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Proceedings of a Seminar sponsored by
North Central Regional Project NC-207
"Regulatory, Efficiency and Management Issues Affecting Rural Financial Markets"
Hyatt-Regency Crystal City
October 3, 1994

University of Illinois
Department of Agricultural Economics
Urbana, IL 61801

April 1995

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The Farm Credit System (FCS) in the United States is a nationwide network of borrower-owned lending institutions and affiliated service entities. The system's primary economic and political function is to provide reliable, competitively-priced credit to its owner-borrowers (Collender et al., 1991). The FCS has been undergoing substantial structural changes. Two important factors in these changes are the passage of the Agricultural Credit Act of 1987 (Act) and the increasing competition from the commercial banking industry.

The Act contains an extensive set of provisions including: (1) the mandatory merger of the Federal Land Bank (FLB) and the Federal Intermediate Credit Bank (FICB) of each district into a Farm Credit Bank (FCB), (2) the development of merger proposals among district FCBs, (3) the voluntary merger for the Bank for Cooperatives (BCs), and (4) the development of merger plans between Federal Land Bank Associations (FLBAs) and Production Credit Associations (PCAs).

As a result, FCBs have been formed in each district[1]. The nation is now served by eight FCBs, while twelve district BCs have merged into three. Furthermore, PCAs and FLBAs in several districts have merged to form Agricultural Credit Associations (ACAs). Direct lending authority has been granted to some FLBAs. These institutions are called Federal Land Credit Associations (FLCAs). Certain FLBAs or FLCAs and PCAs are also jointly managed. The organizational changes among FCS institutions from January 1, 1988 through January 1, 1993 are summarized in Table 1.

The competition among institutions lending to agriculture has increased over the past five years. Commercial banks have increased their emphasis on farm real estate lending and, thus, have increased their volume and market share of outstanding agricultural loans. The total loan volume excluding cooperatives loans for the FCS has decreased from about $61.6 billion (33.8% of total farm debt) in 1981 to about $35.6 billion (25.6% of total farm debt) in 1992. However, total outstanding agricultural loans for commercial banks have increased from about $38.8 billion (21.3% of total loans) to about $51.6 billion (37.0% of total loans) during the same period (U.S. Department of Agriculture, 1993). The future success of FCS institutions depends on their ability to adapt and operate more efficiently in the new environment.

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Some direct lending associations within the FCS have merged to become larger. Managements of other associations are considering whether merging with other associations would help them become more competitive. One motivation for merging is that an association may obtain scale economies by operating at a larger size. Another motivation for merging is that an association may use inputs more efficiently at a larger size. Thus, by reducing the overuse of all inputs, an association would reduce cost inefficiencies. It is not clear, however, if the associations can achieve scale economies or cost efficiencies by getting larger.

In the past few years, many studies have concentrated on analyzing scale economies and cost efficiency of commercial banks (e.g., Evanoff and Israilevich, 1990; Ferrier and Lovell, 1990; Bauer, Berger, and Humphrey, 1991; Berger and Humphrey, 1991; Berger, Hancock, and Humphrey, 1993) and agricultural banks (e.g., Featherstone and Moss, 1993; Neff, Dixon, and Zhu, 1993). However, comparatively few studies have focused on efficiency analysis of FCS institutions (e.g., Collender, 1991; Collender et al., 1991). Furthermore, most studies of bank efficiency used data for a single cross-section of firms, and the separation of inefficiency from random noise required strong assumptions about their distributions.

The objective of this study is to estimate and compare the scale economies and cost efficiencies for Farm Credit System direct lending institutions using a stochastic frontier approach with panel data. The maximum likelihood estimation technique (MLE) is used to obtain the scale elasticity estimates for institutions grouped by sized and cost efficiency measurements for each institution. In the next section, the estimation procedures in the cost frontier model are detailed. The data obtained from the Farm Credit Administration (FCA) Call Reports are also discussed in that section and are followed by results from empirical estimation of the scale elasticities and efficiency measurements. The concluding section summarizes the major findings and results of this study.

