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DETERMINANTS OF AGRICULTURE-RELATED LOAN DEFAULT: EVIDENCE FROM CHINA

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ABSTRACT

This paper investigates agriculture-related loan default in 2002–2009 through a large data set from a leading Chinese state-owned bank. Using logit regression, we find the default rate on agriculture-related loans is significantly higher than that on non–agriculture-related loans. We find that base interest rates, loan maturity, the type of collateral, firm size, ownership structure, and managerial quality rating have a significant impact on agriculture-related loan default, but this also depends on how agriculture-related loans are defined. The results provide insight into the real impact of monetary policy on agriculture-related lending.

Keywords: *Agriculture-related loan; Default; Credit risk; Monetary policy; Collateral.*
JEL Classifications: G38; H23; O13; P23; Q14.

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I. INTRODUCTION

As in many emerging economies, rapid economic growth and industrialization have created an ever-widening gap between urban and rural areas in China in terms of wealth, infrastructure, and public services (Gan et al., 2014; Yin et al., 2019). Because of the large rural population and the implications of underdeveloped rural areas for social stability, the Chinese government, as in many other emerging markets (Savitha and Kumar, 2016; Dorfleitner et al., 2017), has been giving attention as well as priority to the development of rural areas, food security, and improving the income of the rural population (or "*san nong" in the context of Chinese*).[1] One of the most influential policies has been to encourage financial institutions to expand their lending to agriculture-related sectors (Ayygari et al., 2010). Agriculture-related loans are therefore pivotal to rural development in China.

Using a unique database obtained directly from a Chinese leading bank, this paper examines the determinants of agriculture-related loan default. Following Yin et al. (2014) and Yin et al. (2019), we apply a hazard model by conducting logit regressions. We find agriculture-related loans are more likely to result in default than non–agriculture-related loans, after controlling for loan contracts, firms, macroeconomics, and weather factors. Besides, agriculture-related sectors could have country-specific characteristics relating to default, and a international standard definition might not be applicable to single country. In addition, we find loan-specific rates and base interest rates co-determine the default rate of agricultural loans. Furthermore, the redefinition of default would generally affect the influence of contract-specific characteristics on the default of all types of loans. Our findings contribute to the literature by identifying distinguishing features between agricultural loans and loans in general. They also provide further insight into agricultural-related loans based on the work of Yin et al. (2019).

The motivation for investigating the determinants of default on agriculture-related loans is as follows. First, the amounts involved in agriculture-related loans are enormous. By the end of 2014, outstanding agriculture-related loans stood at RMB 23.6 trillion (USD 3.8 trillion), accounting for 29% of all outstanding loans in China.[2] Compared to 2010, not only did size of agriculture-related loans double, but also its proportion of all outstanding loans rose by 4% (Ouyang and Zhang, 2019). Second, agricultural financial risk is substantial (Morgan et al., 2012). Because of the characteristics of the agricultural sector and the underdevelopment of rural areas in China, agriculture-related loans involve higher costs, longer periods, and higher risks compared to bank lending in other sectors. Therefore, as the amount of agriculture-related loans grows, attention has been drawn to the quality of this asset class. Third, as a result of the previous point, subsidies are injected into the market to encourage financial institutions to engage in agriculture-related loans.[3] This leads to the issue of efficiency, i.e., whether the credit risk on agriculture-related loans is fully understood and well managed by state-owned or state-controlled

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[1] These refer to the long-term policy of the Chinese government called the Three Issues, or *san nong* (三农). *San nong* is the abbreviation for increasing agricultural production, increasing farmers' income, and developing rural areas.

[2] See also the *Quarterly Executive Report of Monetary Policy*, People's Bank of China.

[3] See "30% growth in agriculture-related loans and the hidden danger in the subsidised model for growth," *The Economic Observer*, October 17, 2011.

banks when executing *san nong* policies. This is a concern for policymakers and critical to the sustainable development of this market (Xie and Jin, 2015). Fourth, the literature on loan default involves the determinants of default, the effect of collateral on default, and the heterogeneity of borrowers (Savitha and Kumar, 2016; Zhou et al., 2016; Yin et al., 2019). There is a dearth of literature dedicated to the sector-specific credit quality of loans, particularly loans in emerging markets. Finally, in an era of high output volatility of agricultural products, this study of one of the largest agricultural producers is also of general interest to the world community in terms of managing food supply and food security.[4]

This paper contributes to the literature by filling the void in studies dedicated to bank lending in the agricultural sector. The findings reveal the key determinants of the credit quality of agriculture-related loans that inform the business operations of banking institutions. We are specifically interested in two sets of variables that are particularly important in agricultural loans: agriculturally related factors (e.g., temperature and rainfall) and loan-specific interest rates. Indeed, we find that the two sets of variables significantly determine the default rate in this unique sector. We also provide insight for emerging economies on the financial risk in policy-oriented lending to the agriculture sector.

This paper is organized as follows: Section II reviews the literature related to loan default. Section III presents the methodology and data. Section IV interprets the results on the default of agriculture-related loans relative to other types of loan. It also conducts robustness tests. Section V analyzes the determinants of agriculture-related loan default, and Section VI concludes the paper.

