Profitability and Long-term Survival of Community Banks: Evidence from Texas

Ram N. Acharya
Morrison School of Management and Agribusiness
Arizona State University
acharyar@asu.edu

Albert Kagan
Morrison School of Management and Agribusiness
Arizona State University
aaajk@asu.edu

Timothy J. Richards
Morrison School of Management and Agribusiness
Arizona State University
trichards@asu.edu

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California

July 23-26, 2006

Profitability and Long-term Survival of Community Banks:
Evidence from Texas

Abstract

This study examines the impact of distance among competing bank locations on market their pricing behavior. A general spatial autoregressive model that nests both spatial autoregressive and spatial error models is used to examine the impact of distance on pricing behavior of 686 non-metro banks in Texas. Results show that non-metro banks exercise market power in pricing their products. An increase in spatial competition may reduce profitability and challenge long term survival of small community based financial institutions.

This study examines the impact of distance among competing banks on their product pricing behavior. A general spatial autocorrelation model that accounts for both spatial autocorrelation and spatial error is used to examine the pricing behavior of non-metro banks in Texas. Recent studies have raised the concern that increased competition in non-metro banking markets may reduce the profitability of small community based financial institutions. The long-term viability of community banks is an important issue as these banks continue to remain to be the primary lender for small business and agricultural enterprises, which are the backbone of the rural American economy (Akigbe and McNulty, 2003).

Moreover, locational effects such as the distance from the nearest competitor and availability of supporting infrastructure are relatively new concepts in accessing rural financial applications. In particular, this study estimates a general spatial autocorrelation (SAC) model that accounts for both spatial dependence and spatial heterogeneity in pricing behavior that may arise in community banking markets mainly because of difference in the supply of supporting infrastructure such as broadband internet network (Anselin, 1988).

Recent deregulation of the banking sector and innovations in financial and information technologies have substantially increased competition in markets which were primarily served by community based financial institutions. While the deregulation allowed large regional and national banks to operate branch locations in community banking markets, increasing demand for online services particularly from web savvy customers has made it possible for mega banks to penetrate into geographically isolated (non metro) markets without investing resources in developing branch locations. As a result, the number of community banking institutions as well as their deposit and asset share has been diminishing over time (Critfield *et al*., 2004; Berger *et al*., 2005). These declining trends are raising concern about the long term viability of community banks (Elyasiani and Mehdian, 1995; DeYoung, Hunter, and Udell, 2004).

However, despite these deteriorating numbers, recent evidence indicates that community banks continue to play an important role in all types of local banking markets including those which experienced population declines (Critfield *et al*., 2004). Moreover, a number of studies have observed that non-metro community banks are more profit efficient than their urban counterparts (Boyd and Runkle, 1993; Berger and Mester, 1997; McNulty *et al*., 2001; Akhigbe and McNulty, 2003). In particular, community banks' ability to access needs and creditworthiness of borrowers particularly those without long credit histories makes them a more efficient lender than large banks that tend to rely on hard information in making lending decisions. The relative efficiency of community banks might be the force behind a larger number of *De Novo* community bank entries (more than 1250) after 1991 when unit banking was completely removed (Berger *et al*., 2004; Critfield *et al*., 2004). Berger, Goldberg, and White (2001) observed that *De Novo* small banks tend to lend a significantly higher proportion of loans (13.6 percent) to small borrowers who tend to be informationally opaque as compared to their larger counterparts (2.9 percent).

However, most studies attribute the higher efficiency of non-metro banks to market power and raise concern about their long term viability as the deregulation and technology induced competition intensifies (Elyasiani and Mehdian, 1995; DeYoung, Hunter, and Udell, 2004; Akhigbe and McNulty, 2003). This effect would be more pronounced in non-metro areas which tend to be highly concentrated. If these small community-based financial organizations are inefficient then large regional and national banks would enter these market areas. The enhanced competition in non-metro markets could force local market disruptions and decrease the supply of funds particularly to those small borrowers without extended credit histories. Even if these inefficient non-metro community banks are purchased by larger banks, it is likely to reduce the supply of small business loans because larger banks tend to lend relatively smaller proportions of their funds to smaller borrowers (Berger, Goldberg, and White, 2001; Berger *et al*., 2004).

Moreover, although many studies have recognized that bank performance differs by location, its actual impact has not yet been fully explored. In particular, firms that are geographically isolated may behave differently from those that are competing with a next door neighbor. Therefore, it is important to account for the proximity of competing banks in evaluating their pricing behavior. Moreover, the level of consumers demand for internet based banking services depends on the available supporting infrastructure such as broadband internet services, number of other customers using such services (network externalities), and other socioeconomic conditions of bank customers. As a result, community banks operating in remote locations are likely to have fewer internet savvy customers and face limited internet based competition than their urban counterparts.

