FARMERS SHOULD OWN MORE FINANCIAL ASSETS-EVEN IF IT MEANS OWNING LESS LAND

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Farmers Should Own More Financial Assets--Even If It Means Owning Less Land[1]

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Introduction

Ohio farm households own sizeable amounts of assets and have considerable net worth. While large, farm household asset holdings are not well diversified. Most are tangible, farm business assets. This lack of diversification means that the asset holdings of farm households are not "risk efficient." By diversifying their portfolios, they could earn higher expected returns with no increase in risk. Moreover, diversification would make farm households less vulnerable to downturns in the farm economy, such as the one that occurred in the early 1980's.

In this article, we make two points. First, farm households should consider holding relatively fewer farm assets and relatively more financial assets. Second, many farm households could reduce overall risk by choosing financial assets that have high risks and high expected returns. **We caution the reader that these recommendations are based on historical performance, which may or may not be a good predictor of future performance.**

Background Information

In 1992, the average farm household owned $413,000 of assets and had $372,000 of net worth (see Table 1). Asset holdings and net worth tend to increase with farm size. Farms with sales over $100,000, for example, owned $850,000 of assets and had $697,000 of net worth. On the average farm, tangible farm assets accounted for 84.3 percent of total assets. Farms having sales of over $100,000 averaged a much higher percentage, holding 95 percent of their assets as tangible farm assets. By way of comparison, tangible items represent 33.5 percent of all U.S. household assets and 77.5 percent of nonfinancial U.S. business assets.

[1]A draft prepared for inclusion in *Challenge*, a publication of the Department of Agricultural Economics, The Ohio State University. July, 1994.

Investment Options

A classification of investment options, with examples, is shown in Figure 1. Money market instruments are short-term debt obligations of corporations, financial institutions and governments. They typically involve low credit risk and offer low, fixed returns. They are frequently referred to as "cash," and their role is to provide liquidity in a portfolio.

Fixed income capital market instruments are long-term (1 to 30 year) debt obligations of corporations and governments. The credit risk of loss of principal varies from nil for U.S. treasury bonds to high for some corporate "junk bonds." The major source of risk is the potential for market value reductions when interest rates rise. Interest rate risk is higher for longer maturity instruments.

Equity instruments are common and preferred stocks of domestic and international corporations. Risk of loss of principal is highly variable depending on the future income prospects of the issuing company and overall trends in the stock markets as a whole. Income potential consists of dividends and possible increases in market values.

The returns and risks from tangible assets vary greatly, depending on the type of asset. For some, such as antiques, the only prospect for income is an increase in market value. Others, such as real estate, may also offer current income such as rent. Most tangible assets are not homogeneous, so their markets are often small and not well organized. In the case of farmland, no two parcels are alike, and the average parcel changes hands about once every generation.

Derivative markets consist of instruments whose value is **derived** from an underlying commodity or financial instrument. Derivatives are used by producers and buyers of commodities and financial instruments to hedge against adverse price movements. The risks for the speculators who merely trade the instruments with no interest in the underlying commodities is extremely high.

Historical Performance

To illustrate possibilities for diversification in the asset portfolios of Ohio farm households, the performance of four major investments was measured over the 25-year period 1967 through 1991. The investments chosen were U.S. treasury bills, long-term U.S. government bonds, Ohio farmland, and common stocks (Standard and Poor's index of 500 stocks). These assets represent all categories in Figure 1 except derivative instruments.

The average annual rates of return and standard deviations of returns on these four investments are shown in Table 2. The information on the consumer price index is for comparative purposes. The rates of return include current income such as interest payments on T-bills and bonds, dividends on common stocks and cash rent on the farm real estate, as well as year-to-year capital gains or losses. The standard deviation is a common statistical measure of year-to-year variability or risk. A workable interpretation of the standard deviation is that, in two out of three years, the actual rate of return will be within one standard deviation of the mean. For the T-bills, for example, the actual rate of return was in the range 7.3(+/-)2.6 percent (4.7 to 9.9 percent) in 17 of the 25 years.

The data in Table 2 illustrate a fundamental rule of investment analysis: the higher the return, the greater the risk. The rates of return (standard deviations) range from a low of 7.3 (2.6) percent for the T-bills to 12.4 (16.5) percent for common stocks. Note that Ohio farmland was second only to common stocks in overall returns and risk. Even with the large decline in farm real estate values in the early 1980's, land provided higher returns (along with more risk) than money market and fixed income capital market instruments.

To construct a diversified investment portfolio, it is necessary to select assets whose returns over time are not highly correlated. The correlation coefficients for our four assets are shown in Table 3. Correlation coefficients can range from +1.0 (perfect positive correlation) to -1.0 (perfect negative correlation). Notice that the returns from T-bills, bonds and common stocks are all somewhat negatively correlated with Ohio farmland returns. This indicates that the risks of owning farmland can be offset by including nonfarm assets in the portfolio.

Efficient Investment Portfolios

Possible return and risk combinations of combining T-bills, bonds, Ohio farmland, and common stocks are shown in Figure 2, which shows returns on the vertical axis and standard deviations of returns on the horizontal axis. The characteristics of our four individual assets also are shown. For example, T-bills (lower left corner) have expected returns of 7.3 percent and a standard deviation of 2.6 percent. Stocks, on the other hand (upper right corner), have expected returns of 12.4 percent and a standard deviation of 16.5 percent. Riskier assets are above and to the right of less risky assets because they have higher expected returns and higher standard deviations.

The bold line in Figure 2 gives the set of "efficient" portfolios. A portfolio is formed by investing funds in some combination of the four individual assets. The portfolios along the bold line are efficient because they give the highest expected return for each risk level. For example, if an individual wishes to earn expected returns of 10 percent, the lowest standard deviation of returns that can be obtained is about 6 percent. Note that portfolios consisting only of T-bills, bonds, or farm real estate lie below the bold line. This implies that diversified portfolios have higher returns for the same risk level than do investments consisting only of T-bills, bonds, or farm real estate.

Proportions of funds invested in the efficient portfolios are shown in Figure 3. The four lines show the proportion of funds held in each asset for the standard deviations and expected returns listed on the horizontal axis. If, for example, an individual wants a 10 percent return which has a 6 percent standard deviation, the portfolio will consist of 35 percent farmland, 30 percent stocks, 30 percent T-bills, and 5 percent bonds.

We make three points in Figure 3. First, contrary to popular belief, risks are not reduced by investing only in the least risky asset. Of the individual assets we examined, T-bills have the lowest standard deviation (2.6 percent) and the lowest expected return (7.3 percent). The standard deviation can be lowered to 2.0 percent, and the expected return can be increased to 8.1 percent by holding a diversified portfolio made up of 65 percent T-bills, 19 percent farmland, 11 percent stocks, and 5 percent bonds.

Second, efficient portfolios never contain more than 50 percent farmland. This indicates that expected returns can be increased by holding a portfolio of assets rather than only farmland. Farmland has a standard deviation of 13.6 percent. The efficient portfolio with a 13.6 percent standard deviation has an expected return of 12.1 percent, significantly higher than the 10.8 percent expected return from farmland. The efficient portfolio is obtained by investing 19 percent of the funds in farmland and 81 percent in stocks.

Third, more risky assets such as stocks and bonds often are better complements to farmland than are T-bills when farmland constitutes a large portion of asset holdings. The portfolio with 50 percent farmland has an expected return of 11.5 percent and a standard deviation of 9.7 percent (Figure 3). This portfolio contains 48 percent stocks and 2 percent bonds but no T-bills.

The cost of holding more than 50 percent of assets farmland is also shown in Figure 2. Portfolios containing more than 50 percent farmland are illustrated by the short lines labeled 60, 80, and 90 percent farmland. Each of these lines shows maximum returns for a risk level given that at least 60, 80 or 90 percent of the portfolio consists of farmland. All of these portfolios lie below the bold line because they offer lower expected returns for each given level of risk. Possible returns (standard deviations) on a portfolio consisting of 60 percent farmland range from 9.5 (7.3) to 11.4 (9.7) percent. When 90 percent of the portfolio is farmland, expected returns (standard deviations) can range from 10.5 (11.8) percent to 10.9 (12.1) percent. As the percent invested in farmland increases, the maximum possible expected return decreases slightly, and the amount of risk increases significantly. In all cases, highest possible returns require that the portfolio consist only of farmland and stocks.

Ways to Spread the Risks and Increase Returns

All studies of this nature involve data limitations. We used statewide data on cropland rented for cash. Individual parcels in specific locations will perform differently. There are no reliable data on the performance of other farm assets such as machinery, livestock, crop inventories, etc., so they were not included in our analysis. Moreover, past performance does not necessarily translate into future performance. Nevertheless, some useful guidelines can be drawn.

First, farm households holding more than half of their assets in farmland and other farm property should consider holding more financial assets. Given the nature of farming, we realize that most farm households will hold many farm assets. However, there are some strategies for increasing investments in financial assets. For example, it may be better to rent farmland rather than to purchase it. Avoid purchasing farmland just because it becomes available, particularly if the tract is not located convenient to other land that is farmed. The same holds true for machinery. Renting or custom hiring may free up cash for investing in financial assets, particularly in smaller farming operations.

Second, farm households should consider stocks and bonds, assets that have relatively high returns and risks. Including these assets in a portfolio may actually reduce risk more than holding safer assets such as T-Bills. When making stock or bond investments, most individuals should own a variety of instruments. For example holding 10 to 15 common stocks reduces the risk of stock holdings for a given return level. For most people, this diversification is more easily accomplished by investing in mutual funds. Information concerning mutual funds can be obtained by reading the prospectus of the mutual fund. Financial advisors and the financial pages in newspapers and magazines are also sources of information.

We conclude with recommendations for evaluating advice from financial advisors and other sources of information. First, no one--including the "experts"--can predict interest rates, profits, exchange rates and other variables that determine rates of return on investments. Financial markets are highly efficient. Today's market prices incorporate virtually all currently available information.

Second, a "special situation" that promises returns significantly above those offered in the markets is probably too good to be true. Remember the axiom "the higher the expected return, the greater the risk." A promise to double your money in a short period of time has a high probability of a 100 percent loss.

Figure 1. Classification of Investment Choices

Money Markets

- Savings Accounts
- Treasury Bills
- Certificates of Deposit
- Commercial Paper

Equity Markets

- Common Stocks
- Preferred Stocks

Derivative Markets

- Options
- Futures

Fixed Income Capital Markets

- Treasury Bonds
- Federal Agency Debt
- Municipal Bonds
- Corporate Bonds
- Mortgage and Mortgage Backed Securities

Tangible Assets

- Real Estate
- Commodities
- Antiques
- China
- Stamps
- Baseball Cards

Figure 2. Expected Returns—Risk Frontier

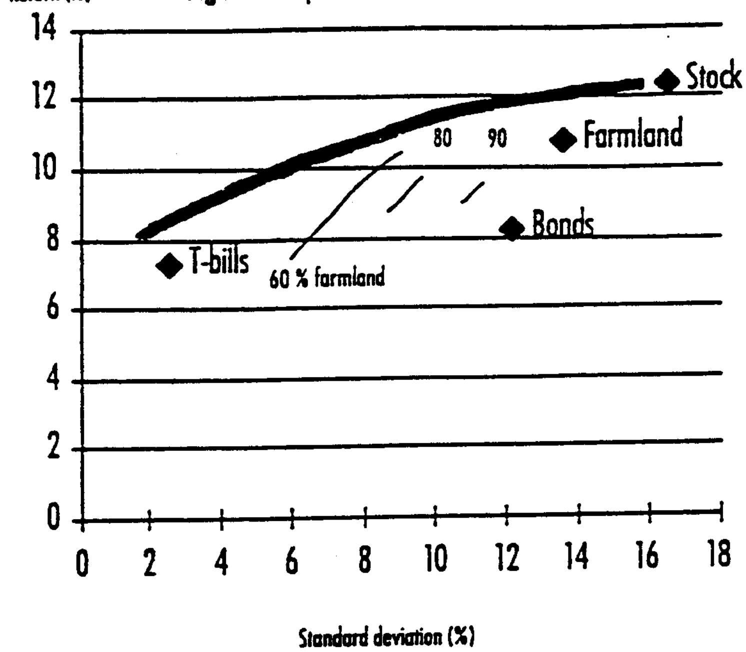

Figure 3. Composition of the Portfolios

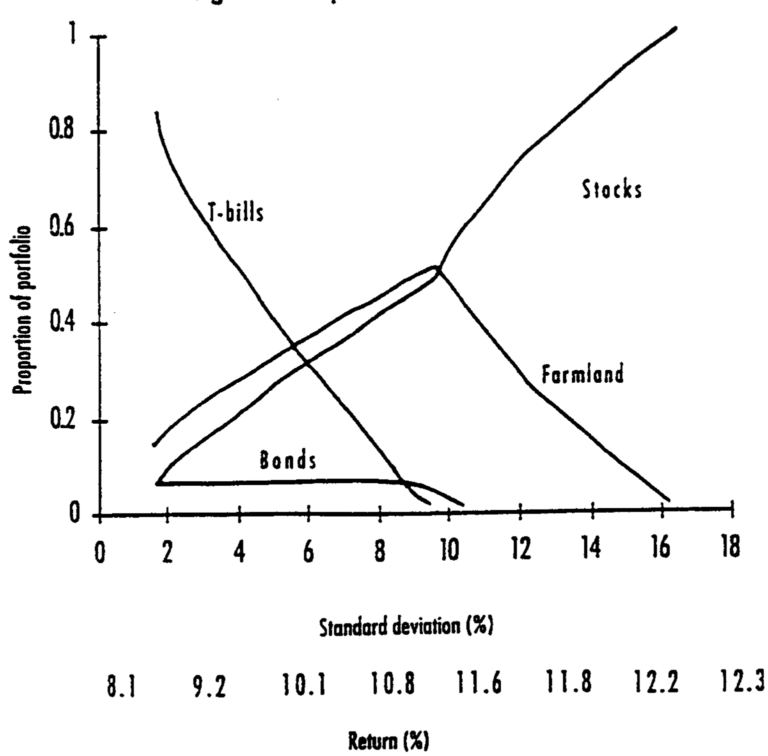

Table 1. Assets and Liabilities, Ohio Farms, 1992

	Farm Size (1992 Gross Sales)			
	< 40,000	40,000 - 99,999	> 100,000	Average
Assets ($000)	314.0	476.0	850.0	413.0
Liabilities ($000)	17.6	47.7	153.0	41.0
Composition of Assets	---------------	-----Percent-----	---------------	---------------
Farm Real Estate	59.0	57.0	59.0	58.7
Farm, Non-Real Estate	19.0	29.0	36.0	25.6
Non-Farm	22.0	14.0	5.0	15.7
	100.0	100.0	100.0	100.0

Source: Ohio Farm Household Longitudinal Survey

Table 2. Returns and Risk Statistics of Farm Selected Investment Alternatives, 1967-1991

	Mean	Standard Deviation
T-Bill	7.3	2.6
Long Term Government Bonds	8.2	12.2
Ohio Farmland	10.8	13.6
S & P 500	12.4	16.5
Consumer Price Index	5.9	3.2

Table 3. Correlations between Investments, 1967-1991

	T-Bill	Long-Term Government Bonds	Ohio Farmland	S&P
T-Bill	---			
Long-Term Government Bonds	.076	---		
Ohio Farmland	-.476	-.387	---	
S & P	-.0854	.392	-.137	---

Table 4. Expected Returns, Standard Deviations, and Composition of Portfolios for Differing Farmland Investment Levels Above 50%

Percent Invested in Farmland[1]	Expected Return	Standard Deviation	------ Percent Invested in ------		
			T-Bills	Bonds	Stocks
60	9.5%	7.32%	20%	20%	0%
	11.4	9.66	0	0	40
70	9.9	8.74	6	24	0
	11.2	9.96	0	0	30
80	10.2	10.19	0	20	0
	11.1	10.90	0	0	20
90	10.5	11.82	0	10	0
	10.9	12.07	0	0	10

[1] The first row for each farmland investment level gives the lowest possible efficient return while the second row gives the highest possible expected return.

