Heterogeneity of Farm Loan Packaging Term Decisions: A Finite Mixtures Approach

Chandra Kant Dhakal
University of Georgia
chandra.dhakal25@uga.edu

Cesar L. Escalante
University of Georgia
cescalan@uga.edu

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BACKGROUND AND MOTIVATIONS

Any lending decision is usually carefully analyzed to discern the extent of objectivity factored into the appraisal of the borrower's credit risk profile, repayment potential, and overall creditworthiness. Loan evaluation and credit risk appraisal methods are usually periodically re-evaluated by lending institutions to ensure their conformity to objectivity standards. However, allegations of biased lending decisions still arise when there is incongruence between lenders' and borrowers' expectations.

In the farm sector, for instance, the U.S. Department of Agriculture (USDA) has been faced with several civil rights lawsuits alleging biased loan decisions made by the Farm Service Agency (FSA), its lending arm, to borrowers belonging to racial and minority groups, such as African Americans, Native Americans, Hispanic, and women farmers. A surge in lawsuits of this nature started in the late 1990s. The African American case, Pigford v. Glickmann, was filed in 1997 while the American Indian case, Keepseagle v. Vilsack, was filed in 1999. Both of these lawsuits even succeeded in getting upgraded to collective class action status. In cases filed by other groups, such as the women farmers' Love v. Vilsack case and the Hispanic farmers' Garcia v. Vilsack case, class status was denied and plaintiffs were instead asked to file individual claims in Court (Feder and Cowan, 2013). The Pigford and Keepseagle cases ended in out-of-court settlements with the USDA in 1999 and 2011. In 2012 USDA also settled with Hispanic and women farmers with offers for cash remunerations, in addition to tax and debt relief provisions (May, 2012). These settlements cost the federal budget more than $2 billion disbursed to African American farmers, $680 million for Native American farmers, and $1.33 billion allocated for Hispanic and women farmers (Feder and Cowan, 2013).

Outside the farming sector, a string of similar lawsuits had been filed alleging discrimination in mortgage lending and automobile financing. Among the well-publicized cases involves Countrywide Financial Corporation that agreed to pay $355 million in 2011 as the Department of Justice has verified and established a pattern of higher fees and rates charged to more than 200,000 minority borrowers from 2004 to 2008 (Savage, 2011). In 2012 the Justice Department also declared Wells Fargo guilty of the same offense committed against more than 30,000 minority borrowers during the period 2004-2009, in addition to steering more than 4,000 minority borrowers into costlier subprime mortgages while white borrowers with similar credit risk profiles were accommodated with regular loans (Savage, 2012). Specifically, the Wells Fargo case revealed that African American and Hispanic borrowers eligible for regular loans were 2.9 and 1.8 times, respectively, more likely to be re-classified into subprime credit packages than equally qualified white borrowers. Wells Fargo agreed to settle the charges through payments of at least $175 million to affected clients. Ally (General Motors' lending arm) and Honda entered into settlement agreements with their minority customers. Ally's case affected about 235,000 minority clients who applied for car loans around 2011 (Isidore, 2013). Last year Honda agreed to pay a settlement of $24 million for charging higher interest rates to thousands of minority car buyers (Meyers, 2015).

A closer scrutiny of lending-related trends provides further support to such allegations and lawsuits. According to the Consumer Federation of America women may generally have higher credit scores than their male counterparts, but they end up being charged interest rates that are 32 percent higher than those given to men with similar level of creditworthiness (Tedeshi, 2007). Boehm, Thistle, and Schlottmann (2006) used American Housing Survey data from 1991 to 2001 to support their claim that African American and Hispanic borrowers pay interest rates that are 20.63 and 11.80 basis points higher than the rate White borrowers pay for loan refinancing transactions. This finding is corroborated by Susin's (2003) study on 12,524 households that estimated the discrepancy at 44 basis points.

Cheng, Lin, and Liu (2015) provide evidence on the effect of borrowers belonging to two minority classifications, such as the African American female borrowers. Their results indicate that African American women pay interest rates that are 26.5 basis points higher than White women clients in the same credit risk category. Notably, African American male borrowers' interest rates are only 9 basis points higher than the rates enjoyed by White American male borrowers.

