The Effects of Business Maturity, Experience and Size on the Farms' Economic Vitality: A Credit Migration Analysis of Farm Service Agency Borrowers

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Abstract

This paper examines the relative financial strength and endurance of several paired classes of farmers according to business maturity (beginning versus mature farm businesses), farm operators' age/experience (young versus older, more experienced farm operators), and farm size (small versus large farm businesses) by utilizing random-effects ordered logistic techniques. Results show that increasing farm size will lead to a higher probability of class upgrades. Being a young farm operator, meanwhile, decreases this probability. Positive changes in money supply and farm real estate values were found to increase the likelihood of credit upgrades. Results also show trend reversal of credit risk movement, where upgrades (downgrades) are more likely to be followed by downgrades (upgrades).

Keywords: credit risk migration, random effects, ordered logit regression, macroeconomic variables, agricultural lending, credit scoring

INTRODUCTION

Small farms have been a vital part of the agricultural sector. Small farms, per se, constitute 92% of the total number of the farms in 2013. However, the number of small farms did not seem to grow significantly in recent years. Based on the USDA ARMS data, the number of farms has fluctuated within a very narrow range, moving within the 146,000 to 147,000 range between 2007 to 2010. Thereafter, there was a sudden decrease in the number of small farms in 2011 and 2012, but eventually the number increased in 2013.

One explanation of small farms' steady growth and eventual increase in more recent years is the change in the preference of consumers in favor of fresh quality goods (Low and Vogel, 2011). Consumers consider organic foods as healthier, fresher, and produced sustainably on small farms (O'Donoghue, 2011), that increases demand for organic products.

Organic farming tends to be labor-intensive compared to conventional farming as most organic farming tasks are done manually. USDA has set standards for organic farming to ensure consumer protection. USDA standards "cover the product from farm to table, including soil and water quality, pest control, livestock practices, and rules for food additives." Based on the 2012 Census of Agriculture, there were 16,525 farms classified as organic certified or exempted farms. This translates to 0.7 percent of all farms in the United States (2,109,303). It has been observed that the organic farming alternative is popular among smaller farms, especially those operated by full-time farmers.

Economic climate in recent years is also a contributing factor to the steady growth of smaller farms. As there is high volatility in the prices of agricultural inputs and farm products, farmers are more cautious when they consider expansion plans for their farms.

While the portion of small farms has increased in more recent years, the proportion of the beginning farms to total farms in the U.S. has been decreasing for the past decades. According to the Farm Service Agency, a farm can be considered as beginning if it has been in the business for 10 years or below. Based on the Census of Agriculture from 1997 to 2002, 30 percent of principal operators had less than 10 years of experience farming in 1997; by 2012, only 22 percent had such experience which translates to 469,098 farms. In addition, beginning farms account for only a minimal portion of total production of the agricultural sector. In 2012, beginning farms constitute only 6.7 percent of the total agriculture production, which was expected as beginning farms normally hold fewer assets vis-à-vis the more established farms (Williamson, 2014). The average size of a beginning farm is smaller compared with mature farms. In 2013, the average size of a beginning farm is 135 acres, while the size of a mature farm is 436 acres. Beginning farms account for only about 6 percent of the total farmland acres operated. This is attributed to the fact that established farms usually obtain their land from relatives or by inheritance. The declining number of farm business start-ups has been an issue in the sector and support for the sector has been a priority of the government in recent years.

It has also been observed that the share of young operators is getting smaller. The average age of the principal operators has increased by 2 percent between 2007 and 2012. Among the principal operators, only 6 percent of the operators are 35 years old and below in 2012, down from 16 percent in 1982.

The downward trend of the number of young farmers reflects farm consolidation, the presence of multiple generations of operators on some farms, and the capital-intensive nature of farming. For example, land prices and start-up capital requirements can make it difficult for beginning farmers to purchase or rent land (O'Donoghue, 2011). In addition, the equipment being used by farms can last more than a decade. The increased proportion of old farmers is also associated with improved health technology that enables farmers to work in their farm businesses for a longer period of time (Mishra et al., 2005). Even though the number of older farmers is increasing, their number declines with the sale class, reflecting the gradual withdrawal from farming of these individuals (O'Donoghue, 2011). The 2012 Census of Agriculture shows that the number of operators who were 65 years old and above decreases with sales class. This age category accounted for 66 percent of total farms that had sales up to $99,000. In contrast, only 25 percent of the farms had sales of $100,000 and above.

