A Panel Data Analysis of the Repayment Capacity of Farmers

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Abstract

Using a balanced panel of 264 unique Illinois farmers from 2000 to 2004, this study identifies the most pertinent factors that explain the repayment capacity of farmers. After correcting for endogeneity bias caused by farmer-specific effects, one year lagged debt-to-asset ratio and soil productivity are both found to be significantly correlated with the coverage ratio at the 5% significance level using random effects. The finding is significant because it can enhance agricultural lenders' ability to assess creditworthiness, screen borrowers, manage loan loss reserves, and price loans, thereby decreasing lenders' costs associated with defaulted loans and ultimately reducing the costs borne by the government and taxpayers.

Key Words: panel data, random effects, coverage ratio, financial efficiency, solvency, liquidity, repayment capacity, profitability, creditworthiness

1. Introduction

The need to analyze loan quality remains an important issue given the large numbers of farmer loan defaults and bank failures (Turvey, 1991). Zech and Pederson (2003) argue that the lack of consensus concerning a unique set of variables to explain creditworthiness creates an environment where lenders develop different models "in search of specifications that best predict farm performance and repayment capacity of farmers".

The main objective of this study is therefore to statistically explore factors that explain the repayment capacity of farmers (a measure of creditworthiness) using individual loan quality information.[1] Possible endogeneity bias caused by farmer-specific effects is accounted for by using panel data instead of cross-sectional data. The data used is obtained from the Illinois Farm Business Farm Management (FBFM) Association between 2000 and 2004. Results from the analysis will help lenders to isolate the most pertinent factors to consider when building credit scoring models in order to ensure accurate estimations of creditworthiness.

Credit scoring models aid in evaluating creditworthiness by monitoring loan quality within the Farm Credit System and other lending institutions. Because financial theory offers little specific guidance as to which explanatory financial variables should be used to assess creditworthiness, a variety of explanatory variables and estimation techniques have been explored for credit scoring models (Oltmans, 1994). For example, Lufburrow et al. (1984) use liquidity, leverage, collateral, and repayment history; Miller and LaDue (1989) use profitability, liquidity, solvency, efficiency, and farm size; Fischer

[1] Individual loan quality information is collected from farm-level business data.

and Moore (1986) use profitability, leverage, and efficiency; and Mortensen et al. (1988) use only leverage and efficiency to explain creditworthiness.

The agricultural finance credit scoring literature includes linear probability models, discriminant analysis models, logit models, probit models and regression models that use discrete dependent variables (Turvey, 1991; Splett et al., 1994; and Turvey and Brown, 1990). Recent studies using linear regression models have utilized continuous dependent variables (Novak and LaDue, 1997; and Oltmans, 1994).

One issue with credit scoring models is that there is no consensus on which structural model to use and which explanatory variables to include to explain variations in credit risk factors (Gustafson, 1989). With a well defined set of explanatory variables, more accurate credit scoring can be achieved. Greater accuracy in credit scoring is more important to agricultural compared to non-agricultural lending institutions; the former cannot diversify their loan portfolio as well as the latter because the riskiness of the loan portfolio is higher in the agricultural sector (Turvey and Brown, 1990).

A more accurate credit assessment model used to evaluate loan applications and creditworthiness of borrowers results in more accurate loan pricing decisions; therefore, reducing the interest charged on loans issued to farmers (Lufburrow et al., 1984). Furthermore, improved credit scoring models enhances lenders' ability to screen potential borrowers and manage loan loss reserves, thereby decreasing the costs associated with defaulted loans. Poor credit assessment methods may increase lending errors. For example, lenders may provide loans to very high risk borrowers (Type I error) or not provide loans to low risk borrowers (Type II error). In both cases, the lender loses profit. For Type I errors, the lost profit includes lost principal, lost interest on the principal, and additional costs incurred for administration, legal fees and insurance coverage. For Type II errors, the lost profit is the difference in expected profit between a good borrower who is denied the loan and an alternative borrower who is issued the loan but may be a high or low credit risk borrower (Nayak and Turvey, 1997). A high number of Type I and Type II errors might negatively affect the amount of credit available to the private sector by depleting banks' capital, increasing banks' deposit liabilities, reducing savings rates, and increasing loan losses. All these factors may result in an economic contraction (Fofack, 2005).

To reiterate, no consensus has been reached on a specific set of variables to explain creditworthiness and, even worse, the effect of endogeneity caused by farm-specific effects is often overlooked. Furthermore, few existing studies on creditworthiness have used a continuous dependent variable.

