WHY ARE BANK PROFITS SO PERSISTENT? THE ROLES OF PRODUCT MARKET COMPETITION, INFORMATIONAL OPACITY, AND REGIONAL/MACROECONOMIC SHOCKS

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ABSTRACT

We investigate how banking market competition, informational opacity, and sensitivity to shocks have changed over the last three decades by examining the persistence of firm-level rents. We develop propagation mechanisms with testable implications to isolate the sources of persistence. Our analysis suggests that different processes underlie persistent performance at the high and low ends of the distribution. Our tests suggest that impediments to competition and informational opacity continue to be strong determinants of performance; that the reduction in geographic regulatory restrictions had little effect on competitiveness; and that performance remains sensitive to regional/macroeconomic shocks. The findings also suggest reasons for the recent record profitability of the industry.

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I. Introduction

Over the last three decades, the banking industry witnessed significant changes in regulation, technology, and financial engineering techniques. Restrictions on deposit prices and geographic expansion were lifted while the regulatory focus shifted toward capital adequacy standards and prompt corrective action. The computer revolution and advances in financial engineering altered the way that banks serve their customers and manage risks. This paper considers banking industry responses to these innovations. In particular, we examine changes in banking product market competition, informational opacity, and sensitivity to regional/macroeconomic shocks over the last three decades.

We study the evolution of the banking industry by conducting nonparametric analyses of 1) the time-series patterns of the banking industry's persistence of firm-level rents, and 2) the sources of this persistence. An industry's persistence of firm-level rents, henceforth denoted by "persistence," is the tendency for individual firms to remain in the same place in the industry's performance distribution. Persistence should reflect the existence of impediments to product market competition and informational opacity in an industry because both of these factors generate market power and allow firms to perform consistently at the high end or low end of their industry's performance distribution. Without market power, relatively high performance by a firm would be eliminated reasonably quickly as other firms enter its local market, imitate its transparent techniques or strategies, bid for its most profitable customers, or bid up the price of its managerial talent. Similarly, no firm would perform consistently at the low end of the distribution in the absence of market power. Such a firm would be forced by competitive pressures to exit the industry or imitate the strategies or bid for the customers and managers of the firms performing at the high end of the distribution.

To the extent that regional shocks are serially correlated (ex post), firms in a region subjected to a string of positive shocks would tend to remain in the high end of the performance distribution, provided that entry into the region is not instantaneous and costless. Analogously, firms in a region subjected to a string of negative shocks would tend to remain in the low end of the distribution, provided that regional exit is not instantaneous/costless. Similarly, if firms are unable to adjust their portfolios or to enter/exit the industry quickly and costlessly in response to changing macroeconomic conditions, firms with high risk or procyclical returns may perform consistently in the high end of the performance distribution during protracted economic expansions and perform consistently in the low end of the distribution during protracted downturns.

We find that U.S. banking industry persistence has increased substantially over the last three decades. Interestingly, the largest increases in persistence have occurred in the recent "boom" period between 1993 and 1997 when aggregate bank performance was at record levels. These upward shifts in industry persistence imply one or more of the following possibilities: 1) product markets have become less competitive; 2) the banking industry has become more opaque, and/or 3) the banking industry has become more sensitive to regional/macroeconomic shocks.

Further exploration reveals that persistence at the high end of the performance distribution has markedly different time series patterns than does persistence at the low end of the distribution, although persistence at both ends of the distribution was relatively high in the boom period. In particular, persistence at the high end of the distribution climbed over the entire time period and accelerated in the boom period, while persistence at the low end dropped in the early 1980s and climbed steadily thereafter. The pattern of persistence at the low end of the distribution is consistent with deposit rate deregulation of the early 1980s having increased the competitiveness of banks at the low end of the distribution, reducing the ability of poorly performing banks to survive. The finding that persistence at both ends of the distribution was relatively high in the boom period is consistent with some common factors influencing persistence during these years.

To conduct our nonparametric analysis of the sources of persistence in the banking industry, we first develop several alternative propagation mechanisms that may generate persistence. The set of mechanisms consists of three "performance source mechanisms" and one "risk position mechanism." Each performance source mechanism is based on a source that drives performance, differs across banks, and is relatively stable over time. Candidates considered for sources of bank performance include 1) local market power derived from impediments to product market competition, 2) informational opacity, and 3) regional/macroeconomic shocks. The risk position mechanism is based on differences in risk/return profiles across banks that are stable over time.

We also develop testable implications of each mechanism for various groups of banks classified by either a performance source or by an accounting-based measure of bank risk. By testing the implications of each mechanism for the pre-boom period (1970-1992) and for the boom period (1993-1997), where persistence in general and bank profits were at historically high levels, we determine why persistence has increased over time and address the questions raised above about how the industry has evolved over the last three decades.

