Spatial Competition and Market Power in Banking

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Abstract

Banks in non-metropolitan areas compete in a spatially-differentiated environment. Particularly with the advent of electronic banking services, however, there is some question as to how much market power is conferred by spatial separation from rivals. This paper estimates a structural model of the supply and demand of banking services in which pricing power is allowed to depend explicitly on the distance between rival banks. A spatial autoregressive econometric model shows that approximately 38.0% of economic surplus earned by firms in non-metropolitan banking in the upper midwest is due to spatial market power.

Keywords: *banking, market power, non-metropolitan markets, spatial econometrics*

JEL Classification: C21, D43, G21, L13

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). Historically, these institutions have tended to be relatively small, independent unit banks or members of limited branch-banking companies. In recent years community banks have been under increased competitive pressure from expanded branch banking, consolidations and mergers, internet banking, and a changing customer perception of “relationship” banking. Non-metro community banks have typically been insulated from the new competitive forces encountered by metro community banks (Kagan and Conklin, 2001; DeYoung and Duffy, 2002; DeYoung, R., W.C. Hunter, and G.F. Udell. 2004), leading to questions as to whether this relative lack of market discipline has adversely affected their willingness to create new loans.

This is an important question because the performance of non-metro banks in extending loans to farmers and other rural businesses is clearly critical in providing a level of capital commensurate with the investment opportunities available. Financing such investment is, in turn, necessary to maintain high rates of economic growth within rural communities. In recent years, a large number of studies have investigated the possibility that inefficiencies, whether technical, allocative or scale, have contributed to lower lending rates by rural and agricultural banks (Featherstone and Moss, 1994; Featherstone, 1996; Marsh, Featherstone and Garret 2003). However, it may also be the case that banks are fully efficient, but intentionally limit loan output in order to take advantage of market power conferred by their relative spatial isolation.

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. Although spatial market power is more commonly associated with commodity sellers (or buyers) whose monopoly power derives naturally from transportation costs (Sexton, 1990), banking relationships tend to involve considerable locational advantages as well. Information regarding local economic conditions, market trends or borrower history is critically important in evaluating investments in small businesses and farms (McNulty, Akhigbe and Verbrugge 2001). This suggests that the question of whether banks in a largely rural area of the U.S. exercise market power in their lending activities, thereby lending less than would be socially optimal, is an important one worthy of careful research.

Regardless of whether they are located in an urban or rural market, or even in the U.S. or abroad, market power in banking has been the subject of a relatively large number of empirical studies.[1] Perhaps the only empirical regularity that emerges from these studies, however, is that the structure-conduct-performance paradigm (Bain, 1956) is not a reliable guide for antitrust policy as nearly any market structure can be consistent with either the presence, or absence, of supernormal profits. Researchers use either (or both) of the principal new "empirical industrial organization" methods to test for market power: (1) the Panzar-Rosse "revenue" model and (2) the Bresnahan-Lau "markup" model. Panzar and Rosse (1987) calculate the elasticity of revenue with respect to each input price, arguing that the sum of all such elasticities for each firm is equal to 1.0 if the firm is competitive, but less than zero if it is either a monopoly or collusive oligopolist. Bresnahan (1982) and Lau (1982), on the other hand, parameterize a firm's deviation from perfectly competitive behavior by deriving a structural model of profit maximization under very general market conditions. If the "conduct parameter" associated with the markup term is significantly greater than zero, then it must be the case that the firm has at least a measure of market power. As explained in greater detail below, there are problems with both tests in firm-level data. The Panzar-Rosse model, for example, relies heavily on the assumption that all firms possess symmetric, zero-degree, homogeneous cost functions (Shaffer, 2004) – a situation that is rarely found to be true in empirical studies. Similarly, the Bresnahan-Lau approach is often criticized for the fact that it attempts to test for a dynamic phenomenon in an inherently static model, among other problems (Genesove and Mullin, 1998). In this paper, we introduce a new alternative. If geographic separation is the basis for market power, then it is logical to use spatial distance as a determinant of supernormal markups. Employing the distance metric (DM) approach of Pinkse, Slade and Brett (2002), Pinkse and Slade (2004) and Slade (2004), we use explicitly spatial econometric methods to test for whether banks tend to exploit the distance from rivals to raise prices. If markups tend to rise in the distance between banks, then we interpret spatial differentiation as a source of market power. In the terminology of spatial econometrics, the test for market power is a simple test of whether there is any evidence of negative spatial autoregression.