The expansion and growth of these types of farm will rely on the availability of borrowed capital, among other options, to supplement existing funds to finance larger operating infrastructure and working capital requirements. Agricultural lending institutions, however, have traditionally tailored their financial services after the needs of large conventional farming systems. As the competition for credit in regular lending institutions becomes tighter, new, small farm businesses, especially those operated by young, beginning farmers, usually turn to the Farm Service Agency (FSA) for their credit needs as FSA lending programs have been designed to assist such disadvantaged borrowers.

This research will examine the relative financial strength and endurance of several paired classes of farmers according to business maturity (beginning versus mature farm businesses), farm operators' age/experience (young versus older, more experienced farm operators), and farm size (small versus large farm businesses). This study's result will help lenders consider modifications in their credit risk appraisal standards and models that will fairly assess the economic vitality of young beginning small farmers. From the lenders' viewpoint, the goal is to be able to determine whether specific classes of borrowers will require more attention in credit appraisal and loan monitoring. From the borrowers' perspective, this study will clarify the relative financial strength of those easily suspected as more vulnerable to economic adversities. This research will also demonstrate how migration rates are conditioned by economic conditions and structural characteristics for each farm type.

LITERATURE REVIEW

There are several studies that focus on how changes in economic conditions affect the credit risk ratings of farms. The analyses of agricultural loan credit rating movement have not been fully explored yet in literature compared to the extensive applications made on bond transactions. Most of these studies were employed using state-level agricultural data that tend to have shorter duration. Some academic assessments have contended that existing risk-rating system may not represent differences in credit qualities, with the tendency of producing high concentrations of ratings in a specific class of institution (Brady, English, and Nelson, 2008).

Agricultural finance literature contains some applications of the transition probability approach in assessing the credit quality of farm borrowers. In the study by Barry, Escalante, and Ellinger (2002), farm-level data from Illinois were used to estimate migration rates for a farmer's credit score and other performance measures under different time-averaging approaches. The credit scoring model used in that study was obtained from a joint statistical and experiential model developed from a workshop of farm lenders in the MidWest and summarized in Splett et al. (1994). Transition rates for credit scores, return on investment (ROE), and repayment capacity were derived. The results suggest greater stability in migration ratings for longer time-averaging periods, although less stable than bond migrations, and for the credit score criterion versus ROE and repayment capacity.

Research by Phillips and Kachova (2004) focused on credit score migration rates of farm businesses, testing whether migration probabilities differ across business cycles. The analysis utilized farm-level data for 1985-2002 from the Illinois Farm Business Farm Management Association. The results suggest that agricultural credit ratings are more likely to improve during expansions and deteriorate during recessions. The analysis also tests whether agricultural credit ratings depend on the previous period migration trends. The findings show that credit score ratings exhibit trend reversal where upgrades (downgrades) are more likely to be followed by downgrades (upgrades).

In the study by Gloy, LaDue, and Gunderson (2005), agricultural credit risk migration is examined using loan records from 589 lenders, which span from 1998 to 2001, to detect factors influencing downgrades. Results indicate that lender risk ratings are much more stable than ratings based on credit scores estimated from financial statements, highlighting the importance played by non-financial factors such as management capacity, character, and collateral in assessing credit risk. Additionally, the borrower's risk tier, personal characteristics, and the stage of business life cycle provide useful information in predicting credit quality downgrades, while the primary agricultural enterprise does not impact the likelihood of a downgrade.

Behrens and Pederson (2007) examined a large data set of loan risk ratings from 1997 to 2004 from four associations in the Seventh Farm Credit District (AgriBank). These four associations represent large geographic areas in North Dakota, Wisconsin, Minnesota, and Arkansas. Using conditional migration matrices, they tested the influence of path dependence, loan size, and loan seasoning in credit movement. The results show that the magnitude of migration reported in previous credit score proxy studies overstates trend reversal in agricultural loans rated by lenders. Their results indicate that retention rates of agricultural loans risk ratings are quite high. Small loans are less likely to migrate while medium- and large-size loans and unseasoned loans are more likely to migrate than seasonal farm loans.