Perhaps surprisingly, our results suggest that local market power derived from barriers to entry caused by regulatory restrictions on branching and expansion did not influence relative bank performance. Other impediments to product market competition, such as local market concentration, appeared to influence relative bank performance more at the low end than at the high end of the distribution of returns. In contrast, we find that market power derived from informational opacity affected relative bank performance more at the high end of the distribution. These findings hold regardless of whether we use data from the pre-boom or the boom periods. Overall, our results suggest that the removal of geographic restrictions on competition had little effect on the competitiveness of the banking industry and that economic rents achieved due to other sources of market power have not been competed away over time.

The evidence also suggests that bank performance remains sensitive to regional/macroeconomic shocks. Geographic expansion and the adoption of financial engineering techniques do not appear to have reduced this systematic portion of bank risk. Moreover, it appears that the increase in persistence in the boom period was due in part to banks with riskier positions on the risk/return frontier benefitting from the extraordinarily protracted economic expansion.

Industrial organization economists have used the concept of industry performance persistence of firm-level rents to evaluate differences in competitiveness across industries due to product market power and informational opacity. Mueller (1977) demonstrated that firm-specific rents generally did not quickly converge to the industry average rent level.[1] More recently, Cubbin and Geroski (1987), Waring (1996), and Roland (1997) measured persistence by using the average speed at which firm level rents converge towards an industry average--a lower average speed of convergence would imply higher performance persistence.[2] In addition, Waring (1996) considered whether industries that are highly concentrated or relatively opaque have relatively slow speeds of convergence of firm profits to the industry average. His empirical tests suggested that persistence was higher in those industries that were more highly concentrated or more opaque.

This paper differs from these previous persistence studies in four significant respects. First, rather than considering the speed of convergence for firm level profits to an average profit level for the industry, we build upon nonparametric measures of persistence that have been used to study mutual fund performance (e.g., Brown, Goetzmann, Ibbotson and Ross 1992, Goetzmann and Ibbotson 1994, Brown and Goetzmann 1995). Second, we define and examine "winning persistence" at the high end of the performance distribution separately from "losing persistence" at the low end of the distribution. Third, as discussed above, we investigate the time series patterns of persistence. Fourth, we develop models of persistence propagation mechanisms and testable implications of such mechanisms for various subgroups of banks. The propagation mechanisms suggest that differences in concentration and informational opacity *within an industry* generate

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[1]Mueller (1977) did not define a metric for industry persistence of firm-specific rents nor did he investigate the sources of such rents.

[2]Roland (1997) decomposed a firm's performance persistence into the tendency for various revenue and cost categories to persist, but did not explain the exogenous sources which would lead to persistence of these accounting categories.

persistence rather than differences in concentration and opacity *across industries*, as is sometimes implicitly assumed in the industrial organization literature (e.g., Waring 1996).

In Section II, we develop our nonparametric measures of winning and losing persistence. In Section III, we present and discuss the time series patterns of persistence for the US banking industry over the 1970-1997 period. The propagation mechanisms and their testable implications are formalized in Section IV. In Section V, we test these mechanisms using banking industry data over the pre-boom (1970-1992) and boom (1993-1997) periods. Section VI concludes by discussing our findings and their implications for why bank profits have been extraordinarily high during the boom period.

II. NONPARAMETRIC MEASURES OF PERSISTENCE APPLIED TO THE US BANKING INDUSTRY

Brown, Goetzmann, Ibbotson and Ross (1992), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), and others developed an easy-to-interpret nonparametric methodology for measuring persistence in the mutual fund industry. This methodology estimates the relationship between "winning" and "losing" in the current and previous periods. We extend this nonparametric methodology by developing separate measures of "winning persistence" and "losing persistence" and by conditioning performance on multiple past periods. In addition, we specify extreme benchmarks for winning and losing, building upon Mueller's (1977) insight that it is the behavior of firms at the extremes of the performance distribution that are most informative about the competitiveness of an industry.

Persistence is defined as the tendency for members of a group to perform consistently above or below a benchmark (i.e., to "win" or "lose") on a consistent basis. The benchmark may be either determined by a performance standard within the group (e.g., the median of the distribution of industry returns) or it can be determined using information outside the group (e.g., the return of a stock index). Here, consistent with the industrial organization literature, we use performance benchmarks determined within the industry.

For expository convenience, we denote the benchmark by α: The proportion α of the banks are "losers" and $1-\alpha$ are "winners." For example, if performance is measured relative to the median return (i.e., $\alpha=.50$), then the probability of winning, $P(W_t)$, or losing, $P(L_t)$, in period t is .50. Analogously, if $\alpha=.90$, then performance is measured relative to the 90^{th} percentile of the performance distribution. In that case, $P(W_t) = .10$ and $P(L_t) = .90$ for all t.