Productive Efficiency in Commercial Banks

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Abstract

Commercial banks are of many different sizes, are subject to a myriad of regulatory guidelines, and have experienced both hardship and (financial) health over the past two decades. This work examines the productive efficiency of commercial banks. Efficiency measures are examined under different bank delineations- small, large, agricultural, nonagricultural, single-office, and multi-office. Productive efficiency is also analyzed with bank loan diversity, market share, market concentration, and profitability. The results are quite like others in that input-output specification, or the decision as to what banks truly produce, and what resources are utilized, markedly influence the findings. Generally, very small banks are not as efficient as large(r) banks. Single-office and multi-office banks perform with similar efficiency, as do agricultural and nonagricultural banks. Surprisingly, bank efficiency is not related to bank profitability, but is higher among banks with less diversified loan portfolios. Well diversified lenders, though, generate higher profits than do the more efficient, less-diversified lenders. Bank market share and banking market's concentration are positively related to efficiency, but there is no significant relationship between the profitability of banks and the concentration of the banking markets in which banks operate.

BACKGROUND

Commercial banks play a vital role in the economy for two paramount reasons. They provide a major source of loanable funds and their checkable deposit liabilities represent the bulk of the nation's money stock. Evaluating their performance and monitoring their financial condition is important to (and the responsibility of) bank managers, bank regulators, and the public at large as bank customers.

Competitive pressures in the marketplace force bank managers to be efficient in terms of both input and output productivity and by choice of the appropriate scale of operation.

Bank regulators, in decisions concerning branching, mergers, and holding company affiliations, must balance the vice of market concentration with the possible benefits of increased efficiency. The more efficiently banks are operated, the larger the earnings flows that may improve safety by absorbing losses, the more efficiently the nation's payments system works, and the more efficiently savings are channeled into investment (Benston et al., 1982). In the actions of dealing with insolvent institutions, regulators have in general taken a more favorable position toward larger, but not necessarily more efficient, multi-office banks applying a double standard in dealing with failed banks; allowing small banks to fail while frequently bailing out large banks. A relevant question is whether such a dual policy is justified on efficiency grounds. Are large banks more efficient than small banks?

RESEARCH APPROACH

Measures of technical, allocative, and scale efficiency are based upon the work of Farrell and extensions of it by Färe, Grosskopf and Lovell. The relative measures are illustrated through the use of Figures 1.1 and 1.2. In Figure 1.1, it is assumed that a bank uses two inputs, capital and labor, to produce loans. Let L_0L_0 and the area above and to the right represent all combinations of capital and labor which yield at least loan level L_0. Given the technology and input prices of capital and labor, represented by KL, efficient operation in production (cost minimization) occurs at point A. If point C represents a particular bank producing at output level L_0, then overall efficiency for firm C is represented by OD/OC. Further decomposed, technical efficiency, OB/OC, measures the bank's ability in generating enough loan volume with given capital and labor. Allocative efficiency, OD/OB, measures the degree to which the bank is using the economically correct combination of capital and labor. Since in ratio form, efficiency measures of unity represent (technical or allocative) efficiency, while efficiency measures of less than 1 imply input use either to the northeast (and off) of production frontier L_0L_0 or on the L_0L_0 frontier, but not at point A.

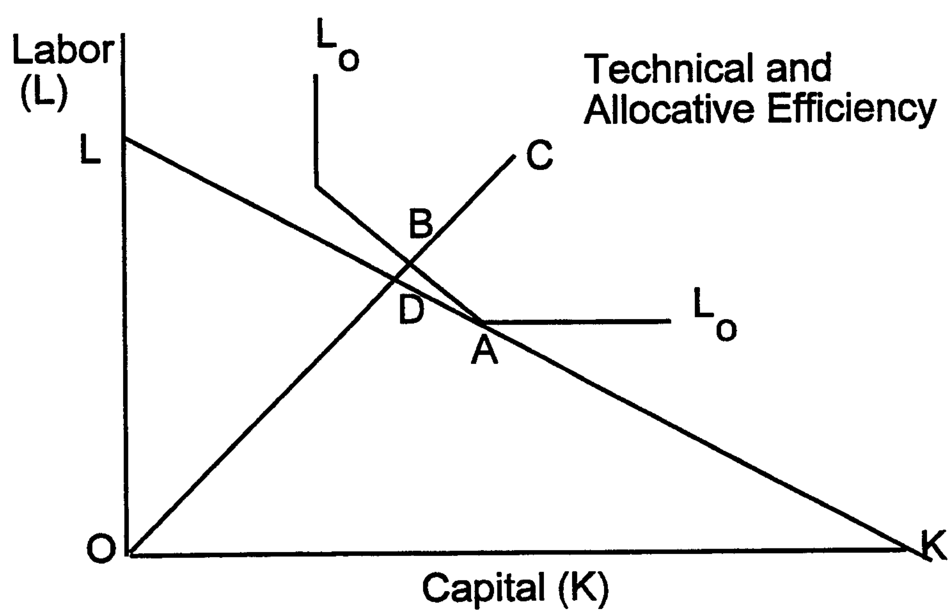

Figure 1.1 Two-Input, One Output Technology and Efficiency Measures

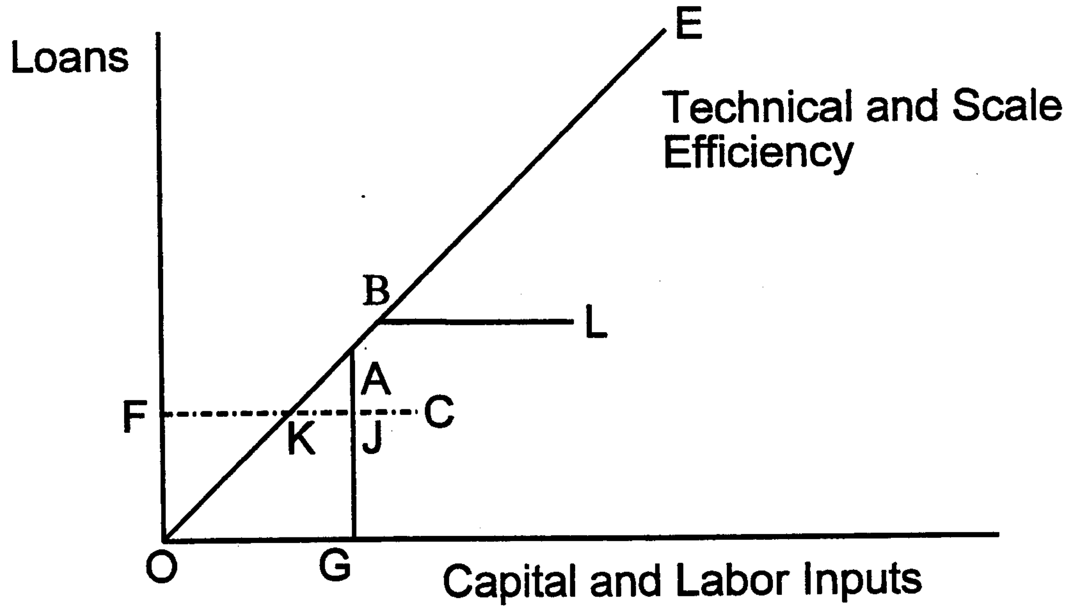

Figure 1.2 Input-Output Relationship and Efficiency Measures

In Figure 1.2, a constant returns to scale production frontier is represented by OE, which traces the potential level of loans which can be produced with given capital and labor inputs. Note the constant slope and bisection of the axes. This implies a proportional increase in loan volume and input utilization over the graph space. In contrast, the production frontier GABL is that of Farrell efficient banks, reflecting increasing, constant, and decreasing returns to scale over its mapping. For firm C, the technical efficiency is measured by FK/FC, which corresponds to OB/OC in Figure 1.1. In order to measure scale efficiency, the operating volume at which unit costs of production are minimized, a ratio of technical efficiency, FK/FC and pure technical efficiency, FJ/FC, is formed. Scale efficiency measures are always less than 1 except at optimal bank size, somewhere on segment AB.

SAMPLE BANKS

Four sets of data are used in this research. The Call and Income Report tapes published by the National Technical Information Service (NTIS) of the Department of Commerce were accessed at the University of Illinois' Department of Agricultural Economics. A quasi-random sample of 200 banks was extracted from the 1990 year-end tapes, and 200 banks extracted from the 1991 year-end tapes. Data tapes were also procured from the Federal Reserve Bank of Richmond. Data from the Federal Reserve System's Functional Cost and Profit Analysis program in 1990 and 1991 results in 208 and 399 useable observations (banks), described in detail in the following tables.

Table 1 Sample Descriptive Statistics, 200 Banks from 1990 Call Report (in millions of dollars, excepted those noted otherwise)

Variable	mean	std.dev.	minimum	maximum
Total Assets	245	244	28	1,560
Total loans	151	210	9.2	1,200
Ag prod. loans	2.1	3.2	0	23.7
Ag re loans	1.7	2.8	0	20.4
Real estate loans	84.2	109	1.8	974
Commercial loans	32.9	120	0	500
Consumer loans	26.8	50	0.2	290
Fed funds sold	12.1	56	0	237
Securities owned	68.2	86	0	586
Prem./fixed assets	3.5	6	0.1	17.2
Nonint. deposits	28.6	43	0	245
interest deposits	183	200	20	1136
Fed funds bought	8.4	21	0	377
Interest income	22	25	1.2	155.7
noninterest income	2.7	4.1	0.07	27
service chge inc.	0.8	1.1	0	6.2
NIBE	1.1	4	0.12	21
sal. and benefits	3.5	4	0.12	21
occupancy costs	1.1	1.6	0.023	7.3
other expenses	2.8	3.8	0.14	21.1
Loan Loss provision	1.9	4	0	58
Employees[1]	120	127	6	681
People Cost[2]	28.9	8.3	12.9	65.1
Other[*]	0.013	0.008	0.0005	0.043
Funds Cost[3]	0.0586	0.008	0.03	0.087
Loan Price[4]	0.113	0.02	0.059	0.166
Ag Bank?[5]	0.025	0.08	0	0.74

[1] Total, full-time equivalency basis
[2] Annual salary in thousands of dollars
[3] Annual dollar cost per dollar deposits
[4] Annual interest charge per dollar loaned
[5] Proportion of loan portfolio agricultural loans

* Other bank expenses generally include, but are not limited to: supplies, postage, courier, freight, travel, marketing, advertizing, and promotion, small fixtures and software, professional services, general insurance, dues, publications, subscriptions, telephone, telegraph, and cafeteria per dollar deposits.

Table 2 Sample Descriptive Statistics, 200 Banks from 1991 Call Report (in millions of dollars, excepted those noted otherwise)

Variable	mean	std.dev.	minimum	maximum
Total assets	288	302	25.2	2,284
Total loans	169	174	7	1,962
Ag production loans	1.6	4	0	17
Ag real estate loans	1.5	3	0	21
Real estate loans	96	111	0	649
Commercial loans	36	55	0	1,627
Consumer loans	30	38	0.006	465
Fed funds sold	16.7	24	0	699
Securities owned	83.6	75	0	526
Prem/fixed assets	4.7	3.3	0.03	41.9
nonint. deposits	33.9	33	0	281
interest deposits	213	174	21	1175
Fed funds bought	7.4	31	0	194
Interest income	24.5	23	0.4	192
noninterest income	3.9	2.6	0.06	39.3
service charge income	1.1	0.9	0	9.8
NIBE	1.8	5.4	-29	20
salaries and benefits	4	3.7	0.3	26
occupancy costs	1.2	1.2	0.02	15.3
other expenses	4	3.4	0.065	35.2
Loan Loss provision	2	5.7	0	35.9
Employees[1]	137	116	11	730
People Cost[2]	29.4	7	10.4	81.3
Other* costs	0.015	0.00	0.001	0.035
Funds Cost[3]	0.0528	0.008	0.041	0.080
Loan Price[4]	0.1063	0.02	0.03	0.178
Ag Bank?[5]	0.019	0.12	0	0.62

[1] Total, full-time equivalency basis
[2] Annual salary in thousands of dollars
[3] Annual dollar cost per dollar deposits
[4] Annual interest charge per dollar loaned
[5] Proportion of loan portfolio agricultural loans

* Other bank expenses generally include, but are not limited to: supplies, postage, courier, freight, travel, marketing, advertising, and promotion, small fixtures and software, professional services, general insurance, dues, publications, subscriptions, telephone, telegraph, and cafeteria per dollar deposits.

