind; Bloomberg; and authors' calculations.

During Q1-2014, 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 and even declined for central SOEs. Lower default probabilities for LGFVs may be attributable to lower asset volatility and leverage.

Figure 6. Leverage and asset volatility by ownership Q1-2014 vs 2008

1. Asset volatility by ownership (percent) 2. Debt-to-equity ratio by ownership



Sources: Wind; Bloomberg; and authors' calculations.

B. Stress test

In this section, we assess how default probabilities might change in an adverse scenario. We implement this scenario by assuming lower equity market valuations and higher equity price volatilities. Our aim is to assess the sensitivity of our estimates of default probabilities to market-based inputs and, as a result, provide an initial assessment of the potential cost of defaults in the event of an economy-wide shock.

For the stress scenario, we use the balance sheet variables as reported in Q1-2014 for listed firms and end-2013 for non-listed firms. We then apply the parameters for the distribution of asset values (including drifts, jumps, and volatilities) that correspond to the quarter between Q1-2006 and Q1-2014 in which each firm's default probability reached the 90th percentile. In practice, we find that these parameters values correspond to the fitted distributions from Q3 or Q4-2008—in other words, default probabilities were at their highest in late 2008. We make two observations about this approach. First, it clearly represents a tail event, albeit one taken from the empirical distribution of default probabilities, and does not reflect the market's current assessment. Second, it implicitly assumes that default risk is highly correlated across firms. This assumption does not seem unreasonable if we are concerned about the impact of macroeconomic shocks and is consistent with previous literature that has examined the time-varying correlation of default probabilities for Chinese firms (Chen and Chu, 2014)

Calibration

The calibrations of this stress test are presented as distributions of firm-specific shocks to equity valuations and asset volatilities in Table 4. For simplicity, we report the annualized standard deviation of daily returns of firm value instead of breaking down the distribution parameters into drift and jump diffusion components. For the 75th percentile firm, the stress scenario assumed that asset volatility increases almost 10 percentage points (ppts) from Q1-2014 levels to 51.4 percent and the equity market capitalization declined about 15 percent.

Table 4. Stress test calibration: Changes in Asset Volatility and Market Capitalization

	Change in asset volatility (percentage points)		Change in market capitalization (percent))	
	Stressed	2014Q1	stressed	2014Q1
10th percentile	22.8	12.7	43.1	25.0
25th percentile	32.6	21.6	15.4	10.7
50th percentile	42.0	31.9	-1.6	0.2
75th percentile	51.4	41.8	-14.8	-7.1
90th percentile	60.5	50.6	-27.4	-14.4

Source: Authors' calculations.

The calibrations by sector are shown for the 25th and 75th percentile firms in Table 5. The largest increases for the upper quartile firm in terms of asset volatility are for mining (higher by 27 ppts to 62 percent) and real estate (higher by 27 ppts to 56 percent). The steepest declines for the lowest quartile firm in market capitalization are for mining (a fall of 23 percent) and utilities (a fall of 22 percent). In general, we find that the more cyclically-sensitive firms (with the exception of utilities) have typically suffered the largest changes in asset volatility and market valuation. It is worth noting that the calibration for construction sector uses a relatively small 8ppt change in volatility and a 15 percent decline in valuation.

Table 5. Stress test calibration: Changes in Asset Volatility and Market Capitalization

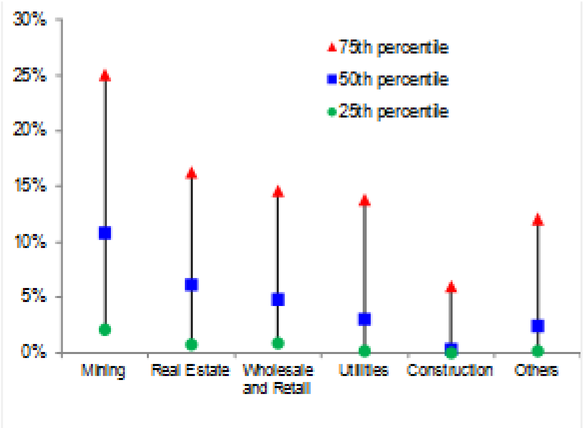
	75th percentile (highest quartile) Change in asset volatility (percentage points)		25th percentile (lowest quartile) Change in market capitalization (percent)	
Sector	Stressed	2014Q1	Stressed	2014Q1
Mining	61.8	35.3	-22.5	-18.2
Real Estate	56.0	28.6	-19.5	-5.1
Manufacturing	50.1	42.0	-14.0	-6.7
Wholesale and Retail	50.1	33.5	-17.4	-7.1
Utilities	50.1	28.2	-21.7	-8.3
Transportation	49.9	32.6	-17.8	-7.5
Construction	39.1	30.7	-15.3	-8.6