We define j-period winning persistence at time t as:

$$WP_{t,j} \equiv P(W_t | W_{t-1}, \ldots, W_{t-j}) \,/\, P(W_t | L_{t-1}, \ldots, L_{t-j}). \tag{1}$$

This is the probability of a win conditioned on a prior string of j consecutive wins divided by the probability of a win given j straight past losses.[3] This ratio is equal to 1 under the null hypothesis that there is no performance persistence. Put differently, at time t-1, the probability of a win next period should be the same regardless of whether the firm has been on a j-period winning streak or on a j-period losing streak. A ratio above 1 indicates that winning is persistent and a value below 1 indicates that persistence follows a reactionary pattern in which a win tends to follow a series of losses. We denote winning persistence relative to the benchmark α by $WP^{\alpha}_{t,j}$.

Similarly, we define j-period losing persistence at time t as:

$$LP_{t,j} \equiv P(L_t | L_{t-1}, \ldots, L_{t-j}) \,/\, P(L_t | W_{t-1}, \ldots, W_{t-j}). \tag{2}$$

That is, the probability of another loss after a string of j consecutive losses divided by the probability of a loss given j prior straight wins. Again, this ratio is 1 under the null hypothesis of no performance persistence, greater than 1 for performance persistence, and less than 1 for reactionary behavior. We denote losing persistence relative to benchmark α by $LP^{\alpha}_{t,j}$.

Total persistence is the geometric mean of winning persistence and losing persistence, or:

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[3] The numerator of the winning persistence ratio is one minus the standard hazard rate of a loss after j consecutive wins, i.e., $P(W_t | W_{t-1}, \ldots, W_{t-j}) = 1 - P(L_t | W_{t-1}, \ldots, W_{t-j})$, and the denominator of this ratio is the hazard rate of a win after a streak of j consecutive losses.

$$TP_{t,j} \equiv WP_{t,j}^{1/2} \bullet LP_{t,j}^{1/2}. \tag{3}$$

This ratio is equal to 1 under the hypothesis that there is no persistence.[4]

Although there is no "optimal" number of past periods j, there are several considerations in choosing which values of j would be most informative. On the one hand, a larger number of past periods allows a clearer distinction between winning and losing persistence. A larger value for j may also allow more time for the convergence of profits in the industry to occur. On the other hand, a larger value for j reduces the sample size considerably because $TP_{t,j}$, $WP_{t,j}$, and $LP_{t,j}$ are computed only when there have been j consecutive past wins or losses.[5] Because of these trade-offs, we analyze persistence using values of j ranging from 1 to 6 years.

Winning persistence and losing persistence are different concepts, but they are likely to be related to each other empirically because both of these types of persistence depend upon there being a limited probability of switching between winning and losing relative to the specified benchmarks. In general, both types of persistence will be large if firms tend to stay in their respective places within the distribution of earnings, and both of these measures of persistence will be small if firms tend to switch places with each other.

A special case in which there is a one-to-one correspondence between winning and losing persistence occurs when the same relative benchmark α is used for the winning and losing measures of persistence and a single past period is specified (i.e., j=1). This is because 1) with a constant α, the probabilities of winning and losing in each period are fixed, and 2) the consideration of only one past period implies that there are no mixed histories which contain both wins and losses. In this

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[4]To put our measures in context, the relative persistence measure employed by Brown and Goetzmann (1995) is the square of our total persistence measure using one past period (j=1), and using the median as the benchmark (α=.50).

[5]In addition, there may be a number k such that $P(W_t | W_{t-1}, \ldots, W_{t-k}) = P(W_t | W_{t-1}, \ldots, W_{t-k}, W_{t-k-1}, \ldots) = P(W_t | W_{t-1}, \ldots, W_{t-k}, L_{t-k-1}, \ldots)$, i.e., such that the probability of winning does not depend on performance more than k periods past. In this event, the persistence measures do not change or give any additional information for j > k, but rather only reduce the sample size available to estimate these probabilities.

special case, the probability of switching from winning to losing can be determined from the probability of switching from losing to winning, since $P(L_t | W_{t-1}) = [\alpha/(1-\alpha)]\, P(W_t | L_{t-1})$.[6]

However, generally there is not a one-to-one correspondence between winning and losing persistence. The correspondence breaks down when there are multiple past periods (i.e., j>1). As the number of past time periods j increases, the past has more mixed histories that contain both wins and losses (e.g., W_{t-1}, L_{t-2}). Therefore, only if j=1 does every firm have the possibility of continuing a winning or losing streak.[7] The correspondence also becomes weak if a benchmark outside of the industry is used for the persistence measures. This is because the probabilities of winning and losing are not fixed, but rather vary with the probabilities of switching between winning and losing (e.g., $P(W_t | W_{t-1})$ increases when $P(W_t | L_{t-1})$ increases).