This study addresses some of the important gaps in the literature. Most notably, this research uses a continuous dependent variable instead of a discrete dependent variable for creditworthiness for Illinois farms. This approach prevents loss of information. Furthermore, this research employs panel data techniques that allow time invariant farmer-specific effects to be explored and corrected for. This is important because farmers might be inherently different from each other. For instance, one farmer might have low risk aversion, another farmer might have high risk aversion, and also each farmer might be different in their savings behavior. The existence of individual farmer-specific effects invariably leads to endogeneity bias. After addressing the issues of endogeneity and using a continuous dependent variable, this study employs a more reliable model for assessing creditworthiness, ultimately improving agricultural lenders' ability to accurately evaluate potential borrowers and maximize loan profitability.

2. Literature Review

As mentioned in the introduction, there are competing approaches for relating financial variables to creditworthiness. Therefore, a variety of explanatory variables and estimation techniques have been used for credit scoring models (Oltmans, 1994). While one set of studies focuses on individual loan quality information, other studies examine aggregate loan quality information to build credit scoring models.[2]

Considering individual loan quality information, Miller and LaDue (1989) observe that financial measures of liquidity, profitability and operating efficiency are good indicators of borrower quality.[3] Mortensen et al. (1988) find that debt-to-asset, a solvency measure, and the operating ratios are the most effective treatment variables in explaining the loan performance of North Dakota farmers.[4] Zech and Pederson (2003) apply both linear and logistic regression to Southwestern Minnesota farm data to predict borrower repayment capacity (which is proxied by the coverage ratio).[5] They discover that the debt-to-asset ratio persistently exhibits a negative relation with farmer repayment capacity. Turvey and Brown (1990) conclude that measures of profitability, solvency,

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[2] The literature of credit scoring models is based mostly on individual rather than aggregate loan quality information. Aggregate loan quality information uses the macro and micro level, whereas individual loan quality information uses only the micro level indicators of loan quality.
[3] Liquidity shows how quickly one can generate cash. Profitability reflects wealth and the ability of a farmer to generate profit. Operating efficiency measures the farm's efficiency of operating expense management.
[4] Debt-to-asset ratio is a measure for expressing farm business risk exposure.
[5] Coverage ratio relates asset returns to debt obligations for a period of time.

financial efficiency, liquidity, and debt repayment capacity should be combined in credit scoring models for Canada's Farm Credit Corporation.[6]

Purdy et al. (1997) examine factors that influence the financial performance of a sample of Kansas farms. They discover that operator age, financial efficiency, farmland tenure position, and leverage negatively impact farm financial performance, while farm size has a positive impact on financial health.[7] Gloy et al. (2002) examine farm profitability in a panel of 106 New York dairy farms over a seven-year period. They use fixed-effects regression models to test hypotheses regarding the effects of managerial factors on farm performance. They find that individual farm effects, such as initial endowments, resource constraints, and production and financial management factors, impact farm profitability. Plumley and Hornbaker (1991) analyze the characteristics of successful Illinois farms, identified by net farm income per tillable acre. Their findings suggest that these successful farms have a balanced composition of assets, lower debt, and higher profitability.

For aggregate loan quality models, Oltmans (1994) shows that aggregate models do not provide early warning signals for changes in loan quality; however, they still indicate key factors that should be analyzed for understanding loan quality. He finds that collateral, liquidity, government program payments, off-farm income, and the debt-to-asset ratio should be analyzed to understand loan quality.[8] Escalante et al. (2004) show that farm-specific factors, such as farm size, tenure, asset turnover, operator age, diversification index, soil productivity rating, and income risk, have little explanatory

[6] Leverage is measured by the debt-to-equity ratio, and expresses the farm business' risk exposure. Financial efficiency represents how effectively a business uses its assets to generate gross revenues.
[7] Farmland tenure position is the ratio of owned acres to total acres operated.
[8] Collateral is the property promised as a guarantee for loan repayment.

power for the probability of credit risk transitions.[9] Instead, macroeconomic factors, such as money supply growth, farmland value growth, changes in agricultural long-term interest rates, and changes in stock price indexes, explain the probability of credit risk migration.

3. Model Specification

Recall that the expected profit of the farmer is given by:

(1) $E(\Pi) = (1\text{-}PD)(1+r)(L) + (PD)((1+r)L\text{-}LGD)$,

where

Π = Profit,

r = Interest rate,

L = Loan amount,

PD = Probability of default and

LGD = Loss given default.[10]

Lenders' objective is to maximize their return on a loan. From equation (1), this implies minimizing the expected losses due to borrower defaults. These expected losses depend on the probability of default (PD) and loss given default (LGD). The magnitude of the probability of default provides a signal about the creditworthiness of farmers (and by implication, the repayment capacity of farmers). One way to obtain an estimate of probability of default is to use farm financial data, which reflects the farmer's

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[9] Note here that farm-specific factors do not mean farm-specific effects. Also, the asset turnover ratio measures the farm's efficiency of asset utilization.