II. LITERATURE REVIEW

A. Determinants of Bank Loan Default

Identification of the determinants of bank loan default can be traced to Campbell and Dietrich (1983), who use US bank loan data to find that the ratio of concurrent payments to revenue, the loan-to-value ratio, the unemployment rate, loan maturity, and the initial loan-to-value ratio have a significant influence on the loan default rate. Berger and De Young (1997) use Granger causality tests and find that, when a bank's capital decreases, the amount of bad loans increases, and there is a bilateral intertemporal relation between the quality of loans and cost efficiency. In addition, cost efficiency is one of the most important factors for predicting bad loans and failing banks.

Elsas and Krahnen (1998) argue that the credit risk with corporations is greater than with non-corporations, i.e., partnerships and sole proprietors involve less moral hazard. Berger and De Young (2001, 2006) suggest that geographic distance increases the costs of information collection and monitoring such that the loan default rate increases with the distance between the borrower and the lender. Jiménez and Saurina (2004) analyze more than 3 million individual loans in Spain between 1988 and 2000 and find that the default rate on collateralized loans is higher than for unsecured loans. They also find that savings banks tend to extend

[4] According to the United Nations (UN) Food and Agriculture Organization, China is the largest producer of wheat, rice, and so forth.

loans with higher credit risk and that closer banking relationships between banks and firms increase bank risk taking.

Landier, Nair, and Wulf (2005) find that an information-based loan lending model can reduce the inefficiency caused by geographic distance, and lenders who use credit scoring models face a lower default rate. Conversely, Rossi (1998) and Flannery and Samolyk (2006) find that an automated lending model is associated with economies of scale, and lending at the breakeven point of credit rating models would lead to a higher default rate. De Young, Glennon, and Nigro (2008) find that longer distances and lower credit ratings lead to a higher probability of default. Jiménez and Saurina (2009) find that default rates are highly correlated with economic cycles. In addition, the credit losses on manufacturing, construction, consumer, and collateralized loans are generally higher. However, Sha and Wang (2019) find that, as long as the debtor's financial information is controlled for, there is no industry effect in determining US default, challenging the intuition that macroeconomic conditions have predictive power for default. Using a micro-level Chinese bank loan database, Yin et al. (2019) reach the same conclusion, that borrower heterogeneity dilutes sensitivity to economic change in co-determining loan default.

In sum, previous research has identified various determinants influencing bank loan default. The role of macroeconomic conditions, previously recognized as a determinant of loan default, is now being challenged with new evidence from various countries. Most of the literature relies on bank-level consolidated data to conducting analyses, and few studies use contract- or individual-level data. Given that the decision to default is ultimately made by the borrower, and not the bank, data obtained directly from the borrower could provide a clearer picture in this research field.

B. Role of Collateral

Many studies focus on the impact of collateral on the default rate. Stigliz and Weiss (1981) and Chan, Greenbaum, and Thakor (1987) argue that banks' requirement for collateral when providing loans reduces the adverse selection problem, which, in turn, leads to a lower default rate. Aghion and Bolton (1992) and La Porta et al. (1998) suggest that, according to creditability threat theory, collateral is an effective tool to guarantee borrowers' good behavior.

Smith and Warner (1979) suggest moral hazard as a determinant of collateral use in loan lending, i.e., collateralized debt prevents the borrower from swapping high quality assetsto low quality assets, and ties up funds that could otherwise be use to finance from projects. Chan and Kanatas (1985) consider the situation in which the borrower cannot change the returns of the lender, i.e., in a perfectly competitive risk-neutral credit market with no moral hazard. When the creditworthiness of the lender and that of the borrower are identical, there is no need for collateral. Besanko and Thakor (1987), Bolton and Scharfstein (1996), and Manove, Padilla, and Pagano (2001) argue that, when firms use external assets as collateral, banks can obtain repayment upon default. This affects borrowers' motivation of technical default and reduces adverse selection. Collateral can substitute for the determinant of the quality of the project to be financed. Jiménez and Saurina (2004) also find

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a negative relationship between the quality of collateral and the credit risk of borrowers. Jiménez et al. (2014) find that lower short-term interest rates encourage small-cap banks to provide more loans to risky firms without collateral, likely leading to greater levels of default. Chen and Lin (2016) show that government bail-out programs reduce the default risk for banks, but indirectly increase the default risk for borrowing firms.

Other studies find a close relationship between collateral requirements and high credit risk in lending. Empirical research shows that collateralized loans face higher risk. To some extent, they are called high–default probability loans (see also Orgler, 1970; Hester, 1979); in other words these loans have a higher risk premium (see also Berger and Udell, 1990; Booth, 1992; Booth and Chua, 2006; Angbazo, Mein, and Sanders, 1998; however, these studies are limited to the US loan market).

Igawa and Kanatas (1990) suggest that, in an ex-ante information asymmetry credit market, collateral will lead not only to the approval of borrowers' loan applications, but also to moral hazard when borrowers use the loans. Freund et al. (1998) argue that collateral-based lending models lead to credit crises.

Manove and Padilla (1999, 2001) think that the higher the amount of collateral required, the worse the quality of the loans (ex post credit risk), and the higher the default rate. First, when banks receive a guarantee for loans, they will have less motivation to filter out potentially problematic borrowers and loans. Second, optimistic entrepreneurs usually underestimate their probability of bankruptcy and are therefore willing to provide any collateral required to obtain funding.