This study employs a comprehensive modeling framework to examine the pricing behavior of community banks using Consolidated Reports of Condition and Income (Call Report) data for 651 Texas community banks that were active as of December 31, 2005. In particular, a general spatial autocorrelation model that embeds both spatial autoregressive (SAR) and spatial error (SEM) models is developed to account for possible locational differences in basic infrastructure among community banking markets (Anselin,1988). Consistent with Pinske and Slade (2002) and LeSage and Pace (2004) a number of instrumental variables and spatial error weight matrices are developed to address the issue of endogeneity and spatial impact on non-metro bank's pricing behavior.

Empirical Model

Location plays a vital role in determining the market structure and profitability of community-based financial institutions. Since customers typically travel to a bank location to complete their transaction, factors such as travel cost, search cost, and other costs associated with informational asymmetries factor in the total cost of choosing one bank over another. As a result, an institution which is located closer to customers than its competitors may posses some degree of market power in pricing its services (Greenhut and Greenhut, 1975; Gabszewicz and Thisse, 1992). This study estimates an empirical spatial pricing model to examine the extent of market power and its impact on the average price of banking services.

Following Pinske, Slade and Brett (2002) and Richards and Acharya (2006), we assume banks serve as upstream suppliers of financial services demanded by downstream borrowers and depositors. Assuming that there are K buyers of $q=(q_1, q_2, \ldots, q_n)$ banking products and the borrowers are located at a point in geographic or product characteristic space the aggregate profit function for the borrowing industry can be expressed as

(1) $$\widetilde{\Pi}(v, p, y) = \sum \widetilde{\pi}_k (v_k, p, y),$$

where $v=(v_1, v_2, \ldots, v_n)^T$ is borrower's output price vector, $p=(p_1, p_2, \ldots, p_n)$ is a price vector for banking services, and $y=(y_1, y_2, \ldots, y_n)$ is borrower's output vector.

Pinske, Slade and Brett (2002) approximate the profit equation in (1) using normalized quadratic function and derive aggregate demand function for the borrowing industry by invoking Hotelling's Lemma. The credit supply function can be derived from the objective function of a representative lender

(2) $$\max_{p_i} (p_i - c_i)\left[a_i + \sum_j (b_{ij} p_j + d_{ij} y_j) \right] - F_i,$$

where c_i firm *i*'s marginal cost and F_i is a fixed cost. Given rival prices, lender's reaction function or best reply function (*R(p)*) can be derived by solving the first order condition of maximizing (2), i.e.,

(3) $$p = R(p) = a + X\beta + Gp + u,$$

where a is *a* vector of intercepts and β is a vector of parameters to be estimated. The matrix G=(gij) has zero diagonal elements and may contain non-zero off diagonal elements that must be estimated.

The reaction function (3) contains current rival prices and may not be independent of the error term u. Pinske, Slade, and Brett (2002) suggest developing exogenous instruments that vary by location such as population and local wage rate. We use zip code level data on median household income, total population, and total household as instruments and estimate price reaction function of following form

(4) $$p = a + \rho W_1 p + X\beta + u \,,$$

$$u = \lambda W_2 u + \varepsilon \,,$$

$$\varepsilon \sim N(0, \sigma^2 I_n) \,,$$

where p=average interest rate on bank loans, W_1 and W_2 are spatial weight matrices, X is vector of exogenous variables that includes four input prices (price of deposits, average wage rate, cost of physical capital, and average cost of financial capital), variables that vary by branch location (total population, total households, and average household income by for the zip code area served by the branch location), number of competitor in the market, and a dummy variable indicating whether the bank is a member of a multi-bank holding company.

Data Description

The empirical data used in this study comes from three different sources. The bank financial data was drawn from the Federal Deposit Insurance Corporation's (FDIC) Reports on Statistics on Depository Institutions (RSDI) and Summary of Deposits (SOD). The FDIC provides a complete set of financial statements for all reporting banks, from which we draw loan and deposit amounts, physical capital, number of employees and other operating characteristics. The variable that vary by location such as zip code level population, total number of households, and median household income was drawn from the 2000 U.S. Census database.

In addition to financial and census data, US Census TIGER line files containing local road networks are used to generate geo-coordinates for 686 branch locations operating in non-metro locations (table 1). In order to focus specifically on banks located in rural areas, where geographic distance is most likely to be a key differentiating attribute, we study the entire population of non-metro banks in Texas. We choose banks in Texas for several reasons. First, the Texas is one of the major agriculturally-intensive regions in the U.S. Because our interest in this study lies in understanding the linkage between banking market power and rural welfare in general, loans from non-metro banks to both farms and rural businesses of all types are relevant.