In this study, we consider winning persistence with high benchmarks and losing persistence

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[6]To see this, we note that the unconditional probabilities are related as $P(W_t) = [(1-\alpha)/\alpha] \bullet P(L_t)$. Breaking these unconditional probabilities into their conditional components yields $P(W_t | W_{t-1}) \bullet P(W_{t-1}) + P(W_t | L_{t-1}) \bullet P(L_{t-1}) = [(1-\alpha)/\alpha] \bullet [P(L_t | W_{t-1}) \bullet P(W_{t-1}) + P(L_t | L_{t-1}) \bullet P(L_{t-1})]$. Setting $P(W_{t-1}) = 1-\alpha$ and $P(L_{t-1}) = \alpha$ and substituting in the identities $P(W_t | W_{t-1}) = 1 - P(L_t | W_{t-1})$ and $P(L_t | L_{t-1}) = 1 - P(W_t | L_{t-1})$, yields the relationship $P(L_t | W_{t-1}) = [\alpha/(1-\alpha)]\, P(W_t | L_{t-1})$ shown above.

Also, applying the identities $P(L_t | L_{t-1}) = 1 - P(W_t | L_{t-1})$ and $P(L_t | W_{t-1}) = 1 - P(W_t | W_{t-1})$ provides three independent linear identities among the four conditional probabilities in the winning and losing persistence formulas. In this special case where j is equal to one, losing persistence is a linear function of winning persistence, whereby $LP^{\alpha}_{t,1} = (2\alpha - 1)/\alpha + [(1-\alpha)/\alpha] \bullet WP^{\alpha}_{t,1}$. This relationship would hold for this special case, regardless of the economic process that underlies winning and losing persistence.

When the median is the benchmark (α=.50) and a single past period is specified (j=1), the above equations imply that the probability of switching from winning to losing equals the probability of switching from losing to winning (i.e., $P(L_t | W_{t-1}) = P(W_t | L_{t-1})$) and also imply that losing persistence equals winning persistence (i.e., $LP^{50}_{t,1} = WP^{50}_{t,1}$). This special case is the one considered in Brown and Goetzmann (1995). Because total persistence is the geometric mean of winning persistence and losing persistence, all three persistence measures are equal to each other.

[7]The use of j past periods allows for 2^j different past permutations of winning and losing, only two of which are the pure all wins ($W_{t-1}, \ldots, W_{t-j}$) or all losses ($L_{t-1}, \ldots, L_{t-j}$) histories in our persistence formulas, so the proportion of mixed histories increases dramatically with j. In terms of our derivation in a prior footnote, the total probability of winning and losing would contain terms like $P(W_t | W_{t-1}, L_{t-2}) \bullet P(W_{t-1}, L_{t-2})$ in the case of j=2, which do not cancel out and cannot be determined ex ante. Therefore, the probability of switching from winning to losing $P(L_t | W_{t-1}, W_{t-2})$ cannot be discerned from the probability of switching from losing to winning $P(W_t | L_{t-1}, L_{t-2})$, and there is no necessary relationship between losing persistence $LP^{\alpha}_{t,2}$ and winning persistence $WP^{\alpha}_{t,2}$.

with low benchmarks for cases where there is not a one-to-one correspondence between the two. These specifications allow us to investigate whether different mechanisms generate persistence at the high and low ends of the performance distribution. For example, we find that informational opacity appears to be important for winning persistence when α=.90 and impediments to product market competition appear to be important for losing persistence when α=.10.[8]

Considerable attention in the literature on nonparametric persistence measures has been paid to "survivorship bias." We believe that this bias is likely to be of small magnitude in our study because rather than excluding failed banks, we identify them as losers relative to all benchmarks in the year of failure.[9] Further, to limit potential bias caused by banks leaving the sample because of consolidation within the industry, we merger-adjusted our banking data. Specifically, we identified the banks that had the same charter at time t and then retroactively combined those banks over the prior j periods (as if the banks were already consolidated in the earlier periods) before calculating the persistence measures for time t.[10]

III. TIME SERIES PATTERNS OF PERFORMANCE PERSISTENCE IN BANKING

To calculate estimates for winning persistence (WP), losing persistence (LP), and total persistence (TP) for the US banking industry, we need to specify what performance measures are of interest, the appropriate benchmarks to consider, and the number of past periods j that are relevant.

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[8]The notion that processes underlying relatively high and low performers may be different is not novel. Brown, Goetzmann, Ibbotson and Ross (1992) discussed the apparent differences between the persistence of positive and negative performance in the mutual fund industry. Hendricks, Patel, and Zeckhauser (1993) found that portfolios made up of mutual funds ranked according to past performance in the low end of the distributions perform poorly relative to standard benchmarks, while those ranked according to past performance in the high end of past distributions perform well relative to standard benchmarks. Carhart (1997) was able to explain the persistence of high performers, but the persistence of low performers remained a puzzle.