Based on output, consumption, and foreign debt, Arellano's (2008) default risk model for emerging economies predicts that interest rates and default incentives are higher in recessions. Li et al. (2013) show that, in the wake of the 2008 financial crisis, agricultural loan delinquency rates were consistently below banks' overall loan delinquency rates. Nwachukwu (2013) identifies the characteristics of the beneficiaries of a government-sponsored agricultural loan program in Nigeria to investigate the high default rates. Weber and Musshoff's (2012) results suggest that, in the Tanzanian loan market, agricultural firms have lower delinquency rates than non-agricultural firms do. Castro and Garcia (2014) and Ouyang and Zhang (2019) find that commodity price volatility and climate factors have a modest impact on agricultural loans, while macroeconomic conditions for the agricultural sector and intermediate input prices have greater influence. Dinterman et al. (2018) study how economic factors have impacted farm businesses in the United States. They find that macroeconomic factors such as interest and unemployment rates have strong predictive power for farm bankruptcies. Escalante et al. (2017) show that non-white male and female farm borrowers are usually charged higher interest rates than others, which could be attributed to lenders' credit risk management strategy.

Bailey et al. (2011) find that firms with poor performance are more likely to receive bank loans, and their subsequent long-run performance is typically poor. The authors also note negative stock market reactions, where the share prices for Chinese borrowers typically decline significantly around bank loan announcements. Chang et al. (2014) used a proprietary database from a large Chinese state-owned bank to examine the usefulness of banking relationships in predicting loan default. They find that the contribution of banking relationships to predicting default is greater than that of other, hard information.

In sum, the literature has documented the unique structure of agricultural-related bank loans under formal and informal financing channel theory. The use of collateral and government involvement confuses the estimation of genuine credit quality of loans in the agriculture sector. Some country-specific research provides insights into the issue, but these studies are limited to survey data and small samples. In lights of these limitations, Yin et al. (2019) has examined the role of collateral played in bank loans by using large dataset from a leading commercial bank. Using the same dataset, we are further interested in the determinants of credit quality in the agriculture sector.

Morgan et al. (2012) and Yin et al. (2019) point out that agricultural businesses are risky. Apart from market and business operation risks, the agriculture sector also suffers from additional, weather-related risks. Banks exercise less monitoring and control, because agricultural production is located in rural areas where transportation and information collection is not so convenient. There is also a lack of instruments that agriculture-related businesses can use to hedge these risks, because the derivatives market is underdeveloped in China (Ouyang and Zhang, 2019). Therefore, we form two research hypotheses. The first hypothesis is as follows.

H1: Agriculture-related loans have a higher probability of default than other types of loans.

Consistent with works of Campbell et al. (2008), Sha and Wang (2019), and Yin et al. (2019), the following logit model is used to examine H1:

$$
\begin{aligned}
&Pr(Default_{it} = 1) = \alpha + \beta_1 AR_{it} + \beta_2 MID_{it} + \beta_3 LONG_{it} + \beta_4 BaseIR_{it} + \\
&\beta_5 FlotatIR_{it} + \beta_6 Amount_{it} + \beta_7 BulletP_{it} + \beta_8 PeriodicP_{it} + \\
&\beta_9 CostomizedP_{it} + \beta_{10} Guaranteed_{it} + \beta_{11} Collaterialized_{it} + \\
&\beta_{12} Pledged_{it} + \beta_{13} Disnotes_{it} + \beta_{14} Excellent_{it} + \beta_{15} Averaged_{it} + \\
&\beta_{16} Restricted_{it} + \beta_{17} Mega_{it} + \beta_{18} Large_{it} + \beta_{19} Medium_{it} + \beta_{20} SOE_{it} + \\
&\beta_{21} CO_{it} + \beta_{22} SC_{it} + \beta_{23} AE_{it} + \beta_{24} LTD_{it} + \beta_{25}\ CORP_{it} + \beta_{26} PRI_{it} + \\
&\beta_{27} FOR_{it} + \beta_{28} TEMP_{it} + \beta_{29} RAIN_{it} + Year_{dummy} + \mu_{it}
\end{aligned}
\tag{1}
$$

where, the borrower *i* at time *t*, *Default* is a binary variable that takes the value of zero when the loan is normal, and one if the loan goes bad (see Section 3 on the data and variables for the definition of a bad loan, or default), and AR is a dummy variable that takes the value of one when the loan is related to agriculture, and zero otherwise, with AR defined according to three criteria (see also Tables A1–A3 in the Appendix). The first criterion is set by the People's Bank of China, the second by the UN, while the third criterion is set by the National Bureau of Statistics of China. Due to the broad coverage of the criterion of the People's Bank of China, it is widely used in the Chinese banking industry. We adopt this criterion to classify agriculture-related loans. The other two criteria are used to check the sensitivity of the results to the choice of agriculture-related loan classification. Due to the higher credit risk involved in agriculture-related lending, the coefficient is expected to bear a positive sign.