Source: Authors' calculations.

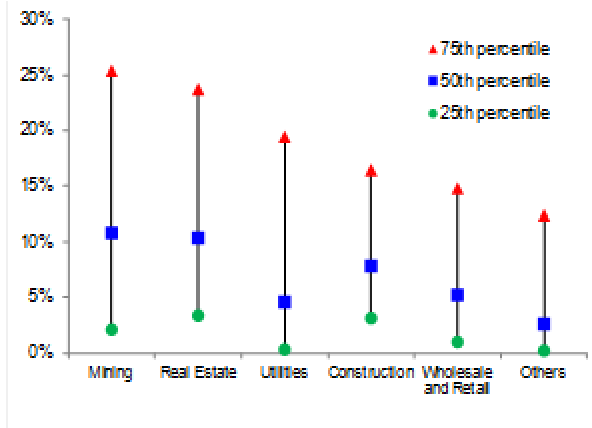
Stress test results indicate that the changes in default probabilities were driven mainly by higher volatilities. Specifically, we find that the largest increases in default risk are for mining, real estate, wholesale and retail, and utilities (Figure 7).

Figure 7. Corporate Sector Default Probabilities of listed firms and non-listed firms

1. Corporate Sector Default Probabilities of listed firms after Stress (Percent)



2. Corporate Sector Default Probabilities of non-listed firms after Stress (Percent)



Sources: Wind; Bloomberg; and authors' calculations.

A natural question to ask is how would such an adverse default scenario play out in China? Our analysis so far has been on a stand-alone risk basis but there may be a higher probability that some costs associated with effective defaults will not be paid by bondholders or other creditors due to third-party bailouts (in various forms). This appears to have been one reason behind the remarkably low rate of actual defaults during our sample period. But the costs would have to be borne somewhere, whether by banks or the public sector, including SOE parents or government. One useful exercise is estimate the potential cost of corporate defaults in an adverse scenario without assuming how these costs would be distributed. We do this by calculating the cumulative distribution of the liabilities of the sample of firms over the closed interval of default probabilities [0,1].

Adjusting for cross-shareholdings

As a preliminary step in this exercise, we need to adjust sample liabilities for cross-shareholdings, particularly among SOEs which account for a large share of firms in our sample. As at the end of Q1-2014, the sample of non-listed firms included 157 central SOEs, 382 local SOEs, and 748 LGFVs which accounted for 81 percent of the total number and 92 percent of total liabilities of the non-listed sample at the end of Q1 2014. The large overlaps in liabilities between our sample of listed and non-listed firms are due mainly to non-listed parent SOEs holding large shares in listed subsidiaries. To reduce the incidence of double-counting, we reduce the total liabilities of the listed firm by the share of the firm owned by the parent.

