ECONOMIC RESEARCH
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WORKING PAPER SERIES

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Working Paper Number	2004-004A
Creation Date	February 2004
Citable Link	https://doi.org/10.20955/wp.2004.004
Suggested Citation	Emmons, W.R., Schmid, F.A., 2004; When For-Profits and Not-For-Profits Compete: Theory and Empirical Evidence from Retail Banking, Federal Reserve Bank of St. Louis Working Paper 2004-004. URL https://doi.org/10.20955/wp.2004.004

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When For-Profits and Not-For-Profits Compete:
Theory and Empirical Evidence from Retail Banking

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February 26, 2004

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* The views expressed are those of the authors and do not necessarily reflect official positions of the Federal Reserve Bank of St. Louis or the Federal Reserve System.

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Abstract

We model competition in local deposit markets between for-profit and not-for-profit financial institutions. For-profit retail banks may offer a superior bundle of financial services, but not-for-profit (occupational) credit unions enjoy sponsor subsidies that allow them to capture a share of the local market. The model predicts that greater participation in credit unions in a given county will be associated with higher levels of retail-bank concentration. We find empirical evidence of this association. The ability of credit unions to affect local banking market structure supports the presumption of current banking antitrust analysis that retail banking markets remain local. We identify local economic factors that modulate the nature of competition between banks and credit unions, including income per capita and population density.

Keywords: Not-for-profit organizations, competition, retail banking, credit unions.
JEL-classification: G21, L31, L13

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When For-Profits and Not-For-Profits Compete:
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Competition between banks and credit unions is interesting in part because it entails a for-profit sector (commercial banks and thrifts) competing with a not-for-profit sector (credit unions). This paper explores competition between retail banks and occupational credit unions in local deposit markets across the United States in recent years. For-profit retail banks may offer a superior bundle of financial services to consumers, but not-for-profit occupational credit unions enjoy sponsor subsidies that allow them to capture a share of the local market. Our model predicts that greater participation in occupational credit unions in a given county will be associated with higher levels of retail-bank concentration.

We use annual county-level observations of commercial bank and thrift deposit market concentration ratios and household participation rates in occupational credit unions during the period 1989-2001. We find evidence of an association between credit-union participation rates and levels of deposit-market concentration among banks and thrifts. The apparent ability of credit-union activity to affect local deposit market structure supports the presumption of current banking antitrust analysis that retail deposit markets remain local (Kwast, Starr-McCluer, and Wolken (1997)). We also identify local economic factors that modulate the nature of competition between banks and credit unions, including income per capita and population density.

The paper is organized into five sections. The first section briefly discusses the existing literature on competition between for-profit and not-for-profit financial institutions. The second section develops a model of spatial competition between credit unions and banks. This model allows for two countervailing influences on occupational credit-union participation rates. First, sponsor subsidies allow occupational credit union to operate at low costs of production. Second, because credit unions offer only a limited number of services, they face decreasing within-group affinity (attractiveness) as the membership increases. The banking sector is modeled as a homogenous Cournot oligopoly; banks interact strategically with each other but not with the credit unions. The third section describes the dataset and the variables we use. The fourth section presents the econometric methods we employ and our empirical results. The fifth section draws conclusions. Three appendixes appear at the end of the paper, detailing the data, construction of variables, and the econometric methodology, respectively.

1. Competition Between For-Profit and Not-For-Profit Financial Institutions

Two important papers by Hart and Moore (1996, 1998) provide a comparative analysis of the governance structures and incentives facing cooperatives and firms with outside ownership. Hart and Moore conclude that firms with outside ownership typically operate more efficiently in competitive environments. However, if members of a cooperative have preferences that are sufficiently homogeneous, then the cooperative firm makes better decisions (in a welfare sense) than the firm with outside ownership. Thus, both types of governance structure might be expected to appear in modern economies. Our paper focuses on the competition between these two types of institutions in the marketplace. We provide a theoretical model of competition between for-profit and not-for-profit institutions, and then we put this model to the test empirically in retail banking markets across the United States.

There is a large and growing literature investigating competition among retail banks (for example, see Berger, Demsetz, and Strahan (1999); Amel and Hannan (1998); Prager and Hannan (1998); Cohen and Mazzeo (2004)). However, very little research focuses on the possible interactions between credit unions and banks (Hannan and Liang (1995), Hannan (2003)). The remainder of this section briefly discusses the importance of concentration ratios in retail banking markets and whether credit unions are important for banking competition.

A. Banking Market Concentration, Prices, and Profits

The number of commercial bank charters in existence has declined by between three and five percent annually since 1988, resulting in a nine-year (1988-97) cumulative disappearance of 33 percent of all bank charters (Berger, Demsetz, and Strahan (1999), Tables 1 and 2). The trend has continued to the present day, with a spate of large bank merger announcements in early 2004. Mergers accounted for about 84 percent of disappearances and failures for 16 percent during 1988-97. Local deposit-market concentration actually declined slightly over this period, however. Average commercial-bank deposit Herfindahl indexes in metropolitan statistical areas fell from 0.2020 to 0.1949, and those in non-metropolitan counties fell from 0.4317 to 0.4114 (Berger, Demsetz, and Strahan (1999), Table 1). Meanwhile, credit-union membership grew more than 38 percent in the decade ending in 1996, while the country's population grew about 10 percent (U.S. Treasury (1997), p. 24).

Does market concentration matter for prices and profits? In a non-banking context, Tirole notes that, "[m]ost cross-sectional analyses find a weak but statistically significant link between concentration and profitability (1988, p. 222)." With regard to banking markets, Gilbert (1984) concluded in an early review of the empirical literature that the economic significance of market concentration by banks before deregulation was very difficult to assess, not least because of the poor quality of much of the empirical research. More recently, Shaffer (1992) summarized the (lack of) current consensus by stating that the degree to which banking market structure matters for competition and performance is "a hotly debated topic."

B. Credit Unions in the Analysis of Banking Competition

The primary focus of bank antitrust enforcement in the merger-review process carried out by the Antitrust Division of the Department of Justice and by federal bank regulators (the Federal Reserve, the Office of the Comptroller of the Currency, and the Federal Deposit Insurance Corporation) is "the availability of banking services, including loans and credit, to small and medium-sized businesses" (Nanni, 1998, p. 193). This focus on the availability of small-business credit means that credit unions, which serve the household sector almost exclusively, are routinely ignored for purposes of regulatory analysis of banking market competition. Compounding the problem of defining and measuring the relevant market, the only comprehensive local market data available are annual observations of commercial bank and thrift deposits.[1]

It has been difficult to find direct empirical evidence that credit unions matter in banking markets. Amel and Hannan (1998) conclude, on the basis of empirically estimated residual deposit supply elasticities, that commercial banks in a local market continue to be their own most relevant competitors. That is, it does not appear that non-local or non-bank financial institutions, such as out-of-market banks, credit unions, other thrift institutions, finance companies, or providers of money-market mutual funds, are important determinants of deposit rate-setting behavior by banks. Emmons and Schmid (2000) find that higher levels of banking concentration in a local deposit market are associated with higher participation rates at occupational credit unions.

There is at least some indirect evidence that credit unions matter to banks, however. Bankers themselves frequently complain about (possibly unfair) competition from credit unions.[2] Banks have collectively spent large sums of money lobbying Congress to inhibit credit-union expansion. Thus, there is at least a reasonable presumption that banks view credit unions as competitors in at least some of their market segments, such as the market for household deposits.

2. A Model of Competition between Banks and Credit Unions

In this section we present a model of spatial competition between for-profit commercial banks and not-for-profit credit unions. We assume that credit unions compete with banks but not with each other. Banks interact strategically with each other, forming a homogenous oligopoly.

Similar to Salop (1979), but with important differences, we model competition between banks and credit unions as a two-stage game. In the first stage, households decide on whether to join credit unions. Credit unions establish and produce financial services for their members; these services are consumed upon production. Then, in a second stage, banks enter the market and compete for the residual demand. The residual demand is for financial services of those households that decided not to join a credit union in the first stage. Banks compete strategically with Cournot conjectural variation. New banks continue to enter the market until an additional competitor could not operate profitably were it to enter the market. To enter, a bank must expect nonnegative profits. Due to the indivisibility in the number of banks, profit typically is positive (but never negative).

We assume that households have rational expectations and, hence, fully understand the economy that we model. There is no uncertainty. When the households make their membership decision in the first stage, they anticipate correctly the price that banks will charge for financial services in the second stage.

In what follows, we first discuss household preferences. Next, we introduce credit unions, then banks. Finally, we derive testable hypotheses related to competition between banks and credit unions.

A. Household Preferences

Household preferences are modeled as locations on a circle of unit length, as introduced by Salop (1979). The circle is covered by a continuum of households, which are identical except for their preferences for financial services. Each household's unique preferences correspond to the household's unique location on the circle. Bundles of services provided in locations other than at the household's address do not fully match its preferences. The more distant these bundles are, the less the household prefers them. The household can consume such bundles through costly traveling in preference space (along the circle).

Banks offer the full range of financial services. This allows banks to match any household's preferences, making these financial institutions ubiquitous on the circle. Credit unions, on the other hand, offer only a limited set of services. Because credit unions are unable to offer every household its most preferred bundle, these organizations exist only at discrete points. The locations of the credit unions on the circle define their common bonds, which are occupational in nature. There are N common bonds, each comprising an equally large, contiguous segment (arc) on the circle. Because the common bond is defined by the households' affiliation with the credit union's sponsor, we implicitly assume that household proximity in preference space—this includes preferences with respect to geographic location—correlates with the employment relation.

B. Credit Union Sector

Credit unions operate as not-for-profit institutions; they are identical except for their locations on the unit circle. We assume that credit unions produce financial services with constant marginal costs, v. We model credit union sponsorship as the employer absorbing the credit union's fixed costs, for instance, by providing free office space and free time for employees who volunteer their services. Thus, the price of a unit of financial services equals the marginal cost of production.

Households face constant marginal costs, t per unit of distance, when traveling to the credit union. Thus, a household located r_j away from credit union i, $i = 1,...,N$, incurs travel costs to the credit union of $r_j \cdot t$. The one person-one vote principle at credit unions ensures that, if a credit union exists for a given common bond, this credit union will be located at the midpoint of the arc on the circle occupied by the members.