Estimation Procedures and Data

Estimation Procedures

Based on economic theory, both the cost function and the production function uniquely define the technology for a firm that is competitive in the input markets. Thus, either the cost function or the production function can be incorporated into the productive efficiency analysis and is normally called the cost frontier and production frontier approach, respectively. However, direct estimation of the production function poses two possible problems (Kumbhakar, 1987). First, estimation of the production function directly is appropriate only when input quantities can be treated as exogenous. Input demand functions are assumed to be independent of the firm's technical inefficiency. However, if outputs are exogenous and inputs are endogenous, direct estimation of the production function using output as the dependent variable is inappropriate. Second, direct estimation of the production function considers only technical inefficiency. Inferences about overall inefficiency cannot be made unless allocative inefficiency is also considered.

A major advantage of the cost function approach is that consistent estimates of the parameters can be obtained if output levels and input prices are exogenous. This is a basic behavioral assumptions behind cost minimization. Thus, in this study, the cost function approach will be used. The cost function considered in this study is the translog cost function. The translog cost function can be viewed as a local, second-order approximation to an arbitrary cost function and has been used extensively in the literature. The translog cost function is specified as follows[2]:

$$\ln TC = \alpha_0 + \sum_{i=1}^{n} \alpha_i \ln w_i + \sum_{k=1}^{m} \beta_k \ln y_k + \frac{1}{2} \sum_{i=1}^{n}\sum_{j=1}^{n} \gamma_{ij} \ln w_i \ln w_j + \frac{1}{2} \sum_{k=1}^{m}\sum_{l=1}^{m} \delta_{kl} \ln y_k \ln y_l + \sum_{i=1}^{n}\sum_{k=1}^{m} \theta_{ik} \ln w_i \ln y_k + \epsilon, \tag{1}$$

where, α, β, γ, δ, and θ are parameters to be estimated, TC is total production costs, w is input price, and y is output quantity. The restrictions for linear homogeneity in factor prices of the cost function are also imposed as:

$$\sum_{i=1}^{n} \alpha_i = 1, \sum_{i=1}^{n} \gamma_{ij} = 0, \sum_{i=1}^{n} \theta_{ik} = 0, \text{ for all j, k.} \tag{2}$$

Following Aigner et al. (1977) and Meeusen and van den Broeck (1977), the error term, ϵ, is composed of two different types of disturbances:

$$\epsilon_{ft} = u_f + v_{ft} \tag{3}$$

where u_f is one-sided distributed, $u_f \geq 0$, which represents inefficiency and v_{ft} is a stochastic variable that represents uncontrolled random shocks in the production process with $f = 1, ..., F$ and $t = 1, ..., T$, where F and T are the total number of firms and time, respectively.

MLE will be used to estimate equation (1) to obtain the cost frontier and the associated inefficiency measurement for each institution. To estimate equation (1) by MLE, the probability density function (pdf) of the composed error term, $\epsilon_{ft} = u_f + v_{ft}$, needs to be derived. The distributional assumptions on the composed error are: u_f is i.i.d. one-sided distributed with half-normal density function, v_{ft} is i.i.d. with mean zero and variance σ_v^2, and u_f and v_{ft} are independent.

Following Pitt and Lee (1981) and Maddala (1983, p.195), the joint pdf $f(\epsilon_{ft})$ of ϵ_{ft} can be defined as follows:

$$f(\epsilon_{ft}) = \frac{2}{\sigma} \phi\left(\frac{\epsilon_{ft}}{\sigma}\right) \left[1 - \Phi\left(\frac{\epsilon_{ft}\lambda}{\sigma}\right) \right] \tag{4}$$

where $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u/\sigma_v$, and $\phi(\bullet)$ and $\Phi(\bullet)$ are the density function and distribution function of the standard normal, respectively. Then the log-likelihood function for the pooled data is

$$\text{(5)} \qquad \ln L = \frac{FT}{2} \ln \frac{2}{\pi} - FT \ln \sigma - \frac{1}{2\sigma^2} \sum_{f=1}^{F} \sum_{t=1}^{T} \epsilon_{ft}^2 + \sum_{f=1}^{F} \sum_{t=1}^{T} \ln [\, \Phi(\frac{\epsilon_{ft}\lambda}{\sigma}) \,].$$

After the model is estimated, the efficiency measurement for each institution can be obtained from the conditional mean of u_f given ϵ_{ft}. Jondrow et al. (1982) have shown that the distribution of u_f conditional on ϵ_{ft} is a normal distribution truncated at zero. The mean of u_f given ϵ_{ft} is expressed as follows:

$$\text{(6)} \qquad E\,(\, u_f | \epsilon_{ft} \,) = (\frac{\sigma_u \sigma_v}{\sigma})[\, \frac{\phi(\frac{\epsilon\lambda}{\sigma})}{\Phi(\frac{\epsilon\lambda}{\sigma})} + \frac{\epsilon\lambda}{\sigma} \,].$$

Given the availability of panel data, Kumbhakar (1986) has shown that the mean of u_f/ϵ_{ft}, a point estimator of u_f, is unbiased and consistent as $t \to \infty$.