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In line with Yin et al. (2019), we use the following loan information variables to explain the probability of default: maturity, amount, repayment method, type of guarantee, and interest rate, where maturity is either short, medium, or long term.[5] We introduce two dummies (*MID* and *LONG*) for the maturity of loans, i.e., the first one taking the value of one if the loan is medium term, and zero otherwise, and the other taking the value of one if the loan is long term, and zero otherwise. We use the logarithm of the loan amount as the size of the loan (*Amount*). The interest rates on loans are calibrated by two variables, i.e., the logarithm of the base interest rate (*BaseIR*) and the logarithm of the range of loan-specific interest rate fluctuations (*FloatIR*). The repayment methods are a bullet payment at maturity (*BulletP*), periodic interest payments plus principal at maturity (*PeriodicP*), customized periodic repayments (*CustomizedP*), and standard periodic payments. The types of guarantee include unsecured (*Unsecured*), guaranteed (*Guaranteed*), collateralized (*Collateralized*), pledged (*Pledged*), and discounted notes (*Disnotes*), which are assigned binary variables of the same name.

To examine the effect of firm-specific characteristics on the quality of loans, following Liu et al. (2019) and Yin et al. (2019), we control for four categories of managerial quality rating, i.e., *excellent*, *average, restricted,* and *knockout*, and firm size, denoted as mega-sized (*Mega*), large (*Large*), medium sized (*Medium*), or small, We also control for the ownership structure, i.e., state-owned enterprises (*SOE*); collectively owned enterprises (*CO*); stock cooperative enterprises (*SC*); associated enterprises (*AE*); limited liability companies (*LTD*); corporations (*CORP*); private enterprises (*PRI*); foreign enterprises (*FOR*), including Hong Kong, Macau, and Taiwanese enterprises; and other enterprises, including, e.g.,, sole proprietor and partnership. These indicators are binary variables of the same name in the analyses.

We control for the size of the borrowers by classifying them as mega-sized, large, medium sized, and small. We use the 12-month-averaged temperature (*TEMP*) and precipitation (*RAIN*) levels in the same area as control variables for the weather (see also Sha and Wang (2019) for a discussion on using the 12-month-averaged value in predicting default). To control for the impact of time-varying macroeconomic factors, we introduce year dummies, and μ as a residual term. We use a logit model to estimate Equation (1). Considering that credit quality is a discrete variable, we also use an ordered logit model to estimate Equation (1).

Monetary policy is an important systemic risk factor in determining credit risk of loans in China, not only because a tighter monetary policy drains liquidity for businesses, but also because it signals the arrival of a less favorable business climate (Ayyagari et al., 2010). We thus propose the following hypothesis.

H2: Compared to changes in loan-specific interest rates, tightening in monetary policy, i.e., an increase in base interest rates, is more likely to lead to default in agriculture-related loans.

[5] To avoid perfect collinearity, we do not include the short-term dummy variable in the regression. Similarly, we do not include the dummy variables proxying for standard periodic payments, unsecured guarantees, knockout ratings, "small-sized" loans, and other enterprises.

To further investigate the determinants of agriculture-related loan default and to test H2, we use the following model to estimate a subsample of only agriculture-related loans:

$$Pr(Default_{it} = 1) = \alpha + \beta_1 MID_{it} + \beta_2 LONG_{it} + \beta_3 BaseIR_{it} + \beta_4 FloatIR_{it} + \beta_5 Amount_{it} + \beta_6 BulletP_{it} + \beta_7 PeriodicP_{it} + \beta_8 CostomizedP_{it} + \beta_9 Guaranteed_{it} + \beta_{10} Collaterialized_{it} + \beta_{11} Pledged_{it} + \beta_{12} Disnotes_{it} + \beta_{13} Excellent_{it} + \beta_{14} Averaged_{it} + \beta_{15} Restricted_{it} + \beta_{16} Mega_{it} + \beta_{17} Large_{it} + \beta_{18} Medium_{it} + \beta_{19} SOE_{it} + \beta_{20} CO_{it} + \beta_{21} SC_{it} + \beta_{22} AE_{it} + \beta_{23} LTD_{it} + \beta_{24}\, CORP_{it} + \beta_{25} PRI_{it} + \beta_{26} FOR_{it} + \beta_{27} TEMP_{it} + \beta_{28} RAIN_{it} + Year_{dummy} + \mu_{it} \quad (2)$$

If H2 is valid, *BaseIR* will have a significant, positive sign, whereas *FloatIR* should be nonsignificant. The control variables include contract- and firm-specific control variables, as well as weather variables and the year dummies, exactly as in Equation (1).

III. DATA AND RESEARCH METHODS

This paper uses corporate loan data for 2002–2009 from a leading state-owned bank in China.[6] To avoid sample selection bias, we exclude loans that were made during this period but which will mature after 2009. In our data set, credit risk is measured by the five categories of loan quality (in descending order), i.e., normal, concerned, subprime, suspicious, and a loss. According to industry practice, the last three categories are usually classified as bad loans. Therefore, we introduce a binary variable that takes the value of one if the loan is subprime, suspicious, or a loss, and zero otherwise. To check the sensitivity of the results to the choice of default, we use the method of Ping and Yang (2009), reclassifying bad loans to also include the concerned category.