In 2004, Escalante, Barry, Park, and Demir employed ordered logit regression techniques on a panel data from Illinois Farm Business Farm Management (FBFM) system during the period 1992 to 2001 to identify factors affecting farm credit transition probabilities. Results indicate that most farm-specific factors do not have adequate explanatory influence on the probability of farm credit risk transition. Macroeconomic factors, meanwhile, significantly affect credit movements. Economic growth signals, such as changes in stock price indexes, were found to be significant indicators of credit upgrades. Increase in interest rates hampers the probability of upgrades.

The study of Deng, Escalante, Barry, and Yu (2007) introduces the application of two Markov chain time approaches, both time-homogeneous and non-homogeneous models, for analyzing farm credit risk migration as alternatives to the traditional discrete-time (cohort) method. The Markov chain models are found to produce more accurate, reliable transition probability rates using the 3x1 migration measurement method used by farm lenders. They found that substantial mean differences in singular value decomposition (SVD) are produced between farm credit risk migration matrices developed under the cohort and Markov chain models than when similar comparisons are made in corporate finance literature using bond ratings migration.

METHODOLOGY

Data

This analysis will use data from the Farm Service Agency (FSA) from 2005 to 2012. The FSA data set was collected as part of the loan covenants with borrowers that require the provision of periodic financial reports to monitor the borrowers' business and financial progress until their loan obligations have been paid. This study's data set covers a national scope of farm level data on financial characteristics and past borrowing records of existing FSA clients. The analysis only includes farms that consistently maintained records over the 8-year period, which covers 1432 farms from all states (except Hawaii, Alaska, and Washington DC). This study will follow the credit-scoring model and classification intervals used by Splett, et al. (1994) with 5-class, with a suggested extension of the intervals to 10-class rating models to see if additional volatility in the transition probability ratings will be obtained.

Aside from data points used in the credit scoring model, the FSA data set also provides information for defining variables that capture the demographic and structural characteristics of their borrowing farms. Other economic variables at the state-level to represent local and national economic factors were drawn from the U.S. Department of Agriculture (USDA) and Bureau of Economic Analysis (BEA). The macroeconomic measures were obtained from Federal Reserve Bank of St. Louis and S&P websites.

Empirical Model

This study will utilize random-effects ordered logistic techniques for panel data to identify factors that significantly influence the probability of farm credit migration rates. The general conceptual form of the estimating equations is:

$$Y_{it}^{*} = \alpha + V_{it}'\beta_1 + W_{it}'\beta_2 + Z_{it}'\beta_3 + \mu_i + \varepsilon_{it}$$

where Y_{it}, the event of interest, is an ordered, discrete migration variable, evaluated on every pair of subsequent periods, where:

$Y_{it} = 0$ for downgrade in credit classification

$Y_{it} = 1$ for remaining in the same class (retention)

$Y_{it} = 2$ for upgrade of credit classification

The farm's credit score is evaluated using *Year-to-Year Transition (1 × 1)*, which measures movements in credit risk ratings from one year (n) to the next (n + 1).

The V_{it}, W_{it}, and Z_{it} vectors (with their corresponding vectors of regression coefficients β_1, β_2 and β_3, respectively) are associated with three groups of independent variables representing structural/demographic, financial and macroeconomic factors that could influence the probability of class migrations; and μ_i and ε_{it} are the model's error terms, with the latter representing the stochastic unit-specific error components.

Explanatory variables include demographic, structural/ financial factors that may influence credit migration. Farm size (FSIZE), a dummy variable which is equal to 1 if farm's gross revenue is at least $250,000 is included in the model. This cut-off gross revenue is being employed by Small Farm Commission to distinguish small and large commercial farms. Larger farms which have greater production efficiencies and economies of scale could influence the probability of upward credit migration.