Table 3 Descriptive Statistics, 208 Functional Cost Participants, 1990 (in millions of dollars, excepted those noted otherwise)

Variable	mean	std.dev.	minimum	maximum
Total assets	303	310	7	5,463
Total loans	194	220	4	4,299
Agricultural loans	1.7	4	0	27
Real estate loans	84	115	0	3,633
Commercial loans	61	70	0	403
Consumer loans	25	35	0	320
Fed funds sold	10	16	0	208
Securities owned	84	83	0.6	1,562
Prem./fixed assets	4.2	4	0.04	117
nonint. deposits	21	18	0	351
Fed funds bought	1.4	10	0	59
Interest income	28	25	0.7	489
noninterest income	2	2.5	0.01	29.6
NI	0.6	4	-100	10
sal. and benefits	4	4.7	0.06	47
occupancy costs	1.2	1.2	0.02	15.3
Loan Loss provision	1.8	6	0.2	70
Officers	33	24	1	246
Employees[1]	108	101	3	1330
Officer cost	51.2	30	23	127
Employee Cost[2]	19.5	9.7	12	42
Funds Cost[3]	0.061	0.009	0.035	0.080
Loan Price[4]	0.11	0.02	0.086	0.156
Ag Bank?[5]	0.009	0.15	0	0.75

[1] Total, full-time equivalency basis
[2] Annual salary in thousands of dollars
[3] Annual dollar cost per dollar deposits
[4] Annual interest charge per dollar loaned
[5] Proportion of loan portfolio agricultural loans

Table 4 Descriptive Statistics, 399 Functional Cost Participants, 1991 (in millions of dollars, excepted those noted otherwise)

Variable	mean	std.dev.	minimum	maximum
Total assets	280	400	8	9,500
Total loans	151	202	3	6,100
Agricultural loans	1.1	4	0	17
Real estate loans	88	101	0	3,633
Commercial loans	53	95	0	950
Consumer loans	22	40	0	505
Fed funds sold	9	12	0	86
Securities owned	86	99	0	4,667
Prem./fixed assets	4.2	4	0.01	176
nonint. deposits	21	21	0	900
Fed funds bought	3.6	18	0	536
Interest income	21	26	0.7	766
noninterest income	4.3	14	0.08	227
NI	0.6	10	-100	86
sal. and benefits	4.2	5.2	0.08	93
occupancy costs	1.2	1.2	0.02	15.3
Loan Loss provision	1.1	5	0.7	49
Officers	32	40	1	1,114
Employees[1]	99	155	3	2,784
Officer cost	59.4	33	4	189
Employee Cost[2]	24.6	17	6	55
Funds Cost[3]	0.51	0.01	0.027	0.075
Loan Price[4]	0.097	0.02	0.057	0.128
Ag Bank?[5]	0.008	0.14	0	0.58

[1] Total, full-time equivalency basis
[2] Annual salary in thousands of dollars
[3] Annual dollar cost per dollar deposits
[4] Annual interest charge per dollar loaned
[5] Proportion of loan portfolio agricultural loans

The underlying advantage of using the Functional Cost data is in their item count variables that better reflect the flow characteristics of banking services. Five services are developed, the data extracted from the Functional Cost tapes, and summaries presented in Table 5.

Table 5 Service Categories, 1990 Functional Cost Participants

Service 1 -	loan applications processed
Service 2 -	Loans serviced
Service 3 -	account closing and/or opening and product sale (i.e., safe deposit box, savings bond, etc.)
Service 4 -	number of accounts serviced
Service 5 -	teller transactions, comprised of account withdrawals, deposits, checks cashed, credit card slips processed, and electronic fund transfer posting.

With heed given to bank's information processing and data storage functions, the computer hours per week for each bank is used as a technological flow of input used in intermediation services. Summaries of these heretofore uninvestigated flow variables of FCA banks are in Table 6.

Table 6 Summary Statistics of Services Functions, 1990 Functional Cost Participants

Variable	mean	maximum	minimum
Service 1	4499	41000	0
Service 2	9347	97654	517
Service 3	12349	208086	76
Service 4	9261	69000	1746
Service 5	4900000	73000000	7200
Bank Offices	5.5	57	1
CPU hours/week	102	168	0

RESULTS

Since no other researchers have included the Functional Cost data along with Call Reports the way this paper has, no prior input-output specifications and standard practices are available against which to compare the above methods and outcomes. Three models share the same output vector novel to FCA users or proprietary (firm level) analysts. The services, or item counts of seemingly equivalent effort tasks, are outputs in Models UF190, UF190A, and UF690. Item counts for all of the inputs - officer, employees, computer hours, ATM machine, and bank offices - are combined to evaluate loan requests, service loans, service bank accounts, sell products, and post transactions, the array of service outputs. The mean efficiency of the 1990 FCA participants under Model UF190 is 60%, with median 56%, and inner quartile range of 33 (76-43). Adding one additional input, point of sale terminals, to the input array of about 3% of the participants's inputs, as expected, reduces mean efficiency to 57% (and median to 53). This is Model UF190A, where efficiency results are highly correlated, 0.89, with Model UF190. Model UF290 shares the common input bundle with Model UF190, but simplifies the output to the Elyasiani and Mehdian choice of revenue. The distributional characteristics of the efficiency results is very similar to Model UF190's results, but correlation of results is only -0.04. The same banks who are good at performing services (a higher efficiency rating in Model UF190), may or may not be good at generating revenue. The services included in the output array may not be priced accurately or even being priced (generating revenue) at all.

Table 7 Overall Efficiency Results, 1990 FCA Sample

	Model					
	UF190A	UF190	UF290	UF390	UF490	UF690
Mean efficiency	57	60	63	71	70	47
Median efficiency	53	56	58	70	69	43
std. dev.	24	24	20	20	19	32
Q_1	41	43	47	57	56	15
Q_3	71	76	76	86	85	71

Table 8 Overall Efficiency Correlations, 1990 FCA Sample

	Model				
	UF190A	UF190	UF290	UF390	UF490
UF190	0.89				
UF290	-0.14	-0.04			
UF390	0.40	0.35	0.28		
UF490	-0.11	0.08	0.65	0	
UF690	0.38	0.35	-0.12	0.21	0.24

In addition, the services included in Model UF190's output bundle are not the major sources of funds for banks. Interest and investment income collections are not necessarily linked to the number of loans processed and serviced, number of accounts serviced, opened, closed, or bonds sold, and transactions recorded. Thus it is not surprising that revenue and services are produced by the FCA participants with roughly the same efficiency, but by different banks. Model UF690 also measures bank's ability to provide service, but with a more intermediary input set. Using officers, employees, offices, their costs, and loan funds, banks provide services with less than encouraging efficiency. The mean efficiency result is

47% (median 43) in Model UF690, with weakly positive correlations with Model UF190A, UF190, UF390, and UF490 overall efficiency results.

Models UF390 and UF490 share a simplified production oriented input bundle, namely officers, employees, and technology per employee to generate intermediatory dollar denominated outputs. In Model UF390, real estate loans, consumer loans, commercial loans, other loans, and demand deposits are produced with an average 71% efficiency (70% median), with moderately positive efficiency correlations with production models UF190A, UF190, and UF290, and no detectable relationship with Model UF490, although their input arrays are identical. In Model UF490, noninterest and interest revenue are the outputs that officers, employees, and capital (technology) are to generate. The efficiency mean result is 70% (median 69), and results most highly correlated with Model UF290, sharer of two inputs in generating revenue, the sum of Model UF490's noninterest and interest revenue.

Functional Cost data are used in Models UF191, UF291, and UF391. The value-added of a bank's safe keeping of depositor's funds, making them readily accessible, and emitting them in loan or securities portfolios is used by some analysts in describing what a bank does. In Model UF191 all transaction deposits and all non- transaction deposits, ordinarily viewed as inputs to a bank are viewed as products (output) depositors desire. In addition, banks make loans and investments. Inputs include premises and fixed asset resources, officer, employees, other expenses, and loan funds. Mean efficiency is 58% (median 59). Changing slightly the output specifications in Model UF291, to include regular demand deposits and regular savings deposits in lieu of all deposits in the prior model, mean efficiency rose to 61% (median 60). The correlation between the two model's efficiency results is 0.83. In Model UF391, officers, employees, noninterest expenses and interest expenses aim to produce demand and savings services, loans, and investments. Mean efficiency level is 56%, and quartile boundaries fall slightly in Model UF391 versus Model UF291. The correlation between Model UF291 and UF391 overall efficiency score is 0.90.

Table 9 Overall Efficiency Results, 1991 FCA Sample

	Model		
	UF191	UF291	UF391
Mean eff'cy	61	58	56
Median eff'cy	60	59	57
std. dev.	27	27	26
Q_1	40	36	37
Q_3	83	80	76

Table 10 Overall Efficiency Correlations, 1991 FCA Sample

	Model UF191	UF291
UF291	0.83	
UF391	0.78	0.90

Table 11 Mean Efficiency Estimates, 1990 FCA Banks

	UF190A	UF190	Model UF290	UF390	UF490	UF690
OE	57	60	63	71	70	47
A	92	94	66	77	77	56
T	62	64	95	92	91	80
S	88	86	98	99	100	99

The 1990 Functional Cost participant's efficiency results are summarized in Table 11. Model UF190A and UF190 are virtually identical in input-output specifications except the seven banks with point-of-sale terminals have this added input, a technology placed into its input array in Model UF190A. Since the service output available given the FCA data is the same for each bank in the two models, the overall efficiency especially of those banks with POS inputs, declines. The banks, though, are generally more allocatively efficient in provision of services than in the provision or production of interest revenue, noninterest revenue, or any other dollar denominated output. This result is consistent with Ferrier and Lovell's findings also using FCA data. When a more production oriented input-output specification is adopted, with flow variables and items counts, technical inefficiency tends to dominate allocative inefficiency. Model UF290 results with item count input and revenue the sole output, more closely resemble Models UF390, UF490, and UF690 in that constant cost scale economics are computed and allocative inefficiency, representing the wrong mixture of inputs, more heavily influences bank's operational efficiency than technical efficiency. The magnitudes of the overall efficiency levels are quite similar to those found using Call Reports but are slightly lower than those derived econometrically. No significant relationship exists between the ranking of banks in their cost efficiency using the translog estimation techniques and programming method. At best, the ranking of the 208 FCA participating banks from 1990 is not in disagreement with the cost frontier construct. At worst, they do not agree either.

Table 12 Mean Efficiency Estimates, 1991 FCA Banks

	Model		
	UF191	UF291	UF391
OE	61	58	56
A	68	64	61
T	88	92	95
S	87	90	91

The 399 analyzed 1991 Functional Cost participating banks efficiency summaries are presented in Table 12. Again, large amounts of improvement can be made to the average firm in either using less resources or using a more correct combination of inputs to emulate those best practice banks among the FCA participants.

This points to one of the many dangers of using deposits, for which banks pay, as an output. Griffel-Tatjé, et al. note this phenomena in their examination of efficiency sensitivity to variable specification. Measured efficiency increases when deposits are treated as inputs as opposed to when treated as outputs or omitted. Not only does the sample's mean efficiency rating increase, but the number of banks in the lowest areas of the ratings distribution is reduced. They show how mean efficiency levels can improve some 20-25% and minimum levels of bank efficiency can nearly double when deposit or other loan fund variables are included as an input using DEA. But the inability of differing input-output specifications to clearly identify the best practice banks from the worst practice banks is disheartening. Even if deposits are included as inputs, as in Elyasiani and Mehdian, and Domenech, the remaining inputs and/or differing output specifications are different enough that little agreement exists in choosing best practice and worst practice entities.

Mean efficiency levels of the 208 Functional Cost participants in 1990 are summarized in Table 13.

Table 13 Mean Overall Efficiency Measures by Bank Size, 1990 FCA Banks

		Model				
Banks	Size	UF190A	UF190	UF290	UF390	UF490
44	Large	59	63	58	74	70
92	Inter.	58	61	62	68	71
45	Small	56	58	66	72	68
27	Very Small	47	50	70	74	75

The mostly production approach to input-output specification and reliance upon flow measures of output tend to somewhat contradict the prefound tendency of the large(r) banks likely being more efficient than the small(er) institutions. Although six of seven model's F-test in the ANOVA procedure is significantly greater then the critical values @α=0.10 (and two of the six at α=0.05), uniformity among bank size-efficiency relationship is absent. Very small banks lag in efficiency under the (very) strict production specifications, using the item counts of services array as the output vector (e.g., Models UF190A, UF190, UF690). This may be due, in part, to the tendency among very small banks to have others (possibly large(r) banks) perform many data intensive tasks for them (e.g. account posting, credit card processing). Similarly, any reliance that very small banks might have upon large(r) banks through a correspondent relationship may be captured in only the small(er) bank's input array and in the large(r) bank's input and output vectors. Yet, when (mostly) item counts as inputs are used and dollar denominated outputs are chosen, the very small banks perform the same if not significantly better than large, intermediate, and small banks (e.g., Models UF290, UF390, UF490).

EFFICIENCY, PROFITABILITY, AND CONCENTRATION

Several profit-concentration studies have noted a mixed set of results in examining their link and suffer from the indistinguishability between market power and efficiency as a source of concentration and profitability (Demsetz and Peltzman). This work's separation, or at least recognition, of reported profitability (albeit influenced by tax rules, accounting practices, and financial strategies) and productive efficiency into two measures is an improvement over most previous research. A bank may intermediate either at a lower cost or provide a differentiated product sufficient enough to gain market share at the expense of smaller competitors, further concentrating the market. Or, the market's most efficient firm could be making the most (high profitability) and have a growing market share (increasing concentration). Yet consumers benefit in either case. The identification of bank's productive efficiency, profitability, and market power, then aids in examining the performance of banks under different structures or concentration regimes.

The market concentration and market power of each of the Call Report banks in the 1990 sample is represented by the HHI of the banking market in which the firm is located and their respective share of the market (MS) (summarized in Table 14). These two statistics are then examined with the efficiency and profitability in testing hypotheses six, a positive relationship between bank profitability, efficiency, and competition.

Table 14 Market Share and Herfindahl-Hirshmann Summaries, 1990 Call Report Banks

	MS	HHI
mean	14.92	2051
median	6.86	1607
std.dev.	19.9	1485
minimum	.01	499
maximum	100	10000

The Pearson product-moment correlation coefficients between overall efficiency (calculated in the various models), profitability (ROA), market share (MS), and market concentration (HHI) are presented in Table 15. Only three of the efficiency-profitability correlations are significant at $\leq$ 0.10. Model FL90, positively correlated, and Model U190 and TL, negatively correlated, are different enough from zero to reject the null hypothesis of no relationship between efficiency and profitability populations.