The descriptive statistics (see Table 1) show that mid- and long-term loans account for only a small proportion of the sample. The loan amount can have a wide range. In terms of repayment types, while customized periodic payments are rarely used, periodic and bullet payments are much more common. Loans backed by discounted notes or collateral are much more common than guaranteed or pledged loans. The borrowers are often small and medium-sized companies. Using the same data set, Yin et al. (2019) find that the default rate of non–agriculture-related loans is 6.38%, whereas that of agriculture-related loans is much higher, at 11.6%. To further analyze the credit risk on agriculture- and non-agriculture–related loans, we compare the status of these two types of loans. While the proportion of non–agriculture-related loans with normal status is higher than that of agriculture-related loans (81.6% vs. 75.84%), the proportions of non–agriculture-related loans with a lower credit quality status are smaller than those of agriculture-related loans (Yin et al., 2014).

[6] According to the bank's request, we are restricted from disclosing further details in published articles.

Table 1.
Descriptive Statistics of Explanatory Variables

This table reports selected descriptive statistics for all variables used in the paper. *AR* is a dummy that takes the value of 1 when the loan is agriculture-related and 0 otherwise; *MID* and *LONG* are dummy variables for loans with mid-term and long-term maturities, respectively; *BaseIR* is the official interest rate set by People's Bank of China, depending on the maturity of the loan; *FloatIR* is the range of loan specific interest rate changes; *Amount* is the log of the amount of the loan; *BulletP*, *PeriodicP*, and *CustomizedP* payment are dummies for loans with these three methods of repayment; *Guaranteed*, *Collateralised*, *Pledged*; and *Disnotes* are dummies for the types of collateral; *Excellent*, *Averaged* and *Restricted* are dummies for borrowers with such managerial ratings; *Mega*, *Large* and *Medium* are dummies for the size of the borrowers; *SOE*, *CO*, *SC*, *AE*, *LTD*, *CORP*, *PRI*, and *FOR* are dummies for the ownership structure of the borrowers. *TEMP* and *RAIN* are the annual mean temperature and mean precipitation respectively.

Variable	Obs	Mean	Std. Dev.	Min	Max
AR	115395	0.1170	0.3154	0	1
MID	115395	0.0277	0.1640	0	1
LONG	115395	0.0007	0.0262	0	1
BaseIR	115395	1.5840	0.3085	-1.2730	2.8904
FloatIR	115395	1.4123	0.0529	-0.8210	2.5832
Amount	115395	13.6674	1.6673	4.6052	22.3327
BulletP	115395	0.3967	0.4892	0	1
PeriodicP	115395	0.5806	0.4935	0	1
CustomizedP	115395	0.0075	0.0866	0	1
Guaranteed	115395	0.0970	0.2959	0	1
Collateralized	115395	0.3916	0.4881	0	1
Pledged	115395	0.0348	0.1833	0	1
Disnotes	115395	0.4516	0.4977	0	1
Excellent	115395	0.5431	0.4981	0	1
Averaged	115395	0.3200	0.4665	0	1
Restricted	115395	0.0613	0.2398	0	1
Mega	115395	0.0657	0.2477	0	1
Large	115395	0.0927	0.2901	0	1
Medium	115395	0.3813	0.4857	0	1
SOE	115395	0.1015	0.3019	0	1
CO	115395	0.0304	0.1716	0	1
SC	115395	0.0850	0.2789	0	1
AE	115395	0.0076	0.0870	0	1
LTD	115395	0.1903	0.3925	0	1
CORP	115395	0.1990	0.3992	0	1
PRI	115395	0.2918	0.4546	0	1
FOR	115395	0.0328	0.1781	0	1
TEMP	115395	2.0475	1.1064	0.5600	3.4700
RAIN	115395	0.0099	0.0160	0.0002	0.0645

IV. EMPIRICAL RESULTS

A. Basic Results

The results presented in Table 2 are based on the People's Bank of China's definition of agriculture-related loans. Table 2 shows a very significant positive relationship between being agriculturally related and default, i.e., agriculture-related loans are more likely to result in default than other types of loans. This result is consistent with H1, i.e., agriculture-related loans in China are riskier and less controllable than other types of loans.

Table 2.
Agriculture-related loans and credit risk

We report the marginal effects of Logit regression following equation (1): $Pr(Default_{it}=1)=\alpha+\beta AR_{it}+\gamma X_{it}+\mu_{it}$ and the results are reported in this table. The detailed description is reported in Section III. Cluster-adjusted standard errors are presented in parentheses. The sample period is 2002-2009.

Variables	Marginal Effects	Standard Error
AR	0.0011***	0.0002
MID	0.0033***	0.0005
LONG	0.0052*	0.0031
BaseIR	0.0047***	0.0006
FloatIR	0.0038***	0.0010
Amount	0.0001**	0.0000
BulletP	0.0003	0.0009
PeriodicP	0.0013	0.0009
CustomizedP	0.0018	0.0015
Guaranteed	0.0003	0.0003
Collateralized	0.0004	0.0003
Pledged	-0.0001	0.0003
Disnotes	-0.0172***	0.0012
Excellent	-0.0047***	0.0005
Averaged	-0.0019***	0.0002
Restricted	-0.0006***	0.0001
Mega	-0.0004	0.0014
Large	-0.0015***	0.0002
Medium	-0.0009***	0.0001
SOE	0.0012***	0.0003
CO	0.0023***	0.0004
SC	-0.0008	0.0003
AE	0.0005***	0.0005
LTD	-0.0007***	0.0002
CORP	0.0007***	0.0002
PRI	-0.0003*	0.0002
FOR	0.0000	0.0003
TEMP	0.0005***	0.0001
RAIN	0.0372***	0.0050
Year Dummy	Yes	-
Observation	115269	
Pseudo R-squared	0.283	

