Gender Bias Claims in Farm Service Agency's Lending Decisions

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This study analyzes the courts' denial of women farmers' motion for class-action certification of their lawsuits alleging gender discrimination in Farm Service Agency (FSA) lending decisions. The plaintiffs' claim of "commonality" of circumstances in women farmers' dealings with FSA is tested using a four-year sampling of Georgia FSA loan applications. The econometric framework has been developed after accounting for the separability of loan approval and amount decisions, as well as endogeneity issues through instrumental variable estimation. This study's results do not produce overwhelming evidence of gender bias in FSA loan approval decisions and in favor of the "commonality" argument among Georgia FSA farm loan applicants.

Key words: class-action suit, credit risk, creditworthiness, gender discrimination, Heckman selection, instrumental variable probit

Introduction

Women farmers—previously relegated to roles as their spouses' "helpmates" usually performing office management and clerical chores—are fast emerging as a significant force in U.S. agriculture as more females take over farm businesses acquired through either inheritance or purchases, and assume more active roles in farm business management (Korb, 2005; Hoffman and Norton, 2005; Sommer, 2001). Periodic nationwide surveys conducted by the U.S. Department of Agriculture (USDA) between 1978 and 2002 report an average growth rate of 18.62% every five years for the number of female-operated farms. The entry rates into farming among women operators were found to be higher than exit rates, thus accounting for the steady growth in female-controlled farming operations over the past several years (Korb).

In transcending previous stereotypes of supporting roles to their spouses, female farm operators are generally faced with many barriers to business survival and success. Credit is one of these challenges. A recent analysis conducted by the Experian National Score Index on gender differences in credit behavior indicates women are actually more creditworthy than their male counterparts. In 2006, women's average credit score was calculated at 682, which is seven points higher than the men's average rating (Tedeschi, 2007; Experian, 2006). A study carried out by the Consumer Federation of America in December 2006, however, showed that women's more favorable credit ratings do not necessarily translate into better

credit terms, as women borrowers have a higher probability of being charged subprime interest rates[1] by lenders than male borrowers (Guy, 2007; Tedeschi).

Gender bias was allegedly more overt in the past. Prior to the passage of the 1974 Equal Credit Opportunity Act, a wife's income was usually discounted by 50% when lenders evaluated mortgage applications (Schafer and Ladd, 1981). The discount rate became even larger when the wife was of child-bearing age and/or when the family still included preschool children. Several more recent studies on entrepreneurship are in similar agreement in their findings that women entrepreneurs striving to enter self-employment were usually disadvantaged by their gender through overt discrimination by bank lenders (Fay and Williams, 1993; Carter and Kolvereid, 1997).

The female borrowers' credit standing with the Farm Service Agency (FSA), the U.S. government's lending arm to the farm sector, has become a case of interest. In 2000, several women farmers filed a suit against the USDA alleging gender bias in the administration of FSA lending programs. Their lawsuit, known as the Love v. Johanns case, is actually just one of several discrimination complaints lodged against the agency (Fox, 2006; Dunne, 2006). The most prominent, thus far, is the Pigford v. Glickman case, a class-action suit involving thousands of African-American farmers (Bennett, 2001; Mittal and Powell, 2000). The suit ended in an amicable settlement in 1999, and cost the government almost $1 billion in remunerations and relief payments to successful plaintiffs.

Recently, the plaintiffs in the Love v. Johanns suit failed in their own bid to duplicate the African-American farmers' feat, as their motion and subsequent appeal for class-action certification of their suit were denied by judicial courts. Currently under litigation at the U.S. District Court for the District of Columbia, the case continues to draw media attention and reiterates the need for scrutiny of FSA's lending policies and decisions (Fox, 2006; Dunne, 2006).

This study derives its motivation from the allegations of gender bias made by the women plaintiffs against the FSA, the judicial courts' contention of a "lack of commonality" in the evidence presented by the plaintiffs, and the corroborating testimonies provided by approximately 2,000 female witnesses across the country. We utilize a localized data set of Georgia FSA borrowers from 1999–2002, in lieu of a national FSA borrower data set which is difficult, if not impossible, to compile. The data set supplied by the Georgia FSA state office allows for the identification of significant determinants of loan approval decisions made by FSA lending officers. Among probable determinants are proxy variables for financial performance measures conventionally used by commercial lenders in evaluation of loan applications, demographic and structural variables that capture the influence of gender, and other relevant attributes such as race, size, and lending program in decisions made by FSA loan officers. The following sections discuss further the study motivations and empirical frameworks and present the econometric results and implications.

Capturing Bias in Lending Decisions

Biases in lending decisions can be manifested as either noneconomic or statistical discrimination (Berkovec et al., 1994). Noneconomic bias is a lender's prejudicial decision influenced by dislike for a certain demographic group. Statistical discrimination is based on

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[1] Subprime interest rates are far above prime mortgage rates. For instance, in 2005, the prime interest rate was 5.87%, while the subprime rate ranged from 7.66% to 9.66% (Tedeschi, 2007).

the preconceived notion that certain minority groups are more likely to falter on loan obligations than others, such that lenders use a demographic variable (associated with the minority group) as a proxy for creditworthiness in marginal cases, after taking into account the applicants' financial performance and credit histories (Lacker, 1995). While statistical discrimination is consistent with any lender's goal of profit maximization,[2] it is nonetheless as illegal as noneconomic discrimination. As Ardalan (2006, p. 31) clarifies, "It is legitimate to consider the observable characteristics of a loan applicant that are related to his or her ability to pay back a loan, but it is illegitimate to use the average observable characteristics of a group to make inferences about the unobservable characteristics of an individual associated with that group."