Table 15 Correlations Between Efficiency, Profitability, Market Share, and Concentration, 1990 Call Report Banks

Overall Efficiency

	U190	U290	U390	A90	FL90	EM90	Y90	TL	ROA	MS
ROA	-.12	-.08	.02	.01	.10	-.07	.08	-.21		
MS	.20[c]	.22[c]	.14[b]	.16[b]	.12[b]	.13[b]	-.07	-.09	.11[a]	
HHI	.18[c]	.19[c]	.11[a]	.21[c]	.13[b]	.18[c]	-.10[a]	-.03	.06	.84[c]

[a] significant @ $\alpha = 0.10$ [b] significant @ $\alpha=0.05$ [c] significant @ $\alpha=0.01$

With Model Y90 and the econometric translog the exceptions, there is a significant positive relationship between the measured overall efficiency of the sampled banks and their respective market share. Market shares may tend to be larger among the most efficient banks because of their operational efficiency and ability to provide services to consumers at (more) competitive prices. Or, the banks with large(r) market shares might be more willing and/or able to concentrate and improve upon operational efficiency at the expense of customer relations, service proliferation, or increased market penetration. Similarly, the HHI is positively related to the efficiency metric in six of the seven programming models, in each, at $\alpha = 0.10$, and in four of the models at $\alpha = 0.01$. Also, the coefficient expressing relationship between market share and profitability is significantly different from zero at $\alpha = 0.10$. Although a very high, and positive relationship is expressed between market share of individual banks and the bank's market HHI, the concentration of a banking market is not significantly related to the profitability of the bank(s) operating in the market. Several of the sample banks are sole players, or at least dominant providers (e.g., MS > 0.50) of banking services in their market. These markets are (generally) characterized by an HHI in excess of 4000. Nonetheless, their profitability is by no means greater than, nor even noticeably different than the profitability of banks located in much less concentrated markets.

Table 16 Correlations Between Efficiency and Profitability 1991 Call Report Banks

	Overall Efficiency							
	U191	U291	U391	A91	FL91	EM91	Y91	TL
ROA	-.01	.01	-.03	-.03	.08	.01	.10[a]	-.08

[a] significant @ $\alpha = 0.10$ [b] significant @ α=0.05 [c] significant @ α=0.01

Table 16 lists the correlation coefficients measured between the overall efficiency of banks in the eight models listed with the profitability (ROA) each reported. Only one of the model's measured efficiency metrics is significantly related to bank profitability, that of Model Y90. The relatively low correlations of the other models leads one to doubt a positive relationship between the profitability and productive efficiency of the sampled banks. Similar inferences can be reached using the 1990 FCA banks, as exhibited in Table 17.

Table 17 Correlations Between Efficiency and Profitability, 1990 FCA Banks

	UF190A	UF190	UF290	UF390	UF490	UF690	TL
ROA	-.05	.00	.03	-.07	-.05	.07	-.03

EFFECTS OF INTEREST RATE SPREAD AND LOAN DIVERSITY

In this, the last section of this paper, each bank's efficiency, profitability, market share, and concentration are examined along with two measures of local economic conditions. These bank-specific measures might be the result of implemented managerial strategies or prior to financial deregulation, influenced quite heavily by legislative and regulatory mandates upon lending. The loan diversity measure (LD) is calculated to represent the breadth of most bank's primary earning asset, its loan portfolio. The bank-specific spread (SP) is the simple difference between the average annual interest rate earned on the bank's loan portfolio and the bank's cost of deposits. Summary statistics of the loan diversity (LD) and spread (SP) for those data sources included in the analysis are in Table 18.

The loan diversity of each bank is quantified in an HHI-type way, squaring, and then summing the proportion of each bank's loan portfolio in various loan categories. Operationally, a single purpose lender might be able to more easily capture the economies of scale associated with a particular loan activity if it is concentrated in that area. Whereas, for risk management or other purposes, a well diversified loan portfolio might be chosen by a bank, not necessarily the most cost effective strategy in asset management, but expected utility maximizing nonetheless. The spread attempts to reflect the lack of competitiveness in lending markets or in the offering of depository services. If abnormally low interest rates received on loans are reported by banks, and their cost of funds via deposit taking is normal, a lower than average spread should reflect the situation. If above normal rates are paid to attract deposits, and loans do not yield above standard returns for banks, the spread is assumed to be smaller than would be if the depository markets were not such an expensive source of loanable funds. In contrast, the spread should be higher than normal in markets with a loyal core of deposits and little competition for the lender in loan granting.

Table 18 Loan Diversity and Spread, All Data Sources

	LD				SP		
	CR90	CR91	FCA90	FCA91	CR90	CR91	FCA90
mean	4389	4842	4723	6839	.054	.053	.049
median	4012	4313	4213	6608	.053	.053	.049
std.dev.	1690	1809	1601	2189	.016	.017	.011
minimum	1822	1981	2750	0	.003	-.04	.021
maximum	10000	10000	9753	10000	.106	.125	.078

As can be seen, the loan portfolios among the sample's banks are rather diverse. Of banks granting loans, 1667 is the minimum LD obtainable, and 10000 is the maximum for a special purpose lender. One participating bank in the 1991 FCA sample chose not to grant loans, explaining the zero LD measure. Instead the institution invested heavily in money market instruments, securities, and the federal funds market. The mean spreads calculated for the samples' banks are very similar to those reported by the FDIC in their summary reports, 1990 and 1991. The negative spread calculated as the 1991 Call Report sample's minimum is the result of rather large loan losses impairing the bank's ability to report net earnings on its loan portfolio.

One might guess that banks offering an array of loans to a variety of client-types may not be as operationally efficient in the administration of their loan portfolio as is a single-purpose lender. Saddled with higher information, personnel, and other expenses than if the firm chose to make one type of loan, to one type of customer, a positive relationship should exist between a bank's LD and overall productive efficiency. Similarly, an elevated spread should translate into higher profits. If lack of competition or market power associated with a large(r) bank is reflected in their ability to procure funds at a lower cost or make loans at higher interest rates than is normal, spread and the bank's MS and/or HHI should also be positively related. Loan diversity is examined with efficiency, profitability, and competitiveness measures using Pearson's r, the correlation coefficient, with significant relationships further analyzed using simple linear regression. Table 19 summarizes the findings using the 1990 Call Report sample.

Table 19 Correlation Coefficients and Relational Results Between Efficiency, Profitability, Competitiveness, Loan Diversity, and Spread, 1990 Call Report Banks

	U190	U290	U390	A90	FL90	EM90	Y90	TL	ROA	MS	HHI
LD	.20[c]	.19[c]	.17[c]	.06	.02	.02	-.02	.08c	-.26[c]	.12[b]	.09
SP	-.20[c]	-.23[c]	-.21[c]	-.14[b]	-.11[a]	-.11[a]	-.03	-.13[b]	.16[b]	-.05	-.05

[a] significant @ $\alpha = 0.10$ [b] significant @ $\alpha=0.05$ [c] significant @ $\alpha=0.01$

In three of the seven models using 1990 Call Report banks and the nonparametric frontier analytic technique, loan diversity is significantly related to overall efficiency. In Model U190, U290, and U390, loan diversity is positively correlated with overall efficiency. Each coefficient is significantly different from zero at $\alpha=0.01$, suggesting that the population distribution of bank efficiency is related to the distribution of bank loan diversity. Regression results of efficiency being dependent upon loan diversity support the positive relationship between loan specialization and productive efficiency. P-values on the slope coefficient in the three regression models are 0.013, 0.012, and 0.012, respectively. The least diversified banks (with respect to loans) are noted with higher operational efficiency measures. The loan diversity measure is negatively related to profitability (r=-0.264), is significantly different from zero at $\alpha=0.01$, and is supported using regression analysis (t=3.85, p-value=0.011). This implies that single purpose lenders tend to lag in profitability versus the diversified banks.

The correlation of spread with Models U190, U290, and U390 overall efficiency estimates are significant. But the interpretation is not like that expressed previously regarding the loan diversity measure. The negative correlations imply that large(r) net interest spreads are affiliated with low(er) levels of efficiency. One possible explanation may be in examining spread's correlation with loan diversity (LD). Their correlation coefficient is significant, and also negative, meaning that single purpose lenders, those with the attributed high(er) efficiency scores, are characterized by low(er) spreads. Those lenders with well diversified loan portfolios, while not normally the most efficient, receive higher net interest spreads. The ultimate outcome may be summarized in examining the LD and SP measures with profitability (ROA). Banks with large spreads, not typically the most highly efficient banks, have a significant positive relationship with profitability (r=.16). In contrast, the special purpose lenders with little loan diversity have a negative relationship with profitability (r=-.26), yet are among the most efficient banks.

Relational results utilizing the 1991 Call Report sample are contained in Table 20. Loan diversity is negatively correlated with profitability (ROA). This is consistent with the prior year's findings. Single purpose lenders tend to lag in profitability relative to banks with (more) diversified portfolios. Spread, as in the previous paragraph, is positively related to profitability, and negatively related to loan diversity (LD). Each of the above three correlations are significantly different from zero, implying that the populations of bank profitability, loan diversity, and interest rate spreads are not independent of each other.

Table 20 Correlation Coefficients and Relational Results Between Efficiency, Profitability, Loan Diversity, and Spread, 1991 Call Report Banks

	U191	U291	U391	A91	FL91	EM91	Y91	TL	ROA
LD	-.02	.01	-.03	-.01	-.02	.00	-.01	.11[a]	-.27[c]
SP	.19[c]	.15[b]	.15[b]	.18[a]	.17[a]	.13[b]	.14[b]	-.04	.27[c]

[a] significant @ $\alpha = 0.10$ [b] significant @ α=0.05 [c] significant @ α=0.01

Loan diversity, when compared to the efficiency, profitability and spread measures of the 1990 and 1991 Functional Cost participants, produces similar results. In Model UF290, the overall efficiency measure and loan diversity are positively related (r=.16), meaning that special purpose lenders, with a high concentration of loans in a few classes, operate more efficiently. The correlation coefficient is significantly different from zero at α=.05. Regression analysis assesses the slope coefficient on loan diversity as also significantly different from zero, with a p-value of 0.063.

The expected negative correlation between LD and ROA is significant at α=.01 in the 1990 FCA sample. Spread is positively related to profitability (r=.25 and significant @ α=.01) and negatively related to loan diversity (r=-.25, also significant @ α=.01).

Model UF690, though, has an unexpected result in that loan diversity or lack thereof, is not associated with a high(er) level of overall efficiency. The correlation coefficient of -0.195 is significantly different from zero at α=0.01, with the result of loan diversity being regressed upon efficiency being t =2.72 and p-value = 0.10 on the slope coefficient. The item count (production) outputs in Model UF690's specification may lend itself to this result, as the number of loans analyzed and services performed (i.e., loan payments and remittances, advances on a credit line, etc.) are deemed production in the output bundle in UF690.

In Model UF191, utilizing the 399 institutions contributing to the 1991 Functional Cost sample, loan diversity is as expected, positively related to overall efficiency, implying that banks with less loan diversity, and thus a higher diversity ranking, tend to have the high(er) overall efficiency levels. The Pearson's r is 0.09, significantly different from zero at α=0.05, with regression analysis producing a p-value on the diversity beta of 0.06.

Correlation summaries using the 1990 Functional Cost participants are in Table 21.

Table 21 Correlation Coefficients and Relational Results Between Efficiency, Profitability, Loan Diversity,and Spread, 1990 FCA Banks

	UF190A	UF190	UF290	UF390	UF490	UF690	TL	ROA
LD	.03	-.04	.16[b]	.05	.10[a]	-.19[c]	-.09	-.22[c]
SP	.01	-.01	.02	-.05	-.14[b]	.04	.12[b]	.25[c]

[a] significant @ $\alpha = 0.10$ [b] significant @ $\alpha=0.05$ [c] significant @ $\alpha=0.01$

SUMMARY

Generally, the findings herein are very consistent with those of most who have performed similar analysis. The models patterned after Aly et al., who analyzed 322 Call Report institutions, find scale efficiency in excess of both technical and allocative efficiency, as did they. Technical efficiency is positively related to both bank size and degree of urbanization in Aly et al. Similarly, large(r) banks are found more efficient than both the small and very small banks and the variability of large banks efficiency measures is greater than is the variability of small banks. No difference is noted between the operational performance of single-office and multi-office banks, just as Aly et al. found in comparing branch and non-branch banks. Likewise, no significant difference is noted between the performance of agricultural and nonagricultural banks.

Ferrier and Lovell utilize Functional Cost data from 575 banks in concluding that costs are about 25-30% higher than need be, on average, and that the smallest banks in their analysis are the most efficient. This work disputes the latter finding, identifying large(r) banks as those most efficient. The correlation of bank rankings under the linear programming technique and econometric estimation in this work, like Ferrier and Lovell's, is unable to agree upon the best practice, or frontier firms. But the results of Models FL90 and FL91 agree very strongly and are highly correlated with other input-output specifications, namely U190, U290, A90, U191, U291, and A91. Agricultural and nonagricultural banks cannot be distinguished from each other in examining their overall efficiency levels.

Elyasiani and Mehdian analyze 144 Call Report banks, finding the largest institutions more efficient than are the smaller ones, similar to this work's results when using similar input-output specifications. They, like these results, site no difference in the overall performance of single-office and multi-office banks, but conclude that locational product and service differentiation enable small, boutique banks to operate successfully alongside larger, more efficient banks.

Yue's study of 60 banks in Missouri concludes that scale inefficiency is not important in banks relative performance. Technical and allocative inefficiencies cost banks much more than does operating at an incorrect scale, as evident in Model Y90 and Y91 results. The only coincident input in all the other models, labor, is not specifically recognized by Yue. Generating flows of revenue and managing flows of expenses comprise the role of banks. This somewhat unusual input-output specification of Yue results in significantly contrary efficiency correlations between Models Y90 and Y91 and all other models.

Consistent with the findings of Grifell-Tatjé et al., as input-output specifications are radically altered, the ability of analysts to predictably identify best and worst practice firms diminishes markedly. The overall efficiency results of Models A90, FL90, EM90, U190, and U290, all reliant upon the 1990 Call Report sample, are highly correlated. Likewise, the models using the 1991 Functional Cost data are highly correlated, since only slight changes are made in specifications across the models. The most discouraging is in the item count (production) and volume of funds (intermediation) disagreement. The results of Models UF190A, UF190, and UF690, with the item count service outputs, are highly correlated. But when input-output specifications are changed to include a mixture of item count inputs and intermediary outputs, any agreement as to consistency in identifying the best practice and worst practice banks disappears. Grifell-Tatjé et al. utilized proprietary data from 58 Spanish savings banks in demonstrating the sensitivity of efficiency scores to variable specification. The findings here are as disturbing in that agreement on a common core of the best and worst practice banks cannot be reached among such varied specifications.