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 in banking. 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 the extent of market power exercised by banks in the U.S. Upper Midwest region. 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.

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

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. Investigating the link between structure and conduct that has been the staple of anti-trust economists and lawyers since Bain (1956), 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. Because the empirical methods used in these studies are designed to detect and not explain market power, they do not consider the explicit spatial nature of banking markets. 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).

Much of the empirical research in bank performance is motivated by a need to understand the market impacts of concentration, specifically the wave of mergers and acquisitions that occurred in the late 1990s and again in the mid-2000s. Berger, Demsetz and Strahan (1999) describe two motivations for undertaking mergers designed to maximize shareholder value: (1) creating market power, and (2) generating either cost efficiency, profit efficiency, or both. Disentangling efficiency and market power in estimating the determinants of profitability, therefore, is critical. Berger (1995) and Berger and Hannan (1997, 1998) accomplish this by including measures of allocative and technical efficiency in traditional structure-conduct-performance (SCP) models of market power. Many authors, however, have criticized the SCP approach to estimating market power on the grounds that there is no logical connection between market concentration and price behavior (Bresnahan 1989). Indeed, Baumol, Panzar and Willig (1982) argue that a contestable market of only two firms can still generate competitive pricing outcomes. Therefore, in this study we estimate market power using a structural model of demand and pricing behavior that accounts for the specific nature of the game played by bankers in the context of an appropriate solution concept. Specifically, we assume banks operate in a differentiated-product oligopoly by setting prices in a Bertrand-Nash equilibrium. We account for potential inefficiency by allowing individual banks to deviate randomly from a best-practice cost function.

Efficient lending is critically important to building and sustaining economic growth. Although well developed credit market is considered as one of the important prerequisite for economic development, very few studies have made an attempt to establish the link between lending and growth. Much of the research in this area focuses on the impact of lending from international institutions such as International Monetary Fund, World Bank, and other financial institutions on growth in developing countries (Burnside and Dollar, 2000; Bird and Rowlands, 2001; Barro and Lee, 2003; Butkiewicz and Yanikkaya, 2005). A few studies, however, show a similar linkage between market structure and growth in domestic lending (Collender and Shaffer, 2002), but not necessarily banking conduct. In general, 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, a much more direct result of a structural model of market power than economic growth.

Empirical Model of Spatial Competition and Economic Welfare

Overview

The empirical analysis is divided into two stages. In the first stage, we use a spatial, discrete-choice model of banking conduct 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 by non-metro banks in the upper midwest region.

Theoretical Model of Demand and Pricing of Banking Services

Competition between banks is inherently spatial, meaning that borrowers typically travel to the branch or outlet in order to complete the transaction. As a spatial problem, transportation costs, search costs and informational asymmetries all factor into the total cost of choosing one bank over another. Any time consumers, or borrowers in this case, 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). Detecting the extent of this market power in spatial price and quantity data is an important and interesting empirical problem.

As suggested in the introduction, there are many possible alternative ways to test for spatial market power. Applying the "new empirical industrial organization" (NEIO) model of Bresnahan (1982) and Lau (1982) is relatively common and widely accepted, but is not without weaknesses (Corts 1988; Genesove and Mullin 1998). Conceptually, conduct parameters estimated in a NEIO context are typically interpreted as "conjectures" of how rival firms are expected to respond to a particular choice of either output price or quantity. The notion of a conjecture, however, is inherently dynamic whereas most NEIO models are completely static. This criticism is typically overcome simply by interpreting the conduct parameter as a measure of the departure from perfect competition – if the conduct parameter equals zero, then banks price competitively and if it equals one, they price as if they are colluding perfectly. Intermediate values are interpreted as some form of Cournot-Nash behavior. Another criticism of the NEIO approach is that, because conduct is derived from markup behavior, tests of market power are overly dependent on accurate estimates of marginal cost. Cost estimates are notoriously difficult to obtain.