A household's demand for financial services is given by $x(p) = (\alpha - p)/\beta$, where p is the price, and $\alpha > p$ and $\beta > 0$ are given parameters. We assume there is no wealth effect operating on the household's demand for financial services due to the household's travel costs. This makes the parameters of the demand function independent of the household's location on the circle and of the credit-union membership decision.

Households maximize their consumer surplus net of travel costs (to credit unions), if any. Consumer surplus is the area under the household's demand curve for financial services, net of the amount spent on these services. If the household joins the credit union, then the surplus equals $(\alpha - v)^2 / 2\beta - r_j \cdot t$. The consumer surplus when doing business with a bank amounts to $(\alpha - p^b)^2 / 2\beta$, with the superscript b indicating banks. Consequently, the membership of credit union i, $i = 1,...,N$, comprises all households *j* within the potential membership—the common bond—for which the following inequality holds:

$$(1) \qquad \frac{(\alpha - v)^2}{2\beta} - r_j \cdot t - \frac{(\alpha - p^b)^2}{2\beta} \geq 0 \ .$$

Equation (1) shows that membership in a credit union is worthwhile for the household only if the credit union's price of financial services is sufficiently lower than the price charged by a bank; this is to offset the travel costs to the credit union.

We define r^* as the distance to the credit union of the marginal member, that is, the household that is indifferent between joining the credit union and buying its financial services at a commercial bank. For $r_j = r^*$, equation (1) holds at equality. Because there is a marginal household on either side of the credit union on the applicable segment of the unit circle, we define the number of credit union members as $m^* \equiv 2r^*$ $(2r^* \geq 1/N)$. Thus, the number of credit union members of any given common bond is given by:

$$(2) \qquad m^* = \frac{(\alpha - v)^2 - (\alpha - p^b)^2}{\beta \cdot t} \ .$$

A sufficient condition for an interior credit union equilibrium is that the benefit from credit union membership, $(\alpha - v)^2 / 2\beta - r \cdot t$, decreases for the marginal households as the number of members, *m*, increases. This condition holds because, as the number of credit union members grows, the price for the credit union's financial services remains unchanged, at v; at the same time, the marginal households' travel costs increase.

For $2r^* \geq 1/N$, the number of potential members, $1/N$, does not suffice for an interior solution; there is a corner solution in which all households join their respective credit union, and no banks exist. Another corner solution results for $m^* \leq 0$; this is a situation where the credit union's marginal cost of production, v, exceeds the price of financial services in the banking sector, p^b, and no credit union exists.

The credit union participation rate is defined as $m \cdot N$—the fraction of the household continuum on the circle that joins credit unions. Equation (2) shows that, the higher is the anticipated price for banking services, p^b, the higher is the credit union participation rate, all else being equal.

C. Banking Sector

There are K identical banks; this number is determined endogenously in the second stage. Costs of entry to, and exit from, the banking sector are zero. The banks face the residual demand for financial services—that is, the demand of all households that did not join a credit union in the first stage. The following demand function defines this residual market:

$$(3) \qquad p^b(x^b) = \alpha - \frac{\beta}{(1 - m \cdot N)} \cdot x^b \ .$$

Unlike credit unions, banks are ubiquitous and, consequently, their markets are not segmented. Thus, each bank faces the total residual market. Also, since banks are homogenous, there is a uniform price for bank services.

We assume that each bank follows a Cournot conjecture—that is, each bank assumes that any variation of its own output will not affect the output chosen by any other bank. The profit of bank j, $j = 1,...,K$ is:

$$\text{(4)} \qquad \pi_j(x_j^b, x_{i \neq j}^b) = p^b(x^b) \cdot x_j^b - w \cdot x_j^b - e \ ,$$

where x_j^b is the output of bank j, and $x_{i \neq j}^b$ is a vector of expectations held by bank j about the output levels of its competitors. The parameters w and e, $0 < w < \alpha$ and $e > 0$, are the bank's marginal and fixed costs of production of financial services, respectively.

Bank j maximizes profit by choosing the optimal amount of output, x_j^b, subject to the assumed conjectural variation. The bank's first-order condition is:

$$\text{(5)} \qquad 0 = \frac{d\pi_j\left(x_j^b, x_{i \neq j}^b\right)}{dx_j^b} = -\frac{\beta}{(1 - m \cdot N)} x_j^b + p^b - w = 0 \ .$$

Solving the first-order condition for x_j^b and aggregating over all K banks delivers the supply of financial services of the banking sector:

$$\text{(6)} \qquad x^b = K \cdot (1 - m \cdot N) \frac{p^b - w}{\beta} \ .$$

Substituting aggregate demand (3) into aggregate supply (6) delivers the market-clearing quantity of financial services provided by the banks:

$$\text{(7)} \qquad x^b = \frac{K}{K + 1}(1 - m \cdot N) \frac{\alpha - w}{\beta} \ .$$

Because the costs of entry and exit are zero, we impose a zero-profit condition on the banking industry. Solving equation (6) for $p^b - w$ and inserting it into the zero-profit condition delivers the equilibrium number of banks:

$$(8) \qquad K^* = floor\left((\alpha - w) \cdot \sqrt{\frac{1 - m^* \cdot N}{\beta \cdot e}} - 1 \right),$$

where *floor* is an operator that rounds down to the nearest integer. Equation (8) states that, for given demand parameters α and β, and given cost parameters of banks, w and e, the number of banks, K^*, is a stepwise monotonically decreasing function of the credit union participation rate, $m^* \cdot N$. By assumption, all banks are the same size. Therefore, the Herfindahl index of concentration, defined as the squared market shares summed up over all banks, equals $1/K^*$. This leads to the following testable hypothesis:

Hypothesis 1: *Retail banking concentration is a non-decreasing function of credit union participation.*

Further, equation (8) shows that the relation between retail banking concentration and credit union participation is dependent on households' demand functions and bank cost function parameters or, more generally, on local economic conditions. This suggests another testable hypothesis:

Hypothesis 2: *The relation between retail banking concentration and credit union participation is a function of local economic conditions.*

In what follows, we test these hypotheses, using annual, county-level data from the period 1989-2001. In this empirical analysis, each county constitutes a unit circle.

3. Data and Definition of Variables

In this section, we offer a description of the dataset and variables employed in the empirical analysis. For details on the data sources and the construction of the dataset see Appendix A. Detailed information on the variables is provided in Appendix B.

We analyze local concentration in retail banking as a function of credit union participation and local economic conditions for the period 1989-2001. All observations are annual and aggregated at the level of the county or, if applicable, independent city. We gauge concentration in retail banking by computing the Herfindahl index of retail deposit shares, including all commercial banks at full weight and thrift institutions at 50-percent weightings. This weighting scheme corresponds to current methods for assessing retail banking concentration by federal regulatory agencies. Credit unions currently are excluded from anti-trust analysis.

We measure credit union participation as the weighted average of the participation rates of individual credit unions operating in a given county; the weights are derived from the number of potential members. The set of credit unions comprises all federally chartered and federally insured occupational institutions.[3] We control for local economic conditions by including personal income per capita and population density (population per square mile) as explanatory variables. These two variables serve as proxies for the household demand function and bank cost function parameters in equation (8).[4] We do not include counties (or independent cities) where there is only one bank (17 county-years) or where there is no credit union (which applies to about two-thirds of the counties and independent cities in any given year). All variables are used in logarithmic form. Because the set of variables shows little variation over time, we analyze each year of the 1989-2001 period individually.[5]

Table 1 provides descriptive statistics for the credit union sample. Like the general population of credit unions and other depository institutions, the number of credit unions included in our sample generally decreased over time, declining from 7,399 in 1989, down to 5,556 in 2000. The most credit unions observed in a single county was 256 in 1989. The mean number of credit unions in counties that contained at least one credit union fell from about six to just under five over the 13-year span of our data, while the median number of credit unions remained steady at two.

Table 2 gives an overview of the credit-union participation rates at county level. As noted above, we discard counties where occupational credit unions do not exist. The range of participation rates in the remaining counties is large, with a low of around 1 percent and a high of 100 percent. The median and mean participation rates show a tendency to increase from the 52-53 percent range in 1989 to a peak in 1994 of around 55 percent. They then decline steadily, reaching the 43-44 percent range by 2001. More than 1,000 counties contain occupational credit unions in each year of our sample.

Table 3 summarizes the Herfindahl index of bank deposit shares. The median and mean values of the annual county Herfindahl index levels declined over our sample period, which is consistent with the index values reported in Berger, Demsetz, and Strahan (1999, Table 1). Concentration ratios generally fell during this period of frequent bank mergers because many combinations were of the "market-extension" type. That is, the number of banks decreased in the country as a whole, while new competitors were entering local markets by means of acquisition. If a new entrant—that is, an acquiring bank—increases its share of the new market, the Herfindahl index of the targeted market can decline even as the number of independent banks in the country as a whole decreases. The number of counties (and independent cities) for which values of the Herfindahl index are calculated varies slightly from year to year because we discard county-years with corner solutions, that is, observations where there are no credit unions or where there is only a single bank.

4. Empirical Methodology and Results

In order to account for the potentially nonlinear influence of local economic conditions and non-vanishing cross-derivatives, we estimate the following nonlinear model:

$$y_i = f(\mathbf{z}_i) + \varepsilon_i \ , \tag{9}$$

where y_i is the logarithmic Herfindahl index of local bank deposits of county i for a given year, and ε is a normally distributed error term with mean 0 and constant, finite variance, σ^2. The vector $\mathbf{z}_i$ comprises the observations of the three explanatory variables (credit union participation, personal income per capita, population density) and the value 1 (the constant regressor) for county i in a given year.

We have no specific hypotheses concerning precisely how local economic conditions, as gauged by personal income per capita and population density, might affect the household and bank cost parameters of the reduced form of our theoretical model, equation (8). Potentially, both variables affect the demand side and the supply side, possibly in a nonlinear manner. This leads us to be conservative in the restrictions we impose on the econometric model. Also, hypothesis 2 states that local economic conditions, which we gauge by these two variables, bear on the relation between retail banking concentration and credit union participation; this implies non-vanishing cross-derivatives.