Ellinger and Neff examine 500 rural, agricultural banks from Call Reports to conclude that large doses of (relative) inefficiency are common in banking, and that measured efficiency as well as rankings by performance change across specifications. They note the inclusion of deposits as inputs in some applications, as outputs in others. Their sample banks have an average market share of nearly 23% and operate in fairly concentrated markets, with average HHI of 2708. This study's average market share among the Call Report institutions is only 15%, and average HHI about 2000. But like Ellinger and Neff, significant amounts of efficiency can be gained if firms can emulate the best practice firms. Improper scale is not the prime component of inefficiency, even among very small banks. Instead, an improper mix of resources, and overuse of resources relative to the frontier firm's standards comprise the bulk of calculated inefficiencies.

Neff et al. estimate both a parametric translog cost frontier and variable profit model using the Fuss normalized quadratic functional form from Call Report data of 1,913 rural, agricultural banks. Interestingly, no significant correlation between the rankings of banks in their cost efficiency and revenue efficiency exists. Banks with large portions of their loan portfolios in agricultural loans are found to be less profitable. Their finding is somewhat consistent with the analysis regarding hypotheses six in that those banks with a less diversified loan portfolio, and thus high(er) LD measure, while possibly very operationally efficient, lag in profitability. Neff et al. findings are also supported by this work in acknowledging a positive link between market share and efficiency. Likewise, Neff's link between a market's

HHI and profitability of the market's bank(s) is consistent with the market share, concentration, and efficiency correlations found using the 1990 Call Report sample. Results of the translog cost estimation in this work detect no difference in relative efficiency across bank sizes, single-office or multi-office designation, or agricultural versus nonagricultural focus. Efficiency levels are extremely sensitive to choice of cost or profit measures in Neff et al. The item count opportunities permitted using the Functional Cost data squelch much of the efficiency disparity evident in the more intermediary-type models.

An expected positive relationship between operational efficiency and profitability is not substantiated by the data. The most efficient banks are not the most profitable. Efficiency, though, is positively paired with a bank's market share and also the concentration of the bank's market, as expressed by the Herfindahl-Hirshmann Index. Efficiency is also most noticeable among the focused lenders, those banks with a less than fully diversified loan portfolio. The single purpose lenders tend to be operationally more efficient, yet are not the most profitable banks. The more diversified lenders tend to generate higher earnings. Surprisingly, net interest spread is not related to a bank's market share nor the (lack of) competition in a banking market, but is positively related to the profitability of analyzed banks. And banks with larger market shares are also more likely to generate higher profits.

CONCLUSION

The use of a bank's efficiency metric by examiners in quantifying the management component in the CAMEL rating would be foolhardy. Knowing that, as analyzed, the most efficient firms are not the most profitable, and that retained profits are the primary source of bank capital, the cushion against which losses are absorbed, the (potential) safety and soundness of a bank is less so if the bank behaves as a cost minimizer. The efficiency measure can be used as an internal assessment vehicle, to rate an operation manager's performance, or to identify, just for operational comparisons, the most (cost) efficient branch or office, given the candidates have the same output components (or product lines) with similar product mixes.

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Analysis of Lender-Borrower Choice and Implications for Federal Farm Credit Policy

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Abstract: A binomial logit model is used to investigate lender-borrower choice among commercial-sized farms using farm- level financial data on indebted farms obtained from the Farm Costs and Returns Survey. The results show evidence that farm lenders ration credit according to operator age, location, and repayment ability. Younger operators or those with limited repayment ability are less likely to be FCS borrowers while operators located in metropolitan regions or in states with restrictive jurisdictional laws are less likely to be commercial bank borrowers.

Keywords: Farm Credit System, Federal credit policy, binomial logit, Farm Costs and Returns Survey, credit rationing

Assuring an adequate supply of capital to agriculture has been a key objective of U.S. farm policy. The Federal Government has played an important role in financing farm businesses as shown by the involvement of the Farm Credit System (FCS) and the USDA's Farm Service Agency (FSA) which, together supply about one-third of the $150 billion of U.S. farm debt.[2] The ongoing consolidation of production agriculture combined with changes in the financial sector contribute to a need to further examine the role of these institutions in agricultural credit markets.

Agricultural production and farm operator debt is increasingly dominated by fewer and larger farms. USDA data shows that by 1993, one-fourth of all farm operator debt was owed by millionaire farmers (Koenig and Dodson, 1995). The entry into farm real estate lending by large regional banks and multi-bank holding companies with ample liquidity to finance farm real estate has contributed to banks' increased market share primarily at the expense of the FCS. The FCS market share of outstanding farm real estate debt has steadily declined since 1985 reflecting greater competition faced from banks (USDA, February 1995). Recently, the FSA's lending has moved from direct to guaranteed loans. As a result, the credit needs of smaller, younger, and limited equity operators are increasingly served by commercial banks. Among commercial operators with less than $250,000 net worth, commercial banks supplied about 40 percent of all

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[2]Credit programs of the former Farmers Home Administration were transferred to USDA's Consolidated Farm Service Agency in late 1994. As of November 1, 1995, the Consolidated Farm Service Agency will be known as the Farm Service Agency.

farm operator debt (Dodson and Koenig, 1995). Banks were the primary supplier of credit to commercial sized operators under 40 years of age.

These trends raise important questions concerning the future direction of Federal farm credit policy. Most farms with net worths exceeding $1 million would probably have access to adequote credit even without the existence of Federal credit programs. Access to farm mortgage credit does not appear to be as much of a problem in the 1990s as in previous decades. Until the 1980s, most commercial banks lacked the liquidity to make farm real estate loans. Consequently, FCS has played an important role as a reliable source of farm mortgage credit. However, that role appears to be changing as banks become a more important source of farm real estate credit. It is also likely that USDA's guaranteed lending program is enabling commercial banks to lend to younger and limited resource operators who, in the past, may have been unable to obtain credit from traditional sources and relied on FSA direct loans.

Given the increasing importance of banks as a source of farm credit, what is the current and future role of FCS and of direct lending programs by FSA? Justification for Federal outlays to FSA or continuing status as a government sponsored enterprise (GSE) for FCS should require that some public purpose is being served. For example, is FSA direct lending and FCS programs serving farmers who may otherwise be rationed out of the market? Policy makers should also address whether achieving the national policy goals with respect to farm credit require the existence of a guaranteed lender, direct lender, and a GSE. These are important questions as Federal policy makers re-examine the Federal government's role in all aspects of the economy. This analysis should provide insights useful in addressing the aforementioned questions. Specifically, the paper attempts to determine if the probability of a farm operator borrowing from a specific type of lender is influenced by the structural, financial, and demographic characteristics of borrowers. These results should provide insight on the existence of credit rationing and the need for Federal intervention in farm credit markets. The analysis is undertaken using a lender-borrower choice model applied to Farm Costs and Returns Survey (FCRS) data from 1991-93.

Conceptual Framework

The FCRS loan data represents equilibrium contracts between borrowers and lenders. The loan contract between a farm operator and a lender reflects preferences of the lender as well as the borrower. Also, the choices made by the borrower and lender may have been unique to the time period in which the loan contract was initiated. This makes it difficult to differentiate whether results are a consequence of lender or borrower's decision or of the time period in which the loan was originated. Alternative data sources which would allow a differentiation of these factors were not available (i.e. data on farm loan applications for all lenders). Conceptual models were presented and used to select dependent variables for inclusion in a qualitative choice model applied to farm-level data.

Credit Rationing and Lender Choice

Credit market studies, especially in residential housing, have focused on how credit rationing influences lender choice. In their seminal article Stiglitz and Weiss defined credit rationing:

> "..among observationally identical borrowers some receive loans and others do not. Potential borrowers who are denied loans would not be able to borrow even if they indicated a willingness to pay more than the market rate or to put up more collateral than is demanded of the recipients of loans".

That is, certain groups of borrowers may not receive credit from private lenders at any price even though many within the group may be credit-worthy. The perception that credit rationing exists has contributed to the enactment of special credit programs by Congress to serve farmers, homeowners, and students.

Previous studies (Gale; Smith and Slutz; Williamson) have shown that credit markets are characterized by certain factors making them vulnerable to rationing. These factors are: (1) asymmetric information and costly acquisition of borrower information by lenders, (2) costly default, and (3) adverse selection and incentive effects.

In credit market equilibrium the supply of funds from depositors (investors) to financial intermediaries (lenders) equals the entrepreneurs derived demand for loan funds. *Asymmetric information* simply means that the lender has less than perfect information concerning the borrower. Borrowers are identified by two types of information: their group identity and location within the group. Group identity is assumed to be public information and will provide a (noisy) signal of the borrower's riskiness. Location within a group refers to the riskiness of the individual's projects and is known only to the individual borrower. Because of *costly default*, lenders will seek to find out as much as possible about the borrower's location within the group, (i.e. repayment ability). A lender may find that while some good credit risks may exist within a group, the cost of acquiring borrower information may be greater than any benefits. Because of adverse selection and incentive effects, lenders would be unable to use interest rates or collateral requirements to all borrowers within a group to limit their risk. *Adverse selection* occurs when for a given level of collateral, an increase in the interest rate results in only borrowers with riskier investments applying for a loan. Similarly, for a fixed rate of interest, an increase in the collateral requirements results in more risk-averse borrowers dropping out of the market. *Incentive effects* occur when managers respond to higher interest rates by choosing riskier projects which display higher potential payoffs but also higher potential for default. These sets of circumstances may lead lenders to ration or "redline" certain groups of borrowers. Redlining refers to a prohibition on lending to particular groups while rationing refers to limiting the total amount of funds to a group.[3]

Federal credit programs are primarily designed to lessen credit rationing primarily by reducing or eliminating the costs of default. If there were no default costs, lenders would have less of an incentive to screen and consequently be less likely to ration debt. Gale (1990) notes that since Federal credit programs target groups thought to be rationed or redlined, Federal credit programs should be more prevalent among groups of borrowers with greater repayment difficulties and, thus, higher expected default costs. Also, it would be expected that federal credit programs should be more prevalent among groups or regions where the costs of screening out poor risks may be high.

Model of Borrower-Lender Choice

According to Williamson, optimal loan contracts between lenders and borrowers should make choices which maximize the expected utility of the borrower, subject to the constraint that the lender receive a return, ($\hat{\rho}$) from the contract that is at least equal to the expected return, r, that could be obtained from other credit markets. Borrower choice of a given lender by borrowers can be represented by a random utility model (Greene). For the ith individual faced with j choices, the utility of choice of j is:

$$(1)\quad Max\ \{U_{ij}\} = \beta'_j x_i + \epsilon_{ij},$$

where x_i is a vector of characteristics for individual i, and ϵ_{ij} represents the unexplained elements of the utility function. If an individual makes lender choice j, it is assumed that individual utility is maximized by that choice. Hence, the statistical model is driven by the probability that choice j is made which is : Prob[$U_{ij=1} > U_{ij=0}$). A borrower's choice of lenders should be related to their goals which are known to vary by characteristics of the farm operator. In the context of an equilibrium, the random utility model is constrained by the requirement that lenders receive a minimun return. It is the relationship between a lenders minimum return and expected return that results in credit rationing.

Reflecting asymmetric information, borrowers are divided into groups based on 2 pieces of information: their group identity and their location within a group. Each lender has access to a technology with which to observe a borrower's type at a cost of γ, where $\gamma \geq 0$. Thus, the expected lender return, $\hat{\rho}_i$, for lending to group i (i=1, ...n) is : .

[3]It should be noted that redlining is frequently associated with prohibition of lending in neighborhoods based on their racial or ethnic composition. However, redlining can be based on any distinguishing characteristic and in this study refers mostly to age, wealth, income, regional location and production specialization.

$$(2)\ \hat{\rho}_i = \phi_i r_i - \gamma_i - (1-\phi_i) * D_i,$$

Thus, the expected return to a lender is a function of interest rates, r, repayment rate, ϕ, screening costs, γ, and default costs,

$$(3)\ \hat{\rho} = f(r_i, \phi_i, \gamma_i, D_i).$$

How the differences between a lender's expected and required return can result in credit rationing is shown by figure 1 for two groups of borrowers. Borrower groups are characterized by two behavioral assumptions. First, the demand for loans is a decreasing function of the interest rate (r) charged by lenders. Second, the repayment rate (ϕ) falls as r rises reflecting adverse selection. For group i, the bank's expected return increases as the interest rate increases to r_i. At rates above r_i, expected lender returns decline as low-risk borrowers choose not to borrow reflecting adverse selection and remaining borrowers choose riskier projects reflecting incentive effects. The maximum return to lenders for lending to borrowers in group i is $\bar{\rho}_I$ which is termed the "optimal lender rate". If the lender's required return was greater than $\bar{\rho}_I$, group i would be

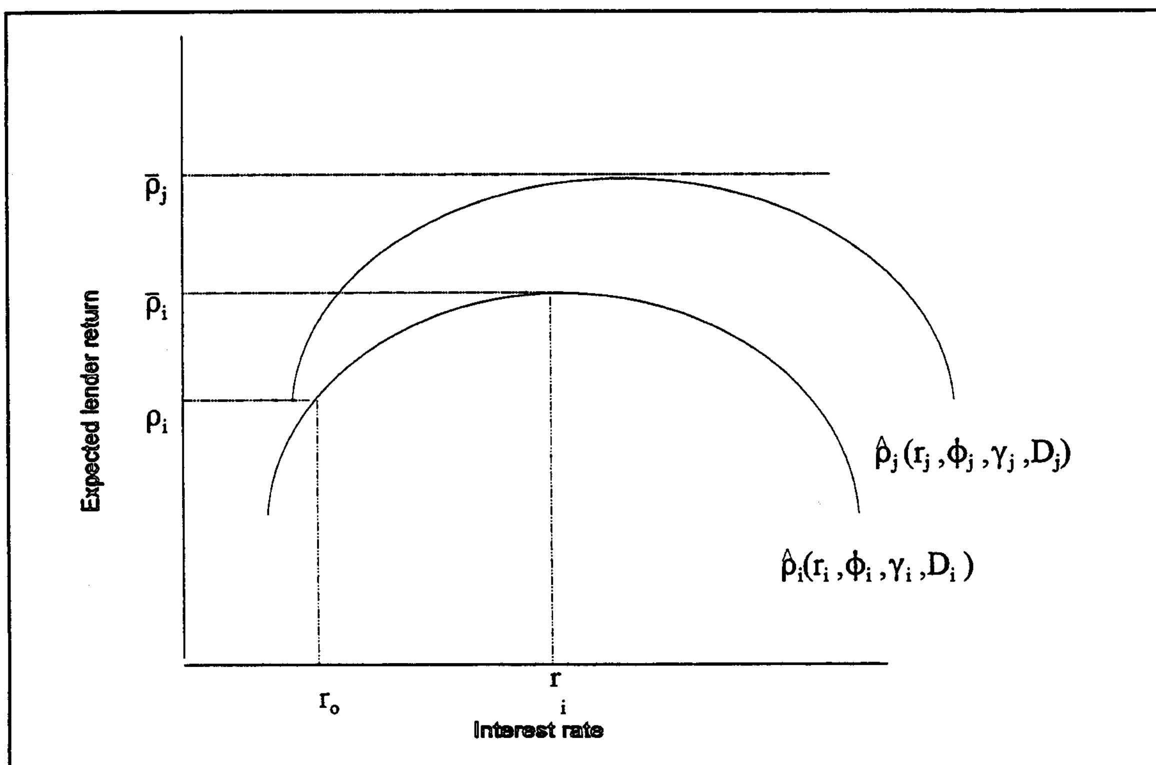

Figure 1. Relationship between expected lender return and interest rate to specific borrower groups.

redlined--that is they would not receive *any* loan funds. At a rate equal to $\bar{\rho}_I$, group i would be rationed--that is they would not be able to receive any *additional* loan funds. Consider group (j) whose expected return ($\hat{\rho}_j$) is greater than group i at all levels. At a required return of $\bar{\rho}_I$, group i would be rationed while group j's credit demand would be met. In this circumstance, group i would be considered targets for Federal credit programs.

