Market Power in Non-Metro Banking

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Paper presented at AAEA Annual Meeting

Portland, OR

July 29 - August 1, 2007

Short Abstract:

Banks in non-metropolitan areas compete in a spatially-differentiated environment. This paper estimates a structural model of the supply and demand of banking services in which pricing power depends on the distance between rival banks. A spatial econometric model finds that approximately 38.0% of economic surplus derives from spatial market power.

Subject Code: Banking and Finance

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1. Introduction

In the U.S., small, rural enterprises tend to be financed by bank loans from local financial institutions such as community banks (Yeager, 2004). With the rapid consolidation wave that followed interstate banking deregulation in the 1990s, many feared that the banks that emerged would be "too big" to lend to rural enterprises (Calem 1994; Keeton 1996; Berger et al. 1998; Gilbert 1997; McNulty, Akhigbe and Verbrugge 2001; Meyer and Yeager 2001; Berger et al. 2005) or would do so only at usurious rates. Non-metro community banks, however, have typically been insulated from the new competitive forces encountered by metro community banks due to the importance of soft information in relationship lending (DeYoung and Duffy, 2002; DeYoung, Hunter, and Udell, 2004). Soft information regarding borrower reputation, local economic conditions, or market trends is critically important in evaluating investments in small businesses and farms (McNulty, Akhigbe and Verbrugge, 2001). Proximity to borrowers, therefore, may be an important source of market power for non-metro community banks. While Petersen and Rajan (2002) provide evidence that geographical distance between borrowers and lenders is becoming less important as improvements in communication technology reduce the importance of soft information, Critchfield et al. (2004) argue that the local, community bank model will remain viable for the foreseeable future. Despite this controversy, there is little empirical research into the role of geography as a source of market power in U.S. banking.

Imperfect competition among banks is an important economic problem because loans from community banks to farmers and other rural businesses are necessary to sustain investment and growth (Berger, Hasan and Kapper, 2004). Insufficient lending may arise from two sources: (1) inefficient banks, whether in the sense of technical, allocative or scale inefficiency, or (2)

banks that reduce the amount of lending in order to exploit any real or perceived market power.[2] In fact, banks that are separated by relatively large geographic distances may have an incentive to limit loan output in order to take advantage of market power conferred by their relative spatial isolation or, conversely, to exploit the relative ease of colluding with banks located nearby.[3] In this paper, we empirically test whether U.S. non-metro banks located in the upper midwest region – Minnesota, North Dakota and South Dakota – are able to exercise market power from either spatial or non-spatial sources.

We focus on non-metro banks in the upper midwest for a number of reasons. First, the upper midwest remains one of the most agriculturally-intensive regions in the U.S. Because smaller, community banks tend to be particularly important sources of financing for small businesses and farms (Critchfield, et al., 2004), higher lending rates are likely to have a disproportionate effect on rural economic welfare. Second, the upper midwest forms a contiguous, relatively isolated market. To the extent that a geographic "market" in banking can be defined, the upper midwest provides perhaps the best example of one in which banks are likely to compete against each other and not against outside influences. Third, much of this region tends to be economically disadvantaged from an historical perspective. For this reason, rural economic welfare is an important topic of study from a public policy perspective. Fourth, because agricultural enterprises are inherently separated from each other and from their lenders by often large distances, there is a high potential for banks to exercise spatial market power.

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[2] The question of inefficiency among rural banks is addressed by Featherstone and Moss (1994), Featherstone (1996) and Marsh, Featherstone and Garret (2003).

[3] See Shaffer (2004) for an extensive, recent review of the literature in this area.

Finally, most of the banks in the upper midwest are headquartered in non-metro locations. In fact, more than 60 percent (951) of the community banks in our sample that were active in December 31, 2004 were based in rural areas. Therefore, while we cannot exclude non-community banks if our sample is to describe the entire non-metro market, the data nonetheless consists of a high proportion of community lenders.[4]

Simultaneously testing for spatial and non-spatial market power requires an approach that is relatively new to the industrial organization and banking literatures. Although there are many alternative tests in the literature, each suffers from well-documented weaknesses (Shaffer, 2004). Consequently, in this study we test for market power due to spatial separation by synthesizing a traditional non-spatial model of firm conduct (Bresnahan, 1989) with the distance metric (DM) model developed by Pinkse, Slade and Brett (2002), Pinkse and Slade (2004) and Slade (2004). In the DM model, the price set by each bank is a function of its proximity to competitor banks. If the price rises the farther a bank lies from others, it is interpreted as exploiting local monopoly power. On the other hand, if prices rise the nearer a bank is to its competitors, then this is regarded as evidence of tacit collusion. By controlling for non-spatial sources of market power (service differentiation, brand loyalty, product variety, etc.), we minimize the likelihood that any evidence of market power is mis-attributed to any source other than spatial separation.

Our findings provide limited support for the spatial-market-power hypothesis. While non-metro banks derive market power from both spatial and non-spatial sources, the non-spatial proportion is many times greater than that due to spatial location. What is interesting, however,

[4] The average size of these institution was less than $85 million and about 19 percent of these institutions are in a category that includes banks with less than $25 million in assets.

is that the collusive effect described above dominates the local monopoly effect for all model specifications. Although this result is typically interpreted as evidence of tacit collusion among clusters of competing businesses, it can also be interpreted as evidence of the inherent advantages of locating near a client's business.

The objective of this study is to determine whether non-metro banks in the upper midwest exercise market power in their lending activities and, if they do, to assess the welfare impacts of imperfect competition. The paper begins with a brief review of the literature on market power and efficiency in U.S. banking. In the second section, we develop a spatial econometric model designed to test for multiple sources of imperfect competition among non-metro banks in the U.S. upper midwest. The third section describes the data used to estimate the model, and provides a detailed explanation of the methods used in estimation. A fourth section presents and interprets the empirical results, and suggests some broader implications for lending markets in other regions of the country. A final section summarizes our findings and provides some suggestions for future research in this area.

2. Background on Market Power in Banking

An efficient and competitive banking sector is critical to building and sustaining economic growth. Several studies document the economic linkage between the financial and real sectors of developing economies (Burnside and Dollar, 2000; Bird and Rowlands, 2001; Barro and Lee, 2003; Butkiewicz and Yanikkaya, 2005), and disadvantaged regions of developed economies (Berger et al 1999). Whereas large firms tend to use public debt and equity markets for most of their capital needs, small businesses and farms, which contribute the bulk of economic activity in

most rural regions of the U.S., typically rely on commercial and real estate loans from banks or other lending institutions. More importantly, small businesses and farms tend to borrow from relatively small, local lending institutions due to the opaque nature of privately-held firm financial data and the consequent need to develop "relationship banking" programs with local banks (Berger et al., 1998). If these banks exercise market power, then they are necessarily not lending as much as they should from a socially-optimal perspective.

Prior evidence on market power in banking is extensive, but weak. Shaffer (2004) reviews a number of studies that find only limited market power among commercial banks in general. Shaffer (1993, 2004) and Shaffer and DiSalvo (1994) find that banks tend to operate in a nearly competitive way even when the market can otherwise be described as highly concentrated. On the other hand, Shaffer (1999) finds a significant departure from perfectly competitive pricing among credit card-issuing banks – approximately equivalent to behavior expected from a three-firm oligopoly pricing according to Cournot rules. Using a different methodology (a Panzar-Rosse instead of a Bresnahan-Lau model), Bikker and Haaf (2002) find evidence of imperfectly competitive behavior only among the smallest group of European banks, and even then the departure is slight.

The empirical methods used in these studies, however, are designed to detect rather than explain market power. Therefore, they do not consider the explicit spatial nature of banking markets as a potential source of market power. Barros (1999) motivates a model of bank conduct in Spain on spatial grounds, but does not include explicit measures of the spatial separation of her sample banks. Interestingly, Barros (1999) finds only weak evidence in support of collusive behavior on the part of local banks, despite expectations otherwise. Other authors suggest, and

even assume, that bank market power derives from spatial separation, whether geographic (Barros 1999; Brickley, Linck and Smith 2003) or attribute-space (Keeley 1990; Repullo 2004) wherein market power may arise naturally due to high fixed costs and high implicit costs of borrower search. In fact, the bank regulation literature suggests that imperfect competition may even be necessary to prevent the excessive risk-taking and network build out that accompanies deregulation (Chiappori, Perez-Castrillo and Verdier 1995; Matutes and Vives 2000; Repullo 2004).