We estimate model (9) using locally weighted regression (LOESS), as developed by Cleveland and Devlin (1988). LOESS is a multi-dimensional smoother that can accommodate not only non-vanishing second derivatives, but also non-vanishing cross-derivatives. In other words, LOESS can accommodate arbitrarily smooth influences of the explanatory variables without imposing the constraint that these influences be linear or additive. As shown by Cleveland, Devlin, and Grosse (1988), LOESS can reproduce peaks and is insensitive to asymmetrically distributed data. What is more, LOESS has many desirable statistical properties, as reviewed in Hastie and Tibshirani (1990) and Goodall (1990). More recently, Fan (1992) has shown that locally linear regression smoothers, such as LOESS, have high asymptotic efficiency. Unlike many other smoothers, locally linear regression is not liable to "boundary effects" that might arise from the lack of a neighborhood on one side of a given data point. For details on the econometric method, see Appendix C.

A. Model Selection and Analysis of Variance

We approach the testing of our hypotheses as a model-selection problem. Starting from the unconstrained model (9), we impose restrictions and test their significance in an analysis of variance. For an analysis of variance to be valid, the fitted values $\hat{\mathbf{y}}$ of the unrestricted model must be unbiased. Under the null hypothesis, the fitted values of the restricted model also are unbiased (Hastie and Tibshirani (1990)).

We start by determining a specification of model (9) that can be assumed to deliver unbiased estimates of the dependent variable; this specification then will serve as the unrestricted model in the analysis of variance. In the LOESS estimation technique, the specification choice is a problem of selecting the smoothing parameter, g—the fraction of sample observations included in the estimation of the functional form around a given data point. The larger the smoother parameter, $0 < g \leq 1$, the smoother is this estimated functional form, possibly at the expense of a bias in the fitted values.

Cross-validation, a commonly used technique for determining the smoothing parameter (or bandwidth, in kernel estimation) does not offer a solution to our specification problem. This is because cross-validation minimizes the average mean squared error, deliberately trading off some variance for a bias (Li (1990); Andrews (1991)). Instead, we employ the *M*-plot method suggested by Cleveland and Devlin (1988). This technique, which is derived from Mallows' (1973) C_P criterion and is detailed in Appendix C, offers a graphical exposition of the contributions of bias and variance to the mean squared error of the fitted values. Most importantly, the *M*-plot method is a way of choosing the smoothing parameter that entails the smallest variance subject to not generating a statistically significant bias in the fitted values. To this end, the *M*-plot method starts by estimating the model with a smoothing parameter that is sufficiently small for the bias to be negligible. The smoothing parameter then is increased in small steps. The largest smoothing parameter that does not generate a statistically significant bias is the model of choice.

Before presenting the *M*-plots and the results of the hypothesis tests from the analysis of variance, we must address the question of normality in the dependent variable—the logarithmic Herfindahl index of bank deposits. Charts 1 and 2 show empirical probability densities for the log Herfindahl index for the last and first years of the analyzed time period, 2001 and 1989; for the other 11 years, the charts look similar. The thick line represents a kernel estimate of the probability density while the thin line shows the probability density of the normal distribution based on the respective means and sample standard deviations. A visual comparison of the kernel density estimate with the normal suggests that, in spite of some skewness, the normal is a good approximation to the empirical distribution.

Charts 3 and 4 show *M*-plots for the years 2001 and 1989, respectively. The diagonal line in the *M*-plot signifies the contribution of variance to the estimated mean squared error, shown on the horizontal axis as the equivalent number of parameters of the fit. The vertical axis displays the *M*-statistic, which is the sum of the respective contributions of variance and bias. For a sufficiently small smoothing parameter, g, the bias of the fit is negligible, delivering nearly unbiased estimates of the variance, σ^2. Cleveland and Devlin (1988) argue that this value for the smoothing parameter, g, is usually in the range of 0.2 to 0.4, from which we chose the midpoint. The rightmost symbol in the *M*-plot indicates the *M*-statistic associated with $g = 0.3$; the estimated bias is zero, by definition. As the smoothing parameter increases from 0.3 to 1 (in steps of 0.05), the contribution of variance decreases and confidence bounds for the bias widen. (For comparison, we also provide the *M*-statistic for the linear model, $y_i = \mathbf{z}_i'\boldsymbol{\beta} + \varepsilon_i$, which is estimated with ordinary least squares and identified in the charts by the □-symbol.) Following Cleveland and Devlin, we choose the largest smoothing parameter that shows no statistically significant bias; for the two years in question, this value is 1.0. These specifications serve as the unrestricted models in the analysis of variance.

Testing hypothesis 1—the nonnegative influence of credit union participation on retail banking concentration—is straightforward. Testing hypothesis 2—the effect of local economic conditions on the influence of credit union participation on retail banking concentration—is more involved. Hypothesis 2 states that the cross-derivatives of the influence of credit union participation on banking concentration are non-vanishing. This means that, under the null, the influence of credit union participation on the one hand, and local economic conditions on the other hand, are additive. This additivity restriction turns model (9) into the following generalized additive model:

(10) $$y_i = f_1(x_i) + f_2(\tilde{\mathbf{z}}_i) + \varepsilon_i \ .$$

We estimate model (10) using LOESS with the backfitting algorithm developed by Hastie and Tibshirani (1986); for details on the estimating method, see Appendix C.

The analysis of variance used for testing the restrictions associated with the null hypotheses rests on an *F*-statistic that is derived from a two-moment χ^2-approximation (Cleveland and Devlin, 1988); this *F*-statistic is detailed in Appendix C. Table 4 shows the results of the analysis of variance for the two hypothesis tests, along with the results of tests on other restrictions of interest. Based on this analysis of variance, we can reject the null of no influence of credit union participation on retail banking concentration for all years of the 1989-2001 period; see the row labeled "Credit Union Participation Rate." Also, for the year 1990 and the recent past—the 1995-2001 period—we can reject the null that the influence of credit union participation (on the one hand) and local economic conditions (on the other hand) are additive; see the row labeled "Non-Additivity." Finally, we can reject the hypothesis that the linear model, $y_t = \mathbf{z}_t'\boldsymbol{\beta} + \varepsilon_t$, delivers an unbiased fit for retail banking concentration; see the row labeled "Nonlinearity."

B. Graphical Exposition

Charts 5 and 6 offer a visualization of the LOESS estimates of the unrestricted, non-parametric model (10). For each of the three explanatory variables—credit union participation rate, personal income per capita, and population density—the regression results are presented in a set of 9 conditioning plots, as suggested by Cleveland and Devlin (1988). Conditioning plots display the estimated partial impact of a chosen explanatory variable, with all other explanatory variables pegged to chosen constants. Because the intercept is not identified in this type of regression, only *changes* in the displayed partial impact (rather than the level itself) can be interpreted in an economically meaningful manner. The variable that is varied in a conditioning plot adopts only values that are actually observed in the neighborhood of the values at which the pegged explanatory variables are set. Specifically, when we peg a variable at its median value, only observations for which this variable adopts values within the closed interval spanned by the 25th and 75th percentiles are included in the conditioning plot. Similarly, when we peg a variable at the 25th (75th) percentile, only observations for which this variable is smaller (greater) than or equal to the median are included in the conditioning plot. From the set of observations chosen in this manner, we discard the 10 most extreme observations (on either side) of the variable varied in the conditioning plot before evaluating the estimated functional form for the displayed range of values. The dashed lines denote 90 percent point-wise confidence bounds, as derived by Cleveland and Devlin. The "whiskers" at the bottom of each chart indicate the dispersion of the observations on the horizontal axis.

Panel A of Chart 5 shows the partial impact of the credit union participation rate on retail banking concentration for 2001. This influence is statistically significant for 2001, as it is in all other years of the sample. The level of the credit union participation rate varies on the horizontal axis, and the levels of the other two explanatory variables (personal income per capita and population density) vary across plots. For instance, in the northwestern plot, personal income per capita is set at its 25th percentile, and so is population density. In the center plot, these two explanatory variables are held at their median values, and in the southeastern plot, they are held at their respective 75th percentiles. Thus, the influence on retail banking concentration of personal income per capita and population density can be read from the differences across plots of the graphically displayed relation between retail banking concentration and credit union participation. Furthermore, the specific influences on retail banking concentration of personal income per capita and population density are visible in Panels B and C, respectively. In each of these panels, the level of the explanatory variable varies on the horizontal axes as described above for the participation rate. These panels show that, all else held equal, retail banking concentration is increasing and convex in personal income per capita (Panel B) and is "u-shaped" in population density (Panel C).

Panel A of Table 5 shows that retail banking concentration is an increasing function of the credit union participation rate (supporting Hypothesis 1) and that the functional form varies with local economic conditions (supporting Hypothesis 2). For instance, for low values of personal income per capita and low population density—characteristic of many rural counties—there is essentially no relation between retail banking concentration and credit union participation (northwestern plot). This is different for counties with high population density but low income per capita (southwestern plot), where retail banking concentration is an increasing function of credit union participation. Even stronger is the influence of credit union participation on retail banking concentration for counties where both population density and personal income per capita are high (southeastern plot); this combination is characteristic of many metropolitan areas. The findings for the other 12 years look similar; chart 6 exhibits the results for 1989.

5. Conclusion

Credit unions are a growing part of the retail financial landscape in the United States. Credit union expansion is a controversial issue, particularly among bank and thrift owners and managers. The strength of opposition by these interested parties alone provides some indirect evidence that credit unions are relevant competitors to banks in some market segments of retail financial services.

This paper models competition in local deposit markets between for-profit and not-for-profit financial institutions. For-profit retail banks may offer a superior bundle of financial services, but not-for-profit (occupational) credit unions enjoy sponsor subsidies that allow them to capture a share of the local market. The model predicts that greater participation in credit unions in a given county will be associated with higher levels of retail-banking concentration. We find evidence of a positive relationship between county-level participation rates in occupational credit unions and the county's bank deposit market concentration.

The ability of credit unions to affect local banking market structure supports the presumption of current banking antitrust analysis that retail-banking markets remain local. We also identify several local economic factors that modulate the nature of bank-credit union competition, including income per capita and population density.

[1] Deposit data do not differentiate between commercial and household ownership of deposits (*i.e.*, business and household deposits).

[2] Credit unions are exempt from federal income taxes, which allows them to operate with low costs of capital. Occupational credit unions also typically receive in-kind subsidies from the sponsoring employer, such as free office space and time-off for employees to work in the credit union.

[3] There are also community, associational, and corporate credit unions. But occupational credit unions are by far the dominant type of retail credit union, holding almost 85 percent of member deposits (U.S. Treasury, 1997, p. 19).

[4] The availability of personal income per capital at the county level is the binding constraint in expanding the period of investigation into most recent calendar years because this variable is available with substantial delay only.