Second, Texas is the largest state with large number of relatively isolated market. Although spatial econometric method is able to endogenize the size of the market through construction of the spatial weight matrix, estimates of the most relevant weights are often biased when a large non-included market exists on the fringe (Shaffer and DiSalvo, 1994). Third, Texas is one of the major community banking states, which remained under a unit banking system until the mid 1980s. Moreover, many of these single unit financial institutions are still in operation. Since most non-metro banks tend to specialize in relationship lending, it is important to understand how spatial competition affects profitability and long term survival of these small community based institutions.

There were 651 small community-based commercial financial institutions operating as of December 2005. About 40percent (221) of these community banks operate only one full service bank location. While more than 55 percent of the community banks are headquartered in non-metro locations, more than 67 percent of the single unit banks are located in non-metro areas.

Results and Discussion

The basic statistics on variables used in the study are reported in table 1. On average banks pay little more than 4 percent to obtain financial capital and charge about 9 percent to their borrowers. Banks are facing at least one competitor in each zip code area they operate and have 50 percent market share in total deposits. The market share of sample banks is much higher than national average reported in other studies. The corresponding figure for metro region in Texas is 20 percent.

The parameter estimates for ordinary least square (OLS), spatial autoregressive (SAR), and general spatial autocorrelation (SAC) models are reported in table 2. In general, estimated parameters are consistent with other studies and hold expected signs. The overall goodness of fit as reflected by R-square value (0.17-0.40) is reasonably high for a study based on cross-sectional data. Since retail deposits are the main source of financial capital for non-metro locations, the cost of financial capital is not significant in all 5 versions of the model reported in table 2. Other three cost variables, average cost of deposit, labor, and physical capita hold expected signs and are mostly significant.

A number of tests (Moran-I, Lagrange Multiplier (LM), likelihood ratio (LR), and Wald statistics) were conducted to select between SAR and SAC models and all test results support SAC model, which accounts for both spatial autocorrelation as well as spatial error. The results show that competition in non-metro banking market is spatial. Many non-metro branch locations enjoy a significant level of market power and price their services accordingly.

Summary and Conclusion

This study examined the impact of geographic distance among competing bank and their pricing behavior using data from non-metro banks in Texas. Although many studies have addressed the impact of market power in bank performance, it is not clear how distance between competing banks affects their pricing behavior. If the performance of non-metro banks, which tend to be local in scope, is primarily based on their locational advantage, increased competition may reduce their profitability and challenge their long term viability.

The results of this study show that non-metro banks exercise a significant level of market power and price their products and services accordingly. Although it is not clear whether the profit margin is high enough to attract new competitors in non-metro markets, an increase in competition is likely to challenge current pricing behavior of existing firms and reduce overall profitability.

References

Akhigbe, A., and J.E. McNulty. “The Profit Efficiency of Small US Commercial Banks.” *Journal of Banking and Finance* 27(2003):307-325.

Anselin,L. *Spatial Econometrics: Methods and Models*. 1988. Dorddrecht: Kluwer Academic Publishers.

Berger, A. N. “Bank Concentration and Competition: An Evolution in the Making.” *Journal of Money, Credit, and Banking,* 36(2004):433-451.

Berger, A.N., S.D. Bonime, L.G. Goldberg, and L.J. White. “ The Dynamics of Market Entry: The Effects of Mergers and Acquisitions on Entry on the Banking Industry.” *The Journal of Business* 77(2004):797-834.

Berger, A.N., A.A. Dick, L.G. Goldberg, and L.J. White. “The Effects of Competition from Large, Mulitimarket Firms on the Performance of Small Single-Market firms: Evidence from the Banking Industry.” Finance and Economics Discussion Series, Federal Reserve Board, Washington, D.C, 2005.

Berger, A.N., A.A. Dick, L.G. Goldberg, and L.J. White. “The Effects of Dynamic Changes in Bank Competition on the Supply of Small Business Credit.” *European Finance Review* 5(2001):115-39.

Berger, A.N. and L.J. Mester. “Inside the Black Box: What Determines Differences in the Efficiency of Financial Institutions.” *Journal of Banking and Finance* 21(1997):895-947.

Boyd, J.H. and D.E. Runkle. “Size and the Performance of Banking Firms: Testing the Predictions of Theory.” *Journal of Monetary Economics* 31(1993):47–67.

Critfield, T., T. Davis, L. Davison, H. Gratton, G. Hanc, and Samolyk. “Community Banks: Their Recent Past, Current Performance, and Future Prospects.” Future of Banking Study Draft FOB-204-03.1.

