

Risk Rating of FSA's Guaranteed Loan Portfolio

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About this Study

Identification and measurement of credit risk are essential aspects of a lender's loan portfolio management. Advances in information technology and greater computer capacity have enabled lenders to better monitor portfolio quality, more accurately determine capital requirements, facilitate loan origination, price loans, and analyze profitability. The USDA Farm Service Agency's ability to quantify credit risk on their guaranteed loan portfolio, however, has been hampered by a lack of data on borrower financial characteristics. Historically, FSA has only maintained data bases necessary for loan accounting—balances owed, terms, and performance. Information on a borrower's financial characteristics as well as farm structural characteristics, such as farm size and farm type, have been maintained by the lender holding the guaranteed loan, and are not readily available to FSA.

Secondary data sources can be used to provide information on a borrower's financial characteristics. USDA's ARMS is a national survey which provides detailed financial, structural, and demographic data for farm business and farm operator households. This analysis merges ARMS data with FSA guaranteed loan data. Specifically, ARMS data from 1996 and 1997 is merged with FSA data on loans obligated between 1994 and 1997 which had outstanding balances at the end of 1997. Their performance was tracked from 1997 through 2007 to determine if the borrower ever defaulted, where default is defined as being 90 days or more past due on any guaranteed loan. This presumes that a default on any guaranteed loan would be treated as a default on all guaranteed indebtedness.

The resulting data set is unique in that it links borrower financial and structural characteristics obtained from the ARMS with FSA loan data. The objective of this study is to utilize this unique data set to determine how borrower financial and structural characteristics may be related to borrower default. Secondly, these relationships are used to classify guaranteed loans according to their predicted probability of default.

Methods

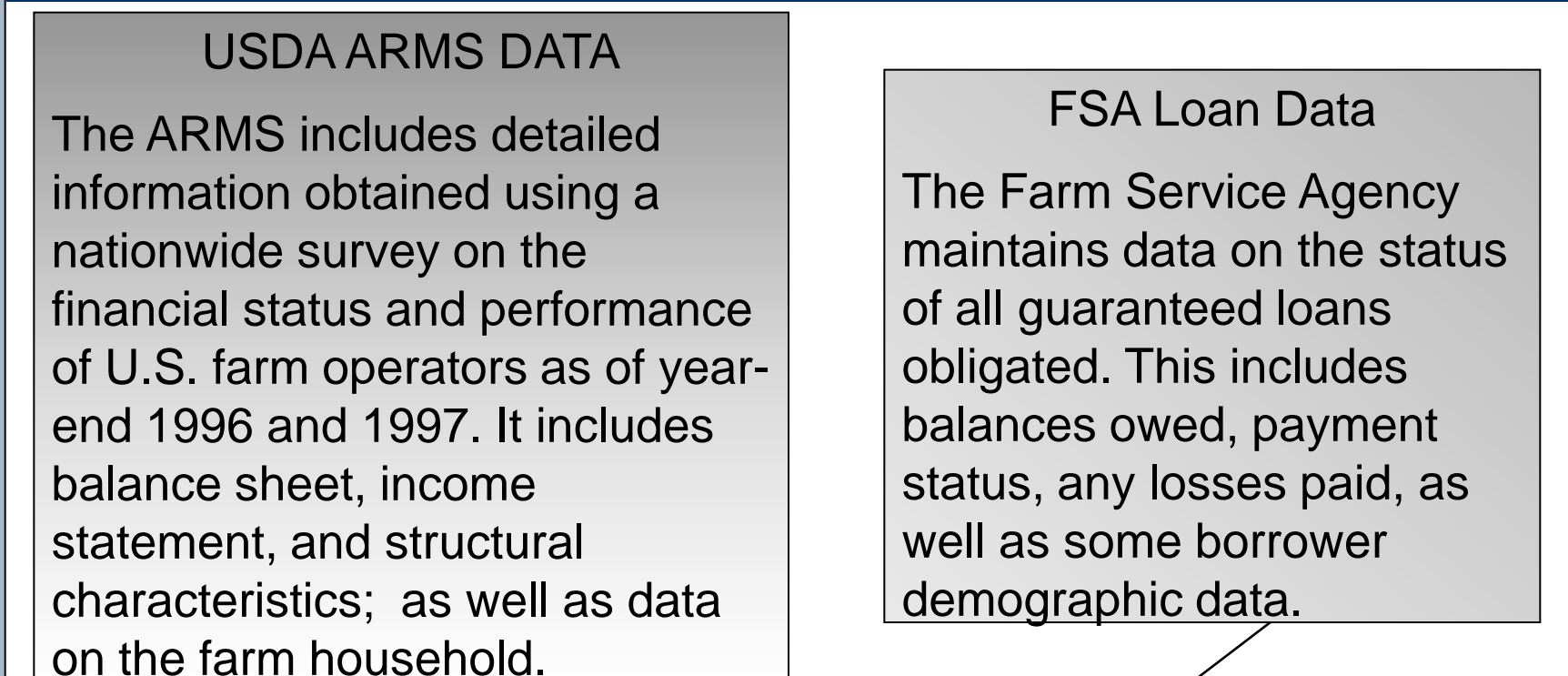
A binomial logit model is developed to evaluate the probability of default (PD) for FSA guaranteed loans. The general form of the logistic model used in this analysis is:

$$PD = \text{PROB}(\text{DELQ}_{90} = 1) = \frac{e^{B'X}}{1 + e^{B'X}}$$

Where DELQ₉₀ is 1 if a borrower is 90 days or more delinquent, 0 otherwise. X represents the set of variables hypothesized to influence default; borrower financial characteristics, farm type specialization, farm size, and regional economic conditions.

Credit risk involves PD as well as loss given default. PD indicates the chance that a loss may occur, while loss given default indicates the severity of the loss to the lender. This analysis focuses only on the PD of the borrower. While PD and expected loss are related, it is a common practice to evaluate the PD independently of losses because of difficulties of tracking loans through the liquidation and recovery process.

Data



The merged data set includes unique information which matches financial and structural characteristics of the borrower with loan performance data. With this data, it is possible to analyze relationships between borrower financial status and guaranteed loan performance.

Factors Expected to Influence PROB(DELQ₉₀)

Variable Name	Definition	Exp. Sign.
COVERAGE	1 if term debt coverage ratio > 1.25; 0 otherwise.	-
LOWINC	1 if primary op. household income < 75% of poverty level; 0 otherwise.	+
WC_RATIO	Working capital (current assets – current liabilities) as % of net worth	-
ROA	Return on assets	-
DAR	Debt-to-asset ratio	+
BEG_YOUNG	1 if primary operator is less than 36 or has less than 10 years of farming experience; 0 otherwise	+
SMALLFARM	1 if primary operator of a small or part-time farm, defined as having annual sales of \$100,000 to \$250,000 or sales of < \$100,000 and primary occupation = farming; 0 otherwise	+
TOT_GTE	Total guaranteed debt outstanding	+
DIRBOR	1 if borrower has a direct loan; 0 otherwise	+
POVCTY	1 if classified as either persistent poverty or having a large black population by ERS; 0 otherwise	+
CORNSOY	1 if borrower a corn-soybean farmer; 0 otherwise	D
LVSK	1 if borrower a cattle or hog farmer; 0 otherwise	D

D=Dependent on commodity

Logistic model statistically significant, but many underlying variables were not.

Variable	e	Error	Chi-Square	Pr > ChiSq
INTERCEPT	-3.615	0.776	21.713	<.0001
TOT_GTE	3.836	1.295	8.775	0.003
COVERAGE	-0.367	0.544	0.455	0.500
WC_RATIO	-0.998	1.167	0.731	0.393
LOWINC	0.407	0.478	0.725	0.395
DAR	0.069	0.842	0.007	0.935
ROA	0.867	1.302	0.443	0.506
SMALLFARM	1.008	0.522	3.728	0.054
POVCTY	1.143	0.476	5.762	0.016
DIRBOR	1.331	0.399	11.162	0.001
BEG_YOUNG	-0.408	0.466	0.764	0.382
CORNSOY	-0.429	0.473	0.822	0.365
LVSK	0.123	0.485	0.064	0.800
Likelihood ratio	3,383			<.0001
Sample size	430			
Weighted # of farms	23,608			
% defaulted (actual)	15.1			