[5] Due to little variation over time, the county-level observations are likely not to be independent in time. Pooling these observations in a panel dataset would exaggerate the significance level by depressing the standard errors.

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Appendix A: Data

Our credit union dataset comprises all federally chartered and federally insured credit unions for the period 1989-2001. The dataset was obtained from the Report of Condition and Income for Credit Unions (NCUA 5300, 5300S), produced by the National Credit Union Administration (NCUA). These reports are issued semiannually, in June and December; we used the December data. The fiscal years of the credit unions are on a calendar basis. The flows in the December income statements cover the entire year; the stocks in the balance sheet are end-of-year values.

We include all occupational credit unions, which are of the following types of membership (TOM): educational (TOM: 4, 34); military (5, 35); federal, state, and local government (6, 36); manufacturing (10-15, 40-49); and services (20-23, 50-53). We do not include community credit unions, associational credit unions, or corporate credit unions. The TOM classification codes are from the NCUA (Instruction No. 6010.2, July 28, 1995).

We excluded credit union observations for any of the following reasons:

- Missing TOM codes
- Activity codes other than "active"
- Number of members or of potential members not greater than one; applies to actual and to lagged values
- Non-positive values for total assets or lagged total assets.

We calculated county-specific Herfindahl indexes as measures of concentration of the local retail deposit market. A Herfindahl index is defined as the sum of squared market shares. We measured each institution's market share as a bank's deposits or 50 percent of a thrift's deposits divided by the sum of banks' deposits plus the sum of 50 percent of thrifts' deposits (as of June 30) within a county (or independent city) based on FDIC Summary of Deposits data. These data are available online at <http://www2.fdic.gov/sod/>.

We used population density to control for cross-sectional differences across counties. Population density was calculated by dividing the total county population by the total land area of the county (or independent city). Both the county population and land area data were obtained from the U.S. Census Bureau <http://www.census.gov>. The population data are Census Bureau estimates as of July 1 of the corresponding year. The land area measurements are from the 1990 census. We included county personal income per capita—personal income divided by county population—to control for economic activity. The personal income data are from the Bureau of Economic Analysis, U.S. Department of Commerce.

Appendix B: Definitions of Variables

All variables use county-level data. There were a total of 3,141 counties (and independent cities) in the United States in 2001, including 43 independent cities (40 in Virginia) and the District of Columbia. The corresponding number for 1989 was 3,139 (*The World Almanac and Book of Facts*, 1990, 2002). Our study covers between 1,093 (in the year 2000) and 1,239 (in 1989) counties (and independent cities) per year—roughly one-third of the total. About two-thirds of the U.S. counties (independent cities included) did not have occupational credit unions (or no occupational credit unions that met the selection criteria outlined in Appendix A).

The county-specific credit-union participation rate was calculated as a weighted average over the participation rates of all credit unions in our dataset. We used the number of potential members to weight the participation rates.

There were 17 county-years where credit unions (that met the selection criteria outlined in Appendix A) existed but where the Herfindahl index was unity. These observations represent corner solutions and, hence, were eliminated from the dataset. There were no county-years were there were credit unions (of the specified type) but no banks.

Definitions of variables and underlying data sources are listed below. For data taken from the Report of Condition and Income for Credit Unions, produced by the National Credit Union Administration, the NCUA mnemonic is in brackets.

(1) Herfindahl index, defined as the sum of squared market shares of commercial banks anmd 50 percent of thrift deposits within a county based on total bank deposits plus 50 percent of thrift deposits. By definition, the Herfindahl index is greater than zero; its maximum value is one.

(2) Participation rate, as measured by the ratio of credit union members [CUSA6091] to the number of potential members [CUSA6092]. County numbers are weighted averages; the weights are based on potential members.

(3) Population density, as measured by the population per square mile in the respective county.

(4) Personal income per capita, as measured by the ratio of county personal income to county population.

Appendix C: Econometric Methodology

We estimate the nonparametric model

(C1) $$y_i = f(\mathbf{z}_i) + \varepsilon_i \ ,$$

where y_i denotes an observation of the dependent variable for county (or independent city) i for a given year, the vector $\mathbf{z}_i$ comprises the observations of the explanatory variables, and ε_i is an independently and normally distributed error term with mean 0 and constant, finite variance σ^2. The dependent variable, y_i, denotes the logarithmic Herfindahl index for county (or independent city) i; the vector $\mathbf{z}_i$ comprises the observations of the explanatory variables, and ε_i is an error term. The Herfindahl index is defined as the sum of squares of market shares. The market shares are measured by the fraction of total bank deposits (as of June 30) within a county (or independent city), based on FDIC Summary of Deposits data for commercial banks and thrifts. The explanatory variables comprise a vector of ones and the logarithmic values of the credit union participation rates, income per capita, and population density. For details on the definition of the variables and the data sources see Appendixes A and B, respectively.

We estimate model (C1) using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988). LOESS estimates the functional form in each observation by defining a neighborhood comprising the fraction g of the data points in the population; this fraction of data points is called the smoothing parameter. The data points to be included in the neighborhood are selected and weighted based on their respective Euclidean distance to the observation in question. We employ a tri-cube weight function, as detailed in Cleveland and Devlin.

LOESS smoothes the vector of observations of the dependent variable vector, $\mathbf{y}$, on the matrix of observations of the explanatory variables, $\mathbf{Z}$. The resulting smoother matrix, $\mathbf{S}$, establishes a linear relationship between $\mathbf{y}$ and the estimate $\hat{\mathbf{y}}$:

(C2) $$\hat{\mathbf{y}} = \mathbf{S} \cdot \mathbf{y} \ .$$

Given that the smooth $\hat{\mathbf{y}} = \mathbf{S} \cdot \mathbf{y}$ is an unbiased estimate of $\mathbf{y}$, an unbiased estimator of σ^2 is

(C3) $$\hat{\sigma}^2 = \frac{(\hat{\mathbf{y}} - \mathbf{y})'(\hat{\mathbf{y}} - \mathbf{y})}{df^{err}} \ ,$$

where $df^{err} \equiv N - \mathrm{tr}(2\mathbf{S} - \mathbf{SS}')$ is the error degrees of freedom and N is the number of observations (Hastie and Tibshirani, 1990).

The regression results are presented in conditioning plots, as introduced by Cleveland and Devlin (1988). Conditioning plots display the estimated partial impact of a chosen explanatory variable, with all other explanatory variables pegged to chosen constants. Because the intercept is not identified in this type of regression, only *changes* in the displayed partial impact (rather than the level itself) can be interpreted in an economically meaningful manner. The variable that is varied in a conditioning plot adopts only values that are actually observed in the neighborhood of the values at which the pegged explanatory variables are set. Specifically, when we peg a variable to its median value, only observations for which this variable adopts values within the closed interval spanned by the 25th and 75th percentiles are included in the conditioning plot. Similarly, when we peg a variable to the 25th (75th) percentile, only observations for which this variable is smaller (greater) than or equal to the median are included in the conditioning plot. From the thus chosen set of observations, we discard the 10 most extreme observations (on either side) of the variable varied in the conditioning plot before evaluating the estimated functional form for the displayed range of values. We use the linearity property from (C2) to derive confidence intervals for the partial impact on the dependent variable displayed in the conditioning plots, as suggested by Cleveland and Devlin (1988).

In an analysis of variance, we estimate a restricted, additive version of model (C1):

$$y_i = f_1(x_i) + f_2(\tilde{\mathbf{z}}_i) + \varepsilon_i \ , \tag{C4}$$

where the scalar x_i is the observation of county (or independent city) i of the log Herfindahl index, and the vector $\tilde{\mathbf{z}}_i$ comprises all other explanatory variables included in $\mathbf{z}_i$ as defined in equation (C1), inclusive of the vector of ones. In model (C4), the influences of the Herfindahl index, x_i, and the joint influences of the other right-hand side variables, $\tilde{\mathbf{z}}_i$, are restricted to be additive.

We estimate model (C4) using the backfitting algorithm suggested by Hastie and Tibshirani (1986). Backfitting consists of alternating the steps

$$\mathbf{f}_1^{(m)} = \mathbf{S}_1^{(m)}(\mathbf{y} - \mathbf{f}_2^{(m-1)}) \tag{C5a}$$

$$\mathbf{f}_2^{(m)} = \mathbf{S}_2^{(m)}(\mathbf{y} - \mathbf{f}_1^{(m)}) \ , \tag{C5b}$$

where $m \geq 1$ indicates the stage of the iteration procedure and $\mathbf{S}_1$ and $\mathbf{S}_1$ are the corresponding LOESS smoother matrices for the partial influences of $\mathbf{x}$ and $\mathbf{Z}$, respectively. We start out by smoothing $\mathbf{y}$ on $\mathbf{x}$ (and a vector of ones). The smoothing delivers fitted values for $\mathbf{y}$, $\mathbf{f}_1^{(0)}$. We subtract $\mathbf{f}_1^{(0)}$ from $\mathbf{y}$ and smooth this difference on $\tilde{\mathbf{Z}}$ (which includes a vector of ones), resulting in $\mathbf{f}_2^{(1)}$. We keep alternating the steps (C5a,b) until the vectors of fitted values, $\mathbf{f}_1^{(m)}$ and $\mathbf{f}_2^{(m)}$, stop changing. For the smoother matrix, we can write (Hastie and Tibshirani (1986, p. 120)):

$$\hat{\mathbf{y}} = \mathbf{S} \cdot \mathbf{y} \equiv \{\mathbf{I} - (\mathbf{I} - \mathbf{S}_2)(\mathbf{I} - \mathbf{S}_1\mathbf{S}_2)^{-1}(\mathbf{I} - \mathbf{S}_1)\} \cdot \mathbf{y} \ , \tag{C6}$$

where $\mathbf{S}_1$ and $\mathbf{S}_1$ the partial smoother matrices obtained in the last round of the iteration procedure and $\mathbf{I}$ is the identity matrix.