DeYoung, R., W.C. Hunter, and G.F. Udell. (2004a). “The Past, Present, and Probable Future for Community Banks.” *Journal of Financial Services Research* 25, 85-133.

Elyasiani, E., S. Mehdian. “The Comparative Efficiency Performance of Small and Large US Commercial Banks in the Pre- and Post-Deregulation Eras.” Applied Economics 27(1995):1069–1079.

LeSage, J. P. 1998. *Spatial Econometrics* Monograph, Department of Economics, University of Toledo, Toledo, OH. December.

McNulty, J.E., A. Akhigbe, and J.A. Verbrugge. "Small Bank Loan Quality in a Deregulated Environment: The Information Advantage Hypothesis." *Journal of Economics and Business* 53(2001):325–339.

Richards, T.J. and R.N. Acharya. 2006. "Spatial Competition and Market Power in Banking." Manuscript.

Pinske, J. and M. E. Slade. 1998. "Contracting in Space: An Application of Spatial Statistics to Discrete-Choice Models," *Journal of Econometrics* 85: 125-154.

Pinske, J., M. E. Slade and C. Brett. 2002. "Spatial Price Competition: A Semiparametric Approach," *Econometrica* 70: 1111-1153.

Pinske, J. and M. Slade. 2004. "Mergers, Brand Competition and the Price of a Pint," *European Economic Review* 48: 617-643.

Pace, R. K., R. Barry, O. W. Gilley, and C.F. Sirmans. 2000. "A Method for Spatial-Temporal Forecasting with an Application to Real Estate Prices," *International Journal of Forecasting* 16:229-246.

Shaffer, S. and J. DiSalvo. 1994. "Conduct in a Banking Duopoly," *Journal of Banking and Finance* 18: 1063-1082.

Table 1. Descriptive Statistics

Variable	N	Mean	Std.Dev.	Minimum	Maximum
Multi-Bank Holding Company	686	0.36	0.48	0.00	1.0
Price (%)	686	9.31	3.48	1.10	30.5
Price of Deposit	686	1.42	0.40	0.24	2.5
Price of Labor	686	47.40	12.59	6.61	98.4
Price of Physical Capital	686	30.74	26.95	2.08	428.6
Price Of Financial Capital	686	4.12	8.98	0.05	124.7
Population	686	12485.05	10939.22	189.00	76146.0
Total Households	686	4492.44	3812.51	64.00	28375.0
Median Income	686	30574.05	4742.52	15228.00	50154.0
Number of Competitors	686	1.25	0.64	1.00	5.0
Market Share	686	0.51	0.35	0.00	1.0

Table 2. Parameter Estimates

Variable	OLS	SAR	SAC	SAR	SAC
Constant	1.2359	-6.3112**	-6.0804**	-11.0997**	-10.8281**
	(1.73)	-(5.75)	-(5.41)	-(4.90)	-(5.03)
Cost of Deposit	0.8145**	0.7442**	0.7298**	0.4713	0.4630
	(2.70)	(2.58)	(2.49)	(1.65)	(1.59)
Wage Rate	0.0236*	0.0287**	0.0308**	0.0340**	0.0356**
	(2.24)	(2.83)	(3.03)	(3.39)	(3.53)
Cost of Physical Capital	0.0427**	0.0427**	0.0429**	0.0439**	0.0439**
	(9.86)	(10.33)	(10.33)	(10.84)	(10.80)
Cost of Financial Capital	-0.0013	-0.0004	0.0005	-0.0008	-0.0003
	-(0.11)	-(0.03)	(0.05)	-(0.07)	-(0.02)
Number of Competitors	0.0764	0.0561	0.0598	-0.1824	-0.1795
	(0.45)	(0.35)	(0.36)	-(1.13)	-(1.08)
Multi-Bank Holding Company	4.2780**	4.4302**	4.4831**	4.7836**	4.8056**
	(12.87)	(13.93)	(14.04)	(15.17)	(15.21)
Population				0.0008**	0.0008**
				(12.13)	(5.95)
Total Households				-0.0018**	-0.0019**
				-(13.65)	-(4.59)
Median Income				0.0002**	0.0002**
				(19.39)	(11.83)
ρ		0.7830**	0.7410**	0.4850**	0.4610**
		(8.89)	(8.03)	(2.40)	(2.83)
λ_ϵ			0.0320*		0.0200**
			(2.02)		(7.18)
R^2	0.3230	0.17	0.3877	0.3791	0.4036
N	686	686	686	686	686

**,* denote significance at 1 and 5 percent level.