If competition among banks is indeed spatial, then it is useful to place the static, non-spatial NEIO approach in the context of spatial oligopoly theory. Greenhut and Greenhut (1975) define a set of analogies between spatial and non-spatial oligopoly models, while Sexton (1990) does the same for oligopsonistic rivalry in a spatial market for raw input-commodities. First, Loschian competition refers to the case where spatially disparate firms regard themselves as monopolists over an area with fixed market boundary. Firms expect any price change to be exactly matched by rivals, so the collusive outcome accrues. On the other hand, Hotelling-Smithies competition is where competitors compete in price, but do not expect rivals to respond to any change in the mill (offered) price. Finally, Cournot-Nash behavior describes the case where competitors do not believe rivals will respond to any change in output. The analogy to non-spatial competition is clear. Loschian competition results in tacit collusion, where output prices are highest. Hotelling-Smithies behavior is analogous to Bertrand price-setting behavior, which generates perfectly competitive pricing with homogenous products and non-binding capacity constraints (Sexton 1990). Finally, Cournot-Nash behavior is directly comparable to its non-spatial analogue and generates an intermediate price.

Among other models of oligopoly conduct among banks, Shaffer (2004) and Bikker and Haaf (2002) apply the Panzar-Rosse revenue model as a means of overcoming the empirical problems associated with obtaining accurate cost estimates in the Bresnahan-Lau approach. However, the Panzar-Rosse model does not provide readily interpretable estimates of market power, nor is it sufficiently well grounded in firm optimization. A more important criticism of both models is that they test for the likely presence of market power, but do not provide any insight as to the *source* of market power.

Consequently, in this study we propose to develop a synthesis of the Bresnahan-Lau approach and an entirely new, explicitly spatial test for market power among banks. Our approach relies directly on defining the source of a banks' market power – their spatial separation in geographic markets. If banks are found to exploit their distance from other banks by pricing as if they were local monopolists, then there is evidence of market power. If spatial distance does not matter to their pricing behavior, then banks must be pricing in a relatively competitive way. Therefore, the primary hypothesis of this study is that banks derive market power from the spatial structure of rural lending markets – if rural financial markets are inherently local as the literature suggests, then local banks are likely to have significant latitude in determining prices. As a result, the test proposed herein is a more direct test of the extent of market power derived precisely from the geographic location of the bank, and its separation from rival banks.

Specifically, a new test for market power in banking is proposed that is based on the spatial competition model of Pinkse and Slade (1998) and Pinkse, Slade, and Brett (2002). With this approach, 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 and deposits outstanding.[1] Econometric models that explicitly recognize the spatial structure of economic problems are becoming increasingly common (Anselin, 2002; Slade, 2004). While many theoretical and methodological advances have been made in applications to real estate (Dubin, 1988; Gelfand, et al.,1998; Kelejian and Prucha, 1998; Pace, et al., 2000, for example), land use (Hsieh, Irwin and Forster, 2005) and industrial organization (Pinkse and Slade,

1. 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).

1998; Pinkse, Slade and Brett, 2002; Kalnins, 2003; Pinkse and Slade 2004), there have been no applications to banking or finance to our knowledge. This is somewhat surprising given the spatial nature of competition in banking.[1]

Econometric models with a spatial lag structure are often motivated by analogy to their time series counterparts. However, Slade (2004) notes four reasons why analogy is imperfect: (1) time is one dimensional, whereas space is at least two-dimensional, (2) economic relationships move only one way in time, but can move in any direction in space, (3) there is a greater likelihood of a unit-root in space than in time (with similar consequences), and (4) spatial phenomena are typically irregularly spaced, unlike daily, weekly, or monthly time-series data. Other than these differences, the structure of a spatial-lag model is similar to its autoregressive time-series analog.