Data

Data needed in estimating the cost function and, thus, the scale economies and cost efficiency include total costs (*TC*), output quantities, and input prices for each institution at each time period. Following Collender (1991), outputs considered in this study are accrual (*Y1*) and non-accrual (*Y2*) loans. Inputs include labor, physical capital, and other operating expenses. Because of data limitations, the price of labor (*W1*) is proxied by the average wage rate of the commercial banking industry in a county where each association located. The average wage rate was an average of the wage rate paid by all bank head offices in a county. This information was obtained from the FDIC Consolidated Report of Condition and Income (FDIC Call Reports). The price of physical capital (*W2*) is obtained by dividing occupancy and equipment expenses by the value of fixed assets. The price of other operating expenses (*W3*) is approximated by dividing total other operating expenses by the total assets. The FCS data are obtained from the FCA Call Reports that contain balance sheet and income statement information collected quarterly from all associations. Quarterly data with time series running from the first quarter of 1988 (1988Q1) through the fourth quarter of 1992 (1992Q4) are used in this study. The summary statistics for data used are presented in Table 2.

Empirical Results

The MLE parameter estimates for the translog cost function are presented in Table 3. Most parameter estimates are significant at the 1% or 5% level. The cost and scale elasticities and the cost inefficiency measure are derived from the parameter estimates (Table 4). The cost and scale elasticities, and cost inefficiency measures are calculated by different size groups for PCAs, ACAs, and FLCAs.

Economies of Scale and Cost Elasticity

The overall cost elasticity, the sum of product-specific cost elasticities, measures the percentage change in cost associated with one percent increase in all outputs. It is the measurement of the economies of scale. An overall cost elasticity less than one indicates that costs rise less than proportionately with an equiproportionate increase in all outputs.

All size groups of FLCAs and all but the largest size groups of PCAs and ACAs exhibit economies of scale (Table 4). For the most part, the smaller institutions had the lowest cost elasticities. The overall cost elasticities for PCAs range from 0.7806 of size less than $25 million in assets to 1.0631 of size more than $400 million in assets. The overall cost elasticities for ACAs range from 0.8777 of size $75-100 million in assets to 1.0343 of size more than $400 million. Overall cost elasticities for FLCAs range from 0.7749 of size $25-50 million to 0.9721 of size more than $400 million.

Comparisons of the overall cost elasticities among PCAs, ACAs, and FLCAs with the same size show that PCAs and FLCAs, in general, exhibit larger scale economies than ACAs. The result above suggests that PCAs and FLCAs will benefit more from restructuring to larger sizes than ACAs.

Scale Elasticity

The inverse of the product-specific cost elasticity is the product-specific scale elasticity that gives the percentage change in a specific output with one percent change in all inputs. The overall scale elasticity, on the other hand, shows the percentage change in all outputs for a one percent change in all inputs. The overall scale elasticity is the inverse of the overall cost elasticity. The returns to scale are often measured through the overall scale elasticity. A firm is considered to exhibit increasing, constant, and decreasing returns to scale as the scale elasticity is greater than, equal to, or less than one, respectively. All of the FLCAs and all but the larger PCAs, and ACAs have increasing returns to scale (Table 4). Only the PCAs with assets over $300 million and the ACAs with assets over $400 million have decreasing returns to scale.

Cost Inefficiency

Table 4 presents the inefficiency estimates for PCAs, ACAs, and FLCAs by size. As shown, PCAs with assets of $300-400 million are the least efficient (0.2578), while PCAs with assets less than $25 million are the most efficient (0.1295). Also, ACAs with assets less than $25 million are the most efficient (0.0892), while ACAs with assets more than $400 million are the least efficient (0.1527). FLCAs with $250-300 million in assets are found most efficient (0.0578), while FLCAs with assets of $50-75 million are the least efficient (0.1463).