Our investigation focuses on the prejudicial or noneconomic discrimination argument presented by Becker (1971) and Arrow (1973) whereby a higher expected profitability (or risk-reduction) requirement is imposed for loans granted to minorities and eventually results in an observable improvement in loan performance for the group, after controlling for other factors affecting credit quality. This idea can be illustrated using the following lending decision framework developed by Berkovec et al. (1994) and modified for the purpose of our study:

$$(1) \qquad\qquad C = \mathbf{Xb} + u,$$

where C is a creditworthiness index that is used to make approval or rejection decisions on loan applications; $\mathbf{X}$ is a vector of loan, borrower, and farm business characteristics (including historical financial performance, security arrangements, and credit records, among others) analyzed by lending officers; $\mathbf{b}$ is the coefficient vector; and u is a random error term observed by lenders, but unobservable to others.

In this model, even borrowers with the same level of C can possibly have different default risks and loan application outcomes due to differences in the value of the unobservable error term. Following this idea, noneconomic discrimination against a certain minority group occurs when the cutoff level for acceptable C (threshold of acceptance) is raised for them relative to other borrowers while holding $\mathbf{Xb}$ constant. This is made possible by significant increases in the value of the average error term (u) for the victimized class of borrowers. As a result, certain borrowers from this minority group who could have qualified under the true C threshold level (applied to other borrowers) are demoted to the rejected loan category.

Objective and Subjective Credit Risk Assessment

Several studies of credit risk assessment methods used by regular, commercial lenders emphasize the importance of credit scoring models in making loan approval decisions. Measures of liquidity, solvency, profitability, efficiency, and repayment are generally used to collectively arrive at a credit score for classifying borrowers across a range of categories that determine success or failure of loan applications (Miller and LaDue, 1989; Turvey, 1991; Kohl, 2003). Such guidelines are designed to provide an objective basis for measuring credit risk and evaluating loan applications.

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[2] The FSA, being a federal government agency, is more concerned about risk reduction rather than the profit maximization objective which is usually associated with commercial lenders.

Yet, even with established, objective standards, lending decisions still may be influenced by the lending officer's subjective biases. The error term in the creditworthiness equation (1), for instance, can capture heuristics, rules of thumb, or principles acquired by lending officers over time that may be factored into the lending decision model beyond established credit risk assessment criteria (Gustafson, Beyer, and Saxowsky, 1991; Miller and LaDue, 1989).

FSA Lending Framework

The administration and implementation of FSA lending programs are based on federal guide-lines that define departure points between federal and commercial lending. Specifically, credit rationing and risk assessment practices often associated with private lenders have less significance to FSA lending decisions. Important facets of the FSA lending framework are discussed in the following sections.

FSA Credit Risk Assessment

The FSA basic notion of creditworthiness is consistent with the traditional definition that included having "(1) character, industry, and ability to carry out the proposed operation, (2) honesty in endeavoring to carry out obligations associated with the loan" (USDA/FSA, 1995, p. 1; also in USDA/FSA, 1997a,b), and (3) realistic payment plans. However, FSA provides special considerations for the following circumstances in defining "historical credit delinquency" or "unacceptable credit history" for borrowers who:

■ have been unable to pay previous loans or have delinquent payments due to temporary circumstances such as job loss, loss of benefits or other income, and increase in living expenses due to illness, injury, or death (USDA/FSA, 1995, 1997a,b); or

■ have no previous credit history (USDA/FSA, 1995).

More often than not, these special considerations represent grounds for outright rejections among commercial lenders. In the FSA case, then, the error term in the creditworthiness equation can be expanded through the addition of such special considerations.

Targeting of Underserved Borrowers

FSA lending programs are guided by the government mission to assist underserved sectors of the farm economy. Among its clientele are beginning farmers who are unable to obtain loans from commercial lenders because of insufficient net worth and/or credit history. The FSA also services the credit requirements of established, seasoned farm operators whose businesses have been plagued by financial setbacks due to natural disasters or economic downturns. Through the "credit-elsewhere" test that screens potential borrowers,[3] FSA maintains a clientele of high-risk, yet creditworthy, farmers experiencing difficulty in gaining credit access through regular lending channels (USDA/FSA, 2003).

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[3] The "credit-elsewhere" test requires FSA loan applicants to present evidence of commercial lender rejection of loan applications.

In order to ensure fair access to federal credit funds, FSA is mandated by law to set aside funds to target socially disadvantaged (SDA) farmers. The Agricultural Credit Act of 1987 defined these SDA borrowers to include racial/ethnic groups and women (Koenig and Dodson, 1999). The Food, Agriculture, Conservation, and Trade Act of 1990 expanded the SDA lending scope to include farm ownership and operating loan programs (Koenig and Dodson).

Funding Constraints

FSA lending programs are also constrained by funding availability and standard loan provisions set by federal regulations. Hence, the credit rationing paradigm ordinarily used by commercial lenders has very limited application to the FSA lending framework.

Each program has a stipulated borrowing cost that is invariably applied to all loan accounts of a given loan type, thus eliminating interest rate as a risk management and credit rationing device. Other provisions of the loan covenant, such as loan maturity, foreclosure conditions, and prepayment/default penalties, are standard among all borrowing accounts.

Finite funding allocations that are available only for a specific period of time also restrict loan approval and disbursement decisions (USDA/FSA, 2004). These allocations, which are part of the USDA budget, are appropriated by Congress in each fiscal year (spanning from October 1st to September 30th of the following year). The FSA then distributes these funding appropriations to state offices based on each state's potential demand for FSA loans. In the event where a certain loan program starts to run low on funding or where many states have already exhausted funding allocations, the FSA can resort to pooling of funds. This is done by placing all unused money from states in surplus into a National Headquarters pool that can be either redistributed among all states or disbursed on a loan-by-loan basis to states making such requests. Congress can also pass a supplemental appropriations bill to make more funds available. Otherwise, approved loan applications in any given year must wait to be funded during the next fiscal year when new appropriations become available.