[10] Exposure at Default is the value of the farm debt at the time of default. Loss Given Default is the percentage of the Exposure at Default that is lost in the event of default. Essentially, Loss Given Default measures the severity of the default, and is set by the lender. For instance, the lender can ask for collateral or loan insurance so that the lender won't be affected adversely in the case of default. Probability of Default, on the other hand, is set by the borrower, and shows the frequency of loss. Characteristics of the borrower determine this probability.

creditworthiness. Therefore, variables used in this study for the farmer repayment capacity are constructed to reflect measures of the farmer's creditworthiness.

All variables analyzed in this study are recommended by the Farm Financial Standards Council (FFSC). Splett et al. (1994) argue that greater uniformity of the explanatory variables used can be achieved if all researchers employ only the FFSC recommended variable measures.

FFSC recommends specific financial measures to evaluate the liquidity, solvency, profitability, repayment capacity and financial efficiency of farmers.[11] Previous studies have also used these FFSC standards to explain farm performance and to determine creditworthiness and credit scoring for farmers (Phillips and Katchova, 2004; Barry et al., 2002; Mishra et al., 1999).

Following Miller and LaDue (1989), the equation defining farmer repayment capacity is given as

$$(2) \qquad Y_{it} = \beta_0 + \sum_{k=1}^{k=5} \beta_{ki} X_{k,it-1} + D_t + error_{it} \;,$$

where

Y_{it} = creditworthiness, which is a continuous random variable proxied by repayment capacity and measured by the coverage ratio for individual i at time t,

$X_{1,\,it-1}$ = financial efficiency of the borrower measured by the asset turnover ratio for individual i at time t-1,

[11] Profitability reflects wealth and the ability of the farmer to generate profit; liquidity shows how quickly one can generate cash; financial efficiency shows how efficiently one can convert financial inputs into financial output; and solvency and repayment capacity show whether one has enough capacity to pay debt. Solvency is a long-term dimension, whereas repayment capacity is a short-term dimension of debt payment.

$X_{2,\ it-1}$ = liquidity of the borrower measured by the working capital ratio for individual i at time t-1,

$X_{3,\ it-1}$ = solvency of the borrower measured by the debt-to-asset ratio for individual i at time t-1,

$X_{4,\ it-1}$ = profitability of the borrower measured by rate of return on equity (ROE) for individual i at time t-1 and

$X_{5,\ it-1}$ = other potential measurements that help to explain the repayment capacity of the borrower, such as the family expenditure and tenure ratios, operator age, soil productivity, and acreage for individual i at time t-1.[12]

These measurements capture the effects of the farmer's experience, soil quality, economies of scale, etc. (Ellinger and Barry, 1987; Purdy et al., 1997; Gloy et al., 2002; Barry et al., 2001; Mishra et al., 1999).

D_t is the time dummy where t = 2001, …, 2003. Note that 2004 is the base year for the study and that observations in the year 2000 are lost because one year lagged values are used as explanatory variables.

Note that a possible criticism of the model given by (2) is that it might in fact be an accounting identity. In other words, (2) is not meaningful if the right side is equivalent to the left side so that the error terms are identically zero. Despite this possible criticism, Zech and Pederson (2003) successfully use a version of (2) involving averages of the dependent and explanatory variables. Miller and LaDue (1989) also employ a version of (2), which uses loan repayment capacity as the dependent variable and proxies for the same set of explanatory variables.

[12] Since age, soil productivity and acreage do not change significantly from year to year, this study uses the lagged values instead of the present values.

In (2) (as in Miller and LaDue, 1989), creditworthiness is based on the previous period's farm financial data, which explains why the model specification includes one period lagged value for explanatory variables.[13] Furthermore, using the lagged explanatory variables implies that the variables are pre-determined. Consequently, there is no endogeneity bias caused by correlation between the matrix of explanatory variables and the error matrix. Table 1 contains the definitions of the variables, as well as expected signs. A discussion of the dependent variable and the explanatory variables for the model follows.