There is not an obvious relationship between size and cost inefficiency (Table 4). Thus, these results provide evidence that a firm cannot use physical inputs more efficiently solely by increasing in size. A large association is just as likely to overuse physical inputs as a small association.

The overall inefficiency for individual PCA ranges widely from 0.047 of one PCA in the Wichita district to 0.528 of one PCA in the St. Spokane district[3]. The inefficiency measurement for each ACA also ranges widely, from 0.058 of one ACA in the Baltimore district to 0.533 of one ACA also in the Baltimore district. The range of inefficiency measurements for each FLCA is not as wide as that of PCAs and ACAs. The lowest inefficiency estimate is 0.032 for a FLCA in the Sacramento Western district, while the highest inefficiency estimate is only 0.273 for a FLCA in the St. Louis district.

Conclusions

The cooperative FCS has been undergoing substantial structural changes. The Agricultural Credit Act of 1987 and the increasing competition from the commercial banks are major driving forces of these changes. The success of FCS institutions depends on their ability to adapt and operate more efficiently in the new environment. Many direct lending associations have merged or are considering merging with other associations to gain scale economies and cost efficiencies. In this study, the scale economies and cost efficiency of the FCS direct lending institutions are estimated using the stochastic cost frontier approach.

Results indicate that FLCAs exhibit persistent economies of scale. PCAs exhibit scale economies until the size exceeds $300 million. Similarly, ACAs exhibit economies of scale until the size exceeds $400 million. PCAs and FLCAs, in general, exhibit larger scale economies than ACAs. Thus, there is evidence that the smaller associations can gain economies of size by merging into intermediate size associations.

Although some economies of scale were observed, there was no consistent evidence of cost efficiencies by size. Thus, it was just as likely that large or intermediate size association misused physical inputs as a smaller association. Moreover, the inefficiency estimates for PCAs and ACAs range widely. The least efficient PCA is 52.8% inefficient relative to the best practice PCA, while the least efficient ACA is 53.3% inefficient relative to the best practice ACA. Additional research could focus on other determinants of cost inefficiencies. Furthermore, changes in efficiency could be investigated.

Continued investigation of efficiencies within the Farm Credit System is warranted. Structural changes within the System are still occurring. Furthermore, it may take time before the structural and managerial changes translate into efficiency changes. The availability of detailed data prohibited direct comparisons among different types of associations or between districts. More complete data from institutions would allow direct comparisons among different types of institutions. This study only investigated the efficiency aspects of the structural changes within the System. Many factors besides cost efficiency are evaluated before mergers are initiated. The abilities of the firms to manage risk is an important factor in assessing a merger between institutions. Thus, motives besides changes in efficiency should be jointly considered when evaluating mergers.

Endnotes

1. The FICB of Jackson is in receivership.

2. For simplicity, the firm (f) and time (t) subscripts are suppressed.

3. Due to the lengthy report, the efficiency estimate for each individual PCA, ACA, and FLCA is not presented here. However, they are available from the authors.

References

Aigner, D.J., C.A.K. Lovell, and P. Schmidt. "Formulation and Estimation of Stochastic Frontier Production Function Models," *Journal of Econometrics*, 6(1977):21-37.

Bauer, P.W., A.N. Berger, and D.B. Humphrey. *Inefficiency and Productivity Growth in Banking: A Comparison of Stochastic Econometric and Thick Frontier Methods*, Working paper 9117, Federal Reserve Bank of Cleveland, 1991.

Berger, A.N., D. Hancock, and D.B. Humphrey. "Bank Efficiency Derived from the Profit Function," *Journal of Banking and Finance*, 17(1993):317-47.

Berger, A.N. and D.B. Humphrey. "The Dominance of Inefficiencies over Scale and Product Mix Economies in Banking," *Journal of Monetary Economics*, 28(1991):117-148.

Collender, R.N. "Production Economies and Inefficiencies in the Farm Credit System,"Paper presented at the AAEA annual meetings in Baltimore, MD, August 8-12, 1991.

Collender, R.N., R. Nehring, and A. Somwaru. *Profit Efficiency of Farm Credit System Associations*, U.S. Dept. of Agriculture, ERS, Nov., 1991.