Borrower Discrimination Lawsuits

Over the past decade, numerous lawsuits based on allegations of discriminatory lending practices have been filed against the FSA. The complainants claimed differential treatment (vis-à-vis other borrower groups) in the handling, approval, and servicing of loan applications. Among the borrowers' complaints are higher probability of denial of loan applications, longer processing times for loan applications, use of more conservative (higher) yield calculation methods resulting in understated projected crop yields, and significant disparity between the loan amount requested and approved (Bennett, 2001; Mittal and Powell, 2000).

Racial Bias

The majority of complaints were racially motivated. The most popular of these suits was the Pigford v. Glickman case, which originated from litigations against the USDA/FSA in August 1997 for two discrimination suits filed by African-American farmers (Vina and Cowan, 2005; Bennett, 2001; Mittal and Powell, 2000). The farmers' individual lawsuits were upgraded into a class-action federal suit that consolidated the African-American farmers' grievances over decades of discrimination by FSA loan officers in "denying, delaying, or otherwise frustrating African-American farmers' applications for farm loans and other credit or benefit programs"

[U.S. Government Accountability Office (U.S. GAO), 2006, p. 1]. The USDA and the farmers' lawyers eventually reached an out-of-court settlement in January 1999, under which a consent decree laid out a framework for the settlement of eligible (upheld) claims within a five-year rectification period starting in 1999 (U.S. GAO; Vina and Cowan; Bennett; Mittal and Powell). During this five-year period, farmers' claims and allegations were reviewed by the USDA, and remunerations—in cash, noncredit awards, or debt relief benefits—were released to successful claimants. As of October 2007, the USDA had reviewed 22,642 cases, of which 15,229 were approved to receive a total of over $960 million in relief payments (Office of the Monitor, 2007).

The USDA also dealt with other sporadic, individual racially motivated lawsuits from some African-American farmers (Steil, 2001) and other racial minority groups such as Hispanic farmers involved in such lawsuits as Williams v. Glickman in 1995 (Bennett, 2001) and Garcia v. Glickman in 2000 (Dyckman, 2002), and Native American farmers who filed the only other class-action suit, Keepseagle v. Glickman, in 1999 (U.S. GAO, 2006). None of these, however, experienced the same stature and success as the Pigford v. Glickman case.

Racial bias in FSA lending decisions was explored in an earlier study by Escalante et al. (2006) using a localized data set of FSA loan applications. Their study did not uncover convincing evidence of racial bias in loan approval decisions, and further noted that the lower loan approval rate experienced by nonwhite farmer applicants resulted from weaker financial conditions vis-à-vis their white farmer-borrower counterparts.

Gender Bias

In October 2000, a number of women farmers led by Rosemary Love from Harlem, Montana, sued the USDA for gender discrimination in the administration of FSA farm loan programs. The plaintiffs in this suit, known as the Love v. Johanns case, are classified under three categories of women applicants who: (*a*) were not provided loan applications; (*b*) were denied an initial farm loan; and (*c*) received an initial loan but "were denied servicing, had difficulty obtaining subsequent loan servicing, or received less loan servicing than needed" (Fox, 2006). In January 2004, the women plaintiffs, supported by nearly 2,000 declarations from other women farmers across the country, filed a motion for class certification for the first two of the above three grievance categories with the U.S. District Court for the District of Columbia (Fox; Dunne, 2006). The motion was denied by the Court later that year and was subsequently referred to the U.S. Court of Appeals. Eventually, the higher court did not act favorably on the female farmers' motion and appeal. The rationale for the denial of the class certification motion at several stages of the filing and appeals process are summarized in the following excerpts from the U.S. Court of Appeals' (2006) decision:

> …[T]he declarants allege that USDA officials told them 'they were too early to apply for a loan, too late to apply for a loan, that they need not bother filling out an application because they were not eligible to receive a loan, or that their husbands should apply.'… Certainly these allegations may give the declarants standing to bring individual suits … (but) did not require the District Court to infer the existence of a 'common policy of discrimination' that affected non-declarants, as well… (pp. 10–11).
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> The District Court was well within the bounds of its discretion to find a lack of commonality where two out of every five of the Appellants' own declarants—to say nothing of the silent non-declarants—would be forced to prove at trial that individual reasons for their loan denials were not pretextual (p. 15).

As a result of this decision, the female farmer cases have been referred back to the District Court where they are currently under litigation.

FSA Borrower Data

This analysis draws from some aspects of the methodology used in an earlier FSA study on racial minority lending trends (Escalante et al., 2006) and utilizes an expanded data set (relative to the previous study) of rejected loan observations and a randomly re-drawn subset of approved loan applications using stratified sampling techniques.[4] The current empirical model includes the financial performance variables used in the previous study derived from commercial lender traditional credit risk assessment models. The empirical analysis also considers the influence of gender and other borrower/loan attributes (such as farm size, race, loan program, and location) on lending officer decisions.

Table 1 presents a summary of the approval and rejection rates of the entire sample and subgroupings according to racial and gender classifications. The data set consists of 367 loan applications filed with the agency from 1999 through 2002. In terms of racial classification, white farmers comprise the majority (85.83%) of the study sample with 315 observations. The dominant gender class is the male borrower with 88.01% of the sample (323 observations). The data set has a loan approval rate of 57.22% (210 out of 367 loan applications).

The borrower data used in this study were obtained from the loan application database of the Georgia FSA state office for the period 1999–2002. The data set consists of a sampling of approved and rejected loan applications which were compiled using separate sampling techniques. The Georgia FSA state office supplied a subset of 210 approved loan observations[5] compiled by the agency using simple random sampling procedures.