Efficient lending is critically important to building and sustaining economic growth. There are a few studies that document the linkage between market structure and growth in domestic lending (Collender and Shaffer, 2002), but not necessarily banking conduct. Typically, a standard empirical growth model is used to estimate the relationship between economic growth and lending (Barro, 1991; Mankiw, Romer, and Weil, 1992). In this study, we adopt a fundamentally different approach and estimate the impact of pricing conduct directly on economic welfare.

3. Empirical Model of Spatial Competition and Economic Welfare

3.1 Overview

The empirical analysis is divided into two stages. In the first stage, we use a spatial, discrete-choice model of banking demand and pricing behavior to estimate the degree of market power exercised by non-metro banks in the upper midwest. In the second stage, these estimates are used in a model of economic welfare to calculate the economic costs of imperfect competition in

lending. In each stage, we use two measures of market power, one based on service differentiation and the other on spatial distance. We begin by deriving both the demand and pricing components in traditional, non-spatial notation and then show how incorporating spatial considerations changes the econometric model.

3.2 Discrete Choice Model of Banking Demand

Banks are assumed to be distributed randomly throughout a relevant market area. All banks are assumed to represent potentially viable competitors for all others and compete on the basis of output price, where outputs are defined according to the intermediation model as total loans outstanding.[5] Following Pinkse, Slade and Brett (2002), banks are assumed to serve as upstream suppliers to loans and deposit accounts demanded by downstream borrowers and depositors. As such, the demand for bank services depends on the utility derived from whatever service is provided to the borrower. Because bank services are differentiated products – differentiated on the basis of spatial location and location in service-attribute space – consumers necessarily choose only one from a potentially vast number of alternatives. Consequently, we represent the demand for banking services with a discrete choice model of differentiated product demand (Anderson, dePalma and Thisse 1992; Berry 1994; Berry, Levinsohn and Pakes 1995; Nevo 2001).

We begin by defining a random utility representation of individual household demand,

[5] The other two models are the value-added approach, wherein outputs consist of loans and total deposits on the argument that deposits provide a vital service to banking customers as stores of value or means of facilitating transactions, or the user-cost approach in which deposits are separated into inputs or outputs based on the results of an empirical test (Shaffer 2004).

and then aggregate over consumers to arrive at a consistent aggregate demand for banking services. The utility household h receives from services provided by bank j is written as:

$$u_{hj} = v_{hj} + \varepsilon_{hj} = \beta_0 + \sum_k \beta_{1k} x_{khj} - \alpha p_j + \xi_j + \varepsilon_{hj}, \tag{1}$$

where v_{hj} is the mean utility, β_0 is the maximum willingness to pay for banking services, p_j is the price of services offered by firm j, $\boldsymbol{x}_{hj}$ is a vector of k attributes for both households and banks, ξ_j is an unobservable (to the econometrician) error term and ε_{hj} is a random error, assumed to be iid extreme value distributed. Household h will choose the product offered by firm j if the utility from this choice is greater than the utility from all other alternatives. As is well understood, if ε_{hj} is distributed extreme value, the random utility model in (1) implies aggregate share functions for each firm $j = 1, 2, \ldots J$ of:

$$S_j = \frac{\exp\left(\beta_0 + \sum_k \beta_k x_{khj} - \alpha p_j + \xi_j\right)}{1 + \sum_{i=1}^{J} \exp\left(\beta_0 + \sum_k \beta_k x_{khi} - \alpha p_i + \xi_i\right)}, \tag{2}$$

where S_j is the market share of firm j. This is a multinomial logit (MNL) model of discrete choice among differentiated products.

It is also well known that the simple MNL model in (2) suffers from the proportionate draw problem (also called the "independence of irrelevant alternatives, or IIA problem), meaning that the cross-elasticities for all alternatives are equal. While Berry (1994) and Nevo (2001), among others, employ a random coefficients version of (2) (the mixed logit) that avoids the proportionate draw problem, in this study we achieve the same result in a more straightforward

manner. Instead of allowing the β_k parameters in (2) to be random variables as in the mixed logit model, we eliminate the proportionate draw problem by explicitly recognizing the spatial dependence of banks that sell very similar services in markets that may potentially overlap. Before allowing space to enter the model, however, we first derive an expression for the supply of banking services and then allow spatial considerations to enter both sides of the model.

The supply of banking services is derived under the assumption that banks compete in prices, or play a Bertrand-Nash spatial pricing game. Details of the optimal pricing equation that results from this assumption are provided in Appendix A, so we summarize the outcome here. If banks maximize profit, then the price charged by bank *j* depends only on the marginal utility of income (α), the marginal cost of producing banking services (c_j), its share of the market (S_j) and a measure of the departure from perfectly competitive pricing (θ):

$$p_j = \frac{\theta}{\alpha(1 - S_j)} + c_j, \tag{3}$$

where θ is interpreted as a measure of market power that is due to product or service differentiation (Bresnahan, 1989).

3.3 Spatial Model of Banking Competition

To this point, the conceptual model of banking demand and pricing reflects relatively standard assumptions in the empirical industrial organization literature. Competition between banks, however, is inherently spatial as borrowers typically travel to the branch in order to complete a transaction, despite the improvement in online banking technologies. As a spatial problem,

transportation costs, search costs and informational asymmetries all factor into the total cost of choosing one bank over another. When borrowers are separated from geographically disparate firms, the firms will posses a degree of market power and can be expected to price accordingly (Greenhut and Greenhut, 1975; Gabszewicz and Thisse, 1992).

Spatial competition, however, imposes additional restrictions on the form of the econometric model. With non-zero transportation costs, a consumer's utility depends on how far he or she must travel to patronize a given bank. Assuming consumers are evenly distributed over the market area, the distance from one bank to the next represents an appropriate proxy for the average distance from a given consumer. Distance, however, is a relative concept. Is distance to be measured along a straight line, a transportation artery or perhaps some other arbitrary definition of the relevant geographic "market?" Therefore, we measure distance in three different ways: (1) Euclidean distance from bank i to each other bank j, (2) whether bank i shares a common market boundary with another bank, j, and (3) if bank i and bank j are either nearest neighbors in an absolute sense, or lie within a small, defined radius of each other. In each case, we define a spatial weight matrix, $\boldsymbol{W}$, where each element (w_{ij}) is derived from a measure of the distance between bank i and bank j and represents the weight or importance attached to other observations in influencing the data observed for bank i. In the Euclidean distance case, distance is measured in terms of inverse, or proximity, so that the weight attached to a distant bank is smaller than one that is near. In the common boundary and nearest neighbor cases, each element w_{ij} is a binary indicator of whether banks i and j share a common market boundary, or are nearest

neighbors, respectively.[6] Without well-defined priors as to the appropriate definition of distance, we estimate the entire structural model including each distance metric and compare the results.

As specified in (3), the logit demand model is highly non-linear in all own- and cross-prices and market shares. However, accounting for spatial correlation is problematic in non-linear models. Therefore, we apply the inversion approach suggested by Berry (1994) and take the log of (3), subtract the share of the outside good (S_0) from both sides, add a spatial autoregressive term and write the result in matrix notation to produce a demand equation that is linear in each of its arguments:

$$\begin{aligned} \ln \boldsymbol{S} - \ln(S_0) &= \boldsymbol{\beta_0} + \boldsymbol{\beta}'\boldsymbol{x} + \boldsymbol{\alpha}'\boldsymbol{p} + \lambda_s \boldsymbol{W} \ln \boldsymbol{S} + \boldsymbol{\xi} \\ \boldsymbol{\xi} &= \lambda_\xi \boldsymbol{M} \boldsymbol{\xi} + \boldsymbol{u}, \end{aligned} \tag{4}$$

where $\boldsymbol{u}$ is an iid error term with variance σ^2, $\boldsymbol{M}$ is a spatial weight matrix (not necessarily using the same distance metrics as $\boldsymbol{W}$) and the λ_is are spatial autoregressive parameters. LeSage (1998) suggests defining $\boldsymbol{M}$ as the inner product of the $\boldsymbol{W}$ matrix in the Euclidean distance case, so we adopt this approach as well.