[9]The time period in which the fewest banks failed, 1993-1997, is the time period in which the persistence measures presented below are of the largest magnitude. This suggests that survivorship bias was not the underlying cause of the strong persistence found in the banking industry data.

[10]Our time series estimates of persistence were also calculated without the failure or merger adjustments, and the results were materially unchanged.

Because we are interested in the banking industry as a whole, rather than just the few, relatively large publicly-traded banking organizations, we use annual Call Report data from 1969-1997, which includes income statement and balance sheet data for all domestically-chartered US commercial banks.[11] Based on these Call Reports, we calculate three performance measures -- return on equity (ROE), return on assets (ROA), and the ratio of revenues to costs (R/C) -- for each bank in the industry. For our winning persistence estimates, we set α=.90, which implies that winning banks are in the top 10% of the distribution. For our total persistence measures, we set α=.50, and for our losing persistence estimates, we set α=.10. Thus, we estimate $WP^{.90}$, $TP^{.50}$, and $LP^{.10}$. As discussed above, we calculate persistence measures that use values of j from 1 to 6 years. The conditional probabilities in equations (1) - (3) are proxied by frequency ratios that were observed in the data.[12]

In Table 1 are persistence estimates for the US banking industry for each of the three performance measures ROE, ROA, and R/C. Each persistence estimate in this table is calculated using one lagged period (i.e., j=1). Strikingly, each of the $WP^{.90}$, $TP^{.50}$, and $LP^{.10}$ persistence estimates is statistically significantly greater than one.[13] Thus, performance is persistent for the US

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[11]Banks were excluded from the sample if their equity was less than 1% of gross total assets or if any of the following measures was negative: gross total assets, securities, total loans, employment, labor expenditures, total fixed assets, and/or total off-balance sheet items, because such data are likely in error or misleading. The data are taken from the December Call Reports, which are considered the most reliable.

[12]For example, if there were 100 banks entering period t that had exceeded the benchmark α for j periods in a row, and 20 of these banks also exceeded the benchmark in period t, then we replace $P(W_t \mid W_{t-1}, \ldots, W_{t-j})$ in the persistence formulas with .20.

[13]To calculate the standard error of the persistence measures, we used the variance of Brown and Goetzmann's (1995) measure of total persistence, TP_{BG}, where $TP_{BG}=TP^2$. The variance of the log of $TP_{BG}= [(1/[W_t, W_{t-1}, W_{t-2}, W_{t-3}]) + (1/[W_t, L_{t-1}, L_{t-2}, L_{t-3}]) + (1/[L_t, L_{t-1}, L_{t-2}, L_{t-3}]) + (1/[L_t, W_{t-1}, W_{t-2}, W_{t-3}])]^{(1/2)}$ for j=3, where the four bracketed denominators refer to the number of banks that have that pattern of wins and losses. The variance of $TP=(1/4)\text{var}(TP_{BG})$. We decomposed the variance given in Brown and Goetzmann to obtain an upper bound on the variance of WP and LP. By the definitions of persistence, the $\log(TP_{BG})=\log(WP) + \log(LP)$. This implies that the $\text{var}[\log(TP)]=\text{var}[\log(WP) + \log(LP)] = \text{var}[\log(WP)] + \text{var}[\log(LP)] + 2\text{cov}[\log(WP),\log(LP)]$. A reasonable assumption is that the covariance between these two measures is positive, therefore $\text{var}[\log(WP)] < \text{var}[\log(TP_{BG})]$ and $\text{var}[\log(LP)] < \text{var}[\log(TP_{BG})]$. We, therefore, use $\text{var}[\log(TP_{BG})]$ for our statistical tests of whether WP and LP differ from 1.

banking industry for each of these three performance measures, for a wide range of benchmarks, and for each year in the sample.[14] On average, the total persistence estimate for the ROE performance measure is 3.4. This implies that bank performance was more than three times as likely to remain either above or below median performance than either rise above or fall below the median. Interestingly, banks that performed in the tails of the distribution (top or bottom 10%) were even more likely to continue to perform in the tails of the distribution -- winning persistence and losing persistence estimates are larger than the corresponding total persistence estimate for every year of the sample for all three measures.