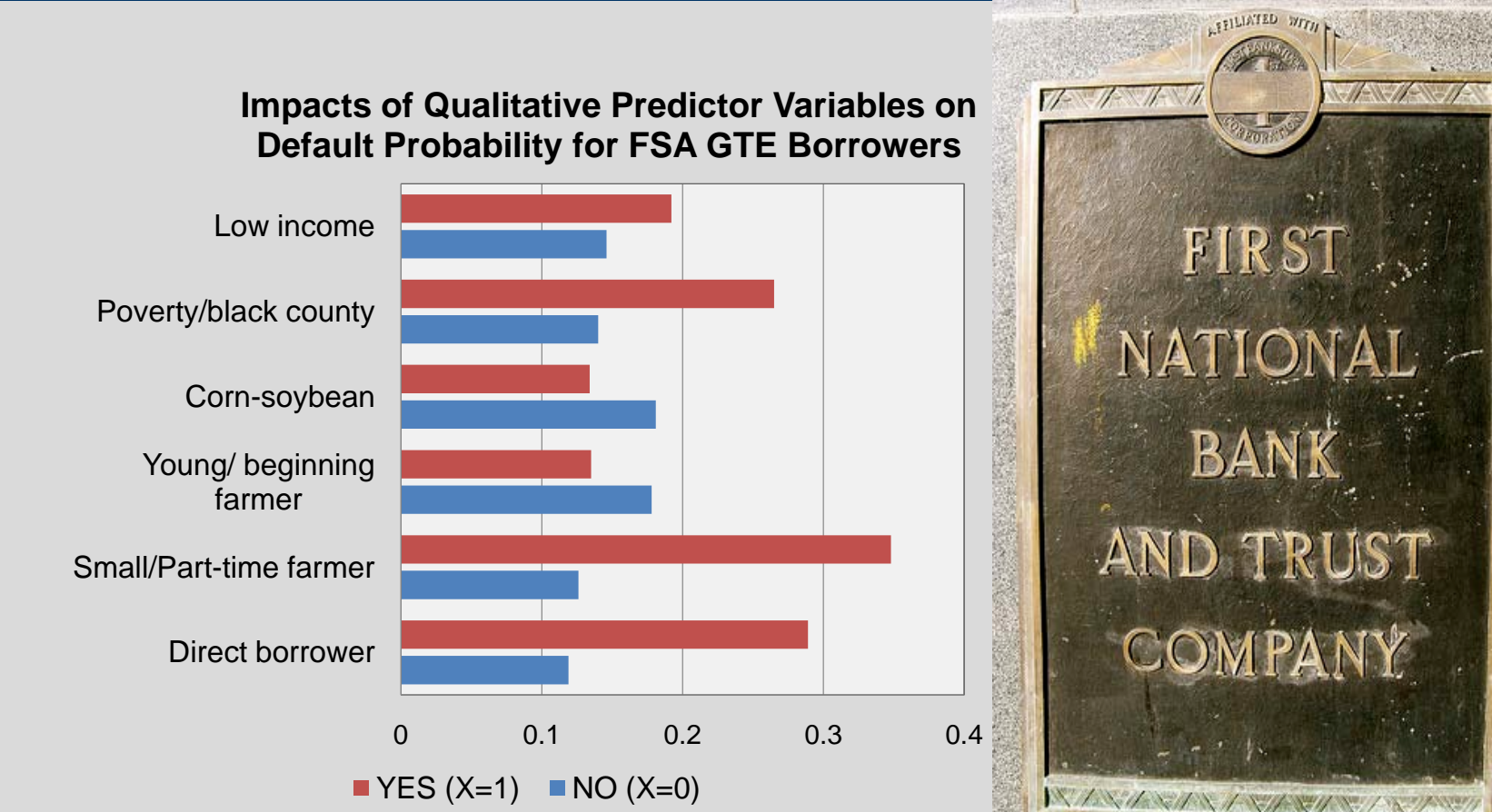
Goodness of fit Statistics

Cut-off for PD	Correct	Sensitivity	Specificity
		% of total	
12.2%	63.3	76.3	60.9
15.1%	70.1	74.8	69.3
16.6%	73.6	73.2	73.7

Is there really no relationship between default and farm financial characteristics?

- Working capital and coverage ratios from the ARMS are end-of-year estimates and are less relevant ratios taken during the production cycle when a farm is likely to have larger amounts of operating loans outstanding.
- The years 1997-2007 represented a prosperous time period for US farmers, and may not be indicative of longer-term trends. Rising farm land values increased solvency, incomes (farm and nonfarm) remained strong, and interest rates were low, resulting in greater debt capacity.
- Sample size was a limiting factor in this analysis. In order to obtain a viable sample size, both operating and real estate loans obligated over several years were included in the analysis. Ideally one would look at cohorts of similar loans obligated over 1 year; for example, real estate loans obligated in 1997.