For the nearest neighbor weight matrix, we define $w_{ij} = 1.0$ for all banks within 1.5 miles of bank i and the spatial error matrix, $m_{ijk} = 1.0$ for the one bank, j, that is nearer than any others. In the common boundary case, we define $\boldsymbol{M}$ as a row-stochastic version of the symmetric $\boldsymbol{W}$ matrix used in the spatial autoregressive equation as suggested by LeSage (1998). Solving (8)

[6] There are an infinite number of ways to define contiguity. For example, Pinkse and Slade (2002) use discrete measures of whether businesses lie on the same street (Pinkse and Slade, 1998), while Kalnins (2003) uses Thiessen polygons to define a set of common boundaries shared by firms in the same market. Pinkse, Slade and Brett (2002), in fact, estimate a semi-parametric model in which they endogenize spatial weights within a generalized method of moments (GMM) procedure.

for ln $\boldsymbol{S}$ gives:

$$\ln \boldsymbol{S} = (\boldsymbol{I} - \lambda_s \boldsymbol{W})^{-1}(\ln(S_0) + \boldsymbol{\beta_0} + \boldsymbol{\beta}'\boldsymbol{x} + \alpha'\boldsymbol{p} + \boldsymbol{\xi}), \tag{5}$$

where $\boldsymbol{I}$ is an N x N identity matrix for N cross sectional observations. Given the expression for market share in (9), the derivative with respect to price, and hence the cross-price elasticity, is a function of all other banks' prices through the spatial weight matrix, thus eliminating the IIA problem typical of non-spatial logit models. Taking the derivative of (9) with respect to $\boldsymbol{p}$, substituting into (6) and solving for $\boldsymbol{p}$ gives:

$$\boldsymbol{p} = (\boldsymbol{I} - \lambda_s \boldsymbol{W_k})^{-1}\left(\frac{\theta}{\alpha(1 - \boldsymbol{S})}\right) + (\boldsymbol{I} - \lambda_s \boldsymbol{W_k})^{-1}(\boldsymbol{c} + \boldsymbol{\mu}), \tag{6}$$

where μ may be spatially autocorrelated as in the case of ξ above. For estimation purposes, equation (10) is written in terms of the absolute price-markup value, or:

$$\boldsymbol{p} - \boldsymbol{c} = \lambda_s \boldsymbol{W}\boldsymbol{p} + \left(\frac{\theta}{\alpha(1 - \boldsymbol{S})}\right) + \boldsymbol{\mu}, \tag{7}$$

so the markup over cost is due to a spatial-differentiation component and a component due to other sources of service-differentiation. The estimating equations are (8) and (11). Note that the equality of λ_s between the demand and pricing equations represents a cross-equation restriction implied by theory that can be imposed and tested in the empirical application below. Further, testing for spatial market power involves testing whether λ_s is equal to zero. Under the null hypothesis the markup is due entirely to service differentiation. However, in the alternative that

λ_s is different from zero, some of the markup is due to spatial separation as well.

3.4 Estimating the Spatial Competition Model

Clearly, both (8) and (11) still consist of endogenous right-hand-side variables. There are a number of reasons why prices are likely to be endogenous. Any market knowledge possessed by the banker but not by the econometrician will influence $\boldsymbol{p}$, but is typically assumed to be part of ξ_j. Spatial models are typically estimated in the structural forms of (8) and (11) so the weighted-average prices of all other banks are also endogenous. The most common way to obtain consistent parameter estimates in this case is to estimate each equation separately using maximum likelihood (Anselin 1988, 2002).[7] In order to express the likelihood function more clearly, simplify notation by writing $\boldsymbol{y} = \ln(\boldsymbol{S})$, $\boldsymbol{\gamma}'\boldsymbol{z} = \ln(S_0) + \beta_0 + \boldsymbol{\beta}'\boldsymbol{x} + \boldsymbol{\alpha}'\boldsymbol{p}$, $\boldsymbol{A} = (\boldsymbol{I} - \lambda_s \boldsymbol{W})^{-1}$, and $\boldsymbol{B} = (\boldsymbol{I} - \lambda_\xi \boldsymbol{M})^{-1}$. In terms of the most general form of the demand equation given in (8), the log-likelihood function is written as:

$$L = -n\ln(2\pi) + \ln|\boldsymbol{A}| + \ln|\boldsymbol{B}| + \left(\frac{1}{2\sigma^2}\right)(\boldsymbol{A}\boldsymbol{y} - \boldsymbol{\gamma}'\boldsymbol{z})^{-1}\boldsymbol{B}'\boldsymbol{B}(\boldsymbol{A}\boldsymbol{y} - \boldsymbol{\gamma}'\boldsymbol{z}), \qquad \textbf{(8)}$$

and a similar function provides the likelihood function for the pricing equation in (11). For estimation purposes, the likelihood function is concentrated with respect to the parameters $\boldsymbol{\beta}$, α,

[7] Kelejian and Prucha (1998) describe a generalized method of moments (GMM) approach that obviates the need to calculate high-dimensional log-determinants in the more usual spatial likelihood function. Bell and Bockstael (2000) provide an application of the GMM method to real estate data. However, for relatively small sample sizes, such as the one proposed herein, maximum likelihood is both more efficient, both in a statistical and computational sense.

and σ and solved with respect to the spatial autoregression and correlation parameters, λ_s and λ_ξ, respectively.

Whether it is necessary to allow for both spatial autoregression and spatial error correlation, however, is an empirical matter. Fortunately, there are a number of tests that can be used with the maximum likelihood approach described above: a Lagrange multiplier test that uses the maximum likelihood estimates directly (LM-SL), and then four tests that define the alternative as OLS regression of only a spatial autogressive version of both models: a Moran I statistic (Z_I), a likelihood ratio test (LR), a simplified Lagrange multiplier test (LM-SEM) and a Wald statistic (WD).[8] In each case, the null hypothesis to be tested is: H_0: $\lambda_\xi = 0$. Based on the results of these specification tests, we test the primary hypothesis of the paper – whether banks in the upper midwest exercise market power in their lending activities.

There are two tests for market power. The first concerns the conduct parameter, θ, which was described above. If this parameter is significantly different from zero, then non-metro banks exercise market power in the traditional way, that is, as a consequence of product or service differentiation. Controlling for this form of market power, the second test for spatial market power concerns the autoregressive parameter, λ_s. If two banks are located at either ends of a Hotelling line, a movement apart is referred to as differentiation or the "market power effect" while moving together, or the principle of minimum differentiation, is the "market share effect" (Pinkse and Slade 1998). In terms of the pricing model, if $\lambda_s < 0$, then rival banks reduce prices as they move closer together and the competitive or market share effect dominates. On the other

[8] LeSage (1998) provides a detailed derivation for each test statistic so we only summarize their application in this paper.

hand, if $\lambda_s > 0$, then rivals raise prices as they move closer together – the collusive or market power effect dominates. Which of these effects is more important depends on whether there is mutual value to providing and receiving soft information. If so, then the welfare implications of geographic separation should be of critical interest to bank regulators.

3.5 Welfare Impacts of Imperfect Competition

One advantage of the logit model used in this study is the straightforward way in which welfare impacts can be calculated. Economic welfare is the sum of consumer surplus and producer surplus. Consumer surplus (CS) is calculated from the indirect utility function defined in equation (3) above, or the "log sum" of utilities obtained from each discrete choice alternative, after accounting for the equilibrium markup:

$$CS = \frac{1}{\alpha}\ln\left(1 + \sum_j \exp(\beta_{0j} + \sum_k \beta_k x_{kj} + \lambda_s \sum_i w_{ij} S_i + \xi_j)\right) - \sum_j c_j(\boldsymbol{w}) - \sum_j \frac{\theta}{\alpha(1 - S_j)}, \qquad \textbf{(9)}$$

where w_{ij} is the *ij* element of $\boldsymbol{W}_k$. Producer surplus (PS), on the other hand, is found by calculating aggregate firm profit at observed prices and output levels using equation (5) above:

$$PS = \sum_j \pi_j = \sum_j \left(\left(\lambda_s \sum_i w_{ij} p_i + \frac{\theta}{\alpha(1 - S_j)}\right) S_j Q - F_j\right), \qquad \textbf{(10)}$$

so total economic welfare is given by $W = CS + PS$. Simulating equations (13) and (14) over alternative values for the spatial autoregressive parameter shows how economic welfare is likely to change over different modes of economic conduct.

4. Data Description

The data used for this study are drawn from the FDIC Reports on Statistics on Depository Institutions (RSDI) and Summary of Deposits (SOD). These data describe the financial and operating characteristics of 1,112 non-metro banks located in the upper midwest region of the U.S. – North Dakota, South Dakota and Minnesota – for calendar year 2005.[9]

Focusing on non-metro banks is important not only for the economic reasons provided in the introduction, but for econometric reasons as well. Spatial econometric methods are only appropriate when location in geographic space is an important differentiating feature among the sample observations. If our sample were to include both metro and non-metro banks, then distance measures lose economic meaning.[10] For example, had we included Wisconsin in this sample, we would have introduced the confounding factor of both the Chicago and Milwaukee banking markets – markets where distance is measured in terms of blocks instead of miles. Including these markets would also have diluted the importance of the non-metro banks in overall lending activity.