Following Cleveland and Devlin (1988), the *F*-statistic for testing the statistical significance of the restriction imposed in model (C4) over model (C1)—under the assumption of normality and the unrestricted model (C1) offering an unbiased estimate (C3)—reads

$$\text{(C7)} \qquad \hat{F} = \frac{(\mathbf{y}'\mathbf{R}_{\mathrm{L}}\mathbf{y} - \mathbf{y}'\mathbf{R}_{\mathrm{S}}\mathbf{y})/v_1}{(\mathbf{y}'\mathbf{R}_{\mathrm{S}}\mathbf{y})/\delta_1},$$

where $\mathbf{R}_{\mathrm{L}} \equiv (\mathbf{I}-\mathbf{L})\cdot(\mathbf{I}-\mathbf{L})'$, $\mathbf{R}_{\mathrm{S}} \equiv (\mathbf{I}-\mathbf{S})\cdot(\mathbf{I}-\mathbf{S})'$, $v_1 = \mathrm{tr}(\mathbf{R}_{\mathrm{L}} - \mathbf{R}_{\mathrm{S}})$, and $\delta_1 = \mathrm{tr}\,\mathbf{R}_{\mathrm{S}}$. The test statistic $\hat{F}$ is approximated by an *F*-distribution with v_1^2/v_2 numerator and δ_1^2/δ_2 denominator degrees of freedom, where $v_2 = \mathrm{tr}(\mathbf{R}_{\mathrm{L}} - \mathbf{R}_{\mathrm{S}})^2$ and $\delta_2 = \mathrm{tr}\,\mathbf{R}_{\mathrm{S}}{}^2$.

Note that the analysis of variance (C7) can easily extended to the linearized version of the nonparametric model (C1),

$$\text{(C8)} \qquad y_i = \mathbf{z}_i'\boldsymbol{\beta} + \varepsilon_i .$$

The ordinary least squares equivalent to the smoother matrix $\mathbf{S}$ reads $\mathbf{Z}\cdot(\mathbf{Z}'\mathbf{Z})^{-1}\cdot\mathbf{Z}'$. We used this "smoother matrix" in the analysis of variance of Table 3 when testing the nonparametric model (C1) against the linear model (C8).

For model selection, we use *M*-plots, as developed by Cleveland and Devlin (1988). *M*-plots offer a graphical portrayal of the trade-off between the contributions of variance and bias to the mean squared error as the smoothing parameter, g, changes. The expected mean squared error summed over all observations and normalized by the variance, σ^2, reads

$$\text{(C9)} \qquad M_g = \frac{E(\mathbf{y}'\mathbf{R}_g\mathbf{y})}{\sigma^2},$$

where the subscript g indicates the chosen smoothing parameter. For a sufficiently small smoothing parameter—let us say, f—the bias of the vector of the fitted values, $\hat{\mathbf{y}}$, is negligible, resulting in a nearly unbiased estimate of σ^2. In this case then, M_g can be estimated by

(C10a) $$\hat{M}_g = \hat{B}_g + V_g \ ,$$

where

(C10b) $$\hat{B}_g = \frac{\mathbf{y}'\mathbf{R}_g\mathbf{y}}{\hat{\sigma}_f} - \mathrm{tr}(\mathbf{I}-\mathbf{S}_g)'(\mathbf{I}-\mathbf{S}_g) \ ,$$

(C10c) $$V_g = \mathrm{tr}\,\mathbf{S}_g\,'\mathbf{S}_g \ .$$

$\hat{B}_g$ is the contribution of bias to the estimated mean squared error, and V_g is the contribution of variance. Cleveland and Devlin show that $\hat{M}_g$ can be implemented as

(C11) $$\hat{M}_g = v_1 \frac{(\mathbf{y}'\mathbf{R}_g\mathbf{y} - \mathbf{y}'\mathbf{R}_f\mathbf{y})/v_1}{(\mathbf{y}'\mathbf{R}_f\mathbf{y})/\delta_1} + \delta_1 - N + 2\,\mathrm{tr}\,\mathbf{S}_g$$

$$= v_1\hat{F} + \delta_1 - N + 2\,\mathrm{tr}\,\mathbf{S}_f \ ,$$

where $\mathbf{y}'\mathbf{R}_f\mathbf{y}$ is the residual sum of squares when the smoothing parameter is f. Because there is an approximate *F*-distribution for $\hat{F}$—as mentioned above—a probability distribution for $\hat{M}_g$ can be derived. Cleveland and Devlin argue that the smoothing parameter f, for which the bias of the fitted values is negligible, is "usually in the range of .2 to .4"; we chose $f = 0.3$. Similar to the analysis of variance (C7), the *M*-plot method can easily be extended to linear models estimated with ordinary least squares.

Table 1

The table presents descriptive statistics for the number of credit unions per county (or independent city). The descriptive statistics includes only counties (or independent cities) that qualify for the quantitative analysis shown in Table 4—that is counties that have occupational credit unions that pass the screen outlined in Appendix A.

Number of Credit Unions per County						
Year	Minimum	Median	Mean	Maximum	Standard Deviation	Total Number of Credit Unions
2001	1	2	4.872	155	9.615	5,564
2000	1	2	5.083	166	9.976	5,556
1999	1	2	5.149	173	10.207	5,767
1998	1	2	5.215	189	10.456	5,909
1997	1	2	5.327	194	10.754	6,062
1996	1	2	5.395	200	10.945	6,210
1995	1	2	5.062	140	9.375	5,837
1994	1	2	5.089	145	9.494	5,918
1993	1	2	5.641	214	11.711	6,606
1992	1	2	5.720	223	12.023	6,773
1991	1	2	5.827	229	12.454	7,004
1990	1	2	5.847	239	12.562	7,157
1989	1	2	5.972	256	13.139	7,399

Table 2

The table presents descriptive statistics for the credit union participation rate at the county (or independent city) level. This county-level credit union participation rate is defined as the weighted average of the participation rates of individual credit unions operating in a given county; the weights are derived from the number of potential credit union members. By definition, the participation rate is greater than zero; its maximum value is one. The descriptive statistics includes only counties that qualify for the quantitative analysis shown in Table 4—that is counties that have occupational credit unions that pass the screen outlined in Appendix A.

Credit Union Participation Rate						
Year	Minimum	Median	Mean	Maximum	Standard Deviation	Number of Observations (Counties)
2001	0.016	0.432	0.443	1.000	0.248	1,142
2000	0.017	0.489	0.493	1.000	0.230	1,093
1999	0.018	0.509	0.513	1.000	0.220	1,120
1998	0.017	0.519	0.524	1.000	0.217	1,133
1997	0.016	0.530	0.531	1.000	0.217	1,138
1996	0.033	0.538	0.545	1.000	0.209	1,151
1995	0.030	0.538	0.541	0.998	0.213	1,153
1994	0.015	0.552	0.552	1.000	0.213	1,163
1993	0.018	0.556	0.559	1.000	0.211	1,171
1992	0.011	0.543	0.549	1.000	0.209	1,184
1991	0.014	0.534	0.536	1.000	0.211	1,202
1990	0.014	0.524	0.533	1.000	0.210	1,124
1989	0.010	0.523	0.532	1.000	0.210	1,239

Table 3

The table presents descriptive statistics for the Herfindahl index, defined as the sum of squared market shares of commercial banks within a county, based on total bank deposits. By definition, the Herfindahl index is greater than zero; its maximum value is one. The descriptive statistics includes only counties that qualify for the quantitative analysis shown in Table 4—that is counties that have occupational credit unions. For details on the selection criteria see Appendix A.

Herfindahl Index						
Year	Minimum	Median	Mean	Maximum	Standard Deviation	Number of Observations (Counties)
2001	0.046	0.206	0.233	0.807	0.114	1,142
2000	0.050	0.205	0.231	0.906	0.114	1,093
1999	0.043	0.209	0.234	0.850	0.114	1,120
1998	0.044	0.211	0.238	0.843	0.120	1,133
1997	0.044	0.214	0.241	0.908	0.116	1,138
1996	0.041	0.216	0.241	0.880	0.116	1,151
1995	0.040	0.214	0.238	0.881	0.119	1,153
1994	0.041	0.216	0.240	0.910	0.120	1,163
1993	0.040	0.215	0.238	0.906	0.119	1,171
1992	0.027	0.214	0.236	0.875	0.118	1,184
1991	0.029	0.211	0.233	0.860	0.211	1,202
1990	0.027	0.207	0.231	0.881	0.123	1,124
1989	0.034	0.262	0.283	0.984	0.136	1,239

Table 4

The table shows the results of an analysis of variance. The unrestricted model is the nonparametric regression equation $y_i = f(\mathbf{z}_i) + \varepsilon_i$. We estimate the model, using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988), for each year in the 1989-2001 period. The dependent variable, y_i, denotes the logarithmic Herfindahl index for county (or independent city) i; the vector $\mathbf{z}_i$ contains the observations of the explanatory variables, and ε_i is an error term. The explanatory variables comprise a vector of ones and the logarithmic values of the credit union participation rates, income per capita, and population density. We impose restrictions on the model by means of imposing linearity—resulting in the linear model $y_i = \mathbf{z}_i'\boldsymbol{\beta} + \varepsilon_i$—or by way of omitting variables. We also impose an additivity constraint, which results in the generalized additive model $y_i = f_1(x_i) + f_2(\tilde{\mathbf{z}}_i) + \varepsilon_i$; the scalar x_i is the credit union participation rate and $\tilde{\mathbf{z}}_i$ comprises the observations of the other explanatory variables, inclusive of the vector of ones. For details on the econometric method and the parametric analysis of variance see Appendix B. The asterisk, *, denotes significance at the 1 percent level. Numerator degrees of freedom are in parentheses.