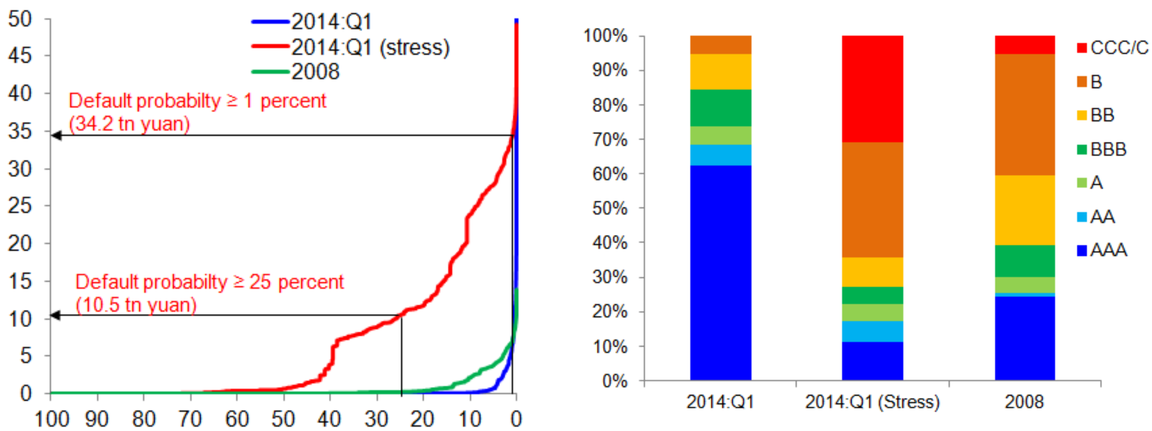
Figure 8 shows the cumulative distributions in yuan of sample liabilities over the default probability interval [0,1] for Q3-2008, Q1-2014, and the stress scenario described in section III B. Even though the stress test scenario uses the same distributional parameters as

Q3-2008, the nominal value of liabilities with default probabilities above various levels, such as 0.25, 0.10, and 0.05 is significantly higher, reflecting the rapid accumulation of debt between 2008-14. In fact, we estimate that the total liabilities owed by firms with default probabilities equivalent to a CCC rating or below will increase to 10.5 trillion yuan or about 25 percent of the total (9.7 trillion yuan or 21 percent if local LGFVs are excluded) in the stress scenario. In the implicit CCC and below rating group, firms in the real estate and mining sectors accounted for 8.8 percent and 7.5 percent of the total number of firms compared to their shares of 6.0 percent and 3.3 percent in the full sample.

Figure 8. Debt-at-risk in the stressed scenario

1. Cumulative Distribution of Corporate Debt by Default Probability

2. Cumulative distribution of liabilities weighted by default probabilities (Percent of total liabilities)



Sources: Wind; Bloomberg; and authors’ calculations.

V. Determinants of Default Probabilities in China

In this section, we establish the empirical link between market-based assessments of default probabilities and a set of potential explanatory variables including accounting-based measures traditionally used to assess default risk and macroeconomic variables for Chinese firms. Our aim is to understand whether market-based measures of default probability are affected by factors that, intuitively, should influence credit risk and which are found to be important in other economies. In other words, are we justified in using standard methods of credit risk assessment in China or is China different?

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 a logistic transformation of risk-neutral default probabilities 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.

A. Methodology and data

Specification and estimation

We use a standard logit pooled regression specification which in it most general form can be written as:

$$y_{it} = \alpha + \boldsymbol{\beta}'\boldsymbol{X}_{it} + \boldsymbol{\gamma}'\boldsymbol{Z}_t + \boldsymbol{\zeta}'\boldsymbol{D} + \lambda_t + \varepsilon_{it} \tag{16}$$

Where

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

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, $\boldsymbol{X_{it}}$ is a (k x 1) vector of k variables specific to firm i, $\boldsymbol{\gamma}$ is an (l x 1) vector of parameters, $\boldsymbol{Z_t}$ is an (l x 1) vector of macroeconomic variables, $\boldsymbol{\zeta}$ 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. 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 $\boldsymbol{X_{it}}$ in (16) directly follows Altman et al. (2011) and is shown in Table 6. 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 6. 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 6. 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	+

Macroeconomic explanatory variables

Our choice of macroeconomic explanatory variables denoted by $\boldsymbol{Z}_{\mathbf{t}}$ in (16) includes a survey of manufacturing activity, monetary conditions, and the real lending rate (Table 7). 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).

Table7. Macroeconomic explanatory variable

Description	Variable	Expected sign
Economic outlook: Official manufacturing PMI	$\ln(PMI_{it-1})$	+
Monetary condition: M2 year-on-year growth deflated by CPI inflation	$Real\ M2\ growth_{it-1}$	+
Monetary condition: Average lending rate deflated by CPI inflation	$Real\ lending\ rate_{it-1}$	–

Industry, period-effect, and ownership dummy variables

We follow Bonfim (2009) and include quarterly (time-effect) and sector dummies as denoted by $\boldsymbol{D}$ 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 a public sector bailout.