Impacts on PD from Changes in Dependent Variables

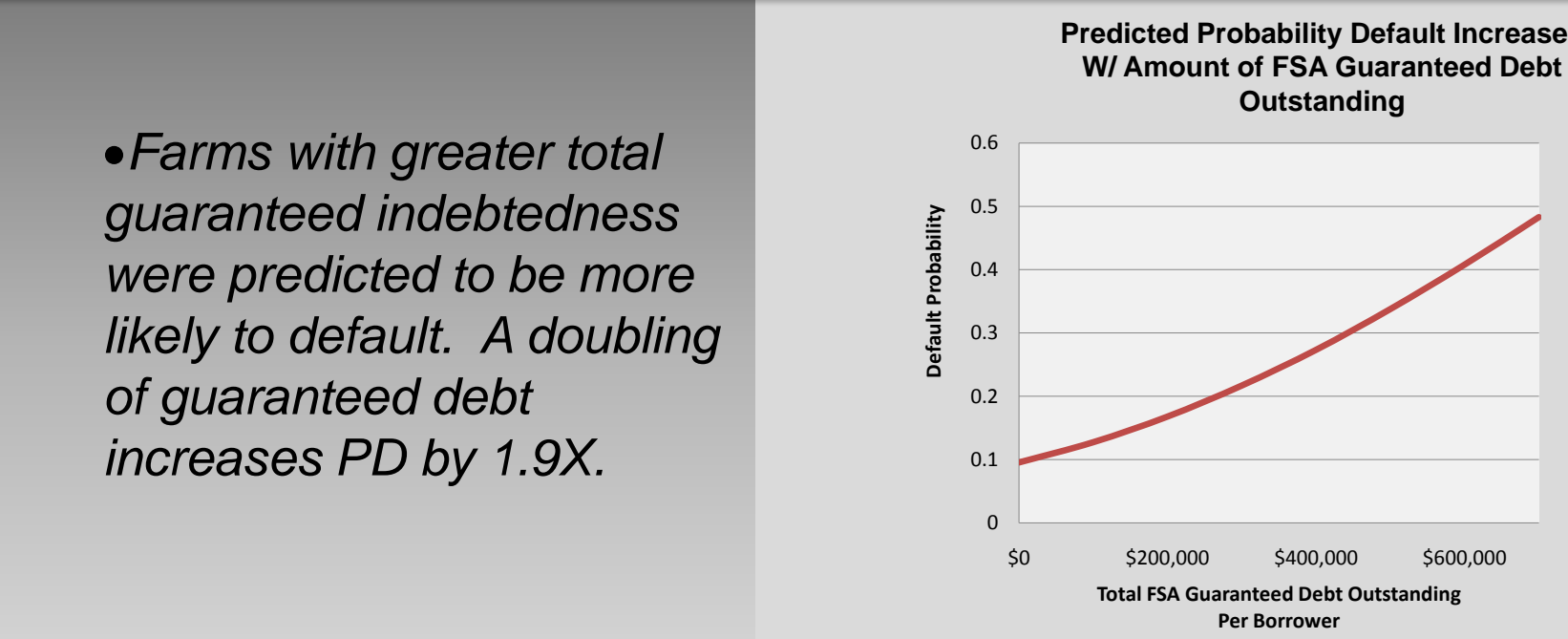


Guaranteed borrowers with direct indebtedness were predicted to be 2.4X more likely to default than those with no direct loans, reflecting differences in eligibility criteria between the two programs. The higher risk of direct borrowers suggests that loan guarantees are likely a necessity to enable direct borrowers to graduate to commercial credit.

Small/part-time farms were predicted to be 2.76X more likely to default than commercial and lifestyle farms, reflecting the squeeze affecting farms that lack both scale and off-farm income.

Farms located in persistent poverty counties or counties with a high concentration of African Americans were predicted to be 1.9X more likely to default reflecting the importance of local economic conditions.

Young and beginning farmers were predicted to be less likely to default than non-beginning and older farmers. While unexpected, this result may be a consequence of the financial training required by FSA of beginning farmers.