Analysis of Variance

Year	2001	2000	1999	1998	1997	1996	1995
Smoothing Parameter	1.0	1.0	1.0	1.0	1.0	1.0	1.0
Denominator Degrees of Freedom	1,141	1,092	1,119	1,132	1,137	1,150	1,151
Credit Union Participation Rate	1.349*** (163)	2.535*** (132)	3.001*** (120)	1.829*** (89)	2.922*** (69)	2.972*** (112)	1.928*** (64)
Income per Capita	31.107*** (111)	31.007*** (104)	34.723*** (108)	38.322*** (140)	35.380*** (136)	35.488*** (132)	40.754*** (94)
Population Density	4.228*** (113)	3.768*** (102)	3.367*** (119)	3.262*** (121)	3.958*** (116)	4.438*** (120)	5.152*** (86)
Non-Additivity	5.500*** (195)	5.607*** (197)	8.474*** (231)	5.288*** (212)	2.643*** (209)	4.301*** (228)	4.071*** (154)
Nonlinearity	7.524*** (179)	7.726*** (157)	6.744*** (192)	5.940*** (153)	7.236*** (130)	5.772*** (169)	4.187*** (108)
Number of Observations	1,142	1,093	1,120	1,133	1,138	1,151	1,153

Year	1994	1993	1992	1991	1990	1989
Smoothing Parameter	0.85	1.0	1.0	0.95	1.0	1.0
Denominator Degrees of Freedom	1,159	1,169	1,182	1,199	1,123	1,237
Credit Union Participation Rate	1.560*** (108)	3.408*** (61)	2.506*** (40)	2.953*** (52)	5.704*** (63)	1.687*** (41)
Income per Capita	18.560*** (103)	38.972*** (121)	37.750*** (77)	49.549*** (113)	48.456*** (97)	40.520*** (93)
Population Density	2.646*** (108)	4.811*** (104)	7.527*** (53)	3.150*** (111)	4.290*** (88)	4.178*** (87)
Non-Additivity	1.123 (202)	0.621 (140)	0.278 (102)	0.095 (191)	1.352*** (136)	0.185 (116)
Nonlinearity	2.809*** (158)	2.042*** (135)	5.016*** (72)	2.750*** (144)	4.370*** (119)	3.167*** (88)
Number of Observations	1,163	1,171	1,184	1,202	1,124	1,239

Chart 1

The chart shows for the year 2001 a kernel estimate (thick line) of the logarithmic Herfindahl index of banking concentration at the county (or independent city). The Herfindahl index is defined as the sum of squares of market shares. The market shares are measured by the fraction of total bank deposits (as of June 30) within a county (or independent city) based on FDIC Summary of Deposits data for commercial banks and thrifts. We use a Gaussian kernel along with an (under the null of normal distribution) optimal bandwidth of $(4/3)^{0.2} \cdot \hat{\sigma} \cdot T^{-0.2}$, where T is the number of sample observations and $\hat{\sigma}$ is the sample standard deviation (Silverman, 1986). The normal probability density (thin line) is the normal based on estimates of the sample mean and standard deviation. The whiskers indicate the dispersion of the observations on the horizontal axis. There is statistically significant skewness (0.196) but no significant excess kurtosis (-0.070).

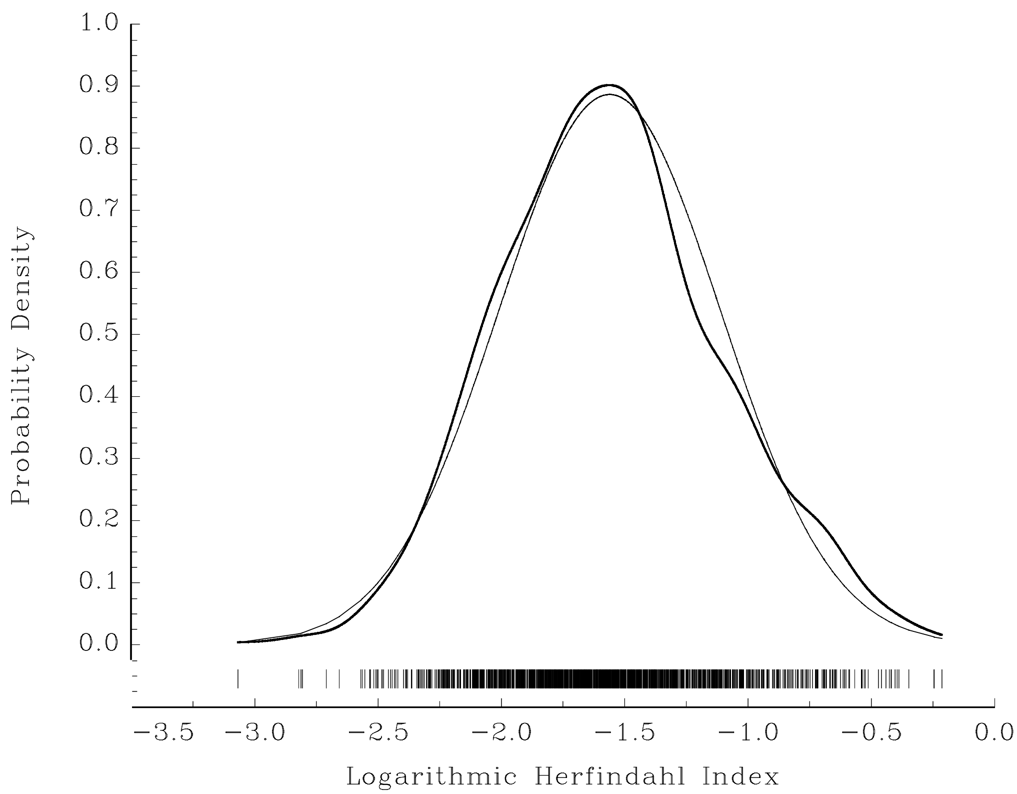

Chart 2

The chart shows for the year 1989 a kernel estimate (thick line) of the logarithmic Herfindahl index of banking concentration at the county (or independent city). The Herfindahl index is defined as the sum of squares of market shares. The market shares are measured by the fraction of total bank deposits (as of June 30) within a county (or independent city) based on FDIC Summary of Deposits data for commercial banks and thrifts. We use a Gaussian kernel along with an (under the null of normal distribution) optimal bandwidth of $(4/3)^{0.2} \cdot \hat{\sigma} \cdot T^{-0.2}$, where T is the number of sample observations and $\hat{\sigma}$ is the sample standard deviation (Silverman, 1986). The normal probability density (thin line) is the normal based on estimates of the sample mean and standard deviation. The whiskers indicate the dispersion of the observations on the horizontal axis. There is statistically significant skewness (-0.448) and excess kurtosis (0.420).

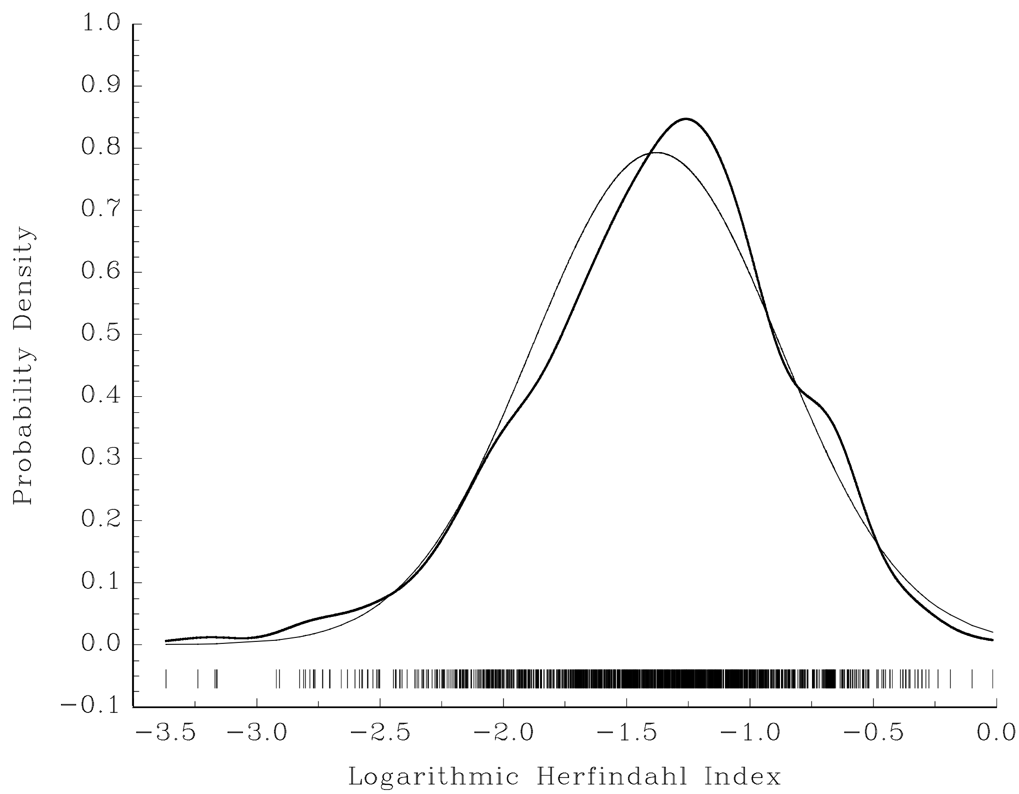

Chart 3

The chart shows an *M*-plot for the year 2001. We estimate for that year the nonparametric model $y_i = f(\mathbf{z}_i) + \varepsilon_i$ using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988). The dependent variable, y_i, denotes the logarithmic Herfindahl index for county (or independent city) i; the vector $\mathbf{z}_i$ comprises the observations of the explanatory variables, and ε_i is an error term. The explanatory variables comprise a vector of ones and the logarithmic values of the credit union participation rates, income per capita, and population density. The *M*-plot shows the trade-off between the contributions of variance and bias to the mean squared error of the fitted values as the smoothing parameter, g, changes. The *M*-statistic is defined as $\hat{M}_g = V_g + \hat{B}_g$, where $\hat{B}_g$ is the contribution of bias to the estimated mean squared error, and V_g is the contribution of variance. V_g is shown as the equivalent number of parameters—a measure of the amount of smoothing done by estimation procedure. On the diagonal line, $\hat{M}_g$ equals V_g. The smoothing parameter ranges from 0.3 (rightmost ×-symbol) to 1 (leftmost ×-symbol) in steps of 0.05. The □-symbol represents the *M*-statistic for the ordinary least squares fitting of the linearized model, $y_i = \mathbf{z}_i'\boldsymbol{\beta} + \varepsilon_i$.