In addition to financial data for each bank, we require geographic coordinates for the location of each bank. Since this information was not directly available, a geocoding procedure was used to match bank street addresses with road network information reported in the 2000 U.S.

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[9] In order to focus the analysis only on competitors in non-metro areas, we also exclude branches of non-metro headquartered banks located in urban areas.

[10] Shaffer and DiSalvo (1994) discuss the problems inherent in defining the geographic extent of a banking market. The spatial approach used in this paper can be used for this purpose, although its not among our specific objectives.

Census Topologically Integrated Geographic Encoding and Referencing (TIGER) line shape files. By matching addresses with census location data, we were able to generate coordinates for each branch location in the sample data. The TIGER road network maps used in the geocoding procedure were obtained from the Environmental Systems Research Institute, Inc. (ESRI) website.

In adopting an "intermediation approach" to define the bank production technology, we consider various types of loans as a composite output variable. Loans, in turn, are comprised of real estate, commercial, agricultural, consumer and credit card lending.[11] An aggregate output price is defined as the ratio of total interest income to the stock amount of all loans. Inputs consist of physical capital (bank premises), total deposits, number of employees and net financial capital (equity). Input prices are defined as the ratio of the total expenditure on each input item to the stock amount reported in the RSDI in December 2005. These variable definitions are standard in the empirical banking-conduct literature so are relatively uncontroversial (Shaffer, 1994, 2004; Berger, 1995, and others). Because each of these quantities is reported only on a corporate-level basis, and we require branch-level data for the spatial competition model, we assume all inputs and outputs at the branch level are proportionate to branch deposits. Branch deposit data are reported in the SOD database. Any branch that reported less than $1,000 in deposits was assumed to be only a single ATM or store-front operation and excluded from further analysis.

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[11] Note that this definition of output aggregates over loans of different size. Although we do not have data on individual loans, because we control for each bank's location and area of specialization, the econometric model accounts for likely differences in portfolio composition. Further non-interest income consists of only 15% of all revenue for the banks represented in the data set. While this is not a trivial amount, excluding non-lending output is consistent with our focus on loan pricing.

The demand model also consists of a number of other explanatory variables. Each of these were either taken from the RSDI data or from Bureau of Census sources on a zip-code level. Specifically, in order to test the hypothesis that customers of primarily agricultural banks are less sensitive to price than other businesses, the demand for banking services is assumed to depend upon the ratio of agricultural to total loans. The second attribute consists of an "efficiency ratio" for each bank. Efficiency in this context is defined as "...noninterest expense, less the amortization expense of intangible assets, as a percent of the sum of net interest income and noninterest income..." (FDIC). Although efficiency can be interpreted as a production attribute, in this context it is a better reflection of the relative aggressiveness of a particular bank in attracting and retaining business. Third, we measure the potential of each bank's local market by including a number of demographic and socioeconomic variables that vary by zip code: total population, median income and household size. While the effect of the first two variables is obvious, the third is intended to capture the greater need for loans by larger families, after controlling for income. In addition to these continuous variables, the demand model also includes fixed state-level and specialty-group effects. These variables also appear in the pricing equation, on the assumption that margins vary by unobserved state and industry attributes. Table 1 provides a summary of all variables used in the econometric model.

[table 1 in here]

5. Results and Discussion

Descriptive data on the nature of the branch network in the upper-midwest, and recent trends, corroborate many of the insights referred to in the community banking literature cited in the

introduction. First, confirming more general, national trends the total number of bank holding companies (BHC) in the upper midwest has declined from 199 in 2000 to 87 in 2005. On the other hand, the number of banks not associated with a BHC have declined more modestly, from 35 in 2000 to 32 in 2005. Second, the difference in composition between the two types of institution (BHC vs non-BHC) has also changed dramatically. While the number of branches associated with each BHC has risen from 6.5 to 12.8, on average, non-BHC branches have remained virtually constant, from 4.6 per bank in 2000 to 5.2 in 2005 (see table 1). Third, multi-BHCs tend to locate in larger population centers (average ZIP code population in 2005 for multi-BHC branches was 11,080) while non-BHC entities choose to locate in smaller communities (6,201 average population for non-BHC branches). Fourth, while all bank-types tend to draw similar average-branch deposits from small markets ($29,575 for multi-BHCs, $23,790 for single-BHCs and $22,765 for non-BHCs), multi-BHCs tend to draw far larger amounts from branches located in larger markets ($95,537 versus $44,786 for single-BHCs and $22,881 for non-BHCs).[12] Finally, multi-BHC branches are located 4.298 miles from their closest competitor, on average, while non-BHC branches are located 4.148 miles away. Although this difference is relatively small (0.15 miles), it is statistically significant. Whether this relative proximity has any effect on pricing power, however, must be resolved through the full spatial pricing model.

Rejection of the null hypothesis that banks price competitively suggests that non-metro banks in the upper midwest do indeed price their services as if they have some monopoly power.

[12] A "small market" is defined as a ZIP code with less than 10,000 population. Similar qualitative conclusions are drawn if population levels of 5,000 or 15,000 are chosen instead.

In terms of alternative models of spatial competition, Bertrand-Nash competition is implied when $\lambda_s = -1$ (with a row-normalized weight matrix) because firms set prices as if any price reduction will earn them additional market share. Collusive rivalry, on the other hand is implied when $\lambda_s = 1$ as firms "collude" to the extent that the tacitly carve up the spatial market into a set of non-overlapping monopolies. Each firm earns a share of the monopoly profits generated by the entire economy. Finally, Cournot-Nash behavior arises when $\lambda_s = 0$ as firms essentially ignore price changes by rivals and set output levels based on their perception of the size of their residual spatial market.

The considerable flexibility of spatial estimation comes with a cost as there are many alternative definitions of the spatial weight matrix (inverse distance, common boundary or nearest neighbor, for example), and different forms within each broad definition. We begin by presenting results from the specification testing procedure described above in order to determine which of the spatial autoregressive (SAR), spatial error (SEM) or more general spatial autocorrelation (SAC) models is to be used to test for market power. Once we have chosen among these three alternatives, it will then be necessary to choose among possible specific definitions of *each type* of weight matrix. These results are presented along with the demand and pricing estimates below. Table 2 shows the results from each of the spatial specification tests described above, for both the demand and pricing models, beginning with the Euclidean distance spatial weight matrix. In terms of the demand model, four of the five tests reject the null hypothesis, suggesting that the data do contain significant spatial error autocorrelation. For the pricing model, however, the specification tests are less conclusive. Each test based on least-squares residuals fails to reject the null, whereas the LM-SAR test, based on the maximum

likelihood SAR residuals, strongly rejects the null. Based on this evidence, therefore, we choose the most general spatial model for the Euclidean weight matrix.

[table 2 in here]

The results in the common boundary and nearest neighbor cases are somewhat less ambiguous. These results are shown in table 3 and table 4, respectively. For both the demand and pricing models, the common boundary results are unequivocal in their support for a general SAC model as the null hypothesis of $\lambda_\xi = 0$ is rejected in either case. When the spatial weight matrix is defined in terms of nearest neighbors, the results in table 4 also suggest the SAC model is appropriate for both demand and pricing models. Consequently, all subsequent demand and market power estimates are based on general SAC model results.

[tables 3 and 4 in here]

Table 5 presents demand estimates for the Euclidean distance, common boundary and nearest neighbor models. In each case, the model appears to fit the data quite well as the R^2 value ranges from 0.533 to 0.549, which is reasonable in cross-sectional data. Although the primary objective of this paper is to test for market power among non-metro banks, the spatial structure of demand for banking services is also critical to their pricing behavior. Specifically, the magnitude of firm-level demand elasticities indicates whether banking services are highly differentiated (low elasticity) or near-homogeneous (high elasticity). In the Euclidean distance case, the estimates in table 5 imply an own-price elasticity of demand of -0.221, while the common boundary model implies an elasticity of -0.267 and the nearest neighbor model -0.244.[13] Comparing the goodness of fit across all three specifications using paired likelihood ratio tests at

[13] The price elasticity of demand is calculated as: $\varepsilon_d = -\alpha p_i(1 - S_i)$.

a 5.0% level suggests that the nearest neighbor model represents the best fit to the demand data, so the latter elasticity is likely the best estimate.[14] Regardless of which model is used, however, it is apparent that the demand for banking services is relatively inelastic. Consequently, banks are able to earn significant markups over cost based on product or service differentiation alone. Among other variables in this table, the demand for banking services is significantly lower for agricultural banks relative to non-agricultural banks and for those that are relatively efficient (low non-expense to interest income ratio). On the other hand, the demand for banking services rises in local population and income (in the Euclidean distance and common boundary cases). Each of these results is consistent with prior expectations.