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, and then aggregate over the distribution of consumer heterogeneity to arrive at a consistent aggregate demand for banking services in the market as a whole. Write the utility for household *h* as:

$$u_{hj} = v_{hj} + \varepsilon_{hj} = \beta_{0j} + \sum_k \beta_{1k} x_{jk} - \alpha\, p_j + \xi_j + \varepsilon_{hj} ,$$

where v_{hj} is the deterministic component of utility, β_{0j} is the maximum willingness to pay for the banking services of firm *j*, p_j is the price of services offered by firm *j*, $\mathbf{x}_j$ is a vector of *k* attributes describing the services offered by firm *j*, 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. In other words, the probability that household *h* chooses *j* over all others is governed by the distribution of ε_{hj} because:

$$Pr(j = 1) = Pr(v_{hj} + \varepsilon_{hj} > v_{hi} + \varepsilon_{hi}) = Pr(v_{hj} - v_{hi} + \varepsilon_{hj} > \varepsilon_{hi}).$$

As is well understood, if ε_{hj} is distributed extreme value, the random utility model in (1) implies share functions for each firm *j* = 1, 2, ... *J* of:

1. As an alternative to geographic space, others interpret the inherently spatial structure of differentiated products as a problem in attribute space (Lancaster 1979; Rosen 1974). Anderson, et al. (1992); Berry, Levinsohn and Pakes (1995), Feenstra and Levinsohn (1995), Nevo (2001) and many others apply discrete choice models of product differentiation to the attribute-pricing problem but do not use spatial econometric methods. However, if prices of differentiated products are akin to points in a dense space occupied by many firms, then their joint endogeneity must be explicitly accounted for.

$$S_j = \frac{\exp\left(\beta_{0j} + \sum_k \beta_k x_{kj} - \alpha\, p_j + \xi_j\right)}{1 + \sum_{i=1}^{J} \exp\left(\beta_{0i} + \sum_k \beta_k x_{ki} - \alpha\, p_i + \xi_i\right)},$$

where S_j is the market share of firm *j*. This is a multinomial logit (MNL) model of discrete choice (Berry 1994) among differentiated products.

It is also well known that the simple MNL model in (3) 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 (3) (the mixed logit) that avoids the proportionate draw problem, in this study we achieve the same result in a more straightforward manner. Because the mixed logit model requires either maximum simulated likelihood or simulated method of moments to estimate, a simpler model that achieves the same ends is of considerable value to practicing econometricians. Instead of allowing the β_k parameters in (3) to be random variables, 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.

The supply of banking services is derived under the assumption that banks compete in prices, or play a Bertrand-Nash spatial pricing game. The profit function for a representative bank is written as:

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

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 unit-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 one unit of output is:

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

where ***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 unit-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 problem defined in (4) 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

$$\partial s_j / \partial p_j = -\alpha s_j (1 - s_j)$$

into (6) and solving for the price charged by bank *j* gives an estimable equation for the inverse supply equation:

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

where (5) is substituted into (7) prior to estimation. In equation (7), the "conduct parameter" I measures any departure from Bertrand-Nash pricing behavior and constitutes the first of two tests for market power. In the next section, we describe the second test, one that relies explicitly on the spatial nature of competition in banking.

Empirical Model of Spatial Market Power

To this point, the conceptual model of banking demand and pricing reflects relatively standard assumptions in the empirical industrial organization literature. Spatial competition, however, imposes additional restrictions on the form of the model that is taken to the data. Even with the popularity of online banking, the market for financial services such as loans and asset management is still location-specific. With non-zero transportation costs, a consumer's utility from using the services of a particular bank depends not only on the attributes described in (1) above, but its distance from other banks.[1] In order to model the effect of distance between banks, we modify the utility function in (1) by including a measure of the cost of patronizing any other bank in the sample relative to bank *j*. Specifically, cost is assumed to rise linearly in distance. Distance, in turn, is measured in three different ways: (1) Euclidean distance from bank *i* to each other bank *j*, (2) whether the market area for bank *i* is contiguous with other banks, or whether two banks share a common market boundary, 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 the first case, the Euclidean distance metric, the spatial autoregressive model requires that we weight all other observations by their inverse distance, so a spatial weight matrix $\boldsymbol{W}$ is defined with element w_{ij} representing the inverse distance from bank *i* to bank *j*.[2] Without well-defined priors as to the appropriate definition of distance, we estimate the entire structural model under each distance metric and compare the results below.