Regarding firm-specific characteristics, medium-term loans (*Medium*) and long-term loans (*Long*) are more likely to default than short-term loans; however, the effect for long-term loans is weak. This finding is consistent with theory and previous empirical studies, (e.g., Campbell and Dietrich, 1983). The base interest rate has a positive relationship with default in logit estimation; i.e., loans granted during a high–interest rate period are more likely to end up in default. The interest rate float (*FloatIR*) has a positive relationship with loan default, i.e., interest rate adjustments specific to large loans are associated with reduced ability to repay. A positive relationship between the loan amount (*Amount*) and default is found, i.e., the larger the loan (higher *Amount*), the more likely the default. However, this relationship has only modest economic significance. In our sample, repayment methods do not have a significant impact on loan default, although one would expect bullet payments to be riskier than periodic repayments, since, in the former, the entire cash flow occurs at maturity. The type of guarantee has a significant impact on default, i.e., loans backed by discounted notes have a much lower chance of default. Discounted notes (*Disnotes*) have stable value and are liquid; therefore, the cost of default for borrowers is high. This result is consistent with the works of Aghion and Bolton (1992) and La Porta et al (1998).

Managerial quality has a significant impact on loan default, i.e., in comparison to firms rated excellent, average, and restricted, those with knockout ratings (*Knockout* = 1) are more likely to default. This finding is intuitive, i.e., low-quality management can make inferior decisions that can lead to the failure of the firm. The effect of firm size on loan default is remarkable; i.e., while mega-sized firms contribute to higher levels of default, large to medium-sized firms are less likely to default. Regarding firm ownership structure, state-owned enterprises and collectively owned enterprises are more likely to default. Logit estimations show that stock cooperative, limited liability, and private firms are less likely to default.

Weather also plays a role in loan default. When *TEMP* and *RAIN* increase, the chances of default increase accordingly. However, the effect of temperature seems to be very modest. This result is consistent with the work of Castro and Garcia (2014), in that warmth and rainfall contribute to agricultural production as long as they do not surpass certain thresholds. The *Year* dummies have an effect on default; however, in this paper, the main idea is for them to absorb macroeconomic factors that are not included in our control variables.

Table 3 shows ordered logit estimations of Equation (1). The results are consistent with those in Table 2, where agriculture-related loans have a higher probability of default than other types of loans.

Table 3.
Agriculture-Related Loans and Credit Risk - Ordered Logit

We report the results of Ordered Logit regression following equation (1): $Pr(Default_{it}=1)=\alpha+\beta AR_{it}+\gamma X_{it}+\mu_{it}$ are reported in this table. X is the vector of control variables that are reported in Section III. The order is as the credit quality of loans which is cut in five categories: Normal=1, Concern=2, Subprime=3, Suspicious=4 and Loss=5. Credit risk increases with the number. Cluster-adjusted standard errors are presented in parentheses. The sample period is 2002-2009.

Variables	Coefficients	Standard Error
AR	0.192***	(0.0279)
MID	0.525***	(0.0445)
LONG	0.860***	(0.200)
BaseIR	0.652***	(0.0819)
FloatIR	2.582***	(0.294)
Amount	0.0659***	(0.00800)
TEMP	0.230***	(0.0185)
RAIN	5.594***	(0.737)
Repayment method	Yes	-
Type of guarantee	Yes	-
Managerial rating	Yes	-
Size	Yes	-
Ownership	Yes	-
Year dummy	Yes	-
Cut1	9.697***	(0.735)
Cut 2	11.38***	(0.736)
Cut 3	11.95***	(0.737)
Cut 4	13.20***	(0.738)
Observations	115,382	
Pseudo R-squared	0.304	

B. Robustness Checks

B.1. Alternative Definitions of Agriculture-related Loans

The results in Table 4 are based on the definitions of agriculture-related loans by the UN and by the Chinese Bureau of Statistics. When the Chinese domestic classification is used, there is a positive relationship between the loan's probability of being agriculture-related and default. This positive relationship is not statistically significant, however, when the UN classification is applied. This result could suggest that agriculture-related sectors have country-specific characteristics and that a international standard is not applicable. Compared to the People's Bank of China's classification, alternative definitions lead to nonsignificant relationships between interest rates and loan default. The repayment method, type of guarantee, firm size, ownership structure, management ratings, and time have very similar effects on loan default, regardless of how agriculture-related loans are defined. Generally, agriculture-related loans are more likely to result in default than non–agriculture-related loans are.

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Table 4.
Agriculture-Related Loans and Credit Risk – Alternative Definition of Agriculture-Related Loan

We estimate the equation (1): $Pr(Default_{it}=1)=\alpha+\beta AR_{it}+\gamma X_{it}+\mu_{it}$ following two standard that defining agricultural loans in China and in UN (see Table A and B in the APPENDIX for details). The table reports coefficients of two regressions. The detailed description is reported in section 3.1. Cluster-adjusted standard errors are presented in parentheses. The sample period is 2002-2009.