RESEARCH GOALS

Drawing upon such controversies and developments, this paper revisits and analyzes FSA's more recent loan transactions with minority (racial and gender) farmers. This study distinguishes itself from other previous lending discrimination studies in two ways. First, this article departs from the conventional analytical approach usually focused on the determinants of loan officers' approval or rejection decisions (Escalante, Epperson, and Raghunathan, 2009; Escalante et. al, 2006). Instead this study analyzes loan officers' decisions on packaging terms for approved loans, such as loan amount, maturity, and interest rates. The parameters of interest in this study are the loan terms stipulated by lenders for borrowers with approved credit applications.

The second area of distinction is the novel analytical method employed in this study. While the variables of interest (loan terms) can easily be linked to clearly observed demographic, financial, and structural characteristics attributed to borrowers, it can be argued that loan terms will vary across certain priori unobserved factors. In these cases, it is very unlikely to assume the same distribution of the outcome variable for different subgroups of the population. Hence, this study allows for the possibility of a priori unspecified unobserved heterogeneity.

DATA AND METHODS

This article utilizes a USDA-FSA national dataset of farm borrowers under its direct loan program. The dataset is a compilation of financial performance measures, demographic attributes, and approved loan terms of FSA's existing direct borrowers from 2004 to 2014 operating single proprietorship businesses. Out of a possible 26,950 observations, a sample of 19,701 borrowers was deemed usable for estimation purposes as missing observations and abnormally large outlier values were discarded.

Table 1 reports a summary of the original dataset's descriptive statistics. Based on the figures obtained, the average farm borrower is most likely Caucasian (white), male, and about 39 years of age. The average farm business has an average gross revenue of about $170,000, is highly liquid given an average current ratio exceeding 6.0, generates about 29% of its income from off-farm sources, and has debt repayment capacity of about twice its loan obligations.

The Finite Mixture Model

This study adopts a Finite Mixture Model (FMM), which primarily contends that observed data come from distinct, but priori unspecified unobserved sub-populations. FMM allows one to identify and estimate the parameter of interest for each sub-population in the data, not just for the entire mixed population, thus providing a natural representation of heterogeneity in a finite number of latent classes (Deb and Trivedi, 1997).

FMM is a semi parametric probabilistic model that combines two or more density functions. In an FMM, the observed response y is assumed to come from g distinct classes $f_1, f_2, ..., f_g$ in proportions $\pi_1, \pi_2, ..., \pi_g$. In its simplest form, the density of g component finite mixture model (Deb and Trivedi, 1997) is

$$(1) \qquad f(y/x; z; \theta_g; \pi_g) = \sum_{j=1}^{g} \pi_j(z) f_j(y/x'\beta_j)$$

where π_i is the probability for the ith class, $0 \leq \pi_j \geq 1$ and $\sum_{j-1}^{g} \pi_i = 1$, and $f_j(.)$ is the conditional density function for the observed response in the *ith* class model. Let *x'* denote the vector of observed characteristics and θ_g denote the parameters of the distribution f_j *(.).*

In this analysis, the underlying unobserved heterogeneity splits the population into two latent classes. Under FMM, the best fitting parameters can be obtained for the two subgroups, even though the information about subjective frames is not available (Wang and Fischbeck, 2004). Moreover, the model can also serve as an approximation to any true, but unknown, probability density (Heckman and Singer, 1984). FMM allows one to identify and estimate the parameter of interest for each sub-population in the data, thus providing a natural representation of heterogeneity in a finite number of latent classes (Deb and Trivedi, 1997). The best fitting parameters can be obtained for the two subgroups, even though the information about subjective frames is not available (Wang and Fischbeck, 2004).

Specifically, the normal Finite mixture model with 2 components is defined as follows

$$(2) \qquad f(y_i/\theta_1, \theta_2; \pi_1, \pi_2) = \sum_{j=1}^{2} \pi_j \frac{1}{\sqrt{2\pi\sigma_j^2}} exp\left(-\frac{1}{2\sigma_j^2}\left(y_i - x_i\beta_j\right)^2\right)$$

Estimations are carried out using maximum likelihood

$$(3) \qquad \max lnL = \sum_{i=1}^{N}\left(log\left(\sum_{j=1}^{g} \pi_j(z) f_j\left(y/x'\beta_j\right)\right)\right)$$

Further, the probability for the *ith* latent class is given by

$$(4) \qquad \pi_i = \frac{exp(\gamma_i)}{\sum_{j=1}^{g} exp(\gamma_i)}$$

where γ_i is the linear prediction for the *ith* latent class. By default, the first latent class is the base level so that $\gamma_i = 0$ and $exp(\gamma_1) = 1$.