1. Anselin (1988) shows that the econometric consequences of failing to account for observations that are spatially dependent is the same as failing to account for autocorrelation in a time-series context. Namely, the resulting parameter estimates will be consistent, but inefficient so inferences drawn from least squares regression will be incorrect.

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, and 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:

$$\ln S - \ln (S_0) = \beta_0 + \beta' x + \alpha' p + \lambda_s W \ln S + \xi$$
$$\xi = \lambda_\xi M \xi + u ,$$

where $\boldsymbol{u}$ is an iid error term with variance σ^2, $\boldsymbol{M}$ is another 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. In the nearest neighbor case, we define $\boldsymbol{W}$ as all banks within 1.5 miles of the bank of interest, so define the alternative, $\boldsymbol{M}$, as only the single nearest neighbor. For the common boundary matrix, we define $\boldsymbol{M}$ as a row-stochastic version of the symmetric $\boldsymbol{W}$ matrix used in the spatial autoregressive equation (LeSage 1998). Solving (8) for ln $\boldsymbol{S}$ gives:

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

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. Taking the derivative of (9) with respect to $\boldsymbol{p}$, substituting into (6) and solving for $\boldsymbol{p}$ gives:

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

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:

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

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

2. 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.

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.

Estimation of the Spatial Market Power 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, indeed any market knowledge possessed by the banker but not by the econometrician will influence ***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 account for the endogeneity inherent in spatial models is to estimate each equation separately using maximum likelihood (Anselin 1988, 2002).[1] In order to express the likelihood function more clearly, simplify notation by writing

$$y = \ln(S),\ \gamma' z = \ln(S_0) + \beta_0 + \beta' x + \alpha' p,\ A = (I - \lambda_s W)^{-1},\ \text{and } B = (I - \lambda_\xi M)^{-1}.$$

In terms of the most general form of the demand equation given in (8), the log-likelihood function is written as:

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

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 β, α, and Õ 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). We describe the nature and the motivation for each of these tests next.

Anselin (1988) maintains that a spatial error model is the most logical representation of spatially correlated data (ie., $\boldsymbol{W} = 0$). Given a theoretical motivation for a direct relationship between prices of different bank products, however, the opposite, or spatial-lag model ($\boldsymbol{W} \neq 0, \boldsymbol{M} = 0$) is more likely to be the case. In the upper midwest U.S., non-metro banks are a good example of a spatially-differentiated oligopoly, so we expect to observe non-zero price responses among ri-

1. 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.

val banks. For this reason, it is more likely that **W** ¼ 0, but whether or not **M** ≠ 0 can be tested. Using consistent estimates of **O** above, we test the null hypothesis that **M** = 0 with a Lagrange Multiplier (*LM-SL*) test statistic. One advantage of using a Lagrange Multiplier test, as opposed to a likelihood ratio test, is that the maintained model need only be estimated once, with the implied restrictions imposed. By forming a gradient vector subject to the unknown parameters under the null, the *LM-SL* statistic in this case becomes (LeSage, 1998):

$$LM - SL = \frac{(\xi' \mathrm{M}\, \xi / \sigma^2)^2}{\mathrm{tr}\,(\mathrm{M.M} + \mathrm{M'M}) - [\,\mathrm{tr}\,(\mathrm{M.W\,A^{-1}} + \mathrm{M'W\,A^{-1}})\,]^2\, \mathrm{var}(\lambda_s)} - \chi^2(1),$$

where ξ is a vector of regression residuals and ***M.M*** indicates element-by-element multiplication. The *LM-SL* statistic is distributed chi-square with one degree of freedom.
If the alternative is a simple regression model instead of the spatial autoregressive variant shown in (8), LeSage (1998) describes a number of different tests of

$$H_0 : \lambda_\xi = 0 .$$

Each of these tests is based on the residuals obtained from estimating the equation of interest (either (8) or (11) in this example) by maximum likelihood. We implement four of these tests: (1) the Moran statistic, (2) likelihood ratio test, (3) a Lagrange Multiplier test and (4) a Wald test. Although these tests are asymptotically equivalent, in small samples they will produce slightly different results. When the spatial-weight matrix is row-normalized, the Moran (I) statistic is given by