Dependent Variable: Farmer's repayment capacity

Previous studies have examined default classification as an indicator of creditworthiness (Turvey and Brown, 1990; Escalante et al. 2004; and Phillips and Katchova, 2004). A problem with default classification is that it is based on subjective judgment on the part of the lender (Lufburrow et al., 1984). Recent studies have also used debt repayment capacity measured by the coverage ratio obtained from farm-level data as an alternative indicator of creditworthiness (Zech and Pederson, 2003; and Novak and LaDue, 1994). The advantage of this measure is that it uses a continuous, quantitative measure instead of a discrete, qualitative measure. However, debt repayment capacity cannot distinguish between variations in profitability and debt levels (Novak and LaDue, 1997). A large (small or negative) coverage ratio implies a highly (less) profitable or less (highly) leveraged farmer. This paper uses the coverage ratio (dependent variable) as a measure of repayment capacity, and thus to measure creditworthiness.[14]

[13] Instead of the current period's explanatory variable.
[14] Coverage ratio = Cash inflow / Cash outflow
Cash inflow = Net farm income from operations + non-farm income + depreciation + interest on term-debt + interest on capital - income taxes -family living withdrawals

Explanatory Variables

Based on Miller and LaDue (1989) and Zech and Pederson (2003), the evaluation in this study focuses on financial efficiency, liquidity, solvency, profitability and other farmer descriptive variables as explanatory measures to explain creditworthiness.

1. Farmer's financial efficiency:

Following FFSC recommendations, the asset turnover ratio is used to measure the financial efficiency of the farmer. The asset turnover ratio measures the efficiency of asset utilization.[15] As the ratio increases, the more effectively assets are used to generate profits. Greater financial efficiency results in a higher repayment capacity. Therefore, a positive relationship is expected with the coverage ratio.

2. Farmer's Liquidity:

The FFSC recommends using the working capital-to-gross farm return ratio as a liquidity indicator.[16] A higher ratio indicates the farmer has a greater ability to generate cash to meet short-term financial obligations. Thus, a positive relationship between the working capital ratio and the coverage ratio is expected.

3. Farmer's solvency:

The debt-to-asset ratio is recommended by FFSC as a measure of farm solvency. It measures both the solvency of the farmer and the degree to which the farmer can meet long-term debt commitments.[17] Higher debt levels indicate greater financial obligations. Thus, the coverage ratio is expected to be lower (Zech and Pederson, 2003).

Cash outflow = Annual scheduled principal + interest payments on term debt and capital leases

[15] Asset Turnover ratio = Value of farm production / Total average farm assets (fair market value)

[16] Working Capital ratio = (Current assets-Current liabilities)/ Value of farm production

Value of Farm Production = Crop returns + Livestock return above feed + Custom work + Other farm receipts

[17] Debt-to-Asset ratio = Total Debt / Fair market value of assets

4. Farmer's profitability:

FFSC suggests that the rate of return on farm assets (ROA) and the rate of return on farm equity (ROE) are useful measures of a farmer's profitability.[18] ROE determines the return on equity after paying interest expense, whereas ROA does not account for the leverage position of a firm. Boessen et al. (1990) show that higher leveraged farms exhibit greater variability in the return to equity compared to ROA. For these reasons, ROE is chosen over ROA as a measure of farm profitability. As ROE increases, cash inflow is expected to increase, thereby improving the coverage ratio.

5. Other variables:

Other variables, such as the family expenditure and tenure ratios, age, soil productivity and acreage, may also help to explain farmer repayment capacity. This paper investigates the effects of these variables in explaining farmers' repayment ability.

Examples of family expenditure include consumption, utilities, medical expenses, clothing, and household durable items.[19] Lower family expense levels provide the farmer with more cash to cover financial obligations. Therefore, a negative relation is expected with the coverage ratio.

The age of the farm operator may provide some information about the likelihood of the lender being fully repaid. Older farmers face declining profitability and lower debt use since they are less productive. The reduction in productivity adversely affects

[18] ROE = (Net farm operating income – Unpaid labor charge for operator and family) / Average farm equity (fair market value)
Net farm operating income = Gross farm revenue – Purchases of market livestock – Cost of purchased feed or grain – Total farm operating expenses – Total interest expense
Equity = Market value of total assets – Total liabilities

[19] Family Expenditure ratio = Family living expenses / Total acres operated

repayment capacity (Barry et al., 2001). Therefore, a negative relationship between age and the coverage ratio is hypothesized.

The tenure ratio indicates the percentage of owned acres compared to total acres operated.[20] Farmers with a higher ratio tend to be less financially leveraged, exhibit less liquidity and earn a lower rate of return on assets (Ellinger and Barry, 1987; and Barry and Robison, 1986). Since most of the assets in a Midwest farm operation are tied to farm real estate, a larger portion of total returns occurs as unrealized capital gains on farmland. Since the farmer may not generate sufficient cash flow from the land itself to meet annual debt payments, the tenure ratio is expected to exhibit a negative relationship with the coverage ratio.