Evanoff, D.D. and P.R. Israilevich. "Deregulation, Cost Economies and Allocative Efficiency of Large Commercial Banks," in *Issues in Financial Regulation*, Federal Reserve Bank of Chicago Working paper 90-19, 1990.

Featherstone, A.M. and C.B. Moss. "Measuring Economies of Scale and Scope in Agricultural Banking," *American Journal of Agricultural Economics*, 76(1994):655-61.

Ferrier, G.D. and C.A.K. Lovell. "Measuring Cost Efficiency in Banking: Econometric and Linear Programming Evidence," *Journal of Econometrics*, 46(1990):229-45.

Jondrow, J., C.A.K. Lovell, I.S. Materov, and P. Schmidt. "On The Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model," *Journal of Econometrics*, 19(1982): 233-238.

Kumbhakar, S.C. "Production Frontiers and Panel Data: An Application to U.S. Class 1 Railroads," *Journal of Business & Statistics*, Vol. 5, No.2 (1987):249-255.

Maddala, G.S. *Limited-dependent and Qualitative Variables in Econometrics*, Cambridge University Press, 1983.

Meeusen, W. and J. van den Broeck. "Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error," International Economics Review, 18(1977):435-444.

Neff, D.L., B.L. Dixon, and S. Zhu. "Measuring the Efficiencies of Agricultural Banks," *American Journal of Agricultural Economics*, 76(1994):662-68.

Pitt, M.M. and L.F. Lee. "The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry," *Journal of Development Economics*, 9(1981): 43-64.

U.S. Department of Agriculture. *Agricultural Income and Finance: Situation and Outlook Report.* ERS, Feb. 1993.

Table 1. Numbers of Farm Credit Institution, 1988Q1 - 1992Q4.

	FLB	FICB	BC	PCA	FLBA	FCB	ACA	FLCA	SC	Total
1988Q1	12	12	13	150	230	12	-	-	4	433
1988Q1	12	12	13	148	229	12	-	-	4	430
1988Q3	1	1	13	143	224	11	-	-	4	397
1988Q4	1	1	13	142	224	11	-	-	6	398
1989Q1	1	1	3	101	148	11	34	4	6	309
1989Q2	1	1	3	96	143	11	39	2	6	302
1989Q3	1	1	3	95	142	11	40	2	6	301
1989Q4	1	1	3	95	148	11	39	2	6	306
1990Q1	1	1	3	94	146	11	40	2	6	304
1990Q2	1	1	3	93	145	11	40	3	6	303
1990Q3	1	1	3	112	144	11	40	4	6	322
1990Q4	1	1	3	112	141	11	40	7	6	322
1991Q1	1	1	3	117	121	11	44	18	5	321
1991Q2	1	1	3	91	96	11	66	19	5	293
1991Q3	1	1	3	87	90	11	70	22	5	290
1991Q4	1	1	3	87	87	11	70	25	5	290
1992Q1	1	1	3	82	84	10	70	24	5	280
1992Q2	1	1	3	75	84	10	70	24	5	273
1992Q3	1	1	3	73	80	10	70	26	5	269
1992Q4	1	1	3	72	78	10	70	27	4	266

Source: FCS Call Reports, 1988Q1-1992Q4, Farm Credit Administration.
Note: FLB-Federal Land Bank, FICB-Federal Intermediate Credit Bank, BC-Bank for Cooperatives, PCA-Production Credit Association, FLBA-Federal Land Bank Association, FCB-Farm Credit Banks, ACA-Agricultural Credit Association, FLCA-Federal Land Credit Association, and SC-Service Corporation.

Table 2. Summary Statistics of Sample Farm Credit Associations.

	PCA (N=1756)				ACA (N=798)				FLCA (N=97)			
Variable	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.	Mean	S.D.	Min.	Max.
Accrual Loans ($million)	68.5	99.5	7.0	932.3	216.9	397.3	17.3	3,276.8	168.2	209.6	23.4	2,037.5
Nonaccrual Loans ($ million)	3.5	6.7	0.001	72.5	6.7	20.8	0.001	225.7	6.5	21.8	0.029	214.1
Price of Labor ($1,000)	27.3	4.4	17.1	61.2	28.6	6.4	18.5	108.2	30.9	5.4	18.5	40.1
Price of Physical Capital ($)	0.072	0.099	0.004	0.923	0.047	0.019	0.008	0.152	0.094	0.123	0.024	0.809
Price of Other Operating Expenses ($)	0.0017	0.0011	0.0002	0.0243	0.0014	0.0007	0.0001	0.0063	0.0013	0.0005	0.0004	0.0031
Total Cost [a] ($1,000)	469.4	807.4	9.0	8,285.0	975.4	1,751.8	118.9	13,146.9	545.1	581.4	100.	5,734.9
Total Assets ($ million)	87.3	135.2	2.1	1,266.6	244.3	459.0	21.6	3,715.5	185.9	239.7	27.6	2,325.8

[a] Non interest operating cost that includes labor, physical capital and other operating expenses.