Figure 1 presents the time-series estimates of persistence contained in Table 1. Several observations are apparent. The years in which there are peaks and troughs in TP, WP, and LP differ from one another. The top panel shows that total persistence rose considerably over the 1970-1997 period, with the most substantial increases in the boom period 1993-1997. The middle panel shows that winning persistence also increases over time and is also generally the highest during the boom period. Losing persistence estimates reached highs during the mid-1970s, reached lows during the early 1980s when deposit rates were deregulated, and then rose in the boom period of the 1990s. These time series patterns for persistence estimates suggest that TP, WP, and LP are influenced by different factors. For example, deregulation of deposit rates may have limited the ability of banks in the very low end of the performance distribution to survive in the early 1980s, but may have had little impact on performance of banks at the high end of the distribution. The finding that all of the persistence measures were relatively high in the boom period is consistent with some common

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[14]The banking industry total persistence estimates differ sharply from comparable estimates that have been calculated for the mutual fund industry. In contrast to our banking total persistence estimates, which are large and statistically significantly different from one in all years, the mutual fund persistence estimates presented in Brown and Goetzmann (1995) were statistically significantly different from one in only seven of twelve years and reactionary ($TP_{t,1} < 1$) in two years of their sample. Moreover, the bank persistence estimates are on average more than four times as large as the mutual fund persistence estimates. Unlike the banking estimates, the mutual fund industry total persistence estimates were not increasing over time.

factors influencing persistence at this time.

The time-series patterns for persistence measures did not appear to critically depend on the choice of performance measure, ROE, ROA, or R/C. Figure 2 displays total, winning and losing persistence estimates based on each of the three performance measures after they have been normalized to unity in 1970. The persistence estimates based on each of these performance measures tend to rise and fall together.[15]

Interestingly, fluctuations in persistence measures may be linked to business cycle fluctuations. Figure 3 demonstrates that sharp declines in the total persistence estimates appear to foreshadow declines in real economic activity (as measured by detrended gross domestic product or by using business cycle peaks and troughs as identified by the National Bureau of Economic Research) during the earlier part of the sample. In the latter part of the sample, declines in persistence coincide with declines in economic activity. These findings suggest that persistence may be related to the business cycle and macroeconomic conditions.

As discussed above, the choice of j, the number of past periods for the nonparametric estimates, is an empirical question. More past periods can provide for a clearer distinction between winning and losing persistence, but the information content of persistence estimates can be reduced because of small sample sizes when j is large. In Figure 4, estimates for total persistence, winning persistence, and losing persistence based on ROE are presented for each j=1,...,6 for the 1975-1997 period. Similar results were obtained for the other performance measures (not shown). Strikingly, regardless of the number of past periods j, each of the persistence estimates was greater than 1. Once j exceeds 3, however, there appears to be greater fluctuations in the persistence estimates, suggesting that the smaller sample sizes are reducing the reliability of the estimates. Therefore, we use persistence estimates calculated using j=3 in the remainder of the analysis.

[15]The Pearson correlation coefficients are .79 for TP between ROE and ROA, .80 for TP between ROE and R/C, and .67 for TP between ROA and R/C. All are statistically different from zero.

In sum, our analysis of the time-series patterns of persistence revealed that: 1) persistence has generally increased over time, particularly in the boom period 1993-1997; 2) the processes generating winning and losing persistence may be different; 3) losing persistence may be linked to deregulation of deposit rates in the early 1980s, 4) macroeconomic conditions may affect persistence, and 5) a reasonable number of past periods to consider in the nonparametric analysis below is j=3. To understand more precisely how a variety of sources would generate persistence, we formalize the propagation mechanisms that may underlie performance persistence measures. To determine whether these sources have changed over time, we test for these mechanisms in the pre-boom (1970-1992) and boom (1993-1997) periods.

IV. Persistence Propagation Mechanisms

We consider two general types of mechanisms that could potentially generate persistence. For the "performance source" type of mechanism, let PF_{it} denote performance of bank i at time t, and let S_{it} denote a potential source of winning or losing persistence for bank i at time t. Suppose that 1) there is variation in the source variable across banks (i.e., $S_{it} \neq S_{jt}$, for some $i \neq j$), 2) the source is relatively stable over time (i.e., $\partial S_{it}/\partial t \approx 0$), and 3) performance is positively correlated with the source of persistence (i.e., $\rho_{PF,S}>0$).[16] If all three conditions are met, then banks with high values of the source variable would tend to perform consistently better than banks with low values, creating persistence. As noted above, we consider three performance source mechanisms: 1) local market power derived from impediments to product market competition, 2) informational opacity, 3) and regional/macroeconomic shocks.

The second type of propagation mechanism, the "risk position" mechanism, operates through banks choosing different points on the risk/return frontier. Let σ^2_{it} denote the variance in performance of bank i and time t. Suppose that 1) banks choose different points on the risk/return

[16]The third condition does not necessarily imply the first, since a positive correlation can exist across time even if there is no cross-sectional variation in the source.

frontier (i.e., $\sigma^2_{it} \neq \sigma^2_{jt}$ for some $i \neq j$), and 2) σ^2_{it} is stable over time for all i (i.e., $\partial\sigma^2_{it}/\partial t \approx 0$). Provided these two conditions are met, we would observe high winning persistence relative to a high benchmark because safe banks with relatively low variance would tend to be consistent losers, and risky banks with relatively high variance would tend to be winners, although the individual risky banks that win each period may differ. By similar argument, these two conditions would also imply losing persistence relative to a low benchmark.