The priori probabilities of class membership are assumed to be constants. However, the posterior probabilities that observation y_i belongs to component g:

$$(5) \qquad Pr[i \in class\ g/x_i, y_i; \theta] = \frac{\pi_g f_g(y_i/x_i, \theta_c)}{\sum_{j=1}^{g} \pi_j f_j\left(y_i/x_i, \theta_j\right)}$$

These posterior probabilities vary across individuals and provide a mechanism for assessing individuals to latent classes.

In the empirical issue of this study, one can argue that interest rate is the function of loan amount and maturity, while maturity itself is a function of interest rate. As the finite mixture model does not have linear instrumental variable analog, we use the control function approach developed and generalized by Newey et. al. (1999) to address the noted relationships between this study's three dependent variables. We claim that there exists a function of first stage residuals in a simultaneous equation system that performs as a control function in the second stage regression in the way that including the residuals function eliminates endogeneity bias.

RESULTS

This analysis explores the possibility of treatment effect heterogeneity in order to estimate heterogeneous effects across the borrowers and to characterize the sources of such unobserved heterogeneity. In applying the FMM approach to this study's empirical issue, we find that finite mixtures of two components are preferred for all three loan terms. Our main finding is that there is substantial heterogeneity on loan amount, maturity period and interest rate across the borrowers. The following sections will provide a detailed discussion of this study's results.

Posterior Probability by Class

The FMM procedure initially involves the identification of subgroups of borrowers for whom outcomes are largely affected while for others least affected or not affected at all. Posterior probabilities of class membership are obtained for all three loan terms using the estimates from FMM. Specifically, we calculate the posterior probability of the latent class with lower loan, higher modal interest rate, and longer maturity. Using regression of posterior probabilities on covariates, the paper establishes the relationship between likelihood of being in latent classes of interest with observed characteristics of borrowers.

Table 2 presents the predicted means and posterior probabilities associated with two latent classes under each of the three variables of interest in this study (amount, maturity, and interest rates). The plots of the posterior probabilities for these three variables are presented in Figure 1.

In terms of loan amount, the first latent class of borrowers receiving smaller loans has a mean of about $27,600, while Class 2 borrowers receive an average loan amount of $121,000. In terms of posterior probability, there is a 49% chance that borrowers fall under the first latent class.

In the loan maturity model, borrowers have a posterior probability of 34% in being categorized under the first latent class that has an average term of 12 years. The second latent class has an average term of about 16 years.

As for loan pricing, borrowers have a 54% chance of being charged an average of 3.43% (Class 1). On the other hand, borrowing farms have a 46% chance of receiving an average interest rate of 4.56% (Class 2).

FMM Estimation Results

Based on the FMM results presented in Table 3, Gross Income, a proxy variable for size, registers significant effects in both low and high loan amount classes, but only in the shorter maturity (Class 1) and higher interest rate (Class 2) latent classes. These suggest that business size is an important consideration in loan amount decisions, regardless of loan size. However, larger farm businesses tend to enjoy the longer of the shorter terms stipulated by lenders among Class 1 borrowers. On the other hand, relatively smaller businesses among those in the higher loan pricing regime (Class 2) are charged high interest rates than others.

Younger farmers also tend to receive smaller loan amounts among Class 1 (smaller loan) borrowers. Loan accommodations to older farmers are prescribed longer maturities among Class 2 (longer maturity) borrowers. In terms of loan pricing, older farmers receive higher interest rates in both latent classes.

In terms of the more controversial, well scrutinized demographic attributes pertaining to race and gender, there are a number of interesting trends. Non-white farm borrowers tend to receive larger loans among those in the lower loan latent class (Class 1), but receive relatively lower loans among those accommodated with larger loans (Class 2). These racial minority borrowers are also charged interest rates higher than their peers in both the low and high interest rate latent classes. This trend is mitigated by the relatively longer maturities this borrower category receives in both latent classes in the maturity model.