B. Results

The results from a range of specifications based on (16) are shown in Table 8.

Table 8. Default Probabilities Pooled Regression, Q1-2006 to Q1-2014

	Dependent variable: logit function of probability of default (specifications 1-10)									
	1	2	3	4	5	6	7	8	9	10
Constant	-4.01**	-2.20**	-2.17**	-47.95**	-4.82**	-3.99**	-2.27**	-2.24**	-47.49**	-4.83**
	(-12.24)	(-4.92)	(-4.76)	(-10.15)	(-9.09)	(-12.19)	(-5.08)	(-4.91)	(-10.05)	(-9.13)
ln(1-EBIT/TA)	-4.76**	-4.54**	-4.72**	-4.02**	-7.84**	-4.69**	-4.49**	-4.69**	-4.00**	-7.79**
	(-5.26)	(-4.99)	(-5.20)	(-4.39)	(-8.33)	(-5.19)	(-4.95)	(-5.16)	(-4.37)	(-8.29)
WC/TA	0.10	0.82**	0.82**	1.19**	-1.12**	0.35	1.04**	1.04**	1.42**	-0.94**
	(0.33)	(2.28)	(2.28)	(3.31)	(-3.13)	(1.15)	(2.91)	(2.91)	(3.95)	(-2.61)
ln(1-RE/TA)	-5.84**	-5.78**	-5.69**	-6.12**	-4.03**	-5.90**	-5.82**	-5.73**	-6.17**	-4.01**
	(-9.03)	(-8.87)	(-8.73)	(-9.39)	(-6.24)	(-9.12)	(-8.94)	(-8.80)	(-9.47)	(-6.21)
Negative DV X	14.80**	14.79**	14.71**	15.18**	12.62**	14.98**	14.92**	14.84**	15.33**	12.64**
ln(1-RE/TA)	(17.99)	(17.89)	(17.78)	(18.35)	(15.49)	(18.26)	(18.10)	(17.99)	(18.59)	(15.55)
1+ln(TA/TL)	9.46**	9.07**	9.07**	9.12**	9.24**	9.42**	9.02**	9.02**	9.07**	9.18**
	(56.66)	(50.43)	(50.43)	(50.68)	(52.99)	(56.31)	(50.11)	(50.11)	(50.35)	(52.65)
Size	-0.01**	-0.01**	-0.01	-0.01	-0.02**	0.00	0.00	0.00	0.00	-0.01**
	(-2.37)	(-2.13)	(-1.88)	(-1.67)	(-4.16)	(-0.25)	(0.01)	(0.25)	(0.54)	(-2.38)
ln(CL/NCL)	-0.002	-0.002	-0.002	-0.003	0.001	-0.001	-0.002	-0.002	-0.002	0.001
	(-0.690)	(-0.740)	(-0.710)	(-1.010)	(0.320)	(-0.490)	(-0.560)	(-0.530)	(-0.820)	(0.460)
Age	0.005**	0.005**	0.005**	0.007**	-0.001	0.004**	0.005**	0.004**	0.006**	-0.002
	(4.860)	(4.840)	(4.750)	(5.920)	(-1.080)	(4.010)	(4.080)	(4.000)	(5.040)	(-1.530)
LGFV dummy	-2.54**	-2.42**	-2.41**	-2.58**	-1.95**					
	(-7.03)	(-6.03)	(-5.99)	(-6.38)	(-4.94)					
Local SOE	-1.36**	-1.42**	-1.41**	-1.56**	-0.94**					
dummy	(-9.39)	(-9.72)	(-9.63)	(-10.68)	(-6.58)					
Central SOE	-0.52**	-0.59**	-0.58**	-0.75**	-0.07					
dummy	(-2.84)	(-3.16)	(-3.12)	(-4.00)	(-0.36)					
Estimated						-2.32**	-2.42**	-2.40**	-2.67**	-1.58**
SOE						(-8.19)	(-8.37)	(-8.32)	(-9.25)	(-5.64)
ln(PMI)				11.29**					11.16**	
				(9.57)					(9.45)	
Real money				9.53**					9.36**	
supply growth				(6.23)					(6.11)	
Real lending				-16.15**					-15.42**	
rate				(-2.72)					(-2.59)	
Dummies										
Industry	N	Y	Y	Y	Y	N	Y	Y	Y	Y
Seasonal	N	N	Y	Y	Y	N	N	Y	Y	Y
Quarterly	N	N	N	N	Y	N	N	N	N	Y
No. of obs.	50,766	50,766	50,766	50,766	50,766	50,766	50,766	50,766	50,766	50,766
R-squared	16.4%	16.6%	16.6%	16.9%	21.2%	16.3%	16.5%	16.6%	16.9%	21.1%