The testable implications of these mechanisms pertain to subgroups of banks. To construct meaningful subgroups, we first rank banks by a source or risk variable. We then form high source or risk subgroups, comprised of the top quarter of banks ranked by average level of the source or risk variable over the four-year period from t-3 to t, consistent with our choice of j=3. Low source or risk subgroups contain the bottom quarter of banks ranked by the average level of the source or risk variable. Each mechanism has implications with regard to 1) the probabilities of winning and losing for the subgroups compared to the industry, and 2) winning and losing persistence for subgroups compared to the industry.

Consider the implications of the performance source mechanism for the probabilities of winning and losing in period t. Since our persistence estimates are based on j=3, we restrict our attention to observations used in the calculation of these estimates--banks that have been on three-period winning or losing streaks. Thus, the probability of winning considered is $P(W_t|[W_{t-1}W_{t-2}W_{t-3} \cup L_{t-1}L_{t-2}L_{t-3}])^{.90}$, which we denote with P(W|.). The probability of losing is calculated analogously and denoted as P(L|.). Given that the subgroups are formed based on ranking banks by the average level of a source variable over current and previous j periods, $P(W|.)_{subgroup} > P(W|.)_{industry}$ for a high source subgroup implies that all three conditions of the source performance mechanism are satisfied.[17] Similarly, evidence that low source subgroups are more likely to lose than the industry

[17]We demonstrate this with three simple contradiction arguments. In each argument, we assume that a condition of the mechanism does not hold and show that this implies no relationship between P(W|.) for

suggests that the three conditions may be satisfied.

Next, consider the implications of the performance source mechanism for winning and losing persistence for the source subgroups relative to the industry as a whole. For convenience, we denote winning persistence for j=3 and α =.90 as WP3 and losing persistence for j=3 and α=.10 as LP3. The performance source mechanism implies that WP3 should be lower for a high source subgroup than for the industry. High source subgroup banks would be closer to, and therefore more likely to switch around a high benchmark than banks in the industry due to other factors affecting performance that are uncorrelated with the source. Similarly, high source subgroup banks would be farther from, and therefore less likely to switch around a low benchmark than banks in the entire industry. Using similar logic, low source subgroup banks would be less likely to switch around a high benchmark and more likely to switch around a low benchmark than would banks in the entire industry. This implies that low source subgroup should have higher WP3 and lower LP3 than the entire industry. We confirm this intuition with simulation analysis.[18]

Now consider the implications of the risk position mechanism. Under this mechanism, banks with high risk positions are more likely to win relative to a high benchmark and to lose relative to

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the subgroups and the industry. First, assume that $S_{it} = S_{jt}$. In this case, ranking by source would provide no information about the P(WI.). Therefore, the first condition holds. Second, assume that $\partial S_{it}/\partial t \neq 0$. In this case, the average rank of the bank by performance source would be a poor proxy for the current rank by source and therefore a poor predictor of the current P(WI.). Therefore, the second condition holds. Third, assume that $\rho_{PF,S} = 0$. In that case, there would not be a relationship between the P(WI.) and the source. Therefore, the third condition holds as well.

[18]In the simulations, performance was a weighted average of two performance sources. Both of these performance sources were drawn for each bank from a uniform distribution on the [0,1] interval and were assumed to be constant over time. A random error was drawn from a uniform distribution on the [0,1] interval for each bank in each time period. Three separate simulations were performed. In the first simulation, the first performance source had a weight of 0.5, the second had a weight of 0.0, and the random error had a weight of 0.5. In the second simulation, the respective weights were 0.25, 0.25, and 0.5, and in the third simulation the respective weights were 0.25, 0.5, and 0.25. In all three simulations, we simulated performance for 10,000 banks over 1,000 periods. We found that WP3 for the high source groups (top quarter of banks ranked by either by the first or second source) was less than WP3 for the industry in all three simulations. Further, we found that WP3 for the low source subgroups are greater than WP3 for the industry. The simulations performed for LP3 were also consistent with the predictions.

a low benchmark than the industry. In contrast, banks with low risk positions are less likely to win relative to a high benchmark or to lose relative to a low benchmark than the industry. The implications for relative persistence between risk subgroups and the industry are 1) low risk banks should exhibit greater winning and losing persistence than the industry, and 2) high risk banks should exhibit less winning and losing persistence than the industry. These implications follow from the facts that high risk banks tend to switch around the extreme benchmarks, and low risk banks tend to stay between these benchmarks. The testable implications for both types of propagation mechanisms are summarized in Table 2.