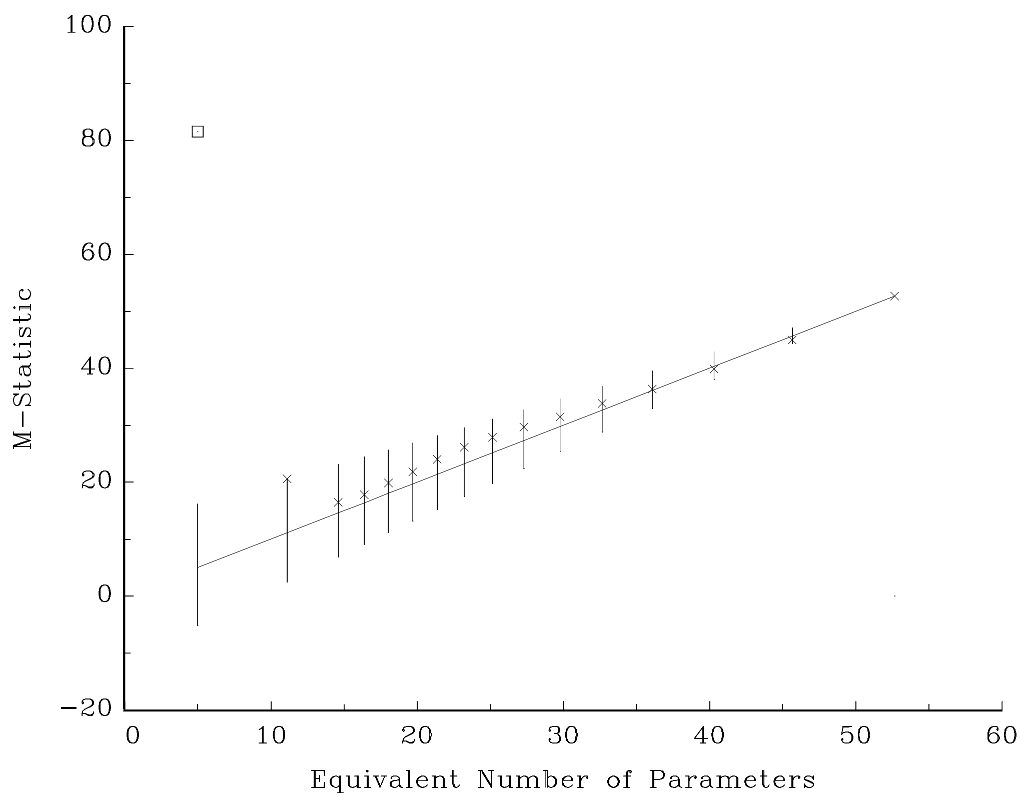

Chart 4

The chart shows an *M*-plot for the year 1989. We estimate for that year the nonparametric model $y_i = f(\mathbf{z}_i) + \varepsilon_i$, using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988). The dependent variable, y_i, denotes the logarithmic Herfindahl index for county (or independent city) i; the vector $\mathbf{z}_i$ comprises the observations of the explanatory variables, and ε_i is an error term. The explanatory variables comprise a vector of ones and the logarithmic values of the credit union participation rates, income per capita, and population density. The *M*-plot shows the trade-off between the contributions of variance and bias to the mean squared error of the fitted values as the smoothing parameter, g, changes. The *M*-statistic is defined as $\hat{M}_g = V_g + \hat{B}_g$, where $\hat{B}_g$ is the contribution of bias to the estimated mean squared error, and V_g is the contribution of variance. V_g is shown as the equivalent number of parameters—a measure of the amount of smoothing done by estimation procedure. On the diagonal line, $\hat{M}_g$ equals V_g. The smoothing parameter ranges from 0.3 (rightmost ×-symbol) to 1 (leftmost ×-symbol) in steps of 0.05. The □-symbol represents the *M*-statistic for the ordinary least squares fitting of the linearized model, $y_i = \mathbf{z}_i{}'\boldsymbol{\beta} + \varepsilon_i$.

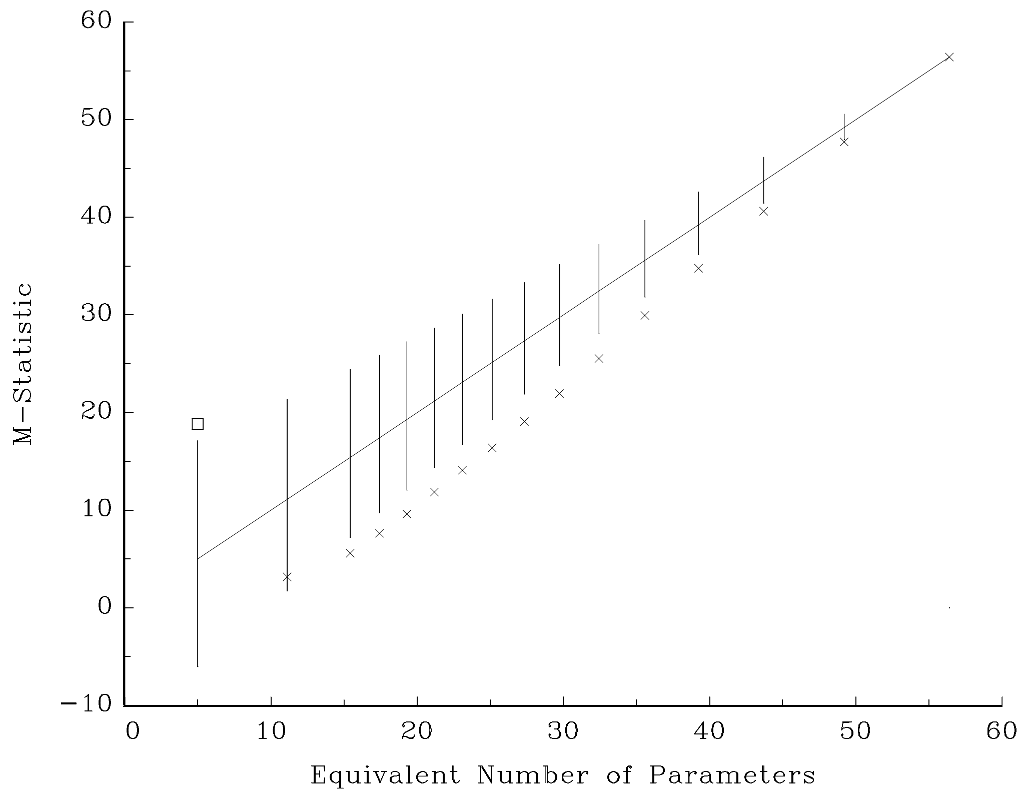

Chart 5

The chart shows sets of conditioning plots of the nonparametric model $y_i = f(\mathbf{z}_i) + \varepsilon_i$, estimated for the year 2001. The dependent variable, y_i, denotes the logarithmic Herfindahl index for county (or independent city) i; the vector $\mathbf{z}_i$ comprises the observations of the explanatory variables, and ε_i is an error term. The explanatory variables comprise a vector of ones and the logarithmic values of the credit union participation rates, income per capita, and population density.

Panel A: Sensitivity of Banking Concentration to Credit Union Participation, 2001