Lender choice was, thus, hypothesized to be a function of the relationship between a lender's required return for borrowers within a given group, $\rho^*(r_i, s)$ and the lender's expected return from lending from that group, $\hat{\rho}\ (r_i, \phi_i, \gamma, D)$.

$$(4) \qquad P_i(EY_{ij} = 1) = \mathbf{f}\left(\frac{\hat{\rho}\ (r_i, \phi_i, \gamma, D)}{\rho^*(r_i', s)}\right).$$

In equation (4), r_i represents the interest rate charged to the borrower while r_i' is market rate of return on investments of comparable risk. The lenders required rate of return, $\rho^*(r_i, s)$, includes the market rate of interest and any subsidies provided the lender. The dependent variable, Y_{ij}, is equal to 1 if lender j, (j=1,. . . n), selects borrower i, (i=1,. . . .k), and 0 otherwise.

A major departure from the competitive framework is that in addition to caring about aggregate demand, lenders differentiate among borrower groups. Based on equation (4), one can see that this differentiation is likely related to the borrower repayment ability, lender's screening costs, default costs, and subsidies provided the lender. Groups perceived to be high risk or where the screening cost is high would be more likely obtain credit through Federal credit programs. This may be augmented by the fact that lenders may have legislative mandates to serve particular groups. For example, the FSA is expected to target beginning or limited resource farmers and is not expected to lend to part-time operators with significant off-farm incomes nor those with large net worth. Thus, an analysis of existing loans such as provided by the FCRS data should show differences among lender groups in the structural, financial, and demographic characteristics of their borrowers. However, since these many of these differences can also be a attributable to borrower choice, results can only provide an indication and not proof of credit rationing by lenders.

Data and Variables

Farm-level financial data was provided by the expenditure version of FCRS. The FCRS is a multiple frame stratified random sampling survey that provides farm expense, income, and balance sheet estimates along with operator characteristics for a calendar year. Estimates discussed represent averages of combined year-end data for 1991-93. The averaging of three years of data was done to increase the reliability of estimates. The expenditure version was the only one which included data on debt by lender as well as loan purpose and terms.[4] The 1994 survey did not include detailed debt data. The FCRS samples roughly 10,000 farms annually, of which about half would receive the expenditure version. The expenditure version of the FCRS included detailed data on debt by farm. Data was collected each loan owed by a farm business. Included was year-end balance, interest rate, year loan was acquired, lender, term, and loan purpose (secured by real estate, secured by nonreal estate, or operating loan). Data concerning metro and nonmetro counties was developed using a classification system developed by USDAs Economic Research Service (Butler and Beale). Data concerning county level land values was provided by the Census of Agriculture.

Repayment Ability and Borrower Characteristics

Since default is costly, lenders have an incentive to choose borrowers with limited risk. Farms likely to experience repayment problems and face credit rationing include those with limited income, lower wealth, less production, and higher debt levels. Lenders typically limit their risk by requiring an upper limit on the amount that can be used for debt service and minimum down payment ratios. An increase in wealth decreases the likelihood that down payment constraints are binding, reducing the likelihood of rationing. Operators with greater wealth would be likely to fully collaterize their loans and have the capacity to meet all obligations. As profitability and farm size increases, the likelihood that income constraints are binding is reduced. If credit history and creditworthiness rise with age, younger operators credit demands would more likely be rationed. Because of the higher risk of default, farms with high debt-asset ratios would be considered stronger candidates for rationing. While government payments reduce income variability, a reliance on them can indicate low value of production due to either low yields or low prices. Thus, operations more dependent on direct Government payments were expected to be candidates for credit rationing. The FCRS included farm-level data for each of these variables: net worth, value of farm production, return on assets (profitability & income), operator age, debt-asset ratio, and the ratio of government payments to gross cash income.

In addition to influencing lender choice, wealth, age, profitability, farm size, and operator age also represent borrower characteristics which can influence borrower behavier. For example, older more established operators may choose sources of credit based on past lending relationships while younger operators may be more willing to use nontraditional sources of credit.

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[4]Other versions included a cost of production survey which was designed to estimate the total per acre cost of producing specific crops and a farm operator resource version. The expenditure version was chosen because it included data on debt by lender.

High screening costs

Some lenders may find it difficult to screen out poor agricultural credits because the fixed lending costs may be considered too high. In metropolitan regions where agriculture represents a small share of the economy, lenders may find that the market potential for agricultural credits to be too small to justify the allocation of any bank resources toward farm lending. The FCRS data base included information on the county in which the farm was located. This information was matched with the Butler and Beale typology to classify farms as to whether they were located in metro or nonmetro regions.

Another possible case where it may be difficult for lenders to filter risky loans is among unique agricultural enterprises. For example, non-traditional enterprises such as nursery and greenhouse or Kansas cotton growers may be avoided by some lenders. Data from USDAs Economic Indicators of the Farm Sector-State Financial Summary was used to identify commodities which contributed less than 5 percent of total cash receipts within a given state. If the FCRS sample farm specialized in the production of these commodities, it was classified as unique. Farms specializing in nursery/greenhouse or fruit/vegetable production were also classified as unique.

Default costs

Some regions may be characterized by lower land appreciation and thus require greater securitization to minimize lender losses associated with default. However, the credit rationing model would suggest that increasing securitization would result in adverse selection and incentive effects. That is, those who choose to borrower would be more likely to adapt riskier projects while more risk averse individuals would be more likely to choose not to borrow. Rather than accept these risks many lenders may ration credit to these regions. County level data from the Census of Agriculture was used to identify counties which had the greatest drop in average land values since the last Census (USDA Economic Research Service, 1995). This was combined with FCRS data concerning county and the year in which a majority of debt was acquired to classify farms according to land value stability.

Another example of items which can increase default costs and could increase credit rationing are state laws affecting lending. Previous studies in residential housing which incorporated jurisdictional laws have shown that judicial foreclosure and . prohibition of deficiency judgements all increase default risk in residential housing (Clauretie and Herzog). Borrowers in states with more restrictive jurisdictional laws would have less repayment ability and higher expected default costs, thus encouraging credit rationing.

Jurisdictional laws specifically deal with the foreclosure process, deficiency judgements, and rights of redemption. There are, in general, two main foreclosure processes used by various States: judicial and non-judicial foreclosures. In a judicial foreclosure, a court orders the foreclosure and supervises the sale and disbursement of proceeds. Judicial foreclosure implies a period of equitable redemption during which the borrower may prevent foreclosure by paying off his entire indebtedness. About one-half of all indebted farms were located in states where judicial foreclosure was the only available foreclosure process (table 2; table 3). Due to its complexity, judicial foreclosure is generally more costly and time-consuming than non-judicial foreclosure.

A deficiency judgement arises when the property's liquidation value is insufficient to pay off the loan balance. Equipped with a deficiency judgement, a lender may seek a recovery of the difference through attachment of a borrower's personal assets. Obviously, lenders would expect greater loan losses if deficiency judgements were not available. The statutory right of redemption gives the borrower the right to redeem his property after the foreclosure sale. The existence of a statutory right of redemption may lower bids at a foreclosure sale since a buyer would have to wait the specified period before obtaining clear title. This effectively raises the costs of foreclosing to a lender because the longer liquidation period adds to carrying costs. States were identified where: (1) judicial foreclosure was the only available foreclosure remedy, (2) redemption periods were greater than 90 days, and (3) deficiency judgements were restricted (Durham). About one-half of all indebted farms were located in States where deficiency judgements were restricted or redemption periods exceeded 90 days (table 2; table 3). The expectation was that farm borrowers in States which either required judicial foreclosure, restricted deficiency judgements, or had longer redemption periods would be more likely to utilize Federal credit programs or nontraditional sources of credit.

Period of Debt Acquisition

As profit maximizers farm operators would choose the lowest cost of credit available. Either through subsidies or loan pricing policies, some institutions have provided lower cost sources of credit, increasing the likelihood that these lenders may be used during certain periods. For example, the FCS followed an average pricing policy until the late 1980's which, during periods of rising interest rates, enabled them to charge borrowers rates which were lower than other lenders. This would result in a greater likelihood that farm real estate borrowers who acquired debt prior to 1985 obtained credit from FCS. Credit policy can also change as was the case for FSA who has moved from direct to guaranteed lending. Consequently, those who obtained real estate credit prior to 1985 would be considered more likely to obtain credit from FSA. Commercial bank presence in real estate lending increased during the late 80's, increasing the likelihood that borrowers who acquired debt in more recent years utilized commercial banks. FCRS data on the year in which each loan was originated was used to calculate a weighted average year of debt acquisition for each sample farm. The year of origination for each loan was weighted by the outstanding loan balance.

Empirical Specification and Model

Logit and probit models represent preferred specifications of qualitative choice models. A binomial logit model was developed where the probability that a borrower owes a given lender is a function of financial, structural, or demographic variables which were chosen based on the theoretical models presented for borrower and lender choice. Independent variables measuring farm equity, farm size, profitability, operator age, and indebtedness were included to reflect repayment ability. Screening costs were represented using geographic location and production specialty. Default costs differences were represented using data on state jurisdictional laws. Dummy dependent variables reflecting time of debt acquisition were included to capture some of the effects of interest rate cycles and changes in credit policy. Separate models were developed for real estate (5) and nonreal estate plus operating loans (6) with individual regressions run for each lender as in the following (see table 1 for variable description). The two models were basically the same with differences in how debt-asset ratio, land value stability, and period of debt acquisition were defined.

$$(5)\quad P_i(Y_{ij}=1) = \alpha + B_1 NETW + B_2 VPRODTOT + B_3 ROA + B_4 AGE + B_5 DAR2 + B_6 RISKLAND + B_7 GOVDEP + B_8 UNIQUE + B_9 METRO + B_{10} JUDFORE + B_{11} DEFJUD + B_{12} REDEMP + B_{13} ACQ90 + B_{14} ACQ85\ .$$

$$(6)\quad P_i(Y_{ij}=1) = \beta_0 + \beta_1 NETW + \beta_2 VPRODTOT + \beta_3 ROA + \beta_4 AGE + \beta_5 DAR + \beta_6 RISKLAND + \beta_7 GOVDEP + \beta_8 UNIQUE + \beta_9 METRO + \beta_{10} JUDFORE + \beta_{11} DEFJUD + \beta_{12} REDEMP + \beta_{13} ACQ90NR.$$

Farms which reported less than $50,000 in total farm production were excluded making commercial farms the focus of the analysis. Equation (5) was applied to farms with real estate debt while (6) was applied to farms with nonreal estate debt, including operating loans. Real estate lenders analyzed included FCS, commercial banks, individuals, FSA and life insurance companies (LICs). LICs were dropped and merchants and dealers included for the nonreal estate debt analysis. Since lender-borrower choice was not defined as mutually exclusive, separate models were run for each lender. Empirical results show the probability of a farm operator owing a given lender relative to all other lenders.

Regression analysis is complicated when the data are from a complex survey design, such as FCRS, because the estimation and accuracy of parameters are not simple. This model was estimated using a weighted maximum-likelihood binomial logit procedure with the error structure modified to account for the stratified sampling in the FCRS. The log-likelihood function is the standard textbook function (for example, see Maddala) which was maximized with an iterative Newton-Raphson routine written in SAS matrix language[5]. Stratified sampling affects only the standard errors and not the coefficients themselves (Fuller). Standard errors with stratified sampling can vary greatly compared to those from simple random sampling. Differences between the actual values of the dependent variable and the predicted values were processed in a manner similar to the standard errors presented earlier. This, plus an additional matrix calculation on the design matrix given by Fuller, yielded the standard errors for the coefficients. Linear probability and binomial probit models with the same structure were also estimated and produced very similar results.

Expected Results

Credit rationing increases the likelihood that FCS, FSA or nontraditional lenders such as individuals will be used. Thus, it would be expected that borrowers with less repayment ability, higher screening costs, and located in states with greater default costs would be more likely to be FCS customers. Because they are private institutions, commercial banks would be considered the lender most likely to ration credit. It would be expected that credit rationing would be more likely among farms near metropolitan regions, with unique enterprises, and in states with more restrictive jurisdictional laws concerning foreclosure. Therefore, farms in these locations would be expected to be more likely to borrow from individuals, merchants & dealers, or FCS and less likely to borrow from banks.

The FSA direct lending programs are targeted toward limited resource and young farmers. Thus, it would be expected that highly indebted, limited equity, and younger operators would more likely to borrow from FSA. It is well known that LICs target large credits which typically have large net worth, high incomes, and high production. Financing by merchants and dealers as well as individuals would be expected among groups most subject to credit rationing. Because of the incentive to sell a product, these lenders are likely to provide their own terms to credit-worthy borrowers who are less likely to obtain conventional financing.

Results

The means of the dependent variables indicated distinct differences in the clientele of the different lenders. FCS borrowers were more wealthy and older than average for both the real estate and nonreal estate market (table 2; table 3). As would be expected FSA borrowers were smaller, less wealthy, and less profitable than average. The focus of LICs on large operations is also apparent with an average net worth for LIC

[5]This procedure was developed for applications using the FCRS by Robert Dubman, Agricultural Economist, who is with the Rural Economy Division of USDAs Economic Research Service, Washington, D.C.

borrowers of $1.080 million which was nearly twice the average. The analysis represents 277,104 commercial-sized farms with real estate debt and 303,512 commercial farms with nonreal estate debt.