Variables	Domestic classification of economic sectors (1)	United Nations classification of sectors (2)
AR	0.020**	0.009
	(0.010)	(0.006)
MID	0.076***	0.076***
	(0.011)	(0.011)
LONG	0.112**	0.112**
	(0.053)	(0.054)
BaseIR	0.004	0.004
	(0.008)	(0.008)
FloatIR	0.060	0.059
	(0.037)	(0.037)
Amount	0.003*	0.003*
	(0.001)	(0.001)
TEMP	0.035***	0.002***
	(0.001)	(0.0002)
RAIN	1.047***	0.055***
	(0.050)	(0.006)
Repayment method	Yes	Yes
Type of guarantee	Yes	Yes
Managerial rating	Yes	Yes
Size	Yes	Yes
Ownership	Yes	Yes
Year dummy	Yes	Yes
Constant	-0.201**	-0.199**
	(0.082)	(0.082)
Observations	115,319	115,319
Pseudo R-squared	0.281	0.281

B.2. Alternative Definitions of Default

We follow Ping and Yang (2009) to redefine default to include loans with a concerned status, to check the sensitivity of the results to the definition of loan default. Table 5 shows that agriculture-related loans have a consistently higher default rate than non–agriculture-related loans do. Both *BaseIR* and *FloatIR* have a much stronger positive effect on default than on the previous definition of default. We therefore conclude that our main findings do not vary due to alternative default definitions.

Table 5.
Agriculture-Related Loans and Credit Risk – Alternative Definition of Default

We estimate the equation (1): $Pr(Default_{it}=1)=\alpha+\beta AR_{it}+\gamma X_{it}+\mu_{it}$ by using Ping and Yang (2009) definition, i.e. redefining default to include loans with "Concerned" status, to check the sensitivity of the results to the definition of loan default. The table reports marginal effects of regression. The detailed description is reported in Section III. Cluster-adjusted standard errors are presented in parentheses. The sample period is 2002-2009.

Variables	Marginal Effects	Standard Error
AR	0.0023**	0.0011
MID	0.0130***	0.0024
LONG	0.0559***	0.0210
BaseIR	0.0249***	0.0032
FloatIR	0.1120***	0.0136
Amount	0.0030***	0.0003
BulletP	0.0305**	0.0126
PeriodicP	0.0468***	0.0102
CustomizedP	0.0860***	0.0308
Guaranteed	0.0505***	0.0054
Collateralized	0.0489***	0.0038
Pledged	0.0127***	0.0038
Disnotes	-0.1196***	0.0046
Excellent	-0.0675***	0.0028
Averaged	-0.0207***	0.0014
Restricted	-0.0074***	0.0013
Mega	-0.0241***	0.0046
Large	-0.0052***	0.0017
Medium	-0.0024***	0.0008
SOE	0.0067***	0.0020
CO	0.0102***	0.0028
SC	-0.0111***	0.0022
AE	0.0028	0.0042
LTD	-0.0122***	0.0014
CORP	-0.0076***	0.0015
PRI	-0.0192***	0.0014
FOR	-0.0231***	0.0014
TEMP	0.0049***	0.0007
RAIN	0.1130***	0.0295
Year Dummy	Yes	-
Observation	115269	
Pseudo R-squared	0.330	

B.3. Determinants of Default on Agriculture-related Loans

To further investigate the determinants of default on agriculture-related loans, i.e., those related to loan contract information and firm-specific characteristics, we run Equation (2) using the agriculture-related loan subsample.

Table 6 shows that medium-term agriculture-related loans are more likely to result in default. The same effect is found for long-term loans, however weak. Generally, our analysis suggests that default increases with loan maturity. The higher *BaseIR* is, the more likely the agriculture-related loan will end up in default, while *FloatIR* does not have a significant impact on agriculture-related loan default. This result is attributed to the vulnerability of the agriculture sector in China;[7] i.e., the resilience of agriculture-related loans to risk is low, and macroeconomic shocks can precipitate their default. This finding confirms H2, i.e., monetary policy is an important systemic risk factor in determining credit risk on loans in China, even when the loan-specific rate is given and controlled for.

Table 6.
Determinants of default on agriculture-related loans

We estimate the equation (2): $Pr(Default_{it}=1)=\alpha+\beta BaseIR_{it}+\gamma FloatIR_{it}+\theta X_{it}+\mu_{it}$ to check the sensitivity of the predicting variables. The table reports marginal effects of regression. The detailed description is reported in Section III. Cluster-adjusted standard errors are presented in parentheses. The sample period is 2002-2009.

Variables	Marginal Effects	Standard Error
MID	0.0146***	0.0048
LONG	0.0349*	0.0187
BaseIR	0.0043**	0.0020
FloatIR	-0.0019	0.0054
Amount	-0.0003*	0.0002
BulletP	-0.0012	0.0082
PeriodicP	-0.0005	0.0097
CustomizedP	-0.0002	0.0090
Guaranteed	-0.0015	0.0064
Collateralized	0.0001	0.0010
Pledged	0.0000	0.0009
Disnotes	-0.0006	0.0010
Excellent	-0.0197***	0.0030
Averaged	-0.0112***	0.0030
Restricted	-0.0034***	0.0009
Mega	-0.0017***	0.0005
Large	0.0003	0.0013
Medium	-0.0027***	0.0008
SOE	0.0000	0.0008
CO	0.0039*	0.0021
SC	-0.0002	0.0014
AE	-0.0025**	0.0013
LTD	-0.0013*	0.0007
CORP	0.0007	0.0009
PRI	-0.0011	0.0007
FOR	0.0007	0.0017
TEMP	0.0038***	0.0009
RAIN	0.1497***	0.0350
Year Dummy	Yes	
Observations	13052	
Pseudo R-squared	0.209	

[7] This vulnerability refers to losses due to adverse weather, natural disasters, and the volatility of the prices of agricultural products.