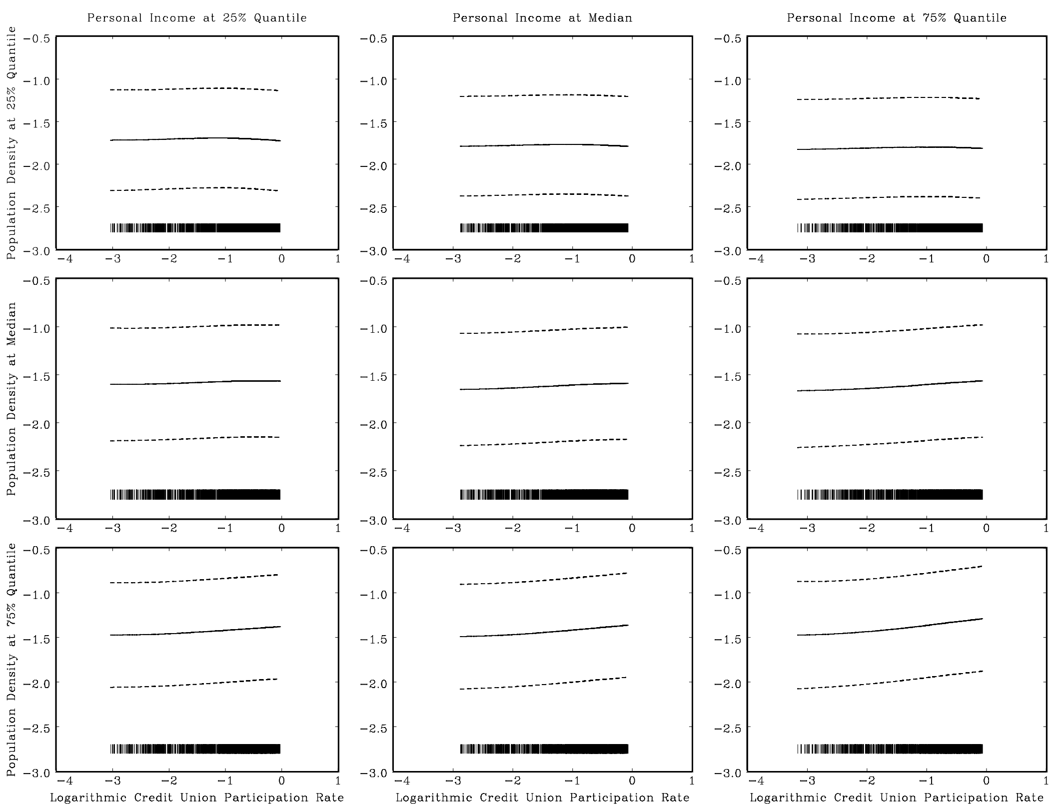

Chart 5, *cont.*

Panel B: Sensitivity of Banking Concentration to Per-Capita Income, 2001

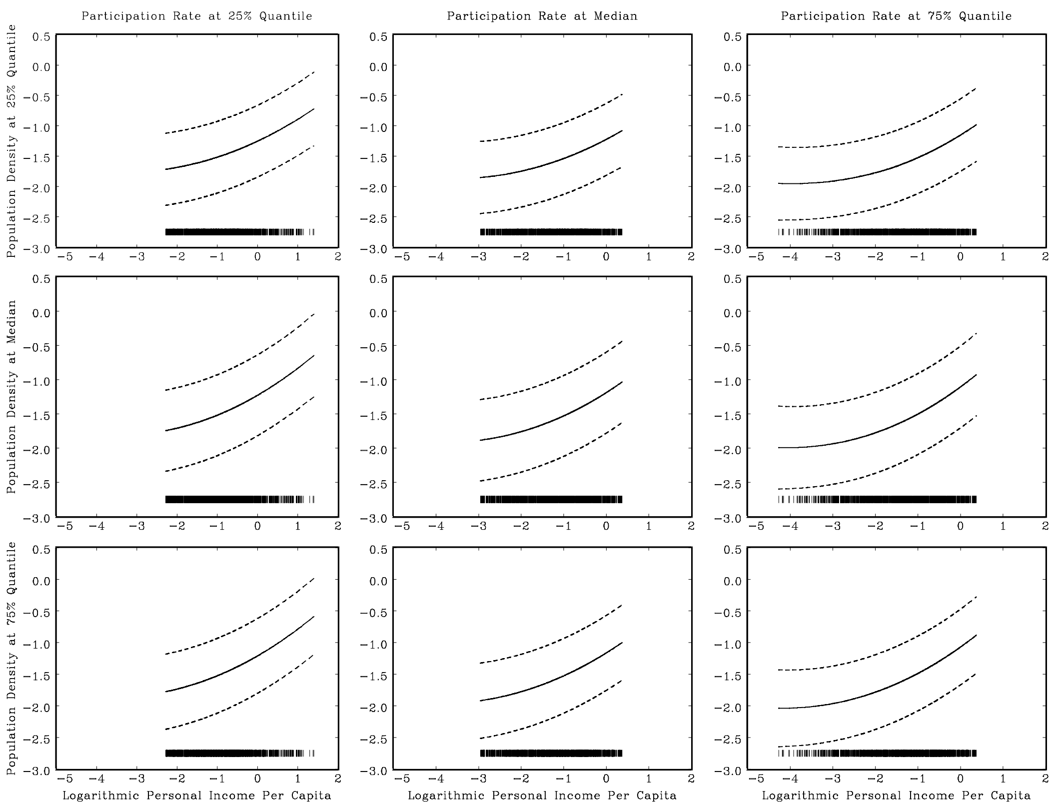

Chart 5, *cont.*

Panel C: Sensitivity of Banking Concentration to Population Density, 2001

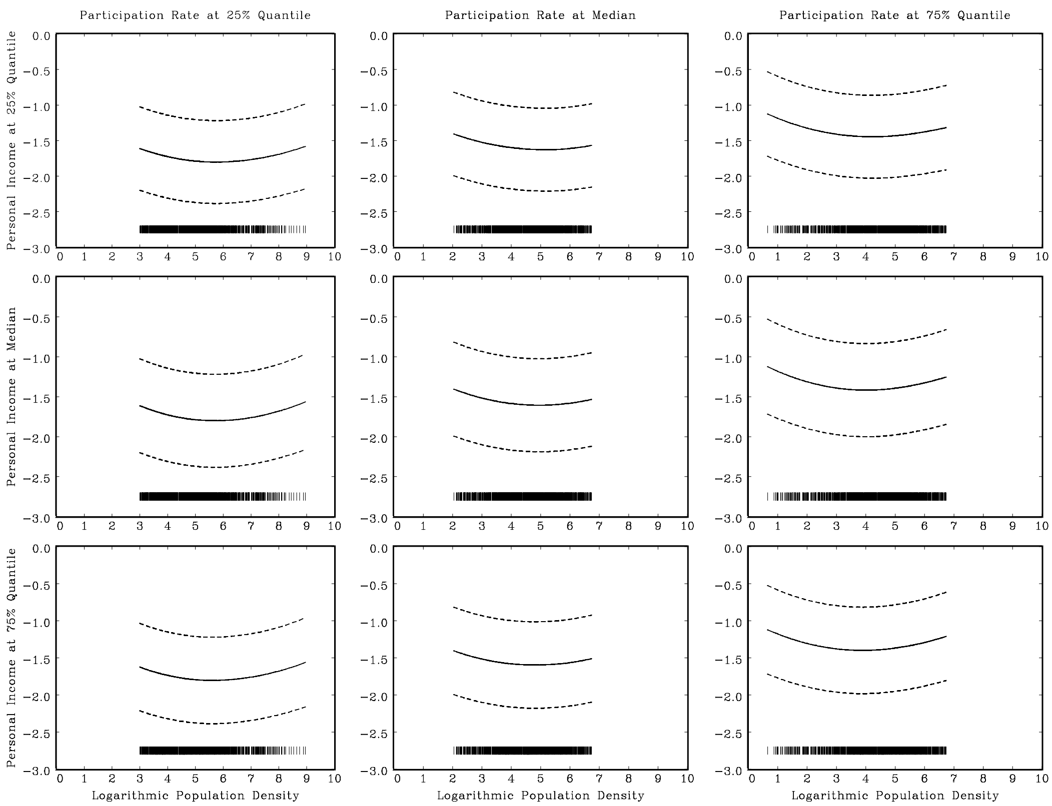

Chart 6

The chart shows sets of conditioning plots of the nonparametric model $y_i = f(\mathbf{z}_i) + \varepsilon_i$, estimated for the year 2001. The dependent variable, y_i, denotes the logarithmic Herfindahl index for county (or independent city) i; the vector $\mathbf{z}_i$ comprises the observations of the explanatory variables, and ε_i is an error term. The explanatory variables comprise a vector of ones and the logarithmic values of the credit union participation rates, income per capita, and population density.

Panel A: Sensitivity of Banking Concentration to Credit Union Participation, 1989

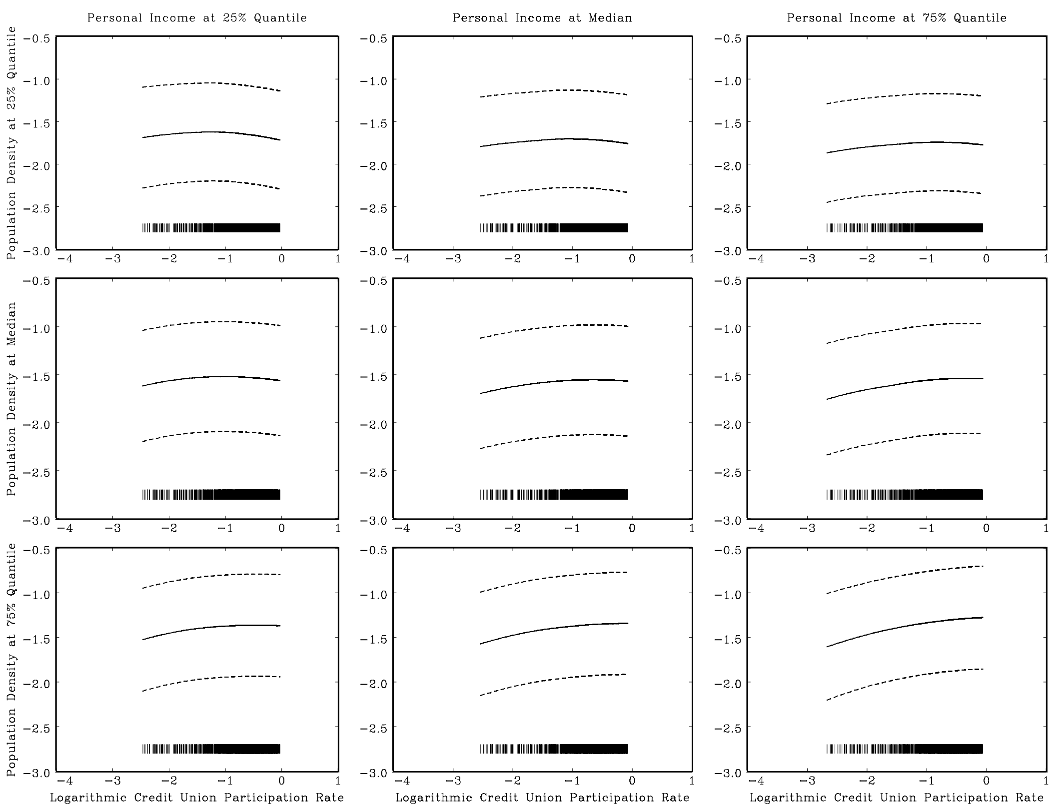

Chart 6, *cont.*

Panel B: Sensitivity of Banking Concentration to Per-Capita Income, 1989

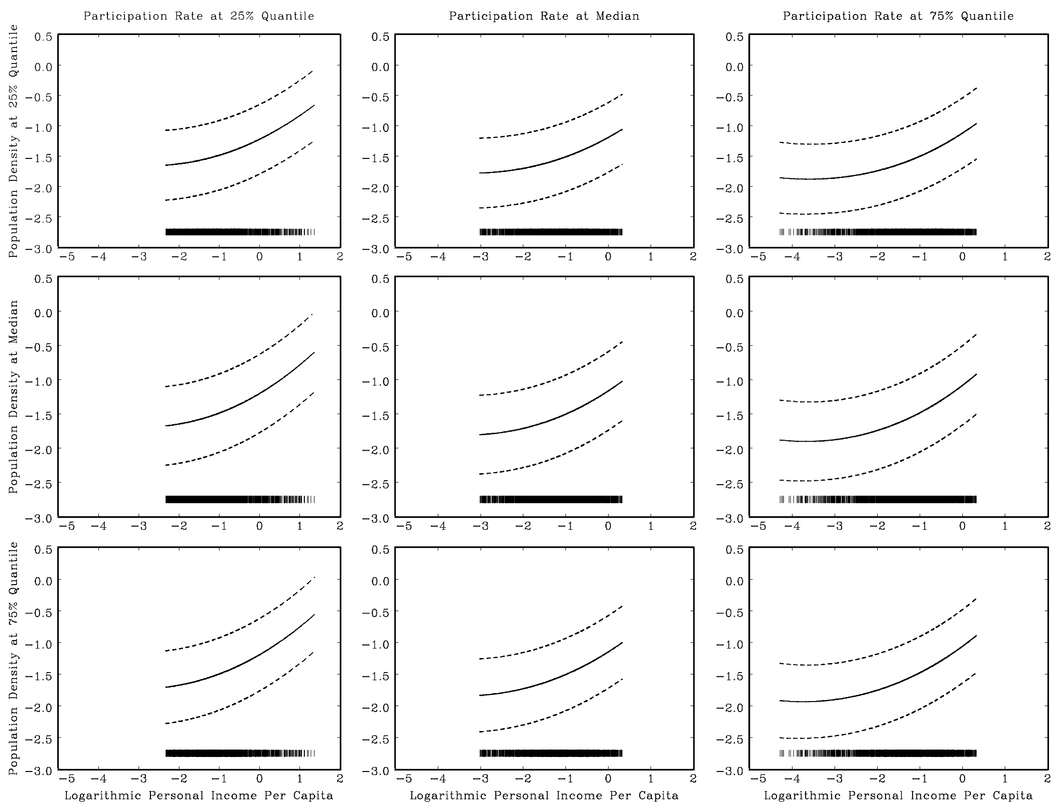

Chart 6, *cont.*

Panel C: Sensitivity of Banking Concentration to Population Density, 1989