Real Estate Debt

Results of the binomial logit model provide little evidence of credit rationing by commercial banks on the basis of repayment ability. On the other hand, results also provide little evidence that FCS serves a group of borrowers rationed out of the market due to their lack of repayment ability. FCS mortgage customers were older and more profitable than other farms with real estate debt. The results were especially dramatic for age where a 65 year old indebted farmer was over 20 percent more likely to obtain funds from FCS than a 35 year old (figure 2). The data points for figure 3 were generated by calculating the dependent variable at different ages given the slope parameters in table 4. All other parameters were held constant at the means (table 2).

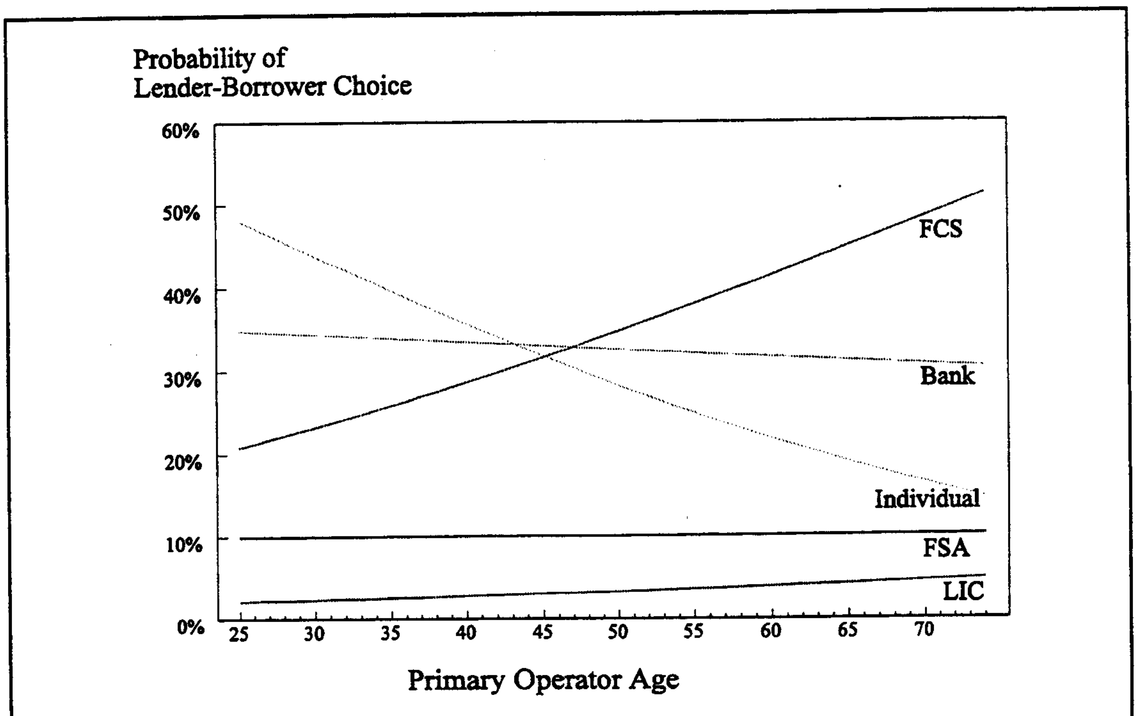

Figure 2. The probability of being an FCS mortgage borrower increases with age while the probability of borrowing from individuals decreases.

A different story emergences, however, when one examines repayment variables associated with geographic factors rather than borrower characteristics. A farm business located in a county with unstable land values, (RISKLAND), was 10 percent more likely to be an FCS mortgage loan customer than farms in other counties. In contrast, indebted farm operators were significantly less likely to be a bank mortgage loan customer in these regions. Also, farms heavily reliant on government payments were 16 percent more likely to borrow from FCS. The importance of FCS in regions with less stable land values and a heavy reliance on Government farm programs suggests that FCS serves regions deemed either too costly or too risky by other lenders.

As expected, farm businesses with less wealth and higher debt levels were more likely to be FSA mortgage loan customers. This indicates FSA direct lending programs are consistent with their public purpose and may be serving borrowers rationed out of alternative credit sources because of their poor repayment ability. It was noteworthy that operator age did not significantly affect the probability of being a FSA borrower suggesting that a large share of FSA's mortgage borrowers may be older operators. Based on the average age of FSA mortgage debt it was likely that these were long term borrowers who have never graduated. According to FCRS, the average age of FSA mortgage debt was 9.9 years compared to 7.2 for all mortgage debt.

Net worth was the only repayment variable which was significant for banks, though the parameter had an unexpected negative sign. This could reflect either a rationing of farms with large net worths, a tendency to finance low equity farms, or a consequence of borrower choice. One possible explanation is that despite banking consolidation, many banks still lack the liquidity to make large real estate loans demanded by farms with high net worths. Also, utilization of the FSA guaranteed loan program enables banks to finance low equity farms. Another explanation is that larger operations may prefer to do business with institutions which have greater expertise in mortgage lending such as LICs or FCS. The parameters for RISKLAND, GOVDEP, and DEF were all negative and significant for bank mortgage credits. In addition, the parameter for REDEMP was negative though not significant at the 0.10 level. Thus, farm operators which were more dependent on Government payments, or located in regions with less stable land values, dependent on Government program payments, or with restrictive foreclosure laws would be less likely to owe mortgage debt to commercial banks.

For most lenders, screening costs were not significant in determining real estate lender-borrower choice. One possible reason that METREG was not significant is that collateral values tend to be stronger in metropolitan regions making mortgage lending more attractive. METREG was significantly negative for FSA and indicated that real estate borrowers in metropolitan regions were 6 percent less likely to borrow from FSA. This would be expected, however, given that collateral values and, therefore, equity, is typically higher in metro regions.

Restrictive jurisdictional laws did not significantly affect the probability of being an FCS mortgage borrower. Location in a state which did not allow non-judicial foreclosure reduced the likelihood of being an FCS customer though this was not significant at the 10 percent level.

Rationing or redlining of real estate loans by banks in States with deficiency judgement restrictions and/or long redemption periods does not necessarily imply a shortage of credit. In such regions, individuals are frequently important sources of credit. Borrowers in States with deficiency judgement restrictions and/or long redemption periods were 8 - 10 percent more likely to borrow from an individual.

It was evident that real estate lender-borrower choice is strongly influenced by the period of debt acquisition. For FSA and commercial banks, the parameters for ACQ90 and ACQ85 were both significant and as expected. Farm operators with real estate debt acquired prior to 1985 were more likely to owe FSA if their debt was acquired prior to 1985 and less likely if debt was acquired after 1990. Those who acquired debt prior to 1985 were 13 percent more likely to have borrowed from FSA while those who acquired debt after 1990 were 12 percent less likely to have borrowed from FSA. This is consistent with the change in policy toward more guaranteed and less direct lending.

The greater presence of commercial banks in real estate financing since 1985 is apparent. Indebted farm operators who acquired debt prior to 1985 were 23 percent less likely to have borrowed from commercial banks while those acquiring debt after 1990 were 10 percent more likely to borrow from banks. Those who acquired debt prior to 1985 were 19 percent more likely to be an FCS borrower. This reflects the lack of competition FCS faced from banks and the pricing advantages provided by the average cost pricing strategy. The fact that many FCS borrowers are older and that much of their debt was acquired prior to 1985 suggests than many of FCS current real estate customers may be easing into retirement, thus providing limited opportunities for loan market growth. Acquiring debt after 1990 decreased the possibility of borrowing from an individual, probably reflecting greater availability of mortgage credit from commercial banks.

Nonreal Estate Debt

Results indicated nonreal estate borrowers who were wealthier, more profitable, older, and had lower debt-asset ratios were more likely FCS borrowers (table 5). As was the case for real estate, there was little indication that FCS serves groups rationed out of credit markets because of a lack of repayment ability. For banks, the only repayment variable which was significant was returns on assets, though this parameter had un unexpected negative sign. A likely explanation is that banks' greater use of FSA's guaranteed loan programs enables them to serve a large number of the smaller, less profitable commercial operations. The general lack of significance of other variables would be consistent with a scenario in which bank nonreal estate lending reflects the underlying characteristics of all farms with nonreal estate debt.

FSA nonreal estate borrowers tended to be less wealthy, smaller, and have higher debt-asset ratios, which would be consistent with their purpose. As was the case with real estate debt, it was interesting that the parameter for operator age was insignificant suggesting that despite programs to serve younger and beginning farmers, FSA still maintains a fairly sizable portfolio with older farm operators.

Younger and more indebted borrowers were more likely to borrow from merchants and dealers. A possible explanation is that because of efforts to market product or equipment, merchants and dealers are providing financing to operators who may have difficulty obtaining credit from the more traditional sources. For operators obtaining nonreal estate credit from individuals, operator age was significantly negative while return on assets was significantly positive. These results could be explained by low tenure operators with low asset bases generating higher returns on assets.

In contrast to the results for real estate debt, there was support for the high screening cost hypothesis. Nonreal estate borrowers in metro counties were more likely to borrow from FCS but less likely to borrow from banks. This could reflect a restriction by banks on nonreal estate lending in metro regions because the high costs of monitoring and screening farm loans. As compared to real estate financing, nonreal estate loans require greater servicing, are riskier (higher loan-value and less stable collateral values). With ample alternative lending opportunities, commercial banks in metro regions may be less willing to allocate such resources to nonreal estate farm lending.

Merchants and dealers were less likely to lend to unique enterprises (i.e. greenhouse/nursery, fruit/nut, or an enterprise uncommon to the region). This may not be due as much to credit rationing as to marketing efforts by merchants and dealers which are likely targeted to the traditional grain or livestock operators. Also, borrowers with unique enterprises tended not to borrow from FCS. This would be consistent with the observation that FCS has historically not been a major supplier of credit to nursery and greenhouse operations (Johnson and Johnson, p.27).

The existence of judicial foreclosure requirements appeared to adversely impact the availability of nonreal estate credit to farm operators from banks. In contrast, the existence of long redemption periods increased the probability of being a bank borrower. The probability of being as FCS customer was not affected by the existence of judicial foreclosure laws but was affected negatively by the existence of long redemption periods. Iindividuals, however, were shown to be a source of credit to borrowers in States with long redemption periods.

As with real estate lending, the choice of nonreal estate lender appears to be strongly influenced by when debt was acquired. A commercial farm operator with nonreal estate debt is more likely to owe FCS if most of their nonreal estate debt was acquired prior to 1990. For comparison, about half of the farms in this sample acquired nonreal estate debt after 1990 (table 3). This is consistent with the results obtained for the real estate debt market and indicates the competitive pressures FCS has been facing, especially from commercial banks. In contrast, a commercial farm operator with nonreal estate acquired after 1990 is 15 percent more likely to be a bank borrower. Those acquiring debt after 1990 are less likely to be an FSA borrower reflecting the agency's movement away from direct lending toward guaranteed lending. Also, those acquiring nonreal estate debt after 1990 were more likely to use merchants and dealers as a lender reflecting their recent emergence as an important source of production credit.

Summary & Implications

Strong evidence was presented that commercial-sized FCS borrowers are older, larger, more profitable, and more wealthy than other indebted commercial farms regardless of whether the debt was for real estate or nonreal estate purposes. Also, younger and low resource operators are less likely to be FCS borrowers. One possible explanation is that as FCS's market share has declined, the average age of its portfolio has increased. A portfolio which contains older loans is likely be associated with older operators who tend to be more wealthy and larger. Another possible explanation is that because of the financial adversity FCS experienced during the 1980s, it has pursued much more conservative lending practices. Whatever the explanation, it appears that many of FCSs current customers could probably obtain credit from other sources.

Neither was there strong evidence that FCS served regions rationed out of the credit markets because of restrictive jurisdictional laws. Mortgage borrowers in States without non-judicial foreclosure were less likely to be FCS borrowers. Nonreal estate borrowers in states with long redemption periods were also less likely to be an FCS borrower. FCS's strongest justification, in terms of serving Federal credit policy, would appear to be providing credit to regions deemed to be either too risky or too costly by other conventional lenders. Examples include nonreal estate credit in metro regions, real estate credit in regions characterized by recent land value declines and loans to operators heavily dependent on direct Government payments.

In contrast to the results for FCS, there was strong evidence that FSA direct lending programs serves borrowers unable to obtain either real estate on nonreal estate credit because of their limited equity. There was not strong evidence, however, that FSA direct lending programs specifically served young farm operators. Many of their customers were older farm operators who had held their FSA loans for long periods.

Commercial bank borrowers tended to have lower farm equity and were less profitable than the average indebted farm. This could be a consequence of commercial banks' strong use of FSA's guaranteed loan program. Among bank loans, FCRS data did not distinguish whether the loans were guaranteed or not. There were indications, however, that banks rationed nonreal estate credit within metro regions and real estate credit within States with restrictions on deficiency judgements or long redemption periods.

Individuals as well as merchants and dealers appear to serve many of the niches apparently subject to credit rationing by other lenders. Individuals provided real estate financing to operators who were younger, less wealthy, and located in regions with restrictive jurisdictional laws. Individuals also served younger nonreal estate borrowers and those located in metro regions.

The results of this analysis are consistent with credit rationing by farm lenders. Younger operators or those with limited repayment ability are less likely to be FCS borrowers while operators located in metropolitan regions or in States with restrictive jurisdictional laws or less likely to bank borrowers. While rationing by lenders provides one explanation, these results could also be explained by borrower choice. It may be that older and wealthier operators prefer FCS because of a long term relationship between the institution and operator. Younger operators may have less loyalty to an institution than their elders and consequently are more willing to use nontraditional financing provided by captive finance companies or individuals.

The implication that many FCS customers could probably obtain credit from private lenders combined with the observation that FCS serves borrowers in regions apparently not served by banks point to a need to examine the current delivery system used by FCS. If the purpose of FCS is to reduce the effects of credit rationing, one could easily argue that an alternative delivery system would be more efficient. Providing credit to farmers in regions subject to credit rationing probably does not require a national portfolio lender local outlets, and agency status, creating a contingent liability for the Federal Government. For example, credit unions in these regions could be provided greater access to loan funds for agriculture through a discount window from Federal Home Loan Board or FCS.