Gender-wise, male borrowers are accommodated with larger loans and longer maturities in both latent classes in the loan amount and maturity models. When the combined racial and gender classification effect is captured through the *non-white-female* interaction term, results indicate that racial and gender minority borrowers tend to receive larger loans among Class 2 (larger loans) borrowers and longer maturities among Class 1 (shorter maturities) borrowers.

Loan packaging decisions are also influenced by the nature of the borrowing transactions captured by the program variables (*beginning, operating loan, and refinancing dummies)*. Beginning farmers enjoy larger loans in both latent classes in the loan amount model. These farmers also are prescribed shorter maturities among those given longer maturities (Class 2) and lower interest rates among borrowers with lower interest rates (Class

1). These results confirm the FSA's commitment to support the proliferation and viability of start-up farm businesses that normally would be shunned away by regular lenders due to lack of business track record, among others.

Borrowers under the operating loan program receive smaller loans under Class 1 and larger loans under Class 2. These borrowers have shorter loan maturities and lower interest rates under both latent classes in the maturity and interest rate models. These term and pricing results reflect the basic distinctions between operating and farm ownership loans.

Among the financial performance indicators, several intuitive relationships are observed. Less financially efficient farm operations (as measured by operating expense ratio) are charged higher interest rates under the higher interest rate regime (Class 2). More liquid business operations (based on current ratio levels) are accommodated with larger loans, regardless of latent class in the loan amount model. Lower non-farm income contributions, regarded as a source of risk diversification effect for income stabilization purposes, are associated with longer maturities in both latent classes.

STUDY'S IMPLICATIONS

The FMM method is an unconventional method for validating the heterogeneity of lending officers' decisions on loan packaging terms attributed to unspecified and unobserved factors, in addition to concrete, observed factors offered by the dataset. Such latent factors could include, among others, the lending officers' subjective inputs in the decision-making process analyzed over latent classes of borrower observations. Thus, this study presents a novel technique that could produce more reliable and insightful findings that lead to a greater understanding of the implementation of FSA loan programs.

This study's results reflect some notable trends and important implications. Racial and gender considerations are indeed factored into loan packaging decisions. The interplay among significant trends in loan packaging terms for racial and gender minority borrowers seems to have some intuitive bases. Specifically, when loan amount, maturity, and loan pricing decisions are lumped into one packaging decision for a particular borrower segment, such as a racial or gender minority farmer, the separate loan packaging decisions seem coherent and justifiable. Smaller loan amount and higher interest rate decisions could reflect the lending institutions credit risk management policies or strategies. Indeed the FSA is expected to assist socially disadvantaged borrowers, but is not mandated to do so blindly and recklessly. Credit risk appraisal standards must be enforced, along with a more perceptive stance on borrower's potentials and capability not captured by existent records. Thus, such lending decisions based on perceptions need to be bolstered by slightly cautiously prescribed terms that may involve an initial smaller loan amount with relatively higher interest rates to somehow "test the waters" and give such borrowers with potentials the chance to establish track records that will allow them to eventually gain more credibility deserving of much better loan terms in future loan transactions. These initially cautious loan terms (amount and interest rates) are however tempered by more considerate longer loan maturities that somehow lessen the periodic financial load of smaller loan amortizations.

The case of beginning farmer clients also supports the same contentions. The recognition of these farmers' latent creditworthiness and business potentials not yet evident in available documents and other hard evidence leads to FSA loan decisions that provide these farmers the requested business opportunity. In contrast to the racial minority farmers' borrowing transactions, beginning farmers receive larger loans, shorter maturities, and lower interest rates that may reflect these farmers' relatively better financial status.

Overall, the results of this analysis will be useful as lenders like FSA continue to strive to enhance the credit access of minority borrowers and other socially, financially disadvantaged clients. The effectiveness of credit as a business viability-enhancing input does not only rely on a prospective borrower's successful loan application. Lenders are also expected to deliberately and consciously prescribe more appropriate loan packaging terms consistent with their credit risk appraisal standards and reasonably attuned to their borrowing client's business situation.