$$Z_I = (I - tr(\mathrm{R\,M}) / (\mathrm{n - k}))\,[\,(1/\mathrm{d})\,(\mathrm{tr}\,(\mathrm{R\,M\,R\,M'}) + \mathrm{tr}\,(\mathrm{R\,M})^2 + (\mathrm{tr}\,(\mathrm{R\,M}))^2) - \mathrm{E}\,(\mathrm{I})^2\,]^{-1/2},$$

$$I = \mathrm{u'Wu} / \mathrm{u'u}\,,$$

which is distributed standard normal after transforming according to:
where

$$\mathrm{R} = (\mathrm{I_n} - \mathrm{X}\,(\mathrm{X'X})^{-1}\,\mathrm{X'}),$$

n is the number of observations, *k* is the number of regressors, and *d* = (*n* - *k*)(*n* - *k* + 2). Second, the likelihood ratio statistic compares the log-likelihood value from the spatial error model (LLF_u) and a non-spatial regression (LLF_r): LR `=` 2 `(LLF sub u `-` LLF sub r) where the result is chi-square distributed with one degree of freedom. One advantage of this test is that it does not require multiplication of the spatial weight matrices, which because they increase in size as the sample grows, can often become intractably large. Rather, the *LR* statistic requires only the direct maximum likelihood estimation of both a general (unrestricted) and restricted model. Third, the Lagrange Multiplier - spatial error (*LM-SEM*) test uses the regression residuals in a manner similar to the spatial autoregressive test in (14) above, but does not include the ***W*** spatial weight matrix. LeSage (1998) derives the resulting *LM-SEM* statistic as:

$$LM\text{ - }SEM = \frac{(\mathrm{u}'\mathrm{M}\,\mathrm{u}/\sigma^2)^2}{\mathrm{tr}\,(\mathrm{M}+\mathrm{M}').\mathrm{M}} \sim \chi^2(1),$$

where ***u*** is again a vector of regression residuals. Finally, the Wald statistic is formed from the maximum likelihood estimate of λ as:

$$WD = \lambda^2\,[tr(\mathrm{M}\,\mathrm{B}^{-1})^2 + \mathrm{tr}(\mathrm{M}\,\mathrm{B}^{-1})'(\mathrm{M}\,\mathrm{B}^{-1}) - (1/\mathrm{n})\,\mathrm{tr}(\mathrm{M}.\mathrm{B}^{-1})^2\,] \sim \chi^2(1),$$

where

$$\boldsymbol{B} = (\boldsymbol{I} - \lambda\boldsymbol{M}).$$

Wald statistics are attractive because the model need not be estimated under both the restricted and unrestricted scenarios in order to generate asymptotically valid test statistics. Rather, the Wald statistic uses only the unrestricted model estimates to calculate the degree of departure from the maintained value for the unknown parameter vector. Based on the results of these five specification tests, we test the primary hypothesis of the paper – whether banks in the upper midwest exercise market power in their lending activities – with either the SAR or SEM model. We test for market power two ways. The first concerns the conduct parameter,θ, which was described above. If this parameter is not significantly different from zero, then the non-metro banks in our sample do not 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. In the simplest analogy, 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 a differentiated product market, firms face these two opposing incentives: do they move together in order to more easily steal another's customers, or do they move apart in order to raise prices and gain market power? In terms of the pricing model, if $\lambda_S < 0$, then rival banks reduce prices as they move closer together (raise prices as they move farther apart) – the competitive or market share effect dominates. On the other 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 in real-world data depends on consumer tastes – are they relatively indifferent between the services (location) of rival banks, or is the unique nature of a particular bank's services (location) all important? Ultimately, however, these tests only determine the statistical significance of market power in banking. For policy purposes, the economic significance depends upon the welfare impacts of imperfect competition and spatial differentiation.

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:

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

where w_{ij} is the *ij* element of ***W***, or the inverse distance between bank *j* and bank *i*. Producer surplus (PS), on the other hand, is found by calculating aggregate firm profit at observed prices and output levels using equation (5) above:

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

where total economic welfare is given by $W = CS + PS$. Simulating equations (17) and (18) over alternative values for the spatial autoregressive parameter shows how economic welfare is likely to change over different modes of economic conduct.