Higher soil productivity is also a factor that may increase/maintain production, thereby enhancing repayment capacity. Soil productivity is likely to be positively correlated with the coverage ratio.

As acreage increases, farmers take greater advantage of economies of scale or scope.[21] Intuitively, this likely results in a greater repayment capacity and higher coverage ratio.

4. Data and Descriptive Statistics

The empirical analysis uses farm financial records collected from the Illinois FBFM Association to identify factors that explain borrower repayment capacity. The FBFM data comply with “FMV Balance Sheet Certification” and “Family Living/Sources

[20] Tenure ratio = Owned acres / Total acres operated
[21] Acres = Acres operated

and Uses Certification”.[22] Although it may be more beneficial to use real lender data instead of farm-level data, obtaining lender data is both difficult and costly. Previous studies have successfully employed farm-level data as a proxy for lender data (Katchova, and Barry, 2005; Escalante et al., 2004). Zech and Pederson (2003) and Novak and LaDue (1994) have also used farm business data to determine creditworthiness, proxied by the coverage ratio. Furthermore, an advantage of farm-level data is that it often includes farmers with low and high credit risks, in contrast to lender data that contains only low credit risk farmers (Escalante et al., 2004).

The FBFM data is not completely random. Rather, it is obtained by means of a self-selection process, where farmers elect to provide their financial statements in return for technical advice from the FBFM staff. Despite this self-selection process, the data contain enough variability to distinguish between different farmers. The FBFM data include above-average and larger commercial farms in Illinois. Hence, they differ in their debt-to-asset ratios and they utilize debt with a wide range of financial performance (Katchova, and Barry, 2005). Also, the FBFM database reports accrual measures rather than cash measures, with fair market value asset valuation. Accrual measures are preferred to cash measures when classifying farmers by financial stress (Lins et al, 1987). The accrual measures ensure that all expenses that have been incurred but not paid for and all revenue that has been earned but not received are accounted for. For instance, an accrual cost is an accrued interest that is owed but not paid for and accrual revenue is unsold grain inventory. Accrual accounting recognizes the present value of all expenses and revenue and accounts for all impacts on current wealth of earnings during that period.

[22] FMV and Family Living/Sources certified data are the most reliable data available.

This study uses a balanced panel of 264 unique farmer identities from 2000 to 2004.[23] This time period is chosen because it provides the greatest number of unique farmer identities given the available dataset. Table 2 displays mean values for variables under both "overall" and "year categories". Table 2, column one contains the overall mean values for all variables from 2001 to 2004.[24] For instance, the coverage ratio has a mean value of 0.87. Since this ratio is less than one, it implies that on average cash inflow is less than cash outflow for Illinois farmers. Asset turnover, working capital and debt-to-asset ratios all have mean values around 0.30. Moreover, ROE, which represents profitability, has a mean value of 0.12. The second, third and fourth columns of table 2 report the mean values for each year from 2001 to 2004. The highest average annual coverage ratio is 1.54 in 2003, while the lowest is 0.48 in 2001. The standard deviation of the coverage ratio is moderately stable over the time period, but peaks in 2003 with a value of 14.81. Meanwhile, ROE and the family expenditure ratio reach their maximum values in 2003, with values of 0.35 and 3.78, respectively. ROE has a standard deviation of 3.73 and the family expenditure ratio has a standard deviation of 45.48 in 2003. The lowest average asset turnover ratio for Illinois farmers is recorded in 2003, with a value of 0.21 and a standard deviation of 0.40. Mean acreage of Illinois farms also increases each year attaining a high of 804 acres in 2004. Mean values for the working capital ratio, age, the tenure ratio and soil productivity are stable from 2001 to 2004.

[23] Note that a unique farmer identity is not necessarily one observation. One farmer can have more than one observation.
[24] The year 2000 data point is deleted from the data since the explanatory variables are lagged one period. Consequently, the mean values for 2000 are also omitted.

5. Panel Data Estimation Procedures

To identify the best linear unbiased estimator (BLUE) to use, recall that the general static panel-data model is given by

(3) $$y_{it} = \sum_{g=1}^{g=k} (x_{it,g})^{'}\beta + v_{it} ,$$

where

$x_{it,g}$ = explanatory variable g for individual i at time t for g = 1, 2, ---, k,

$v_{it} = c_i + u_{it}$ for t = 1, 2, ---, T and i = 1, 2, ----, N,

c_i = unobserved effect (time invariant individual specific effect) and

u_{it} = idiosyncratic error term (time and individual variant disturbance term).