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Table 1: Summary statistics of variable used in the model

	Mean	Standard Deviation
Gross revenue ($'000)	171.714	305.687
Non White	0.09	0.29
Sex (Female=1)	0.12	0.32
Non-white*female	0.01	0.12
Age (years)	38.62	14.24
Beginning farmers dummy	0.44	0.50
Operating loan dummy	0.65	0.48
Refinancing loan dummy	0.14	0.34
Term debt coverage ratio	2.25	43.20
Asset turnover ratio	24.38	2,232.81
Current ratio	6.90	397.72
Operating expense ratio	82.97	3,136.09
Return on assets	133.67	17,907.47
Nonfarm income ($)	0.29	0.31
Debt to assets ratio	282.81	16,994.92
Number of Observations	26,950	

Table 2. Predicted mean and posterior probability by class of loan packaging terms

	Mean	Standard Deviation
Amount of loan ($1000)		
Predicted mean	75.77	31.79
Class 1	27.58	16.74
Class 2	121.47	54.86
Posterior probability: Class 1	0.49	0.42
Loan Maturity (Years)		
Predicted mean	14.32	8.30
Class 1	11.91	6.31
Class 2	15.55	9.37
Posterior probability: Class 1	0.34	0.46
Interest rate (Percent)		
Predicted mean	3.95	1.15
Class 1	3.43	1.72
Class 2	4.56	0.51
Posterior probability: Class 1	0.54	0.37
Observations	26,950	

Table 3. Finite mixture model estimation results for loan packaging terms (standard errors in parentheses)

	Loan Amount ($1000)		Maturity (Year)		Interest Rate	
	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2
Gross income ($'000)	0.0475***	0.0440***	0.0000***	-0.0000	0.0000	-0.0001***
	(0.0018)	(0.0021)	(0.0000)	(0.0002)	(0.0000)	(0.0000)
Non White	1.5328**	-7.0331**	0.0130***	0.4213*	0.1634***	0.0491**
	(0.6546)	(3.3117)	(0.0027)	(0.2560)	(0.0441)	(0.0232)
Sex (Female=1)	-4.6495***	-15.1224***	-0.0062**	-0.6119***	-0.0548	0.0103
	(0.5585)	(3.1930)	(0.0027)	(0.2225)	(0.0372)	(0.0222)
Nonwhite*Female	0.0892	19.3349**	0.0130*	-0.1508	0.0269	-0.0381
	(1.6065)	(9.2540)	(0.0072)	(0.6714)	(0.1184)	(0.0609)
Age	-0.0435***	-0.0074	0.0000	0.0917***	0.0078***	0.0136***
	(0.0126)	(0.0573)	(0.0001)	(0.0045)	(0.0008)	(0.0005)
Beginning farmers	9.0230***	26.9018***	-0.0004	-2.3742***	-0.4947***	0.0021
	(0.4063)	(1.7365)	(0.0015)	(0.1366)	(0.0225)	(0.0132)
Operating loan dummy	-1.2246***	15.4774***	-13.0594***	-18.9706***	-3.5124***	-0.9640***
	(0.4022)	(1.6420)	(0.0015)	(0.1407)	(0.0299)	(0.0153)
Refinancing loan dummy	9.3825***	10.1741***	0.0424***	-1.1212***	0.0858**	-0.2235***
	(0.6158)	(2.3145)	(0.0020)	(0.2105)	(0.0382)	(0.0172)
Operating expense ratio ($'000)	-0.0028	0.9617	-0.0013	-0.0350	-0.0042	-0.0182***
Return on assets	(0.1271)	(1.3783)	(0.0018)	(0.0655)	(0.0113)	(0.0060)
	-0.0003**	0.0054	-0.0000	-0.0002*	-0.0120	-0.0126**
Debt to assets ratio	-0.0001	-0.0001			-0.0001	0.0002***
	(0.0000)	(0.0000)			(0.0000)	(0.0000)
Current ratio	0.0006***	0.1072**				
	(0.0002)	(0.0433)				
Term debt coverage ratio	-0.0023	-0.0059			0.0001	0.0001
	(0.0023)	(0.0260)			(0.0002)	(0.0001)
Asset turnover			0.0000	0.0031	0.0001	-0.0000
			(0.0000)	(0.0032)	(0.0001)	(0.0000)
Nonfarm income ratio			-0.0212***	-0.8338***		
			(0.0027)	(0.2336)		
Residuals			0.0002***	-0.0024**	-0.0003	-0.0009***
			(0.0000)	(0.0010)	(0.0002)	(0.0001)