[table 5 in here]

Of greater relevance to the objectives of this study, however, are the spatial autoregression parameters in table 5. In two of three cases (Euclidean distance and nearest neighbor), the spatial autoregression parameter (λ_s) is significantly different from zero, suggesting that the demand for banking services is, in part, determined by a bank's location relative to its competitors. Perhaps counterintuitively, market power increases with the proximity of a bank to its rivals. This result, however, follows directly from the strategic complementarity of prices. Specifically, increasing the market share of a bank that is nearer / contiguous / a neighbor leads to a greater share of the own-bank. If bank A raises its loan rates, it will expect a lower market share. However, if a neighboring bank B also raises its rates in response to the perceived increase in demand that results from bank A raising its rates, then it can

[14] The critical value of a χ^2 distributed random variable with four degrees of freedom at a 5.0%is 9.49, while the calculated statistic is 36.784 for the nearest neighbor / Euclidean distance pair and 14.996 between nearest neighbor and common boundary.

expect a lower share to result. Because both banks' market shares move in the same direction, this is evidence of tacit collusive behavior. The relative magnitude of banks' collusive market power, however, appears to be limited as the point estimate ranges from 0.029 in the common boundary case to 0.301 in the nearest neighbor model – both far below the perfectly collusive benchmark of 1.0. Moreover, spatial market power estimates from the demand model are necessarily inconclusive because they do not take into account the cost of providing banking services, nor mark ups due to product differentiation.

Estimates of the pricing model in table 6, on the other hand, provide a more conclusive test of imperfectly competitive behavior among banks. Based on likelihood ratio tests, the Euclidean distance model is preferred to either the common boundary or nearest neighbor models. With this definition of distance, or proximity, the spatial autoregression parameter, λ_s, is again significantly greater than zero. Although this estimate of spatial market power is relatively small, the fact that it is significantly different from zero indicates that geographic distance does indeed play a role in determining market power.[15] The interpretation of this parameter is similar to that given in the demand model above. Namely, if a bank is relatively close to its rivals, it will be able to charge higher prices. Given the strategic complementarity of prices, this is evidence of weakly collusive pricing behavior among non-metro banks. While somewhat surprising given the more common expectation that geographic separation generates pricing power, this result is fully consistent with the literature on the value of soft information to community banks (Berger

[15] In the theoretical model, λ_s from the demand model should be the same as the estimate in the pricing model. The fact that they differ is a consequence of the sequential estimation procedure used here. Statistical tests (likelihood ratio) confirm that this difference is significant. However, the fact that the estimates are qualitatively the same suggests that spatial market power is indeed an artifact of the data.

and Udell, 2002; Scott, 2004). If banks tend to locate near their customers, then proximity among banks implies proximity to businesses. Proximity to clients, in turn, is regarded as one of the ways in which community banks are able to exercise a strategic advantage over larger rivals in the acquisition of soft information.

Finding that the degree of geographic market power is small in an economic sense is due to the fact that much of the departure from competitive pricing in this model is explained by non-spatial factors. Indeed, estimates of θ suggest that much of a bank's market power derives from product and service differentiation. If we had not allowed for both spatial and non-spatial sources, our conclusions regarding the existence of geographic market power would have been significantly biased. Similarly, if we had not allowed for spatial market power, our results would likely have attributed too much significance to service differentiation, brand loyalty or other traditional sources of pricing power.

[table 6 in here]

Due to the fact that there are many ways to define economically-relevant measures of distance, spatial econometric results tend to yield a proliferation of parameter estimates. Therefore, we summarize the market power results from all forms of the demand and pricing models in table 7. While the numerical estimates of market power may vary among the definitions of distance, the qualitative conclusions are consistent – spatial separation is indeed an important source of market power.

[table 7 in here]

Whether due to spatial or non-spatial competition, the importance of imperfectly competitive pricing behavior depends on the welfare effects relative to a competitive benchmark.

One of the advantages to using a logit model of demand and pricing is the ability to recover welfare results in a simple and straightforward way. Therefore, to assess the relative importance of spatial market power on welfare outcomes in the upper midwest, we simulate the welfare model in (17) and (18) using the parameters shown in tables 5 and 6 for the preferred pricing model (Euclidean distance) relative to a competitive benchmark, collusion and spatial Cournot. For comparison purposes, we also simulate welfare outcomes under alternative assumptions of non-spatial market power. In the base case, the non-spatial conduct parameter is set equal to its value in table 6. Alternative values for θ range from 1 (collusion, or monopoly outcome) to 0, or Bertrand-Nash rivalry. The results of all of these simulated scenarios are shown in table 8.

[table 8 in here]

Clearly, the spatial autoregressive, or spatial market power, parameter has a significant impact on consumer surplus, producer surplus and, therefore, on the ultimate welfare outcome. Because the estimated value of λ_s is relatively close to zero in the base case (0.096), moving toward a competitive outcome (scenario 5 in table 8) represents a relatively modest change in economic value. Consumer surplus rises by approximately $77.0 million, while producer surplus falls by $45.0 million, for a net gain of $32.0 million. Comparing this scenario to the base case nonetheless demonstrates that fully 38.0% of bank surplus ($45.0 million on $118.92 million) is due to spatial market power. However, moving from the base case estimate of 0.096 to a more collusive outcome (scenario 4 in table 8) is expected to cost the upper midwest economy some $35.0 million in economic output in the extreme case ($\lambda_s = 1$) or $22.5 million at the value estimated using the nearest neighbor spatial model ($\lambda_s = 0.626$). While these amounts may be trivial in regions or urban areas with higher per capita GDP, they represent significant losses in

the non-metro upper midwest.

Perhaps not surprisingly given the relatively high estimate of non-spatial market power in the Euclidean distance model, variations in θ between the extremes of collusion and competitive conduct have an even greater impact on welfare. In fact, even at the base-case spatial market power estimates, the greatest welfare outcome occurs under Bertrand-Nash conduct. Moving from the base-case scenario of $\theta = 0.56$ to a fully collusive outcome of $\theta = 1.00$ reduces consumer surplus by $245.0 million, while generating $90.4 million in producer surplus for a net loss of $154.2 million. Similarly, moving to the competitive outcome ($\theta = 0.0$) creates $111.5 million in consumer surplus, at a cost of only $113.0 million in producer surplus for a net gain of nearly $200.0 million. Finally, removing both sources of market power results in a net gain of $273.1 million, due entirely to a gain in consumer surplus of $388.1 million and a near total loss of producer surplus.

Although these welfare results appear to be significant in an economic sense, they are perhaps more meaningful when placed in the context of the magnitude of general economic activity in the region. Relative to a more general benchmark – the total GDP provided by banking and financial services in each state – the lost welfare due to non-spatial market power is approximately 1.7% while that lost due to spatial market power is 0.2%.[16] In an absolute sense, therefore, the amount of economic value lost to both sources of market power is not inconsequential. Further, despite the fact that spatial market power does play a role in pricing bank services, traditional sources of market power – differentiation, key personnel, relationship –

[16] Estimates of GDP associated with "federal reserve banks, credit intermediation and related services" are provided by the Bureau of Economic Analysis for the most recent year, 2004.

continue to play a more important one.

These results are not inconsistent with recent findings on the importance of geographic distance in lending reported by Petersen and Rajan (2002) in that we also find that geography has a relatively small role in the total market power exercised by a non-metro bank. On the other hand, finding that bank market power rises in the proximity to their customers is fully consistent with Berger and Udell (2002) and Scott (2004) who describe the strategic advantages local banks enjoy in overcoming the inherent organizational disadvantages experienced by larger, centralized lending institutions. In general, our results are indeed complementary to the existing literature as we add quantitative measures of both the absolute importance of spatial market power, and its importance relative to non-spatial sources.

6. Conclusions and Implications

This study investigates the role of geographic distance among banks in the non-metro upper midwest as a source of market power. If community banks are indeed able to use their proximity to local businesses as a source of strategic advantage over larger, more distant competitors, then it should be the case that nearness represents a source of pricing power. While the theoretical literature suggests that banks no longer need to be located near their rivals, there are nonetheless powerful arguments to the contrary. Namely, for small, community banks to profit from soft information and relationship lending, proximity is necessary.

Previous studies report little evidence of market power of any type. However, none of the prior literature considers the independent effects of spatial and non-spatial market power in the same model. Consequently, their market power estimates are likely to be biased. We incorporate

both sources of market power in a structural, spatial econometric model of the non-metro upper midwest banking industry.