Asset turnover ratio (ATO), the farm's asset acquisition decisions, is calculated by dividing gross farm revenues by total farm assets. This measure reflects the efficiency of farm's use of its assets to generate revenues. The higher the ratio, the higher revenue a farm is producing based on its assets. Therefore, a higher ratio is preferable to a lower one.

Dummy variable beginning farm (BEGFM) takes a value of 1 if the farm has been in the industry for 10 years or below in 2005. Beginning farms typically have fewer assets compared with mature ones, which could have an effect on the migration rates.

Dummy variables that indicate each farm borrower's regional affiliation (WESTERN, MIDWESTERN, NORTHEASTERN, SOUTHWESTERN, and SOUTHEASTERN) are also included in the analysis. Different U.S. regions have different weather, policies, and type of soil that would affect a farm's profitability and productivity. As such, location of the farm would have an expected effect on the credit rating of each farm.

Dummy variable for the age (YOUNG) will take a value of 1 if the farm operator is 45 years old or below. Empirical studies show that older farmers tend to be more risk averse (Patrick, Whitaker, and Blake, 1980). This study will look at whether this variable has significant effect on how credit scoring was determined by lending institutions.

Macroeconomic factors considered in this analysis include measures associated with economic growth, lending conditions, price level, and investor expectations. These variables are beyond the operator's control and could affect implementation of risk-reducing and growth-enhancing business plans.

Annual growth rates of state level farm real estate values (REAL) serve as indicators of economic growth activity. Changes in real estate value reflect farm credit condition, government policies, and production risk.

The annual change in money supply (MNYSUP) reflects changes in credit availability condition. Previous studies show that business failures happen among small firms during tight money conditions as bank institutions end up lending to fewer small businesses to protect their portfolios (Altman, 2001). This economic variable may affect the credit risk quality of farms.

Annual changes in S&P 500 index (SNP) are used in the analysis to reflect the overall performance of the stock market. These changes reflect changes in the investor's demand for holding stocks, which reflects willingness to pay of investors for risky financial assets (Altman, 2001). This could have an effect on the credit risk quality of farms.

Lastly, previous period migration trend (LAGMOVE) is also included in the model to analyze whether the changes in credit risks rating from last year (upgrade, retention, or downgrade) could affect the movement of credit risk ratings in the current year. Findings by Philips and Kachova (2004) show that credit score ratings exhibit path dependence where upgrades are more likely to be followed by downgrades, and vice versa.

RESULTS

The models provide interesting results on how explanatory variables affect the migration trend of farms. Table 1 shows the coefficients and resulting z-statistics of ordered logit models for 5-class and 10-class migration. A positive (negative) coefficient for an explanatory variable suggests increases (decreases) in the probability of a credit risk rating upgrade.

Table 1. Results of Random-effects Logit Regression, Multinomial Dependent Variable

Year-to-Year Transition Random Effects Ordered Logit Model					
	5 Credit Classes			**10 Credit Classes**	
Variables	Coefficient	z-statistic		Coefficient	z-statistic
FSIZE (farm size)	**0.18485*****	4.18		**0.17785*****	4.13
ATO (asset turnover)	**0.068533****	1.97		0.052415	1.59
BEGFM (=1 if beginning farm, 0 otherwise)	-0.03466	-0.63		-0.05292	-0.99
YOUNG (=1 if 45 years old or below, 0 otherwise)	**-0.15225*****	-2.93		**-0.12618****	-2.49
WESTERN	0.09299	0.86		0.037935	0.36
MIDWESTERN	0.080746	0.9		0.048207	0.55
NORTHEASTERN	0.019513	0.17		-0.01353	-0.12
SOUTHWESTERN	-0.05977	-0.55		-0.09039	-0.85
MNYSUP (money supply growth, %)	**0.050112*****	4.75		**0.03751*****	3.64
SNP (change in S&P 500 index, %)	**-0.00523*****	-4.72		**-0.00433*****	-4.01
REAL (farmland value growth, %)	**0.007081*****	2.63		**0.009453*****	3.6
LAGMOVE (previous period migration trend)	**-1.08741*****	-34.33		**-0.74691*****	-28.9
Log likelihood	-8259.925			-8936.7666	
Wald Chi^2	1247.81***			902.58***	

*, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

Three demographic, financial/structural variables produced significant coefficients for the 5-class approach, while two of such variables are found significant in the 10-class model. Farm size is significant for 5-class and 10-class models suggesting that increasing farm size will lead to a higher probability of credit upgrade. Asset turnover ratio also turned in a significant positive coefficient in the 5-credit class model that suggests that higher efficiency of use of assets of farms will increase the probability of credit class upgrade. Dummy variable for younger operators (YOUNG) is also found significant for the 5-class and 10-class models. This variable, however, suggests that being a young operator has a lower probability of upgrade compared with more mature farm operators, holding other variables constant.

All macroeconomic variables produced significant coefficients. Annual changes of money supply variable (MNYSUP) has positive coefficients for the 5-class and 10-class models, which is in line with the expected sign as increase in money supply could lessen credit availability constraints for farms. The positive coefficient of changes of farm real estate values, on the other hand, suggests that improving farm economy could also lead to class upgrades. Change in S&P 500 index (SNP) also has a significant effect in the 5-class and 10-class models. The sign, however, is not expected as improving stock market is anticipated to increase probability of class upgrade.

LAGMOVE, which is included to the model to capture the effect of previous period migration trend to the present year, also has a significant coefficient. The variable has a negative coefficient, which suggests that an upgrade in previous period decreases the probability of a credit upgrade. This is in line with the findings of previous studies on trend reversals in farm's credit scores.

Marginal effects were also derived to estimate the extent or magnitude of the regressors' effects on the dependent variable. Table 2 shows marginal effects of significant variables for 5-class and 10-class models. Results show that the likelihood of an upgrade increases by a range of 0.0328 to 0.0377 if the farm's gross revenue is at least $250,000. A unit increase in ATO, meanwhile, increases the likelihood of an upgrade by 0.0122. The variable YOUNG, on the other hand, decreases the likelihood of an upgrade by a range of 0.0268 to 0.0270.

Table 2. Marginal Effects of Significant Explanatory Variables

	Five Credit Classes		
Significant Variables	**Downgrade**	**Retention**	**Upgrade**
FSIZE (farm size)	-0.0295288	-0.0033023	0.0328311
ATO (asset turnover)	-0.0109478	-0.0012243	0.0121721
YOUNG (=1 if 45 years old or below, 0 otherwise)	0.0243215	0.00272	-0.0270414
REAL (farmland value growth, %)	-0.0011312	-0.0001265	0.0012577
MNYSUP (money supply growth, %)	-0.0080051	-0.0008952	0.0089003
SNP (change in S&P 500 index, %)	0.0008352	0.0000934	-0.0009286
LAGMOVE (previous period migration trend)	0.1737073	0.0194263	-0.1931336
	Ten Credit Classes		
FSIZE (farm size)	-0.035043	-0.0027115	0.0377545
ATO (asset turnover)			
YOUNG (=1 if 45 years old or below, 0 otherwise)	0.0248627	0.0019238	-0.0267865
REAL (farmland value growth, %)	-0.0018625	-0.0001441	0.0020067
MNYSUP (money supply growth, %)	-0.0073909	-0.0005719	0.0079628
SNP (change in S&P 500 index, %)	0.0008536	0.0000661	-0.0009197
LAGMOVE (previous period migration trend)	0.1471682	0.0113875	-0.1585557

Two of the macroeconomic variables, REAL and MNYSUP, have negative marginal effects on downgrade and retention probabilities, and have positive marginal effect on the probability of upgrades. Results show that MNYSUP yields larger marginal effects on credit class movements compared with REAL. The other significant macroeconomic variable, SNP, has positive marginal effects in downgrade and retention probabilities, while its marginal effect on the probability of upgrades is negative. Overall, significant macroeconomic variables have weaker marginal effects on class risk movements compared with demographic and structural variables.

LAGMOVE produced the strongest marginal effects among explanatory variables. This variable decreases the likelihood of an upgrade by a range of 0.159 to 0.193. The variable's effect on downgrade probabilities is positive, which ranges from 0.147 to 0.173. The marginal effect of this variable on the probability of retention is also positive by a range of 0.0114 to 0.0194.