The 157 rejected loan observations (which were fully documented) were taken from a database of 330 records of documented rejections of loan applications filed with the agency during the four-year period, made available by the FSA. This total figure of 330 partially and fully documented loan denials is actually understated given undocumented cases of rejection and application withdrawals. It is possible that loan rejection may have occurred even before borrowers could submit loan application documents. Such decisions, probably based primarily on basic program eligibility considerations, could have been made by loan officers after a quick phone call or a short interview with prospective borrowers.

As a result of the understated aggregate loan rejection numbers, the proportion of this study's sample of (documented) rejections relative to total (documented) loan rejections in Georgia (47.48%) is much larger than the proportion of the study's loan approval sample to the actual number of FSA loan approvals during the study's four-year period (table 1). The denied loan observations used in this study consist of applications with complete, usable records maintained by the eight FSA district offices in the state. More than half of the loan rejection records contain very minimal information (hence, were unusable and discarded for the purposes of this study).

The data used in this study were extracted by the FSA state office from borrower declarations in income statements, balance sheets, and application forms filled out and submitted to the FSA by prospective borrowers. Portfolio data were verified by FSA loan officers through tax returns, lien searches, and credit checks.

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[4] Stratified sampling was used by FSA by separately and randomly drawing from databases of approved loan applications filed by male and female farm operators. This technique was employed to ensure that adequate observations from female borrowers, comprising less than 15% of the entire database, would be available for this study.

[5] This number represents 7.85% of all loan approvals (2,676) made by the state office during the four-year period.

Table 1. Loan Data Sampling and Approval Rates of Georgia FSA Loans, 1999–2002

Categories	Number of Borrowers		Approval Rate (class sample) %	Approval Rate (study's sample) %	Proportion of Sample Approvals and Rejections to Total Georgia FSA Approvals and Rejections (%) [a]	
	Approved	Rejected			Approved	Rejected
All Loans	210	157	57.22	57.22	7.85	47.48
White Borrowers	189	126	60.00	51.50	7.06	38.18
Non-White Borrowers	21	31	40.38	5.72	0.78	9.39
Male Borrowers	181	142	56.04	49.32	6.76	43.03
Female Borrowers	30	14	68.18	8.17	1.12	4.24

[a] Rejection numbers are based only on documented cases of rejections. During the four-year period, Georgia FSA had a total of 330 documented rejections. The approval numbers are based on a total of 2,676 approvals made by FSA during the same period.

Econometric Framework

Econometric techniques are employed to identify the most appropriate model consistent with the nature of FSA loan approval decision and loan amount determination processes.[6] A Heckman model, using maximum-likelihood estimation, is adopted to test for the separability or independence of these two decisions made by FSA lending officers. An instrumental variable probit (IV probit) approach then explores the simultaneity of these two decisions by accommodating the endogeneity of the loan amount variable in the loan approval equation. A straightforward probit model is also formulated to resolve independence and endogeneity issues in the previous two approaches.

Probit Model

The basic probit approach is a binary choice model used to empirically identify the determinants of FSA officer loan approval decisions. The fundamental tenet of loan approval decisions is that a loan officer approves a loan application if the expected utility of loan approval is greater than the expected utility of rejecting the loan application. Since the expected utility of approving a loan application is unobservable, we model the difference between the expected utility of loan approval and rejection decisions as:

$$(2) \qquad \mathbf{z}_i^* = \boldsymbol{\beta}' \mathbf{x}_i + \varepsilon,$$

where $\mathbf{z}_i^*$ is the unobservable variable, $\mathbf{x}_i$ is a vector representing the variables that affect likelihood of approval of a loan application, $\boldsymbol{\beta}'$ is a vector incorporating the corresponding parameters, and ε is assumed to have a normal distribution with mean 0 and variance 1.

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[6] The previous study on FSA racial minority lending (Escalante et al., 2006) used a binomial logistic model that considered loan approval decisions only.

The binary dependent variable can be defined as $z = 1$, if $\mathbf{z}_i^* > 0$, otherwise $z = 0$. In this analysis, the dichotomous dependent variable takes a value of 1 for approved loan applications and 0 for denials. It follows that:

$$(3) \qquad\qquad \mathrm{Prob}(z = 1) = \mathrm{Prob}(\varepsilon > -\boldsymbol{\beta}'\mathbf{x}_i)$$
$$= F(\boldsymbol{\beta}'\mathbf{x}_i),$$

where F is the cumulative distribution function of ε (Greene, 2003). Since a normal distribution is assumed for ε, the model's probit form is estimated here. The probit distribution is given by

$$(4) \qquad\qquad \mathrm{Prob}(y = 1) = \int_{-\infty}^{\boldsymbol{\beta}'\mathbf{x}_i} \varphi(t)\, dt,$$

where φ represents the standard normal distribution. A maximum-likelihood procedure is used to estimate the parameters of the above binary choice model. Because the estimated coefficients arising from these regressions are not marginal effects, additional calculations are necessary.

The $\mathbf{x}_i$ vector in this analysis is comprised of a set of proxy financial measures (*FV*) that represent financial performance categories which are considered important indicators of borrower credit risk. These categories include leverage, profitability, financial efficiency, liquidity, and repayment capacity. The following financial performance measures[7] representing such categories have been identified from various experimental and statistical credit risk assessment models developed by lenders and analysts, and are published in the agricultural finance literature (Miller and LaDue, 1989; Turvey, 1991; Splett et al., 1994; Kohl, 2003):

- Debt-Asset Ratio (*LEV*) representing leverage conditions;

- Return on Assets (*ROA*), calculated as the ratio of net farm income to total assets, as a measure of profitability;

- Net Farm Income Ratio (*NFIRAT*), calculated as the ratio of net farm income to gross revenues, as a measure of financial efficiency;

- Current Ratio (*CURAT*), calculated as the ratio of Current Assets to Current Liabilities, to capture liquidity position; and

- Capital Debt Repayment Margin Ratio (*REP*), calculated as the ratio of net cash margin to the amount of debt servicing requirements, as a measure of repayment capacity.