Structural models consider the demand, supply and equilibrium market price of banking services. The demand model consists of a discrete-choice, random-utility specification in which borrowers are assumed to choose the bank that provides the highest utility. The supply of loans, on the other hand, is implied by estimating a normalized quadratic cost function along with the first order conditions to a Bertrand-Nash game in loan pricing. On both the demand and supply sides of the market, we explicitly take into account the fact that demand and pricing behavior is likely to be inherently spatial, or depend on the distance between banks. In this way, we are able to test for both spatial and non-spatial sources of market power. Simulating economic equilibrium under a variety of competitive assumption allows us to make more concrete assessments of the relative economic importance of market power in banking.

Spatial relationships among non-metro banks are defined in three ways: (1) Euclidean distance, (2) contiguity, or sharing a common boundary and (3) two definitions of whether banks can be described as "nearest neighbors." Estimates of the resulting spatial, discrete choice equilibrium model show significant market power from both spatial and non-spatial sources, although non-spatial market power appears to be more important in an economic sense, than spatial market power. Perhaps most importantly, we find that spatial market power derives from banks locating near to each other, and hence their customers, rather than in more distant, local monopolies. This result supports the theoretical literature on relationship banking that argues for the existence of significant strategic advantages possessed by local banks that are better positioned to obtain valuable soft information from otherwise "informationally opaque"

borrowers.

Simulating equilibrium economic welfare under various competitive assumptions show that the estimated outcome represents a net loss of economic welfare of approximately $388.1 million, most of which, however, is due to non-spatial sources of market power. The fact that most of the economic welfare losses are due to traditional sources of market power may be due to the proliferation of internet banking services and the declining importance of physical distance and location in banking. That said, however, internet banking should also reduce many of the other non-geographic sources of differentiation and should lead to convergence in service attribute space as well as it has in physical space.

Despite the promise of spatial econometric methods in contributing to research on the competitive structure of banking, future research can improve on our approach in several ways. First, Berger and Humphrey (1991) and Berger and Hannan (1998) and others account for the potential confounding effects of inefficiency in a much more rigorous way than we have here. Second, Pinkse, Slade and Brett (2002) estimate a semi-parametric model of spatial rivalry that combines the different definitions of space that we have used here. Combining these approaches may yield a more definitive result with respect to our finding of non-spatial market power. Third, testing this approach using data from other geographic markets at other time periods may produce significantly different results depending upon the nature of the banks involved and the competitive environment in which they operate. Fourth, a more direct test of the findings of Petersen and Rajan (2002) regarding the declining importance of space in lending to small businesses would involve allowing both spatial and non-spatial market power to vary over time. Doing so, however, would require a more lengthy time series for each bank and a spatio-temporal

extension to the one presented here. Finally, because our data describes only non-metro banks located in a relatively rural area, the results are not likely to generalize to the bulk of the banking industry in the U.S.

7. Appendix A

In this appendix, we derive the pricing equation (3) in the text. The optimization problem for a representative bank is written as:

$$\pi_j = \max_{p_j} (p_j - c_j)S_jQ - F_j,$$

where c_j is the marginal cost of banking services, Q is the size of the total market, and F_j is the fixed cost of bank j. The marginal cost of production is assumed to be derived from a normalized quadratic cost function, C_j. A normalized quadratic cost specification is chosen because it is flexible (meaning that it is an approximation to an arbitrary functional form), it is inherently homogeneous in prices, it is affine in output without further restriction, and it imposes convexity in output, while concavity in prices, symmetry, and monotonicity can be maintained and tested. Total production and marketing costs are a function of the primary inputs to providing banking services: labor, physical capital, and deposits, so the cost of producing output q_j is:

$$C_j(\boldsymbol{w},q_j) = \gamma_1^T\boldsymbol{w} + \gamma_2 q_j + (1/2)(\boldsymbol{w}^T\gamma_3\boldsymbol{w} + \boldsymbol{w}^T\gamma_4 q_j) + \mu_j.$$

where $\boldsymbol{w}$ is a vector of normalized input prices (normalized by a producer price index for financial services), q_j is the output of bank j (= S_jQ), μ_j is an iid normal error term. With this cost function, the marginal cost of banking services ($c_j = \partial C_j/\partial q_j$) is linear in normalized prices, so retains the attributes described above.

Assuming a Bertrand-Nash equilibrium, the first order condition to the firm's profit maximization problem defined above becomes:

$$\frac{\partial \pi_j}{\partial p_j} = S_j Q + (p_j - c_j) Q \left(\frac{\partial S_j}{\partial p_j} \right) = 0.$$

Substituting the expressions $\partial S_j / \partial p_j = -\alpha S_j (1 - S_j)$ into this solution, solving for the price charged by bank *j*, and adding a parameter, θ, that measures any deviation from the hypothesized Bertrand-Nash outcome, gives an estimable equation for the inverse supply equation:

$$p_j = \frac{\theta}{\alpha(1 - S_j)} + c_j,$$

which appears in the text. In this equation, the "conduct parameter" θ constitutes the usual "new empirical industrial organization (NEIO)" test for market power (Bresnahan, 1989).

8. Reference List

Anderson, S. P., A. de Palma and J. -F. Thisse. 1992. Discrete Choice Theory of Product Differentiation Cambridge, MA: MIT Press.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models* Dordrecht, NL: Kluwer.

Anselin, L. 2002. "Under the Hood: Issues in the Specification and Interpretation of Spatial Regression Models," *Agricultural Economics* 27: 247-267.

Barro, R. J. 1991. "Economic Growth in a Cross Section of Countries." *Quarterly Journal of Economics* 106: 407–433.

Barro, R. J., and Lee, J. W. 2003. "IMF programs: Who is Chosen and What are the Effects?" Australian National University, Economics RSPAS, Trade and Development.

Barros, P. P. 1999. "Multimarket Competition in Banking, with an Example from the Portuguese Market," *International Journal of Industrial Organization, 17*(3), 335-352.

Bell, K. P. and N. E. Bockstael. 2000. "Applying the Generalized-Moments Estimation Approach to Spatial Problems Involving Microlevel Data," *Review of Economics and Statistics* 82: 72-82.

Berger, A. N. 1995. "The Profit-Structure Relationship in Banking – Tests of Market-Power and Efficient-Structure Hypotheses," *Journal of Money, Credit and Banking* 27: 404-431.

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

Berger, A. N. and T. Hannan. 1997. "Using Measures of Firm Efficiency to Distinguish Among Alternative Explanations of the Structure-Performance Relationship," *Managerial Finance* 23: 6-31.

Berger, A. N. and T. Hannan. 1998. "The Efficiency Cost of Market Power in the Banking Industry: A Test of the Quiet Life and Related Hypotheses," *Review of Economics and Statistics* 80: 454-465.

Berger, A. N., A. Saunders, J. M. Scalise and G. F. Udell. 1998. "The Effects of Bank Mergers and Acquisitions on Small Business Lending," *Journal of Financial Economics* 50: 187-229.

Berger, A. N., R. S. Demstez, and P. E. Strahan. 1999. "The Consolidation of the Financial Services Industry: Causes, Consequences, and Implications for the Future," *Journal of Banking and Finance* 23: 135-194.

Berger, A. N. and G. F. Udell. 2002. "Small Business Credit Availability and Relationship Lending: the Importance of Bank Organisational Structure," *Economic Journal* 112: F32 - F53.

Berger, A. N., I. Hasan, and L. F. Klapper. 2004. "Further Evidence on the Link Between Finance and Growth: An International Analysis of Community Banking and Economic Performance." *Journal of Financial Services Research* 25: 169-202.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan and J. C. Stein. 2005. "Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks." *Journal of Financial Economics* 76: 237-269.

Berry, S. 1994. "Estimating Discrete-Choice Models of Product Differentiation," *Rand Journal of Economics* 25: 242-262.

Berry, S., J. Levinsohn, and A. Pakes. 1995. "Automobile Prices in Market Equilibrium," *Econometrica* 63: 841-890.

Bikker, J. A. and K. Haaf. 2002. "Competition, Concentration and their Relationship: An Empirical Analysis of the Banking Industry," *Journal of Banking and Finance* 26: 2191-214.

Bird, G., and D. Rowlands. 2001. "World Bank Lending and Other Financial Flows: Is There a Connection?" *The Journal of Development Studies* 37: 83–103.

Bresnahan, T. F. 1989. "Empirical Studies of Industries with Market Power." in R. Schmalensee and R. D. Willig, eds. *Handbook of Industrial Organization, vol. II.* New York: North-Holland. pp. 1011-1057.

Brickley, J. A., J. S. Linck and C. W. Smith, Jr. 2003. "Boundaries of the Firm: Evidence from the Banking Industry." *Journal of Financial Economics* 70: 351-383.