Table 3. Parameter Estimates for the Translog Cost Function.

Variable	Parameter Estimate	Standard Error
Log(Y1)	0.7515	0.0630*
Log(Y2)	0.1311	0.0457*
Log(W1)	1.0939	0.1871*
Log(W2)	0.0450	0.1154
Log(Y1)log(W1)	-0.0819	0.0086*
Log(Y1)log(W2)	-0.0094	0.0080
Log(Y2)log(W1)	-0.0026	0.0060
Log(Y2)log(W2)	-0.0101	0.0043**
Log(Y1)log(Y1)	0.0897	0.0042*
Log(Y1)log(Y2)	-0.0132	0.0026*
Log(Y2)log(Y2)	0.0205	0.0023*
Log(W1)log(W1)	-0.0434	0.0277
Log(W1)log(W2)	0.0414	0.0160*
Log(W2)log(W2)	-0.0776	0.0102*
$1/\sigma$	3.9562	0.1277*
λ	1.0088	0.1203*
Constant	-3.5929	0.7580*
σ_u^2	0.0322	
σ_v^2	0.0317	
Log of Likelihood Function	401.94	

Note: Y1 - accrual Loans, Y2 - Nonaccrual Loans, W1 - Price of Labor, W2 - Price of Physical Capital.
*Statistically significant at the 99% level
**Statistically significant at the 95% level

Table 4. Cost and Scale Elasticities and Inefficiency Estimates by Asset Size.

Institution	Asset Size ($1,000,000)	Overall Cost Elasticity	Overall Scale Elasticity	Inefficiency Estimate
PCA	0 - 25 (N=316)	0.7806	1.2810	0.1295
	25 - 50 (N=424)	0.8186	1.2216	0.1432
	50 - 75 (N=461)	0.8653	1.1557	0.1476
	75 - 100 (N=217)	0.8804	1.1358	0.1585
	100 - 150 (N=193)	0.9108	1.0980	0.1564
	150 - 200 (N=60)	0.9131	1.0951	0.1476
	200 - 250 (N=5)	0.905	1.1050	0.1409
	300 - 400 (N=11)	1.0225	0.9780	0.2578
	More Than 400 (N=69)	1.0631	0.9406	0.2124
	All Sample (N=1756)	0.8548	1.1698	0.1489
ACA	0 - 25 (N=8)	0.8787	1.1381	0.0892
	25 - 50 (N=47)	0.8843	1.1309	0.1239
	50 - 75 (N=106)	0.8884	1.1257	0.1448
	75 - 100 (N=79)	0.8777	1.1394	0.1206
	100 - 150 (N=125)	0.9046	1.1054	0.1432
	150 - 200 (N=145)	0.9306	1.0745	0.1328
	200 - 250 (N=72)	0.9153	1.0925	0.1322
	250 - 300 (N=70)	0.9203	1.0865	0.1406
	300 - 400 (N=89)	0.9658	1.0354	0.1389
	More Than 400 (N=57)	1.0343	0.9669	0.1527
	All Sample (N=798)	0.9215	1.0852	0.1367
FLCA	25 - 50 (N=6)	0.7749	1.2905	0.074
	50 - 75 (N=5)	0.8693	1.1503	0.1463
	75 - 100 (N=18)	0.8833	1.1321	0.1246
	100 - 150 (N=12)	0.9147	1.0932	0.1146
	150 - 200 (N=39)	0.9202	1.0868	0.0622
	200 - 250 (N=1)	0.8643	1.1570	0.0683
	250 - 300 (N=6)	0.9353	1.0691	0.0578
	More Than 400 (N=10)	0.9721	1.0287	0.0840
	All Sample (N=97)	0.9068	1.1028	0.0874

Note: N represents number of observations.