Source: Authors' estimates.

1/ Firm specific variables winsorized at 1th and 99th percentiles. Balance sheet and macro variables lagged by 1 quarter. ** represents statistically significance at 5% level. T-statistics in parentheses.

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 either similar or somewhat higher to the study of U.S. firms by Altman et al. (2011) as shown in Table 9. 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 probability, all else equal. The estimate of the coefficient on ln(1-EBIT/TA) does, however, rise in absolute terms when we include quarterly dummies which suggests that investors extract signals from profits stripping out seasonal effects. 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, and in some cases deeply 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. 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.

Table 9. Comparison of coefficients with Altman's model for US firms

Explanatory variables	Specification 1 coefficients	Altman et al. (2011) coefficients
Constant	-4.01 (-12.24)	2.52 (152)
$\ln\left(1-\frac{EBIT_{it-1}}{TA_{it-1}}\right)$	-4.76 (-5.26)	-4.25 (-55.9)
$\frac{WC_{it-1}}{TA_{it-1}}$	0.10 (0.33)	0.78 (49.8)
$\ln\left(1-\frac{RE_{it-1}}{TA_{it-1}}\right)$	-5.84 (-9.03)	-0.81 (-129)
$Neg.RE\ dummy \times \ln\left(1-\frac{RE_{it-1}}{TA_{it-1}}\right)$	14.80 (17.99)	-
$\left(1+\ln\frac{TA_{it-1}}{TL_{it-1}}\right)$	9.46 (56.66)	2.11 (304)
$IndRisk_{it-1}$	-	-32.25 (-328)
$Size_{it-1}$	-0.01 (-2.37)	0.58 (299)
$\ln\left(\frac{CL_{it-1}}{NCL_{it-1}}\right)$	-0.0020 (-0.6900)	-0.13 (-62.6)
Age_{it}	0.0053 (4.8600)	0.0015 (74.8)

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

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 by 0.13 percent. For the same firm, a decline in the return-on-assets ratio of 10ppts would increase the default probability by 0.03 percent.

Macroeconomic explanatory variables

The estimated coefficients on the macroeconomic variables—denoted by $\boldsymbol{\gamma}$ in (16)—are correctly signed, statistically significant, and robust to changes in specification. A rise in the PMI index of manufacturing activity, an increase in the growth of real monetary aggregates, or a decline in the real lending rate lower the probability of default, all else equal. These results are consistent with Bonfim (2009) and Jacobson et al. (2013). To put these estimated coefficients into context, consider an A-rated firm with a 1-year default probability of 0.07 percent (Table 3). Using the results from specification 4 in Table 8, for a one standard deviation (one point) decline in the PMI, this firm's default probability would rise by about 0.02ppt, which pushes the rating towards the lower end of the A-rating range. The impact of the financial variables is larger. For a one standard deviation (5ppt) fall in real M2 money growth, the default probability for the same firm would rise by 0.25ppt, which implies a downgrade to BBB. Similarly, a one standard deviation increase in the real lending rate (1.6ppt) would increase the default probability by 0.36ppt and imply a downgrade to BBB. We were able to reject the null hypothesis that these macroeconomic and financial variables have no impact on default probability at the usual levels of confidence (Table 10).