Pooled OLS (PLS) is consistent if

(4) $$E\,(x^{'}_{it}\, v_{it}) = 0 \text{ for } t = 1, 2, ----, T.$$

If Var (v_{it}) is constant, then PLS is also efficient (Wooldridge, 2002). Equation (4) indicates that the data must satisfy strict exogeneity. To test for strict exogeneity, a test by Wooldridge (2002) is applied. The model for the test is as follows:

(5) $$y_{it} = x_{it}\beta + M_{it+1}\alpha + v_{it},$$

where x_{it} refers to the explanatory variables at time t for individual i, which in this case are the lagged values for the financial measures used in our model, such as one year lagged value of ROE, one year lagged value of the working capital ratio, etc, and M_{it+1} refers to the value of the explanatory variable at time t+1. After running this regression with FE, we performed a joint F-test to test for the significance of α, where H_0: $\alpha = 0$. The F-test statistic is found to be 0.37, with a p-value of 0.9492. Since the null hypothesis of strict exogeneity cannot be rejected, the strict exogeneity assumption is satisfied.

Next, a test for heteroskedasticity in a panel data setting is executed. The specific test applied is the White general test for heteroskedasticity, which has a null hypothesis of homoskedasticity. Since the White's general test statistic is 84.51388, with a p-value of 0.4637, the null hypothesis of homoskedasticity cannot be rejected.

To check for AR (1) serial correlation in the idiosyncratic error terms of the linear panel-data model, another test due to Wooldridge's test is used. The F-statistic is 2,403.696, with a p-value of 0.0000.[25] Therefore, we conclude that there is serial correlation among idiosyncratic error terms. This means that any estimator that is selected as the BLUE estimator should necessarily account for autocorrelation.

Even though the test result concludes that strict exogeneity holds, the possibility of endogeneity caused by individual specific effects and non-constant variance means that Pooled Least Squares (PLS) is often inconsistent or inefficient, so an alternative estimator, such as random effects (RE) or fixed effects (FE), may be preferred. Recall that RE is the GLS estimator, so it is the most efficient estimator under strict exogeneity.

We employ a test designed by Hausman (1978) and reproduced in Wooldridge (2002) to decide between the FE and the RE estimator.[26] To operationalize this test, individual means are added to the rest of the explanatory variables and estimation is done by fixed effects. The null hypothesis that all the individual means are jointly zero is tested against the alternative that the null is not true. Failure to reject the null hypothesis means that RE is the preferred estimator. By contrast, a rejection of the null implies that FE is

[25] Xtserial command in Stata is applied.

[26] In order to decide between RE and FE estimation, the traditional Hausman test is performed, which is identical asymptotically to the Wooldridge test. The results from Hausman test indicate a chi-sq of 2.27, with p-value of 0.9973. Again, the null is not rejected: the difference of coefficients from FE and RE estimation is not systematic. Therefore, the RE estimation is consistent and efficient. We also note that the traditional Hausman test has been severely criticized in the STATA community of users so the Wooldridge test result is more credible.

the preferred estimator. The test results show a chi-sq of 2.84, with a p-value of 0.9702, so the null hypothesis is not rejected and RE is consistent and efficient. However, the selection of RE over FE does not necessarily imply that there are no individual effects, but it does indicate that there is no correlation between the unobserved time invariant individual effects and the explanatory variables. This means that if individual specific effects are present, they are not causing endogeneity bias. Based on the outcome of the Wooldridge test, we select the RE estimator as the preferred estimator. To account for serial correlation, we use the robust command in Stata to compute the robust version of the RE estimator.

6. Results

Table 3 displays the main results of the study. These results are obtained by using a balanced panel data from 2000 to 2004, with 264 unique farmer identities. No outlier adjustment is performed.[27]

As mentioned in the econometric section of this paper, the panel data analysis is performed for the balanced panel data from 2000 to 2004 to achieve two main objectives: (1) identify which explanatory variables are significantly correlated with the dependent variable and (2) investigate whether individual, farmer-specific effects are causing endogeneity bias in the coverage ratio regression. One year lagged debt-to-asset ratio and one year lagged soil productivity are all found to be significant at the 5 % significance level. Accounting for endogeneity bias in this model is pragmatic because there are likely

[27] Even if outliers that are three standard deviations from the mean are deleted, the results stay the same. Furthermore, the correlation matrix indicates that the correlation among explanatory variables is low. Based on Kennedy (2003), a correlation coefficient in absolute value of 0.8 or 0.9 is assumed to have high collinearity.

farmer-specific effects that are time invariant but vary from farmer to farmer because no two farmers are exactly identical in their savings behavior. These farmer-specific effects may cause endogeneity bias. Results from the analysis indicate that there is no correlation between the unobserved time invariant farmer effects and the explanatory variables. Since the null hypothesis of strict exogeneity is tested and accepted, the RE estimator is chosen as the best candidate for the BLUE estimator. The Wooldridge test of endogeneity confirms that RE (the GLS estimator) is preferred to FE (the consistent estimator) and RE is the BLUE estimator for this study.