Constant	16.1383***	91.5597***	20.1288***	25.4456***	5.5310***	4.6899***
	0.6574	2.8008	0.0026	0.2503	0.0381	0.0223
imlogitpi1	-0.0530**		-0.6683***		0.1678***	
	(0.0236)		(0.0155)		(0.0280)	
Ln (signma)	2.6835***	4.2565***	-2.9044***	2.0092***	-0.0601***	-0.7245***
	(0.0157)	(0.0075)	(0.0112)	(0.0062)	(0.0099)	(0.0124)
Observations	19701		19701		19701	

Note: Asterisks denote significance at the 99% (***), 95% (**), and 90% (*) confidence levels.

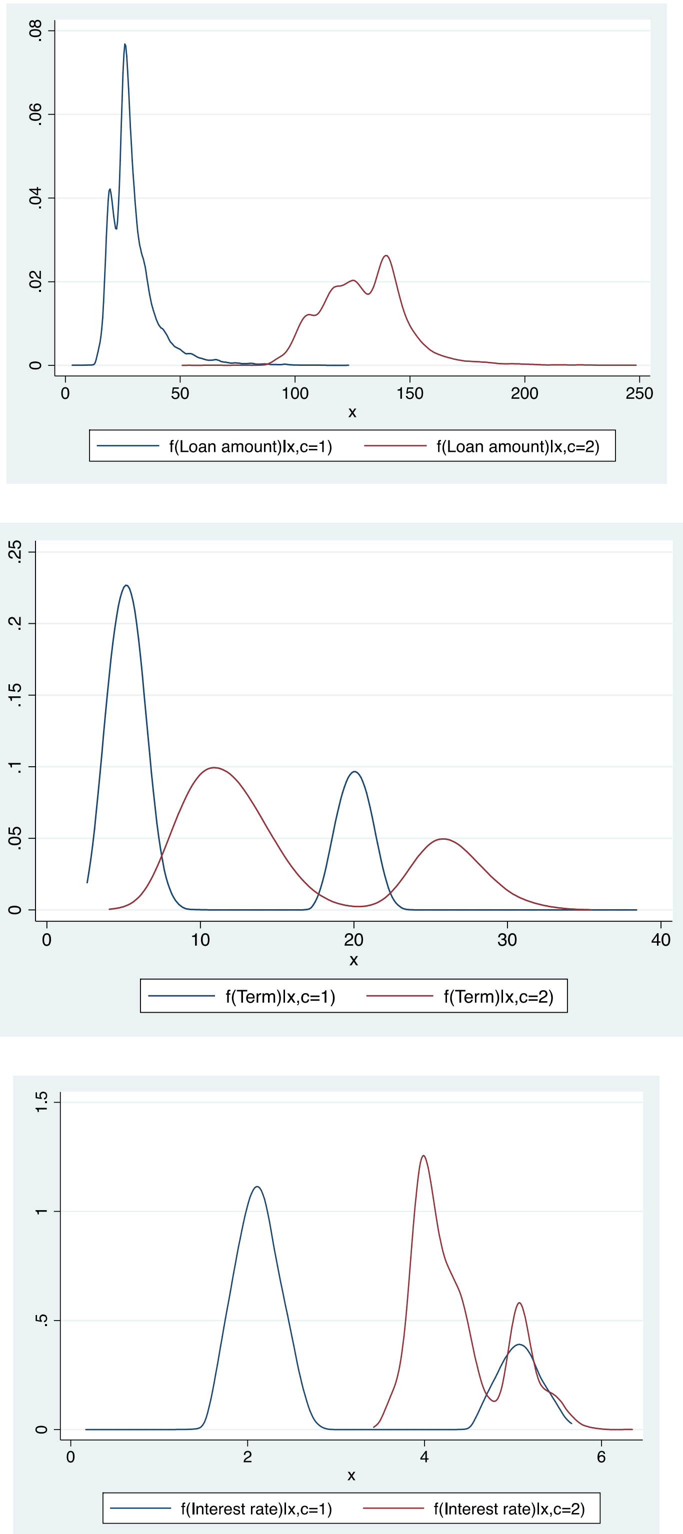

Figure 1. Posterior Probability Plots for Amount, Maturity, and Interest Rate Latent Classes