Table 10. Wald test results of coefficients of macroeconomic variables

Specification with ln(PMI) only		Specification with ln(PMI) and Real M2 growth only		Specification with ln(PMI), Real M2 growth and Real lending rate	
Constraints	Chi-squared	Constraints	Chi-squared	Constraints	Chi-squared
(1) $\beta_{\ln(PMI)}$=0	170.59**	(1) $\beta_{\ln(PMI)}$=0	151.48**	(1) $\beta_{\ln(PMI)}$=0	83.81**
		(2) $\beta_{\text{Real M2 growth}}$=0	34.07**	(2) $\beta_{\text{Real M2 growth}}$=0	33.14**
				(3) $\beta_{\text{Real lending rate}}$=0	5.46**
Wald test statistics	170.59**	Wald test statistics	96.9**	Wald test statistics	64.93**

Source: Authors' calculations.
** represents statistically significant at 5% level.

Ownership

State ownership appears to increase the stand-alone probability of default, all else equal. 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, consider a privately-owned firm with a 1-year stand-alone probability of default of 0.07 percent and an implicit rating of A. Using the results from specification 4 in Table 8, for the same set of firm-specific and macroeconomic variables, the default probability of a central SOE, local SOE, or LGFV would increase by 0.03ppt, 0.09ppt, and 0.16ppt, respectively. This would imply credit ratings towards the bottom end of the A-range for the central SOE and around the middle of BBB for the local SOE and LGFV. 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 9, the estimated coefficient implies that for an A-rated firm, the default probability would rise by 0.02 percent 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 11).

Table 11. Wald test results of coefficients of state ownership variables

Specification 4		Specification 9	
Constraints on parameter vector **ζ**	Chi-squared	Constraints	Chi-squared
(1) $\zeta_{\text{Central SOE}} = 0$	16.00**	(1) $\beta_{\text{SOE shareholding}}=0$	85.64**
(2) $\zeta_{\text{Local SOE}} = 0$	114.03**		
(3) $\zeta_{\text{LGFV}} = 0$	40.72**		
Wald test statistic	43.36**	Wald test statistic	85.64**

** represents statistically significant at 5% level.

Overall model fit and robustness

In line with 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 16-21 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 (2007). At the same time, it suggests that other important variables may be missing from the model, including unobservable market sentiment 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 are quantitatively similar to the results in Table 8—the size of significant firm-specific and macroeconomic variables are somewhat lower and higher, respectively. The adjusted R-squared rises to about 33 percent.

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 12. 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.

Table 12. Default Probabilities Pooled Regression, Q1-2006 to Q1-2014

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	Dependent variable:							
	Borrowing rate-based probability of default				Market-based probability of default			
	1	2	3	4	5	6	7	8
Constant	4.94**	5.12**	5.08**	5.08**	-2.74**	-3.25**	-3.09**	-2.98**
	(80.64)	(59.32)	(58.19)	(58.51)	(-4.30)	(-3.56)	(-3.35)	(-3.24)
ln(1-EBIT/TA)	0.02	0.09	0.08	0.09	-2.26	-5.28**	-5.27**	-5.25**
	(0.16)	(0.74)	(0.67)	(0.70)	(-1.62)	(-3.54)	(-3.54)	(-3.53)
WC/TA	0.69**	0.78**	0.80**	0.80**	0.95	-0.18	-0.36	-0.26
	(12.97)	(13.89)	(14.10)	(14.11)	(1.56)	(-0.27)	(-0.54)	(-0.39)
ln(1-RE/TA)	-0.96**	-0.93**	-0.92**	-0.92**	-6.74**	-4.80**	-4.93**	-4.89**
	(-9.06)	(-8.72)	(-8.58)	(-8.58)	(-5.45)	(-3.85)	(-3.93)	(-3.92)
Negative DV X	-0.11	-0.11	-0.08	-0.08	16.20**	13.78**	13.70**	13.61**
ln(1-RE/TA)	(-0.78)	(-0.77)	(-0.56)	(-0.56)	(10.67)	(9.01)	(8.90)	(8.89)
1+ln(TA/TL)	-0.64**	-0.69**	-0.68**	-0.68**	8.17**	8.03**	8.06**	7.99**
	(-17.98)	(-18.87)	(-18.70)	(-18.71)	(22.43)	(21.64)	(21.67)	(21.52)
Size	0.01**	0.01**	0.01**	0.01**	-0.01	-0.01	-0.02**	-0.01
	(6.46)	(7.42)	(6.96)	(6.42)	(-1.37)	(-1.73)	(-2.08)	(-0.94)
ln(CL/NCL)	-0.0024**	-0.0021**	-0.0020**	-0.0020**	-0.0056	-0.0032	-0.0039	-0.0038
	(-4.5200)	(-3.8800)	(-3.6700)	(-3.6600)	(-1.0300)	(-0.6000)	(-0.7400)	(-0.7300)
Age	-0.0015**	-0.0015**	-0.0017**	-0.0017**	0.0049**	-0.0020	-0.0010	-0.0011
	(-9.0500)	(-8.9700)	(-9.9000)	(-9.7500)	(2.6100)	(-0.9900)	(-0.4900)	(-0.5600)
LGFV dummy			0.19**				-1.53**	
			(3.48)				(-2.35)	
Local SOE			0.09**				-0.60**	
dummy			(4.39)				(-2.37)	
Central SOE			0.09**				0.15	
dummy			(3.24)				(0.48)	
Estimated SOE				0.24**				-1.42**
shareholding				(5.51)				(-2.88)
Dummies								
Industry	N	Y	Y	Y	N	Y	Y	Y
Seasonal	N	Y	Y	Y	N	Y	Y	Y
Quarterly	N	Y	Y	Y	N	Y	Y	Y
No. of obs.	15,043	15,043	15,043	15,043	15,043	15,043	15,043	15,043
Adj. R-squared	8.3%	14.6%	14.7%	14.7%	9.0%	13.6%	13.6%	13.6%