Data Description

The bank financial data for this study will mainly be drawn from the 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.

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 Minnesota, North Dakota, and South Dakota – a region typically described as the "upper midwest." We choose banks in the upper midwest for several reasons. First, the upper midwest remains one of the most 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. However, agricultural lending tends to be a topic of particular interest due to the primacy of farming in the upper midwest economy, the sheer number of farms in the region and their often precarious financial state.

Second, the upper midwest forms a contiguous, relatively isolated market. While our 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.[1] For example, had we included Wisconsin in this sample, we would have introduced the confounding factor of both the Chicago and Milwaukee banking markets. This would have diluted the importance of the non-metro banks in overall lending activity.

Third, much of this region tends to be economically disadvantaged from an historical perspective. For this reason, rural economic welfare is an inherently important topic of study. Fourth, because agricultural enterprises are distributed in a relatively uniform manner over all states in the study frame, there is a high potential for spatial market power among the banks in our data set. In areas of greater population (and business) density, clearly spatial separation is less of a factor in pricing banking services.

1. 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.

Finally, most of the banks in Minnesota, North Dakota, and South Dakota are headquartered in non-metro locations. For instance, more than 60 percent (951) of the community banks in the upper midwest that were active in December 31, 2004 (1422) were headquartered in non-metro locations. 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.
In addition to financial data for each bank, we require geographic coordinates for the location of each bank in order to calculate the spatial weight matrices and implement the spatial econometric model. 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. 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. 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.
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 data used in the econometric analysis.

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	0.39
Share	1112	0.000	0.004	0	0.122
ND	1112	0.216	0.412	0	1.000
SD	1112	0.219	0.413	0	1.000
MN	1112	0.566	0.496	0.000	1
Group 1	1112	0.498	0.500	0.000	1
Group 2	1112	0.001	0.030	0.000	1
Group 3	1112	0.356	0.479	0.000	1
Group 4	1112	0.008	0.090	0.000	1
Group 5	1112	0.002	0.042	0.000	1
Group 6	1112	0.002	0.042	0.000	1
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

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

Results and Discussion

If non-metro banks in the upper midwest do indeed price their services as if they have some monopoly power, then we expect to reject the null hypothesis that banks behave competitively. In terms of alternative models of spatial competition, Hotelling-Smithies competition is implied when $M_s = -1$ (with a row-normalized weight matrix) because firms set prices as if any price reduction will earn them additional market share. Loschian competition, on the other hand is implied when $M_s = 1$ 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 $M_s = 0$ 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. 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: M = 0.

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 $M_O = 0$ 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.

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 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.[1] Comparing the goodness of fit across all three specifications using paired likelihood ratio tests at 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.[2] 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.

1. The price elasticity of demand is calculated as: epsilon sub d `=` - ` alpha ` p sub i ` (1 ~-~ S sub i ) `.
2. The critical value of a $\hat{U}^2$ 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.

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
M_s	0.113*	4.923	0.029	1.296	0.301*	3.979
M_O	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		1112.000		1112.000	

[a] In this table, a single asterisk indicates significance at a 5% level. The variables in this table are defined as follows: 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, M_s is the spatial autoregressive parameter for the demand equation, and M_O is the spatial error-correlation parameter.