Bureau of Economic Analysis. *Regional Economic Accounts* (https://www.bea.gov/regional/gsp/action.cfm). February 19, 2007.

Burnside, C. and D. Dollar. 2000. "Aid, Policies, and Growth." *American Economic Review* 90: 847–868.

Butkiewicz, J. L. and H. Yanikkaya. 2005. "The Effects of IMF and World Bank Lending on Long-run Economic Growth: An Empirical Analysis." *World Development* 33: 371-391.

Calem, P. 1994. "The Impact of Geographic Deregulation on Small Banks," *Federal Reserve Bank of Philadelphia Business Review* November/December: 17-30.

Chiappori, P., D. Perez-Castrillo, and T. Verdier. 1995. "Spatial competition in the banking

system: Localization, cross subsides and the regulation of deposit rates," *European Economic Review, 39*(5), 889-918.

Collender, R. N. and S. Shaffer. "Local Bank Office Ownership, Deposit Control, Market Structure and Economic Growth." *Journal of Banking and Finance* 26(December 2002): 21-51.

Critchfield, T., T. Davis, L. Davison, H. Gratton, G. Hanc, and K. Samolyk. 2004. "The Future of Banking in America: Community Banks: Their Recent Past, Current Performance, and Future Prospects." *FDIC Banking Review* 16: 1-56.

DeYoung, R. and D. Duffy. 2002. "The Challenges Facing Community Banks: Straight from the Horses' Mouths." Federal Reserve Bank of Chicago, *Economic Perspectives* 26: 2-17.

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

Featherstone, A. M., and Moss, C. B. 1994. "Measuring Economies of Scale and Scope in Agricultural Banking." *American Journal of Agricultural Economics* 76: 655-661.

Featherstone, A. M. 1996. "Post-acquisition Performance of Rural Banks." *American Journal of Agricultural Economics* 78: 728-733.

Federal Deposit Insurance Corporation. *Statistics on Depository Institutions*. (http://www2.fdic.gov/sdi/main.asp). March, 2006.

Gabszewicz, J. J. and J.-F. Thisse. 1986. "Spatial Competition and the Location of Firms." *Fundamentals of Pure and Applied Economics* 5: 1-71.

Gilbert, R. A. 1997. "Implications of Banking Consolidation for the Financing of Rural America," 131-140.

Greenhut, J. G. and M. L. Greenhut. 1975. "Spatial Price Discrimination, Competition and Locational Effects." *Economica* 42: 401-419.

Kalnins, A. 2003. "Hamburger Prices and Spatial Econometrics," *Journal of Economics and Management Strategy* 12: 591-616.

Keeley, M. C. 1990. "Deposit Insurance, Risk and Market Power in Banking," *American Economic Review* 80: 1183-1200.

Keeton, W. R. 1996. "Do Bank Mergers Reduce Lending to Businesses and Farmers? New Evidence from the Tenth District States." *Federal Reserve Bank of Kansas City Economic Review* 3rd Quarter: 63-75.

Kelejian, H. and K. R. Prucha. 1998. "A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances," *Journal of Real Estate and Finance Economics* 17: 99-121.

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

Mankiw, N. G., Romer, D., and Weil, D. N. 1992. "A Contribution to the Empirics of Economic Growth." *Quarterly Journal of Economics* 107: 407–437

Marsh, T. L., A. M. Featherstone and T. A. Garrett. 2003. "Input Inefficiency in Commercial Banks: A Normalized Quadratic Input Distance Approach," Federal Reserve Bank of St. Louis, Working Paper, November.

Matutes, C. and X. Vives. 2000. "Imperfect Competition, Risk Taking, and Regulation in Banking," *European Economic Review* 44: 1-34.

McNutly, J. E., A. O. Akhigbe, and J. A. Verbrugge. 2001. "Small Bank Loan Quality in a Deregulated Environment: the Information Advantage Hypothesis." *Journal of Economics and Business* 53: 325-339.

Meyer, A. P. and Y. J. Yeager. 2001. "Are Small Rural Banks Vulnerable to Local Economic Downturns?" *Federal Reserve Bank of St. Louis Review* March/April: 25-38.

Nevo, A. 2001. "Measuring Market Power in the Ready-to-Eat Cereal Industry." *Econometrica*, 69: 307-342.

Panzar, J. C. and J. N. Rosse. "Testing for "Monopoly" Equilibrium." *Journal of Industrial Economics* 35(1987): 443-456.

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

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

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

Repullo, Rafael. 2004. "Capital Requirements, Market Power, and Risk-taking in Banking," *Journal of Financial Intermediation* 13, 156-182.

Scott, J. A. 2004. "Small Business and the Value of Community Financial Institutions," *Journal*

of Financial Services Research 25: 207-230.

Shaffer, S. 1993. "A Test of Competition in Canadian Banking," *Journal of Money, Credit and Banking* 25: 49-61.

Shaffer, S. 1999. "The Competitive Impact of Disclosure Requirements in the Credit Card Industry," *Journal of Regulatory Economics* 15: 183-198.

Shaffer, S. 2004. "Patterns of competition in banking," *Journal of Economics and Business* 56, 287-313.

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

Slade, M. 2004. "The Role of Economic Space in Decision Making," Working paper, Department of Economics, University of Warwick, Warwick, UK. March.

Yeager, T. J. 2004. "The Demise of Community Banks? Local Economic Shocks are not to Blame.*" Journal of Banking and Finance,* 28: 2135-2153.

Table 1. Non-Metro Banking Data Summary Statistics: ND, SD, MN for 2005

Variable[a]	N	Mean	Std. Dev.	Min	Max
Price	1112	0.086	0.031	0.048	0.391
Share	1112	0.000	0.004	0.000	0.122
% in ND	1112	0.216	0.412	0.000	1.000
% in SD	1112	0.219	0.413	0.000	1.000
% in MN	1112	0.566	0.496	0.000	1.000
Group 1	1112	0.498	0.500	0.000	1.000
Group 2	1112	0.001	0.030	0.000	1.000
Group 3	1112	0.356	0.479	0.000	1.000
Group 4	1112	0.008	0.090	0.000	1.000
Group 5	1112	0.002	0.042	0.000	1.000
Group 6	1112	0.002	0.042	0.000	1.000
Group 7	1112	0.031	0.172	0.000	1.000
Group 8	1112	0.103	0.303	0.000	1.000
Ag Loan (%)	1112	0.180	0.171	0.000	0.790
Efficiency Ratio (%)	1112	61.335	11.763	28.326	127.050
Population ('000)	1112	8.079	10.381	0.036	54.880
Median Income ($ '000)	1112	36.071	8.151	7.188	84.385
Population Density (per household)	1112	2.520	0.227	1.349	3.743
Interest Expense (%)	1112	0.021	0.005	0.006	0.043
Salary Expense ($ 000 / worker)	1112	53.318	10.167	18.000	159.710
Facilities and Equipment (%)	1112	0.340	0.311	0.000	4.500
Capital Cost (%)	1112	0.086	0.051	-0.081	0.361
BHC Branches (2000)	1075	6.450	8.271	1.000	34.000
BHC Branches (2005)	1107	12.772	23.758	1.000	89.000
non-BHC Branches (2000)	157	4.554	3.929	1.000	12.000
non-BHC Branches (2005)	165	5.218	4.154	1.000	14.000

[a] Source: FDIC, Bureau of Labor Statistics and Bureau of Economic Analysis.

Table 2. Spatial Banking Services Demand Model Specification Tests, Euclidean Distance Weight Matrix: MN, ND, SD Non-Metro Banks, 2005

	Demand Model		Pricing Model	
Test	**Test Stat**	**Critical Value**	**Test Stat**	**Critical Value**
1. Moran-I	3.686		1.391	
2. LM-SAC	12.156	17.611	1.571	17.611
3. LR-SAC	13.311	6.635	1.409	6.635
4. Wald-SAC	52.477	6.635	0.947	6.635
5. LM-SAR	101.826	6.635	157.433	6.635

[a] In this table test statistics 2 - 5 are chi-square distributed, while the Moran-I statistic is asymptotically normal. Tests 1 - 4 are based on least squares residuals, while test 5 is based on SAR maximum likelihood residuals. In each case, the null hypothesis is H_0: $\lambda = 0$.

Table 3. Spatial Banking Services Demand Model Specification Tests, Contiguity Weight Matrix: MN, ND, SD Non-Metro Banks, 2005

	Demand Model		Pricing Model	
Test[a]	**Test Stat**	**Critical Value**	**Test Stat**	**Critical Value**
1. Moran-I	6.387		11.187	
2. LM-SAC	36.795	17.611	118.598	17.611
3. LR-SAC	36.200	6.635	97.098	6.635
4. Wald-SAC	227.755	6.635	995.601	6.635
5. LM-SAR	64.855	6.635	2222.622	66.35

[a] In this table test statistics 2 - 5 are chi-square distributed, while the Moran-I statistic is asymptotically normal.