This study uses farmer repayment capacity as a proxy for farmer creditworthiness. Concluding that the lagged debt-to-asset ratio and lagged soil productivity are significant does not completely agree with the conclusions of Escalante et al. (2004). Escalante et al. (2004) find that farm-specific factors, such as soil productivity, have little explanatory power associated with the probability of credit transitions.[28] On the other hand, this study suggests that there is a positive relationship between one year lagged soil productivity and the farmer's coverage ratio (and by implication the farmer's repayment capacity), conforming to expectations. However, the coefficient for lagged soil productivity is small (0.02), though significant, creating concern regarding the significance of this variable in determining farmer repayment capacity. The elasticity estimate for soil productivity calculated at the means of the dependent and explanatory variables is 1.89, so the response is elastic in spite of the small magnitude of the coefficient. One way of explaining the small magnitude for lagged soil productivity may be that it validates the low significance Escalante et al (2004) find.

[28] Note here that farm-specific factors do not mean farm-specific effects.

The one year lagged debt-to-asset ratio, which measures the solvency of a farm business, affects the coverage ratio negatively at the 5% significance level, confirming to expectations and consistent with the results of most previous studies, such as Zech and Pederson (2003) and Mortensen et al. (1988). As the lagged debt-to-asset ratio increases, the financial obligation of the farmer increases. This implies that there is a higher probability that the farmer will not be able to repay debt. Therefore, the coverage ratio is expected to be negatively correlated with the debt-to-asset ratio. The regression results indicate that as the lagged debt-to-asset ratio increases by one unit, the coverage ratio decreases by 4.04 units. The elasticity of the lagged debt to asset ratio with respect to the coverage ratio is -1.67, so in percentage terms the lagged debt to asset ratio is responsive (though negatively) to the coverage ratio.

The year 2001 dummy is significant at 5%. Considering that our base year is 2004, we conclude that farmer repayment capacity changes over time. In other words, a significant event occurred in year 2001 when compared to 2004, but the same can not be said for the other year dummies. Recall that the September 11 attack on the World Trade Center escalated the slow down of the economy, so this might explain the significance of the year 2001 dummy.

When joint significance is tested under the null hypothesis that coefficients of all explanatory variables are zero, a chi-sq test statistic of 41.22, with a p-value of 0.0000, is obtained and the null hypothesis is rejected. The rejection of the null hypothesis implies the model is valid. Also, a look at the R-sq statistics for the random effects model shows that it is 0.0056, 0.0670, and 0.0241 for within, between and overall, respectively.

Although these numbers are relatively small, they are consistent with estimates in the previous literature that include ROE measures in their analyses.

7. Summary

This paper aims to identify those factors that are pertinent in explaining farmer repayment capacity by using the FBFM data for Illinois farms. A related objective is to help agricultural lenders more accurately evaluate credit risk, better screen borrowers, arrange their loan loss reserves, price their loans more accurately, and decrease the probability of bankruptcy due to defaulted loans. A reduction in the costs associated with defaulted loans will ultimately translate into lower costs borne by the government and taxpayers.

Although various studies in the literature have used different financial measures to explain creditworthiness, no research has considered the possibility of endogeneity bias due to farmer-specific effects in a panel data setting. After controlling for individual specific effects, the RE estimator is chosen as the BLUE estimator. By employing panel data techniques to a sample of Illinois farmers, this study finds that one year lagged values of soil productivity and the debt-to-asset ratio, which is a solvency measure, are the most significant factors in explaining farmers' coverage ratios. These results suggest that these two explanatory factors should be included in any set of variables used in credit scoring models. However, the low impact of soil productivity, in terms of its coefficient, in explaining the coverage ratio (a measure of farmer repayment capacity) deserves attention.

The results from this study are significant in that previous studies in the financial literature have come up with different indicators of creditworthiness depending on the explanatory variables used. This paper considers how the possible existence of individual farmer-specific effects impacts the factors for the determination of farmer repayment capacity.