Of greater relevance to the objectives of this study, however, are the spatial autoregression and autocorrelation parameters in table 5. In all cases, M_O is significantly different from zero, confirming the specification test results discussed above that support the use of a SAC model of demand. Further, in two of three cases (Euclidean distance and nearest neighbor), the spatial autoregression parameter 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. More specifically, the fact that this parameter is positive suggests that increases in the log share of banks that are nearer / contiguous / neighbors leads to a greater share of the own-bank. The intuition behind this result is straightforward. 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 expect a lower share to result. Because both banks' market shares move in the same direction, this is evidence of tacit collusive, or Loschian behavior in the lexicon of spatial rivalry. 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. Because the theoretical model suggests that M_s in the demand equation is equal to the spatial autoregressive parameter in the pricing model, we first test whether this is indeed the case. For each model, however, likelihood ratio tests suggested rejection of the null hypothesis that the spatial relationships in bank pricing and demand are the same. However, the estimates in table 6 indicate that the differences are quantitative and not qualitative as M_s is significantly greater than zero in two of three cases. While point estimates of the spatial market power parameter are relatively close to zero in the Euclidean distance and common boundary cases, the nearest neighbor estimate suggests strongly collusive behavior – 0.626 where an estimate of 1.0 indicates a perfectly collusive outcome. However, based on the likelihood function values reported in the table, the Euclidean distance model is preferred for the pricing equation so we attach less confidence to the higher spatial market power estimate. One reason why the estimate of M_s is relatively low in the Euclidean distance case could be due to the fact that much of the departure from competitive pricing in this model is explained by non-spatial factors. In fact, estimates of the parameter on m hat (the fitted inverse demand elasticity) suggest that much of a bank's market power derives from product and service differentiation. This result, however, is not supported by either of the other spatial models. Nonetheless, the Euclidean distance model is preferred on statistical grounds, so this evidence is relatively strong.

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	0.000	1.291	0.000	2.180	0.000	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	7.41	0.178	6.76
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
bold m hat	0.560	2.681	0.040	0.175	0.107	0.355
M_s	0.096	2.662	0.045	1.341	0.626	6.055
M_O	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] 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, m hat is the fitted price-markup term from the first-stage demand model, M_s is the spatial autoregressive parameter for the pricing equation, and M_O is the spatial error-correlation parameter.

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 (Hotelling-Smithies competition), collusion (Loschian competition) 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 I 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 7.

Table 7. 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. M_S = 0.096, I = 0.560	345.062	4.026	118.922	5.318	463.984	6.598
2. M_S = 0.096, I = 1.000	100.355	4.026	209.357	5.318	309.737	6.598
3. M_S = 0.096, I = 0.000	656.517	4.026	5.883	5.318	662.421	6.598
4. M_S = 1.000, I = 0.560	272.578	4.026	156.648	5.318	429.217	6.598
5. M_S = -1.000, I = 0.560	421.979	4.026	73.877	5.318	495.852	6.598
6. M_S = 0.626, I = 0.560	300.512	4.026	140.971	5.318	441.482	6.598
7. M_S = -1.000, I = 0.000	733.17	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.

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 M_S is relatively close to zero in the base case (0.096), moving toward a Hotelling-Smithies outcome (scenario 5 in table 7) 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 7) is expected to cost the upper midwest economy some $35.0 million in economic output in the extreme case ($M_S = 1$) or $22.5 million at the value estimated using the nearest neighbor spatial model ($M_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 I 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, or Hotelling-Smithies conduct. Moving from the base-case scenario of I = 0.56 to a fully collusive (Loschian) outcome of I = 1.00 destroys some $245.0 million in consumer surplus, while generating $90.4 million in producer surplus for a net loss of $154.2 million. Similarly, moving to the competitive outcome (I = 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, of course from a gain in consumer surplus of $388.1 million and a near total loss of producer surplus. Consequently, despite the fact that spatial market power does play a role in pricing bank services, traditional sources of market power – differentiation, key personnel, relationship – continue to play a more important one.

Conclusions and Implications

This study investigates the role of geographic distance among banks in the non-metro upper midwest in creating local banking monopolies in certain rural regions. Previous studies report little evidence of market power of any type, but do not recognize the proximity of bank branches as one potential source of market power. This study uses spatial econometric methods developed recently in the real estate and economic geography disciplines to estimate a model of imperfect competition in a specific, relatively isolated market. With this approach, spatial market power is suggested if prices of two competitors located near each other tend to vary together more closely than the prices of competitors located far away.

We model the banking services industry by creating a structural model of the demand, supply and equilibrium market price and quantity sold. Consumers are assumed to choose the bank that provides the highest utility according to a random-utility decision process. The resulting multinomial logit discrete choice demand equations are used to derive first-order conditions that, when estimated, provide a way 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 is only statistically significant in the Euclidean distance case. 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. Finally, 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.

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