Table 4. Spatial Banking Services Demand Model Specification Tests, Nearest Neighbor Weight Matrix: MN, ND, SD Non-Metro Banks, 2005

	Demand Model		Pricing Model	
Test[a]	**Test Stat**	**Critical Value**	**Test Stat**	**Critical Value**
1. Moran-I	8.594		14.595	
2. LM-SAC	56.208	17.611	173.375	17.611
3. LR-SAC	36.365	6.635	843.837	6.635
4. Wald-SAC	65.946	6.635	191.639	6.635
5. LM-SAR	11.755	6.635	11.123	6.635

[a] In this table, the nearest neighbor matrix is defined as all banks within 1.5 miles of the observation bank, where the weight is row-standardized to sum to 1.0. Test statistics 2 - 5 are chi-square distributed, while the Moran-I statistic is asymptotically normal.

Table 5. Spatial Banking Services Demand Model Estimates, Euclidean Distance, Common Boundary and Nearest Neighbor Weight Matrices: MN, ND, SD Non-Metro Banks, 2005.

	Euclidean Distance		Common Boundary		Nearest Neighbor	
Variable[a]	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
Constant	-4.583*	-11.808	-2.089*	-3.999	-0.127	-0.198
s_2	-0.087	-0.726	-0.063	-0.473	-0.085	-0.721
s_3	-0.201	-1.912	-0.160	-1.358	-0.168	-1.616
sg_2	-2.628*	-15.263	-2.507*	-13.954	-2.331*	-12.364
sg_3	0.521	0.416	0.961	0.776	0.962	0.779
sg_4	-2.420*	-17.596	-2.264*	-15.309	-2.166*	-13.801
sg_5	-1.537*	-3.610	-1.179*	-2.784	-1.268*	-2.985
sg_6	-3.111*	-3.584	-2.657*	-3.101	-2.913*	-3.399
sg_7	-0.422	-0.482	-0.337	-0.390	-0.002	-0.003
sg_8	-2.620*	-10.498	-2.494*	-9.614	-2.348*	-8.904
z_1	-1.561*	-4.120	-1.622*	-4.207	-1.350*	-3.551
z_2	-2.248*	-11.224	-2.121*	-10.422	-2.126*	-10.183
z_3	0.230*	6.725	0.219*	5.996	0.219*	6.454
z_4	0.509*	2.599	0.534*	2.530	0.331	1.659
z_5	-0.081	-0.473	-0.070	-0.341	-0.118	-0.665
p	-2.550	-1.962	-3.080*	-2.272	-2.828*	-2.212
λ_s	0.113*	4.923	0.029	1.296	0.301*	3.979
λ_ξ	0.145*	6.637	0.265*	4.796	0.034*	2.401
R^2	0.533		0.546		0.549	
LLF	-771.727		-760.833		-753.335	
N	1112		1112		1112	

[a] In this table, a single asterisk indicates significance at a 5% level. The variables in this table are defined as follows: z_1 = the ratio of agricultural to total loans, z_2 = efficiency ratio, z_3 = population in zip code, z_4 = median income in zip code, z_5 = the number of people in each household, s_1 = a dummy variable that = 1 for banks in ND, s_2 = a dummy variable that = 1 for banks in SD, s_3 = a dummy variable that = 1 for banks in MN, $sg_{1\text{-}8}$ = dummy variables for banks in specialty groups 1-8 where 1 = international specialization, 2 = agricultural specialization, 3 = credit-card specialization, 4 = commercial lending specialization, 5 = mortgage lending specialization, 6 = consumer lending specialization, 7 = other specialized < $1.0 billion, 8 = all other < $1.0 billion, p is the ratio of total loan income to total loans outstanding, λ_s is the spatial autoregressive parameter for the demand equation, and λ_ξ is the spatial error-correlation parameter.

Table 6. Spatial Banking Pricing Model Estimates, Euclidean Distance, Common Boundary and Nearest Neighbor Weight Matrices: MN, ND, SD Non-Metro Banks, 2005.

	Euclidean Distance		Common Boundary		Nearest Neighbor	
Variable[a]	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
w_1	-1.119*	-6.265	-1.031*	-5.977	-0.965*	-5.603
w_2	0.002	1.291	0.002*	2.180	0.001*	8.536
w_3	0.009*	3.375	0.010*	3.893	0.010*	3.715
w_4	0.072*	4.228	0.061*	3.601	0.074*	4.413
s_1	-0.014	-0.408	0.061	1.792	0.005	0.113
s_2	-0.003	-0.084	0.068*	2.003	0.009	0.223
s_3	-0.021	-0.583	0.055	1.630	0.001	0.016
sg_2	0.029*	9.573	0.027*	8.248	0.022*	7.408
sg_3	0.194*	7.529	0.190*	7.413	0.178*	6.764
sg_4	0.027*	8.430	0.026*	7.649	0.022*	7.035
sg_5	0.041*	4.230	0.041*	4.420	0.037*	3.940
sg_6	0.038*	1.996	0.038*	2.061	0.031	1.646
sg_7	0.031	1.460	0.033	1.834	0.031	1.631
sg_8	0.045*	8.121	0.046*	8.208	0.041*	7.679
θ	0.560*	2.681	0.040	0.175	0.107	0.355
λ_s	0.096*	2.662	0.045	1.341	0.626*	6.055
λ_ξ	0.516*	51.074	0.406*	21.721	-0.023	-1.699
R^2	0.299		0.300		0.266	
LLF	3511.803		3502.306		3492.255	
N	1112		1112.000		1112.000	

[a] In this table, a single asterisk indicates significance at a 5% level. The variables in this table are defined as follows: w_1 = the price of deposits, w_2 = the price of labor, w_3 = the price of bank premises or physical capital, w_4 = the price of financial capital, s_1 = a dummy variable that = 1 for banks in ND, s_2 = a dummy variable that = 1 for banks in SD, s_3 = a dummy variable that = 1 for banks in MN, $sg_{1\text{-}8}$ = dummy variables for banks in various specialty groups, θ is an estimate of the departure from Bertrand-Nash pricing due to non-spatial sources, λ_s is the spatial autoregressive parameter for the pricing equation, and λ_ξ is the spatial error-correlation parameter.

Table 7. Summary of Market Power Estimates

Parameter[a]	Definition	Euclidean Distance	Common Boundary	Nearest Neighbor
λ_s^d	Spatial market power - demand	+*	+	++*
λ_s^p	Spatial market power - pricing	+*	+	+++*
θ	Non-spatial market power	+++*	+	+

[a] In this table, λ_s^d is the estimate of spatial market power from the demand model, λ_s^p is the estimate from the pricing model, and θ is the estimate of non-spatial market power. The symbol + refers to an estimate between 0 - 0.25, ++ between 0.26 and 0.50, +++ between 0.51 and 0.75, ++++ between 0.76 and 1.00. An asterisk indicates statistical significance.

Table 8. Welfare Outcomes Under Alternative Competitive Assumptions, Monte Carlo Simulation: MN, ND, SD Non-Metro Banks, 2005

Scenario	CS		PS		Total Welfare	
	Estimate	Std. Err.	Estimate	Std. Err.	Estimate	Std. Err.
1. λ_s = 0.096, θ = 0.560	345.062	4.026	118.922	5.318	463.984	6.598
2. λ_s = 0.096, θ = 1.000	100.355	4.026	209.357	5.318	309.737	6.598
3. λ_s = 0.096, θ = 0.000	656.517	4.026	5.883	5.318	662.421	6.598
4. λ_s = 1.000, θ = 0.560	272.578	4.026	156.648	5.318	429.217	6.598
5. λ_s = -1.000, θ = 0.560	421.979	4.026	73.877	5.318	495.852	6.598
6. λ_s = 0.626, θ = 0.560	300.512	4.026	140.971	5.318	441.482	6.598
7. λ_s = -1.000, θ = 0.000	733.172	4.026	3.935	5.318	737.105	6.598

[a] Values in scenario 1 represent the "base" or estimated case. CS is calculated using equation (17) in the text and PS using equation (18). Welfare outcomes are calculated using Monte Carlo simulation with 1,000 draws from the demand and pricing equation errors. All calculations are based on *ceteris paribus* assumptions, meaning that all parameters other than the control parameter are held at base case values for each simulation. All values are scaled to represent $ millions.