The $\mathbf{x}_i$ vector also consists of a set of dummy structural/demographic variables (*ST*) that are also included to discern whether the loan approval process is significantly influenced by gender, size, race, and FSA program considerations. These variables include *FM* (with a value of 1 for a female primary borrower and 0 otherwise to discern gender impact), *SIZE* (which takes on a value of 1 for small farms with gross revenues below \$250,000, and 0

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[7] The financial variables were calculated from historical financial figures compiled by FSA lending offices. They do not include the requested loan amounts and/or the projected financial condition resulting from the availability of the loan.

otherwise),[8] *NW* (with a value of 1 for nonwhite borrowers and 0 otherwise to capture racial impact), and *DRT* (which takes on a value of 1 for loans accommodated under the direct lending programs and 0 otherwise).

Following Greene (2003), the marginal effects for the probit model, computed at the means of $\mathbf{x}_i$, are given by:

$$(5) \qquad \frac{\partial E[z \mid \mathbf{x}_i]}{\partial \mathbf{x}_i} = \varphi(\boldsymbol{\beta}'\mathbf{x}_i)\boldsymbol{\beta}.$$

Heckman Selection Model

The Heckman approach considers the separability of two decisions made by FSA loan officers: approval or denial of loan applications and loan amount disbursed to successful applicants. This approach produces consistent, asymptotically efficient estimates for all parameters in the model being fitted. The Heckman selection model consists of the following selection mechanism and outcome equations (Greene, 2003):

(6) Selection Mechanism:
$$\mathbf{z}_i^* = \boldsymbol{\gamma}'\mathbf{w}_i + \boldsymbol{\mu}_i,$$
$$\mathbf{z}_i = 1 \quad \text{if } \mathbf{z}_i^* > 0,$$
$$\mathbf{z}_i = 0 \quad \text{if } \mathbf{z}_i^* \le 0,$$
$$\text{Prob}(\mathbf{z}_i = 1) = \phi(\boldsymbol{\gamma}'\mathbf{w}_i),$$
$$\text{Prob}(\mathbf{z}_i = 0) = 1 - \phi(\boldsymbol{\gamma}'\mathbf{w}_i),$$

(7) Outcome Model:
$$\mathbf{y}_i = \boldsymbol{\beta}'\mathbf{x}_i + \boldsymbol{\varepsilon}_i \quad \text{if } \mathbf{z}_i = 1.$$

In the first stage, a probit estimation technique generates the selection equation. The dichotomous dependent variable is the same variable defined in equation (2). Hence, probit regression estimates the probability of success of a loan application. Moreover, the probit equation is estimated by maximum likelihood to obtain estimates of the following inverse Mill's ratio, calculated as the ratio of the density (ϕ) and cumulative (Φ) probability density functions, for every selected (approved) loan applicant (Greene, 2003):

$$(8) \qquad \hat{\boldsymbol{\lambda}}_i = \frac{\phi(\hat{\boldsymbol{\gamma}}'\mathbf{w}_i)}{\Phi(\hat{\boldsymbol{\gamma}}'\mathbf{w}_i)}.$$

In the second stage, the regression or outcome equation is applied to the selected (approved) loan observations to estimate the determinants of the amount of the loan received from the FSA. The dependent variable in this equation ($\mathbf{y}_i$) is the log transformation of the loan amounts of the successful loan applicants [ln(*LSIZE*)]. The inverse Mill's ratio is included in this estimation as a separate predictor variable.

This analysis employs the maximum-likelihood approach, rather than the Heckman two-step procedure, in estimating the Heckman model. Under the maximum-likelihood method,

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[8] The cut-off of $250,000 gross revenues for classifying small and large farms is consistent with the USDA/ERS definition of farm typology groups (Hoppe, Perry, and Banker, 2000). Additional analyses were made on credit risk analysis standards employed on small and large farms, which can be made available to interested readers from the authors upon request.

the outcome and selection models are jointly estimated. Previous studies using the Heckman approach contend that even with correct model specification, the two-step procedure produces less efficient estimates than the full maximum-likelihood method (Sales et al., 2004).

In this analysis, the expanded form of the selection and outcome equations is given, respectively, as:

(9) $$\mathbf{z}_i^* = \gamma_0 + \gamma_1 \mathbf{FV}_i + \gamma_2 \mathbf{ST}_i + \boldsymbol{\mu}_i$$

and

(10) $$\mathbf{y}_i = \beta_0 + \beta_1 \mathbf{FV}_i + \beta_2 \mathbf{ST}_i + \beta_3 \mathbf{REQ}_i + \boldsymbol{\mu}_i.$$

The *FV* and *ST* variables in the selection equation (9) are retained in the outcome equation with the addition of a set of variables (*REQ*) to determine the magnitude of FSA loan exposure to successful loan applicants. The *REQ* variables include *WC*, an estimate of the farm's working capital requirement (the difference between current assets and current liabilities), and asset turnover ratio (*ATO*), calculated as the ratio of gross farm revenues to total farm assets, to account for the productivity of existing farm assets. These variables may determine the operating capital and fixed asset loan requirements of a farm business.