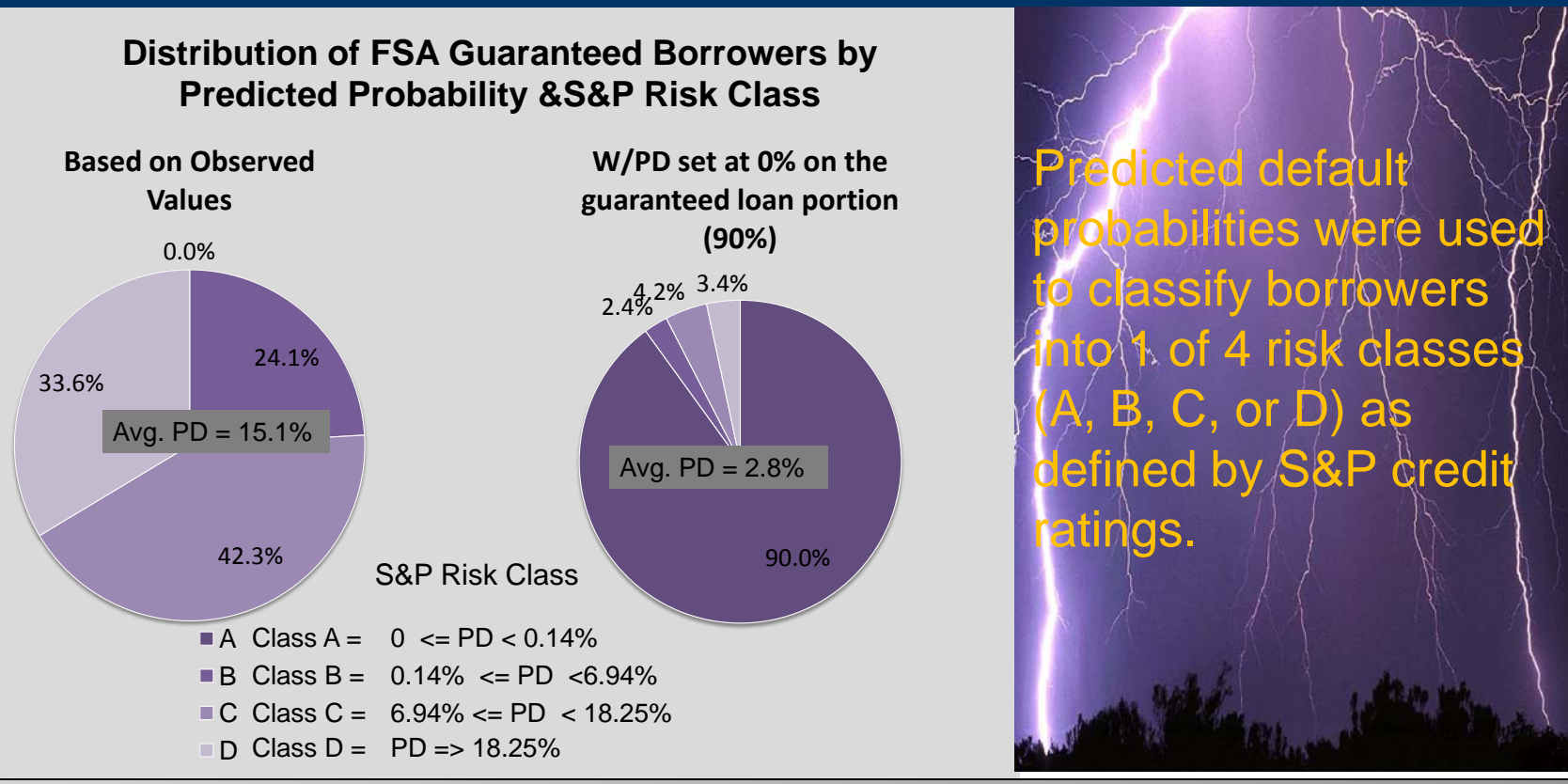
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Risk Rating of FSA Probabilities Guarantee Borrowers Using Predicted Default



There were no borrowers with a PD (w/PD estimated on observed values) placing them in Class A; 24.1% were placed in Class B, 42.3% in Class C; and 33.6% in Class D.

The FSA guarantee effectively moves the credit risk of default from the lender to the government. On the portion of loan guaranteed, the lender would have 0% PD. Re-estimating the predicted PD's assuming 0% PD on the guaranteed portion (90%) and the full predicted PD on the 10% lender's un-guaranteed share, greatly changes the risk profile with 90% of the outstanding balance classified as Class A credits.

On average, lenders making these loans without the presence of a guarantee would have experienced an expected PD of 15.1%. With a FSA guarantee the effective PD would fall to 2.8%.

Summary Points

- It is feasible to merge FSA loan data with USDA ARMS data to produce a unique data set incorporating FSA guaranteed loan performance with borrower financial data.
- Model results indicated a strong and positive relationship between the predictors and PD, with the model correctly classifying three-fourths of the observations. The PD was especially sensitive to the amount of guaranteed debt, the presence of direct loans, and whether or not the farm was considered a small/part-time operation.
- For a typical portfolio of FSA guaranteed loans, the presence of a guarantee reduces the lenders exposure to default from 15.1% (Class C credit) to 2.8% (Class B credit).

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