Table 1. Definition of Variables

Symbol	Variable Description
Dependent	
P_i	Probability that borrowers in group i obtain real estate credit from lender j.[1]
Y_j	1 if borrower in group i owes real estate debt to lender j, 0 otherwise.
Repayment ability	
NETW	Ending of year farm net worth as reported on the FCRS ($100,000).
VPRODTOT	Annual value of farm production ($100,000).
ROA	Return on assets measured as [(Net farm income-management charge - unpaid family labor + interest paid)/ Total farm assets (year end)].
AGE	Age of the primary operator.
DAR2	Total farm real estate debt/ total farm real estate assets
DAR	Total farm debt/ total farm assets.
RISKLAND	1 if at the time the loan was originated, the farm was located in the lower 50 percent of non-metro counties according to the change in land values since the last Census.
GOVDEP	1 if farm received over 20 percent of gross cash farm income in direct government payments, 0 otherwise.
Screening costs	
UNIQUE	1 if farm specialized in the production of a commodity (or related group of commodities) which made up less than 5 percent of the States total receipts or the farm speialized in nursery, vegetable, and fruit production, 0 otherwise.
METREG	1 if indebted farm was located in a metro county, 0 otherwise.
Jurisdictional laws	
JUDFORE	1 if the farm was located in a State where judicial foreclosure was the only available foreclosure remedy, 0 otherwise.
DEFJUD	1 if the indebted farm was located in a State which did not allow deficiency judgements, 0 otherwise.
REDEMP	1 if the indebted farm was located in a State which had a 90 day or greater redemption period.
Debt Acquisition	
ACQ90	1 if a majority of real estate debt was acquired from 1991-93.
ACQ85	1 if a majority of real estate debt was acquired before 1985.
ACQ90NR	1 if a majority of norreal estate debt was acquired from 1991-93.

[1]J here represents one of six potential lending sources: FCS, commercial banks, USDA's FSA, individuals, life insurance companies, and merchants and dealers

Table 2. Mean of Variables for Farm Businesses with Real Estate Debt, 1991-93 averages.

Variables	All farms	FCS	Commercial Banks	FSA	Individuals	LICs
NETW ($)	578,274	647,200	519,810	367,110	592,870	1,080,500
VPRODTOT ($)	223,282	247,460	229,390	167,130	205,660	334,600
ROAT (%)	2.23	2.64	2.38	<u>1.22</u>	1.83	<u>3.86</u>
OP_AGE (years)	47.8	50.7	46.5	48.0	45.0	50.4
DAR2	0.28	0.30	0.29	0.44	0.29	0.32
RISKLAND	0.41	0.45	0.39	0.46	0.39	0.42
GOVDEP	0.10	0.15	0.08	0.14	0.07	<u>0.07</u>
UNIQUE[1]	0.21	0.21	0.20	0.19	0.21	0.16
METREG[2]	0.25	0.24	0.26	0.17	0.25	0.27
JUDFORE[3]	0.48	0.45	0.49	0.49	0.50	0.48
DEFJUD	0.52	0.53	0.47	0.52	0.59	0.52
REDEMP	0.50	0.48	0.47	0.49	0.60	0.57
ACQ90	0.21	0.13	0.31	0.06	0.18	0.25
ACQ85	0.46	0.61	0.28	0.72	0.44	0.46
Y (FCS)	0.35	----	----	----	-----	-----
Y (Banks)	0.35	----	----	----	-----	-----
Y (USDA)	0.17	----	----	----	-----	-----
Y (Individual)	0.29	----	----	----	-----	-----
Y (LICs)	0.03	----	----	----	-----	-----
Sample	4,253	1,691	1,436	716	1,102	213
Population	277,104	96,730	96,594	47,691	80,458	9,550

Note: Estimates that are underlined have coefficients of variation (CVs) in the range of 25 to 50 percent. All other estimates have CVs less than 25 percent.

[1]Determined using data from Economic Indicators of the Farm Sector-State Financial Summary.

[2]Determined using county typology described by Butler and Beale.

[3]Determined using data on state jurisdictional laws (Dunham).

Table 3. Mean of Variables for Farm Businesses with Nonreal Estate Debt,, 1991-93 averages.

Variables	All farms	FCS	Commercial Banks	FSA	Individuals	Merchant & Dealer
NETW ($)	506,196	626,300	485,690	304,890	578,480	501,710
VPRODTOT ($)	235,893	281,320	241,060	179,370	291,150	220,820
ROAT(%)	2.28	2.89	2.15	<u>1.15</u>	2.68	<u>1.10</u>
OP_AGE (years)	47.1	48.7	46.8	46.2	44.7	44.8
DAR	0.20	0.23	0.26	0.38	0.27	0.27
RISKLND2	0.11	0.15	0.10	<u>0.07</u>	0.17	0.10
GOVDEP	0.10	0.07	0.09	0.13	0.06	0.14
UNIQUE	0.20	0.19	0.19	0.19	0.23	0.15
METREG	0.22	0.30	0.20	0.23	0.31	0.20
JUDFORE	0.47	0.46	0.45	0.50	0.50	0.45
DEFJUD	0.51	0.47	0.52	0.53	0.58	0.53
REDEMP	0.51	0.40	0.55	0.48	0.55	0.50
ACQ90NR	0.66	0.57	0.71	0.36	0.55	0.73
Dependent Variables						
Y (FCS)	0.17	----	----	----	----	----
Y (Banks)	0.68	----	----	----	----	---
Y (USDA)	0.09	----	----	----	----	----
Y (Individuals)	0.08	----	----	----	----	----
Y (Merchant & dealer)	0.19	----	----	----	----	----
Sample	4,858	1,001	3,116	425	440	995
Population	304,512	50,746	206,732	27,618	25,622	57,750

Note: Estimates that are underlined have coefficients of variation (CVs) in the range of 25 to 50 percent. All other estimates have CVs less than 25 percent.

Table 4. Lender-borrower logit model results for real estate debt of commercial farms.

Variables	FCS			Banks			USDA		
	Coefficients	t-Statistics	$\partial P_i/\partial X_j$	Coefficients	t-Statistics	$\partial P_i/\partial X_j$	Coefficients	t-Statistics	$\partial P_i/\partial X_j$
INTERCEPT	-2.5883	-8.750[a]	-----	0.3897	1.410	------	-2.0271	4.651[a]	-----
NETW	0.0032	0.441	0.072	-0.0122	-2.203[b]	-0.281	-0.0754	88.54[a]	-1.080
VPRODTOT	0.0058	0.820	0.079	0.0012	0.888	0.030	0.0011	0.066	0.009
ROAT	0.0101	2.212[b]	0.232	-0.0035	-0.831	-0.028	-0.0026	-0.537	-0.031
OP_AGE	0.0282	5.648[a]	0.661	-0.0041	-0.829	-0.087	0.0006	0.095	0.022
DAR2	0.0000	0.012	0.003	0.0008	0.935	0.020	0.0076	1.949[c]	0.106
RISKLAND	0.3584	2.727[a]	9.627	-0.2950	-2.308[b]	-7.695	0.1438	0.894	2.066
UNIQUE	0.0469	0.313	2.404	-0.0821	-0.581	-2.716	0.0186	0.112	0.257
GOVDEP	0.6131	3.298[a]	15.999	-0.3630	-1.810[c]	-7.523	0.1921	0.890	-2.066
METREG	0.1755	1.147	3.800	-0.1703	-1.132	-2.985	-0.4478	-2.198[b]	-6.142
JUDFORE	-0.1953	-1.608	-4.745	0.0008	0.007	0.154	0.0101	0.072	0.043
DEF	0.0658	0.557	1.730	-0.2377	-1.853[c]	-5.631	0.1008	0.690	1.027
REDEMP	-0.0414	0.349	0.211	-0.1974	-1.503	-6.617	-0.0814	-0.561	-1.504
ACQ90	-0.2045	-1.260	-5.622	0.3797	2.528[b]	9.791	-1.1177	-3.281[a]	11.693
ACQ85	0.8010	6.328[a]	18.935	-1.0396	-7.806[a]	23.102	1.0539	5.924[a]	13.488
8 F-Statistic		8.14(14,∞)[a]			9.66 (14, ∞)[a]			21,885(14∞)[a]	
Pseudo-R^2		0.631			0.674			0.829	

[a], [b], and [c] denote significance at the 1%, 5%, and 10% levels respectively.
When the j^{th} explanatory variable is a dummy variable, the change in probability is computed as: $P_i(Y_{ij}=1|X_j=1) - P_i(Y_{ij}=1|X_j=0)$ with all other Xs held at their mean levels; otherwise it is calculated as: $\alpha_j P_i (1-P_i)$ with P_i held at its estimated value.

Table 4. (continued)

Variables	Individuals			LIC's		
	Coefficients	t-Statistics	$\partial P_i/\partial X_j$	Coefficients	t-Statistics	$\partial P_i/\partial X_j$
INTERCEPT	0.6185	1.913[b]	-------	-4.5716	-5.243[a]	-----
NETW	0.0086	1.684[a]	0.166	0.0128	1.686	0.045
VPRODTOT	-0.0134	-1.540	-0.237	0.0009	0.717	0.003
ROAT	-0.0000	-0.767	-0.000	-0.0000	-0.360	-0.000
OP_AGE	-0.0342	-6.385[c]	-0.705	0.0175	1.415	0.058
DAR2	-0.0028	-1.633	-0.059	0.0002	0.667	0.000
RISKLAND	-0.1973	-1.489	-4.456	0.1429	0.487	1.806
UNIQUE	0.0387	0.279	0.574	-0.4506	-1.285	-6.048
GOVDEP	-0.5280	-2.519[b]	-10.89	-0.6035	-1.370	-8.491
METREG	-0.1350	-0.867	-3.337	0.1307	0.249	1.408
JUDFORE	0.0947	0.802	2.267	-0.0282	-0.082	-1.017
DEFJUD	0.3603	2.980[a]	8.126	-0.0687	-0.214	-1.356
REDEMP	0.4771	3.989[a]	10.785	0.3734	1.313	5.564
ACQ90	-0.4260	-2.445[b]	-9.587	0.3873	1.140	6.933
ACQ85	-0.1556	-1.196	-3.357	0.1637	0.453	1.914
F-Statistic		7.58 (14, ∞)[a]			1.32(14, ∞)	
Pseudo-R^2		0.741			0.949	

Table 5. Lender-borrower logit model results for nonreal estate debt for commercial farms.

Variables	FCS			Banks			USDA		
	Coefficients	t-Statistics	$\partial P_i/\partial X_j$	Coefficients	t-Statistics	$\partial P_i/\partial X_j$	Coefficients	t-Statistics	$\partial P_i/\partial X_j$
INTERCEPT	-1.5653	-4.886[a]	------	0.4875	1.558	------	-2.0564	-3.475[a]	-------
NETW	0.0082	1.671[a]	0.114	-0.0059	-1.155	-0.129	-0.0356	-136.801[a]	-0.294
VPRODTOT	-0.0004	-0.200	-0.006	0.0110	1.576	0.239	-0.0201	-55.620[a]	-0.165
ROAT	0.0090	3.295[a]	0.125	-0.0095	-3.690[a]	-0.208	-0.0007	-0.186	-0.006
OP_AGE	0.0107	2.112[b]	0.149	-0.0036	-0.761	-0.080	-0.0015	-0.151	-0.013
DAR	-0.5368	-1.844[c]	-7.454	0.3964	1.591	8.641	2.0241	6.438[a]	16.699
RISKLND2	0.1084	0.448	1.655	0.0544	0.263	1.135	-0.8425	-1.814[c]	-7.389
UNIQUE	-0.2372	-1.512	-3.373	0.0779	0.532	1.622	-0.0904	-0.459	-1.013
GOVDEP	-0.2841	-1.334	-3.915	-0.2669	-1.474	-5.843	0.2729	0.924	3.361
METREG	0.3391	1.801[c]	5.271	-0.4071	-2.481[b]	-8.943	0.3193	1.031	3.898
JUDFORE	0.0509	0.356	0.759	-0.2791	-2.496[b]	-5.897	0.1098	0.486	1.256
DEF	-0.0552	-0.397	-0.822	-0.1245	-1.124	-2.617	0.2548	1.196	2.902
REDEMP	-0.5093	-3.369[a]	-7.358	0.4250	3.440[a]	8.994	-0.2147	-1.157	-2.453
ACQNR90	-0.3985	-3.067[a]	-6.056	0.6640	6.232[a]	14.616	-1.4284	-5.899[a]	-14.46
F-Statistic	5.805(13,∞)[a]			6.433 (13,∞)[a]			19,058(13,∞)[a]		
Pseudo-R^2	0.790			0.649			0.913		

[a], [b], and [c] denote significance at the 1%, 5%, and 10% levels respectively.
When the j^{th} explanatory variable is a dummy variable, the change in probability is computed as: $P_i(Y_{ij}=1|X_j=1) - P_i(Y_{ij}=1|X_j=0)$ with all other Xs held at their mean levels; otherwise it is calculated as: $\alpha_j P_i (1-P_i)$ with P_i held at its estimated value.

Table 5. Lender-borrower logit model results for nonreal estate debt for commercial farms. (continued)

Variables	Individuals			Merchants & Dealers		
	Coefficients	t-Statistics	$\partial P_i/\partial X_j$	Coefficients	t-Statistics	$\partial P_i/\partial X_j$
INTERCEPT	-1.6975	-3.861[a]	-------	0.7125	-2.149[b]	-----
NETW	0.0077	1.194	0.119	0.0073	1.226	0.056
VPRODTOT	0.0000	0.022	0.001	-0.0038	-0.802	-0.030
ROAT	0.0075	1.714[c]	0.115	-0.0032	-1.301	-0.025
OP_AGE	-0.0211	-2.891[a]	-0.325	-0.0219	-4.064[a]	-0.169
DAR	0.2998	0.897	4.608	0.4294	1.820[c]	3.309
RISKLND2	0.3652	1.029	3.383	0.0638	0.249	1.031
UNIQUE	0.1450	0.673	1.256	-0.3506	-2.041[b]	-5.180
GOVDEP	-0.3685	-1.221	-2.714	0.4169	2.025[b]	7.248
METREG	0.2704	0.913	2.369	-0.1166	-0.571	-1.817
JUDFORE	0.1486	0.875	1.248	-0.0883	-0.659	-1.403
DEF	0.3410	1.981[b]	2.805	0.0333	0.246	0.530
REDEMP	0.1471	0.853	1.227	-0.1120	-0.791	-1.784
ACQNR90	-0.4999	-2.984[a]	-4.311	0.3412	2.410[b]	5.187
F-Statistic		$4.255\ (13, \infty)$[a]			$2.961(13, \infty)$[a]	
Pseudo-R^2		0.908			0.794	

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