The IV Probit Model

The IV probit tool is a maximum-likelihood estimation technique that fits models with dichotomous dependent variables and endogenous explanatory variables. For a single endogenous regression, the model can be stated as:

(11) $$\mathbf{z}_{1i}^* = \alpha \mathbf{z}_{2i} + \omega \mathbf{W}_i + \boldsymbol{\mu}_i,$$

$$\mathbf{z}_{2i}^* = \boldsymbol{\pi}_1 \mathbf{W}_i + \boldsymbol{\pi}_2 \mathbf{V}_i + \mathbf{v}_i,$$

where $i = 1, \ldots, N$; $\mathbf{z}_{1i}^*$ is a dichotomous dependent variable; $\mathbf{z}_{2i}^*$ is a vector of endogenous variables; $\mathbf{W}_i$ is a vector of exogenous variables; $\mathbf{V}_i$ is a vector of instruments that satisfy conditions of instrumental exogeneity and relevance; α and ω are vectors of structural parameters; and $\boldsymbol{\pi}_1$ and $\boldsymbol{\pi}_2$ are matrices of reduced-form parameters. The $\mathbf{z}_{2i}^*$ equation is written in reduced form and both equations are estimated simultaneously using maximum-likelihood techniques. As a discrete choice model, $\mathbf{z}_{1i}^*$ is not observed because the model instead fits $z_{1i} = 1$ for $\mathbf{z}_{1i}^* \geq 0$, and $z_{1i} = 0$ for $\mathbf{z}_{1i}^* < 0$.

In this analysis, the IV probit model is formulated under the assumption that loan amount decisions may be made simultaneously with loan approval decisions. Thus, the loan amount variable is included in the estimating equation as an instrumented variable. Specifically, the model is estimated as follows:

(12) $$\mathbf{z}_{1i}^* = \gamma_0 + \alpha \ln(\mathbf{LSIZE}_i) + \omega \mathbf{W}(\mathbf{FV}_i, \mathbf{ST}_i) + \boldsymbol{\mu}_i,$$

$$\ln(\mathbf{LSIZE}_i) = \boldsymbol{\pi}_1 \mathbf{W}(\mathbf{FV}_i, \mathbf{ST}_i) + \boldsymbol{\pi}_2 \mathbf{REQ}_i + \mathbf{v}_i,$$

where $\mathbf{z}_{1i}^*$ is the same binary dependent variable in equations (2) and (9); $\ln(\mathbf{LSIZE}_i)$, the instrumented variable $(\mathbf{z}_{2i}^*)$ in this model, is the log transformation of the loan amount

variable;[9] **FV**$_i$ and **ST**$_i$ are the same set of financial measures and structural/demographic variables, respectively, included in equation (4) and are the exogenous variables (**W**$_i$) in this model; and **REQ**$_i$, consisting of **WC**$_i$ and **ATO**$_i$, are the instruments (**V**$_i$) for **ln(LSIZE**$_i$).

Results

Tables 2–5 present the results from various analytical approaches used in this study. The descriptive analytical results allow the comparison of mean financial performance values across loan decision and gender categories. The econometric results clarify the nature of FSA loan approval and amount decisions, validate whether there is gender bias or not, and establish the relative importance of financial performance and structural variables in such decisions.

Descriptive Analysis

A significance test of the mean differences of financial performance variables reported in table 2 indicates that farms with successful loan applications have better profitability, repayment, and liquidity conditions than rejected farms. Among racial classes, white farmers have significantly larger operations (in terms of assets and revenues) with more favorable profitability, financial efficiency, and liquidity results than non-white farmer applicants.

Interestingly, while male farmers in the sample have larger gross revenues, their female counterparts have significantly better financial efficiency, repayment, and leverage ratios. Moreover, larger loan amounts are associated with white, female, and successful loan applicants.

Table 3 introduces another layer in the gender class analysis by incorporating the loan approval decision classification. At the 95% confidence level, the approved male and female applications expectedly have superior financial conditions when compared to their respective rejected counterparts. However, comparing inter-gender loan approval decision categories, rejected male farm operators have larger farm assets and gross revenues than the rejected female applicants. On the other hand, successful female applicants have significantly higher repayment, leverage, and financial efficiency ratios than male farm operators with approved loans, although the latter have larger gross revenues and better profitability (return on assets) than the successful female loan applicants in the study sample.

Econometric Analyses

As reported in table 4, the χ^2 statistic obtained under the LR test of independence applied to the Heckman maximum-likelihood model is not significant at the 95% confidence level. This result establishes the separability of decisions on the approval/rejection of loan applications and the amount of loans disbursed to successful loan applicants. The Wald test of exogeneity applied to the alternative IV probit model also yields an insignificant χ^2 statistic. This then rules out the endogenity of the loan amount in determining loan approval decisions under a simultaneous loan approval-amount decision framework.

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[9] There is a difference in the number of observations for the ln(*LSIZE*) variable in the Heckman and IV probit models. The latter model considers all observations for this variable, while this variable is considered only for successful (selected) loan applications in the Heckman model.

Table 2. Means of Financial Performance Measures by Loan Decision and Racial and Gender Classes

Financial Variables	All	Loan Decision		Racial Classes		Gender Classes	
		Approved	Rejected	White	Non-White	Male	Female
Total Assets ($)	504,819	541,593	455,630	549,928***	231,560***	505,957	496,465
Total Net Worth ($)	165,461	191,125	131,132	181,485***	68,387***	159,318	210,554
Gross Farm Income ($)	272,649	295,331	242,311	295,087***	136,727***	287,058***	166,878***
Net Farm Income ($)	58,060	68,919**	43,535**	63,595***	24,528***	59,470	47,705
Return on Assets (%)	23.21	29.64**	14.61**	23.68	20.40	24.00	17.43
Net Profit Margin (%)	19.82	26.36***	11.06***	21.28**	10.97**	18.32***	30.82***
Repayment Margin Ratio	1.36	1.75***	0.84***	1.40	1.12	1.18***	2.67***
Current Ratio	2.97	4.78**	0.55**	3.39**	0.45**	1.87	11.05
Debt-Asset Ratio	0.90	0.76	1.08	0.91	0.81	0.93*	0.64*
Loan Amount ($)	165,127	179,422**	146,007**	170,620***	131,853***	154,399***	243,882**
No. of Observations	367	210	157	315	52	323	44

Note: Single, double, and triple asterisks (*,**,***) denote significance of pairwise comparison of means at the 90%, 95%, and 99% confidence levels, respectively.