Regarding loan contract-specific information, the type of guarantee has no effect on agriculture-related loan default, as for other types of loan. With respect to firm-specific information, firm size affects the default rate: mega- and medium-sized firms are found to have lower chances of default. Managerial quality ratings have a significant effect on default, i.e., borrowers rated as excellent have the lowest default rate, followed by average borrowers and restricted borrowers, with knockout borrowers most likely to default. This finding is consistent with other types of loans. The weather effect is still significant and consistent with non–agriculture-related loans.

V. CONCLUDING REMARKS

This paper investigates agriculture-related loan default in China. Consistent with our hypotheses, agriculture-related loans are more likely to result in default than non–agriculture-related loans, after controlling for other factors. The only exception is when the UN classification is used. This could suggest that agriculture-related sectors have country-specific characteristics and an international standard definition is not applicable to single country. An alternative definition of default does not change the conclusion that agriculture-related loans are more likely to default than non–agriculture-related loans are. However, such a redefinition of default generally affects the influence of contract-specific characteristics on the default of all types of loans.

In the analysis of the determinants of agriculture-related loans, we find that default increases with maturity. However, unlike other types of loan, long-term agriculture-related loans do not show a significantly higher credit risk than their short-term counterparts. This result could be because the agriculture-related subsample does not encompass as many long-term loans, since financial institutions engaged in agriculture-related lending do not usually wish to have prolonged exposure to a single entity. We also find that the higher the base interest rate, the more likely agriculture-related loans will end up in default, while loan-specific interest rate fluctuations do not have a significant impact on agriculture-related loan default. These two findings are consistent with our hypotheses and could be attributed to the low resilience of the agriculture-related sector to macroeconomic shocks. Guaranteed and collateralized agriculture-related loans are also more likely to result in default. This finding suggests that the moral hazard arising from the introduction of guarantees and collateral requirements could contribute to the credit risk of agriculture-related loans. Firm-specific characteristics, such as firm size, the borrower's managerial quality, and ownership structure also have a significant influence on the default of agriculture-related loans. Remarkably, the agriculture-related loans in our sample show a downward trend in default between 2003 and 2008.

Our findings confirm the concerns of financial institutions that agriculture-related loans are generally riskier than non–agriculture-related loans. Policymakers should pay more attention to the impact of macroeconomic policies, such as monetary policy, on systemic risk in the agriculture-related loan market. An agriculture-related derivatives market, such as weather derivatives, could be developed to help agriculture-related businesses better manage their uncontrollable risks. For financial institutions, borrower-specific risk characteristics should play an important role in lending decision, while the design of loan contracts is also essential. The systematic study of the determinants of agriculture-related loan default contributes to the literature on the credit risk of loans from a sector that is critical to the fundamental wellbeing of the world population.

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APPENDIX

Table A1.
Definition of agriculture-related loans – People's Bank of China Classification

Loan Type Code	Loan Type
1111	Agriculture
1211	Forestry
1311	Livestock farming
1411	Fishing
1511	Service to agriculture, forestry, livestock farming and fishing
1611	Agricultural infrastructure
1621	Agricultural product processing
1631	Agricultural product export
1632	Circulation of other agricultural material
1641	Agricultural science and technology
1651	Rural area infrastructure
1661	Manufacturing of agricultural tools and equipments
1711	Other agriculture-related
1811	Particular non agriculture-related
2111	Agriculture - individual
2121	Forestry – individual
2131	Livestock farming - individual
2141	Fishing - individual
2151	Service to agriculture, forestry, livestock farming and fishing - individual
2161	Other individual agricultural activities
2211	Rural student loans
2221	Other rural consumer loans
9999	Other

Table A2.
Definition of agriculture-related loans – China domestic classification

Loan Type Code	Loan Type
A101	Agriculture
A102	Forestry
A103	Livestock farming
A104	Fishing
A105	Service to agriculture, forestry, livestock farming and fishing

Table A3.
Definition of agriculture-related loans – UN classification*

Loan Type Code	Loan Type
A011	Grains and other crops planting
A012	Vegetables and horticultural products planting
A013	Fruits, nuts, beverage and fragrance products planting
A014	Herbal medicine crops planting
A021	Trees planting and cultivation
A022	Timber and bamboo logging
A023	Forestry products collection
A031	Livestock breeding
A032	Pig breeding
A033	Poultry breeding
A034	Hunting
A039	Other livestock farming
A041	Sea fishing
A042	Inland fishing
A051	Services to agricultural sector
A052	Services to forestry sector
A053	Services to livestock farming industry
A054	Services to fishing industry

*International Standard Industrial Classification of All Economic Activities Rev 4

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