Source: Authors' estimates.

1/ Firm specific variables winsorized at 1th and 99th percentiles. Balance sheet variables lagged by 1 quarter. ** represents statistically significance at 5% level. T-statistics in parentheses.

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.

VI. Conclusion

As China opens up its financial system, investors, banks, policymakers, and regulators, both in China and overseas, all have a stake in monitoring and quantifying the credit risk of China's firms, including at the aggregate level. China's unique economic and financial system which has been characterized by a large role for the state may make complicate this assessment. The notion that the state implicitly guarantees a significant proportion of total corporate liabilities is likely to have distorted risk pricing and, if true, artificially depressed the actual rate of defaults on bonds and bank loans.

In this context, there are at least two reasons to devote more research effort to enhance credit risk analysis in China. First, if policymakers continue to deepen the role of the market in the financial system then the notion that debts are implicitly guaranteed will likely weaken. This will involve a rising frequency of actual defaults but also greater incentives to price risk and allocate capital more efficiently. Second, even if the costs of some firm defaults are borne less by lenders and investors and more by the state or other state-backed entities, estimating the total contingent cost of greater corporate distress will be an integral component of any analysis of the aggregate banking system, public finances, and the broader economy. This is particularly true following the sharp rise in overall corporate debt since 2009.

We conclude, on the basis of our analysis in this paper, that it is possible to go further than simple descriptive statistics when measuring corporate credit risk in China. We provide one specific example—structural credit models that estimate the stand-alone 1-year probability of default can be usefully applied in China. The aggregation of results based on recent data and stress tests based on historical calibrations provide intuitively appealing and understandable results. More importantly, we find that these default probabilities are affected in a similar way by firm-specific and macroeconomic variables as in other countries, including the United States. Stress tests indicate that there remains an urgent need for policies to address corporate credit risk that could deteriorate sharply in the event of an adverse shock.

Our analysis provides some guidance for policies that aim to facilitate a disorderly and gradual deleveraging of China's corporate sector. The rolling back of implicit guarantees will likely mean higher risk premiums and borrowing costs for unprofitable and leveraged firms, particularly SOEs. Evidence such as the regression results in Table 12 suggest that the risks of default are not yet accurately reflected in the costs of debt. At the same time, this effect on risk premiums could be partially offset by transitioning towards more mixed-ownership, particularly in SOE-dominated sectors that are relatively unprofitable. The regression results in Table 8 indicate that that privately-owned and profitable firms are less likely to experience financial difficulties compared to SOEs, all else equal. Refocusing SOEs on profitability and allowing the market to play a more decisive role should help lower the frequency of corporate defaults (or the necessity for costly public sector support) as implicit guarantees are gradually withdrawn.

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