Table 3. Means of Financial Performance Measures of Approved and Rejected Loan Applications by Gender Class

Financial Variables	Male Borrowers		Female Borrowers	
	Approved	Rejected	Approved	Rejected
Total Assets ($)	529,089	476,471	619,632	258,341
Total Net Worth ($)	182,086	130,297	247,543	139,041
Gross Farm Income ($)	313,379	253,507	182,684	136,321
Net Farm Income ($)	70,212	45,777	60,845	22,302
Return on Assets (%)	32.12	13.65	14.19	23.71
Net Profit Margin (%)	24.41	10.56	38.57	15.83
Repayment Margin Ratio	1.45	0.83	3.58	0.91
Current Ratio	2.92	0.54	16.45	0.60
Debt-Asset Ratio	0.78	1.13	0.63	0.67
Loan Amount ($)	160,228	146,969	299,221	136,893
No. of Observations	181	142	30	14

Table 4. Heckman, Instrumental Variable, and Probit Estimation Results, All Borrowers

Variables	HECKMAN		IV PROBIT	PROBIT	
	Approval Coefficient	Loan Amt. Coefficient	Coefficient	Coefficient	Marginal Effect
Intercept	0.5233*** (0.1739)	12.1167*** (0.1492)	10.8279 (11.8783)	3.0182** (1.2670)	
A. Financial Performance Indicators:					
Return on Assets (*ROA*)	0.1707 (0.1779)	−0.0021 (0.0926)	0.0704 (0.1559)	0.0316 (0.1399)	0.0072 (0.0320)
Current Ratio (*CURAT*)	0.0529 (0.0400)	−0.0017 (0.0020)	0.1073* (0.0585)	0.1247* (0.0709)	0.0284** (0.0119)
Debt-Asset Ratio (*LEV*)	−0.0586 (0.0455)	0.1134 (0.1398)	−0.0455 (0.0475)	−0.0571 (0.0430)	−0.0130 (0.0103)
Repayment Capacity (*REP*)	1.0145*** (0.1760)	0.0044 (0.0344)	1.7983*** (0.2871)	1.8634*** (0.2820)	0.4249*** (0.0866)
Financial Efficiency (*NFIRAT*)	0.0811 (0.2342)	0.2459* (0.1314)	0.0101 (0.2369)	−0.0241 (0.2169)	−0.0055 (0.0494)
Working Capital (*WC*)		5.56e-07** (2.65e-07)			
Asset Turnover Ratio (*ATO*)		0.0333 (0.0228)			
B. Structural and Demographic Dummy Variables					
Female (*FM*)	−0.1211 (0.2729)	0.5116*** (0.1916)	0.1293 (0.5224)	−0.1583 (0.3085)	−0.0384 (0.0793)
Non-White (*NW*)	−0.1412 (0.2246)	−0.1684 (0.2028)	−0.0870 (0.2682)	−0.0890 (0.2499)	−0.0210 (0.0614)
Direct Loan (*DRT*)	−0.5040*** (0.1686)	−1.0773*** (0.1362)	−0.9483 (0.8496)	−0.4029** (0.2050)	−0.0881* (0.0495)
Business Size (*SIZE*)	−0.2663* (0.1628)	−0.6859*** (0.1234)	−1.0091 (0.7182)	−0.5602*** (0.1932)	−0.1172*** (0.0442)
C. Log of Loan Size [ln(*LSIZE*)] [a]			−0.8278 (0.9502)	−0.2042** (0.0988)	−0.0466* (0.0250)
Model's Explanatory Power (χ^2)	129.64***		71.18***	145.13***	
Other Model Statistics:	LR Test of Independence (χ^2)		Wald Test of Exogeneity (χ^2)	Pseudo-R^2 (%)	
	2.20		0.49	30.81	

Notes: Single, double, and triple asterisks (*,**,***) denote significance at the 90%, 95%, and 99% confidence levels, respectively. Values in parentheses are standard errors.
[a] The instruments used for ln(*LSIZE*) in the IV Probit model are *ROA*, *CURAT*, *LEV*, *REP*, *NFIRAT*, *FM*, *NW*, *DRT*, *SIZE*, *WC*, and *ATO*.

Thus, due to lack of evidence from the independence and endogeneity tests, standard probit estimation is justified as the most logical, relevant approach in modeling loan approval decisions. Based on the results reported in table 4, only two financial performance variables, *REP* and *CURAT*, significantly affect loan approval decisions. The coefficient results suggest borrowers with stronger historical repayment capacity and liquidity conditions are more likely to be successful with loan applications. This finding is consistent with FSA established guidelines for credit risk assessment that emphasize the importance of repayment capacity and liquidity among the various financial performance areas. Interestingly, the same trend

among financial performance variables is obtained even under a model that assumes an endogenous ln(*LSIZE*) (IV probit). The *REP* variable remains the only important financial performance variable in the loan approval decision equation of the Heckman model.

Among other significant regressors in the probit model, the program dummy variable (*DRT*) coefficient is negatively signed, which suggests applications under the guaranteed lending program have a greater chance of approval. It is apparent that the inclusion of a third party (the lending institution that has previously assessed the loan application) in a guaranteed lending arrangement with the FSA can enhance the likelihood of loan approval.