Future study might consider using aggregate as well as individual loan quality information. The possibility of nonlinear relationships between farmer repayment capacity and explanatory variables might also be a topic worthy of future research. Additional effort could also be directed toward acquiring a larger dataset, since the central limit theorem maintains that the consistency of parameter estimates improves as the dataset expands. Another opportunity for further research could be to include the lagged dependent variable as one of the explanatory variables and repeat the analysis performed. This will invariably involve the use of dynamic panel estimators and will provide a medium to investigate the role, if any, for dynamics.

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Table 1: Variable Definitions and Expected Signs

Dependent Variable: Coverage ratio[c]		
Explanatory Variables	Definitions	**Expected Signs**
Financial Efficiency:		
Asset turnover ratio	Value of farm production / Total average farm assets	**+**
Liquidity:		
Working capital ratio[a]	Working capital / Value of farm production	**+**
Solvency:		
Debt to asset ratio	Total debt / Total assets (fair market value)	**-**
Profitability:		
ROE[b]	Net farm operating income - unpaid labor charge for operator and family / Average farm equity (fair market value)	**+**
Other:		
Family expenditure ratio	Family living expenses / Total acres operated	**-**
Age	Age of the operator	**-**
Tenure ratio	Owned acres / Total acres operated	**-**
Soil productivity	Soil productivity rating	**+**
Acres	Acres operated	**+**

[a]Value of farm production = Crop returns + livestock return above feed + custom work + other farm receipts

Working Capital = Current assets - Current liabilities

[b]Net farm operating income = Gross farm revenue – Purchases of market livestock – Cost of purchased feed/grain – Total farm operating expenses – Total interest expense

[c]Coverage ratio=Cash inflow/ Cash outflow

Cash inflow= Net farm income from operations + non-farm income + depreciation + interest on term-debt + interest on capital - income taxes -family living withdrawals

Cash outflow= Annual scheduled principal + interest payments on term debt and capital leases

Table 2: Mean Values for Variables

Variables	Overall	Year 2001	Year 2002	Year 2003	Year 2004
Coverage ratio	0.87	0.48	0.58	1.54	0.89
	(7.66)	*(1.60)*	*(2.02)*	*(14.81)*	*(2.97)*
Asset turnover ratio	0.32	0.35	0.35	0.21	0.39
	(0.28)	*(0.20)*	*(0.20)*	*(0.40)*	*(0.23)*
Working capital ratio	0.30	0.27	0.26	0.31	0.36
	(0.53)	*(0.55)*	*(0.51)*	*(0.52)*	*(0.51)*
Debt to asset ratio	0.36	0.37	0.37	0.36	0.34
	(0.19)	*(0.19)*	*(0.19)*	*(0.18)*	*(0.18)*
ROE	0.12	0.06	0.02	0.35	0.06
	(2.02)	*(0.79)*	*(0.60)*	*(3.73)*	*(1.19)*
Family expenditure ratio	0.94	-0.64	0.84	3.78	-0.23
	(28.20)	*(20.89)*	*(17.08)*	*(45.48)*	*(19.53)*
Age	51	49	50	51	52
	(9)	*(9)*	*(9)*	*(9)*	*(9)*
Tenure ratio	0.25	0.23	0.24	0.26	0.26
	(0.25)	*(0.23)*	*(0.24)*	*(0.27)*	*(0.27)*
Soil productivity	82	83	82	82	83
	(10)	*(10)*	*(10)*	*(10)*	*(10)*
Acres	772	736	762	784	804
	(478)	*(435)*	*(466)*	*(490)*	*(518)*
Number of observations	1,056	264	264	264	264

The numbers in parenthesis are standard deviations.

Table 3: Random Effects Results

Lagged asset turnover ratio	-0.26
	(0.37)
Lagged working capital ratio	0.89
	(0.75)
Lagged ROE	0.01
	(0.01)
Lagged family expenditure ratio	0.00
	(0)
Lagged debt to asset ratio	-4.04
	(1.62)**
Lagged age	-0.04
	(0.03)
Lagged tenure ratio	-1.18
	(1.5)
Lagged soil productivity	0.02
	(0.01)**
Lagged acres	0.00
	(0)
Year 2000	NA
	NA
Year 2001	-0.50
	(0.23)**
Year 2002	-0.28
	(0.2)
Year 2003	0.74
	(0.92)
Constant term	2.66
	(2.05)
Wald Chi2(13)	133.05
Prob>Chi2	0.0000
R-sq within	0.0056
R-sq between	0.0670
R-sq overall	0.0241
Number of observations	1,056
Number of groups	264

*The numbers in parentheses are standard errors, and ***, **, * represent significance at 1, 5, and 10% respectively.

*Lagged values are one year lagged values.