SUMMARY AND CONCLUSIONS

This research utilizes random-effects ordered logistic techniques in order to determine the factors that significantly influence the probability of farm credit migration rates. This employed the pre-determined weights and measurement procedure assigned to each component of the credit-scoring model and classification intervals used by Splett, et al. The credit score is evaluated using year to year transition to determine the credit score movement. Demographic and financial/structural variables, macroeconomic variables, and a multinomial variable that reflects previous period migration trend were used as regressors in the model.

The results of this study show that larger farm size and older farm operators have higher probabilities of credit upgrades. This suggests that these kinds of farms have will most likely succeed in obtaining loans from lending institutions. Small young farms, meanwhile, may have difficulty meetings lender's requirements. Financing capital is needed by these small young farms to supplement existing funds to finance their operating infrastructure and working capital requirements. As such, these results underscore the need for lenders' better understanding of the small young farmers' operating structures and business potentials and consider the adoption of more appropriate credit risk assessment models that should more accurately capture their credit risk conditions.

Coefficients of macroeconomic variables suggest that the economic activities have significant roles in credit risk movements of farms. The government should consider the nature and magnitude of their support for the sector especially for small young farms in order for them to withstand volatile, more challenging economic conditions, such as a recessionary period.

This study’s results also indicate that farm credit score movements exhibit trend reversal. This contradicts studies that show downward momentum bond ratings (Bangia et al., 2002). Further studies are needed to clarify whether there are significant differences in migration rates for different types of farmers – from beginning and small farms, to mature and large farms – that translate to differences in credit quality and financial performance, especially during periods of economic shocks.

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APPENDIX A

Credit Scoring Classification Intervals (Source: Splett et al.)

Variables (Measures/Classes	Interval Ranges	Weights
LIQUIDITY (Current Ratio)		
Class 1	> 2.00	
Class 2	1.60-2.00	
Class 3	1.25-1.60	
Class 4	1.00-1.25	
Class 5	< 1.00	___x 0.10 =____
SOLVENCY (Equity-Asset Ratio)		
Class 1	> 0.80	
Class 2	0.70-0.80	
Class 3	0.60-0.70	
Class 4	0.50-0.60	
Class 5	< 0.50	___x 0.35 =____
PROFITABILITY (Farm Return on Equity)		
Class 1	> 0.10	
Class 2	0.06-0.10	
Class 3	0.04-0.06	
Class 4	0.01-0.04	
Class 5	< 0.01	___x 0.10 =____
REPAYMENT CAPACITY (Capital Debt-Repayment Margin Ratio)[a]		
Class 1	> 0.75	
Class 2	0.50-0.75	
Class 3	0.25-0.50	
Class 4	0.05-0.25	
Class 5	< 0.05	___x 0.35 =____
FINANCIAL EFFICIENCY (Net Farm Income from Operations Ratio)		
Class 1	> 0.40	
Class 2	0.30-0.40	
Class 3	0.20-0.30	
Class 4	0.10-0.20	
Class 5	< 0.10	___x 0.10 =____
	Total Score (Numeric)	

[a] Term debt coverage ratios were used to measure repayment capacity in this study.

APPENDIX B

CREDIT SCORE CLASSES

Five Credit Classes

Credit Score Classes	Interval Ranges
Class 1	1.00 - 1.80
Class 2	1.81 - 2.70
Class 3	2.71 - 3.60
Class 4	3.61 - 4.50
Class 5	4.51 - 5.00

Five Credit Classes [b]

Credit Score Classes	Interval Ranges
Class 1	1.00 - 1.40
Class 2	1.41 - 1.80
Class 3	1.81 - 2.25
Class 4	2.26 - 2.70
Class 5	2.71 - 3.15
Class 6	3.16 - 3.60
Class 7	3.61 - 4.05
Class 8	4.06 - 4.50
Class 9	4.51 - 4.75
Class 10	4.76 - 5.00

[b] The ten credit classes were derived from the original five credit classes defined by Splett, et al. (1994) where class 1 in the latter classification was split into classes 1 and 2 of the new ten-class approach, and so forth.