The significant, negative *SIZE* dummy coefficient indicates larger operations tend to succeed more with loan applications than smaller farms. In contrast, the ln(*LSIZE*) negative coefficient suggests borrowers with lower loan amount requests are more likely to be successful with loan applications. This decision criterion reflects the FSA fund availability situation where finite, limited allocations are usually exhausted before the end of each fiscal year. The FSA challenge has always been to assist as many eligible, creditworthy borrowers as possible rather than using up sizeable portions of the funding allocations on just a few farms with large loan requirements.

Focusing on the gender issue, there are two compelling pieces of evidence in this analysis that counter the "commonality" claim of the women farmer plaintiffs in the Love v. Johanns case. First, the gender dummy variable (*FM*) coefficient has been consistently insignificant in all variations (Heckman, IV probit, and probit versions) of the estimating equation, thus indicating that applicant gender may not influence loan approval decisions. Second, as can be gleaned from results of separate probit estimations made for male and female borrowers focusing solely on loan size and financial performance variables (table 5), there appears to be no gross disparity in the objective criteria for loan approval decisions in the two delineated gender models. Both models produce coefficient significance for a common financial performance variable (*REP*), with the male borrower model adding a second significant regressor (*CURAT*) coefficient.

Statistical test results on the differences between significant coefficient estimates for regressors in the male and female borrower models are also reported in table 5. The Wald χ^2 statistic for evaluating the significance of statistical difference is calculated as:

$$(13) \qquad \frac{\left(b_M - b_W\right)^2}{\left[\text{s.e.}(b_M)\right]^2 + \left[\text{s.e.}(b_W)\right]^2} \, ,$$

where b_M and b_W are the coefficient estimates for the male and female models, respectively, and s.e.($\cdot$) denotes the corresponding estimated standard errors. The Wald χ^2 statistic derived for each variable has one degree of freedom.

Results for the probit coefficient difference tests suggest that only the *REP* criterion had a significantly stronger influence on loan approval decisions among male borrowers vis-à-vis their female counterparts. In terms of marginal effects, a unit change in the *REP* measure will result in a 0.7452 increase in the probability of loan approval among male borrowers, while the applicable effect among female borrowers is only 0.0006. As reported in table 2, female borrowers have significantly better repayment ratios than male borrowers, whose mean *REP* only barely exceeds 1.0. It appears this general notion has led lending officers to cautiously assess male borrower repayment capacity when making loan approval decisions.

Table 5. Probit Coefficient Differences for Male and Female Borrowers

Variables	Male Borrowers		Female Borrowers		Wald χ^2 for Coefficient Difference
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	
Intercept	−0.2515 (0.9516)		−0.0172 (2.9571)		0.01
Return on Assets (*ROA*)	0.0451 (0.1806)	0.0146	−1.2590 (0.8079)	−0.0007	2.48
Current Ratio (*CURAT*)	0.1293* (0.0749)	0.0419	0.1710 (0.1957)	0.0001	0.04
Debt-Asset Ratio (*LEV*)	−0.0704 (0.0488)	−0.0229	0.0768 (0.2843)	0.0001	0.26
Repayment Capacity (*REP*)	2.2969*** (0.3126)	0.7452	0.9342* (0.5669)	0.0006	4.43**
Financial Efficiency (*NFIRAT*)	−0.0326 (0.2425)	−0.0106	2.1856 (1.5976)	0.0013	1.88
Log of Loan Size [ln(*LSIZE*)]	0.0232 (0.0821)	0.0075	−0.0490 (0.2538)	−0.0000	1.11
Model's LR χ^2	114.05***		22.29***		

Notes: Single, double, and triple asterisks (*,**,***) denote significance at the 90%, 95%, and 99% confidence levels, respectively. Values in parentheses are standard errors.

Summary and Conclusions

Drawing upon the allegations of the plaintiffs and the 2,000 women farmers across the country who provided supporting testimonies in the Love v. Johanns lawsuits, a sampling of Georgia FSA borrowers is analyzed to verify any gender bias in the loan approval decisions made by FSA lending officers during a four-year period (1999–2002). The findings of this analysis are consistent with the judicial courts' contention of a lack of commonality in the loan and business circumstances of rejected female loan applicants. Specifically, this analysis does not produce any overwhelming evidence of discrimination against Georgia female loan applicants in FSA loan approval decisions given the extent of representation afforded here of factors considered in the loan approval decision process. Contrary to allegations, results of varied versions of the lending decision model (incorporating separability, endogeneity, and exogeneity issues in loan approval and amount decisions) indicate that borrower gender has not been a significant consideration in such decisions.

Caution, however, must be observed in interpreting the econometric results considering the small proportion of loan applications filed by women farmers relative to the sample size. The task of compiling an adequately acceptable multistate data set for this analysis can certainly be difficult, if not completely infeasible. While documentation for approved loan accounts is readily available in any FSA lending office nationwide, such is not the case for rejected loans—which are complicated by a serious lack of official and unofficial documentation for cases of loan rejection. For one thing, certain applications fail to progress through the loan approval process because of insufficient supporting loan documents. Moreover, quick rejection decisions through phone calls or face-to-face interviews between the loan officers and walk-in prospective borrowers are seldom documented.

This investigation takes advantage of the rare availability of a data set representing both the successes and failures of FSA loan applications. Notwithstanding its limitations, this study is a significant attempt in presenting important evidence that can motivate further investigation of the commonality issue of gender discrimination, hopefully using a more geographically extensive data set to capture a greater number of borrower experiences and more aspects of the entire spectrum of lending decisions.

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