V. Tests Of The Persistence Propagation Mechanisms

We test whether the data are consistent with the testable implications of three performance source mechanisms and the risk position mechanism. The three performance sources we consider are: 1) market power derived from regulatory restrictions or other impediments to product market competition; 2) market power derived from informational opacity; and 3) regional/macroeconomic shocks. We also examined a fourth performance source, accounting bias (not shown in tables), but the results were considered unreliable because of difficulties in finding adequate proxies for this source.[19] To test each mechanism, we use a three-step process. First, we form subgroups of banks (using various proxies and indicator variables) to represent high or low source subgroups (for the performance source mechanism) and high or low risk (for the risk position mechanism). Second,

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[19] We identified two groups of banks that may be subject to performance-augmenting accounting biases. The first subgroup, banks with high four-year loan growth, may be subject to the accounting bias generated by "loan seasoning." Loans typically do not have reported performance problems until they have been "seasoned" and the borrowers have had time to develop difficulties in repaying their obligations (Avery and Gordy 1997). The second subgroup, publicly traded banks, may be subject to an accounting bias stemming from the use of stock-option based compensation plans. Banks that rely heavily on these types of compensation schemes can systematically understate their compensation expenses with a consistent overstatement of their accounting performance as a result. FAS 123 established fair value as the measurement basis for transactions in which employees receive shares of stock or other equity instruments of the employer or the employer incurs liabilities to employees in amounts based on the price of its stock for fiscal years beginning after December 15, 1995. However, it permits any entity to continue to apply the accounting provisions of Opinion 25 to its stock-based compensation plans.

subgroups are based on barriers to entry associated with regulatory geographic restrictions on branching and expansion. Table 3A presents estimates of P(WI.), P(LI.), WP3, and LP3 for these subgroups of banks.

The probability of losing and losing persistence estimates for banks grouped by conventional measures of local market power are almost entirely consistent with the predictions of the propagation mechanism. For example, banks in the high Herfindahl subgroup had P(LI.) and LP3 estimates of 0.038 and 0.041, respectively, which are significantly lower than the industry estimates of 0.049 and 0.054, respectively. It appears that banks with high local market power rarely perform in the bottom 10% of the distribution. In columns 5 and 6, the P(LI.) estimates for banks in the high market power subgroups (pre-boom and boom periods, respectively) are markedly and significantly lower than the industry estimates, which are indicated in the last row of each column. The LP3 estimates for these subgroups of banks (columns 7 and 8) were weakly and insignificantly higher than the industry estimates. Analogously, in columns 13 and 14, the P(LI.) estimates for banks in the low local market power subgroups (pre-boom and boom periods, respectively) are strikingly and significantly higher than the industry estimates. Further, the LP3 estimates for low market power subgroups (columns 15 and 16) are significantly lower than the industry estimate for two-thirds of these estimates.

The probability of winning and winning persistence estimates for banks grouped by conventional measures of local market power provide only lackluster support for the propagation mechanism. It does not appear that banks with high market power are guaranteed performance in the top 10%. In the pre-boom period, only two out of three P(WI.) estimates for banks in the high local market power subgroups are higher, albeit marginally, than the industry estimates (column 1). In the boom period, only one out of three such estimates is higher (column 2). The WP3 estimates for these high market power subgroups in the pre-boom period (column 3) are consistent with the propagation mechanism (i.e., these estimates are less than the industry estimate). Only one boom period WP3 estimate for high local market power groups is consistent with the propagation mechanism. None of the P(WI.) estimates for the low market power subgroups (columns 9 and 10) are consistent with this mechanism. The WP3 estimates for low market power subgroups (columns 11 and 12) are also consistent with the propagation mechanism in the pre-boom period, but not the boom period.

With respect to the regulatory geographic restrictions on branching and expansion, there appears to be little support for the proposition that these restrictions generated either winning or losing persistence. Very few of the estimates for subgroups based on regulatory restrictions are consistent with the propagation mechanism, and those that are consistent are not generally statistically different than the industry estimate.

Overall, the estimates presented in Table 3A suggest that market power derived from impediments to product market competition has and continues to affect the performance of the worst performers within the distribution of banking industry returns (i.e., it generates losing persistence). However, there appears to be little connection between market power (defined using either conventional measures of local market power or regulatory geographic restrictions on branching and expansion) and winning persistence.[21] Further, the easing of regulatory restrictions on branching and expansion appear to have not had much effect of the performance of either the best or the worst performers in the banking industry.

DID MARKET POWER DERIVED FROM INFORMATIONAL OPACITY GENERATE PERSISTENCE THROUGH A PERFORMANCE SOURCE MECHANISM?

Probability and persistence estimates for "high informational opacity" and "low informational opacity" subgroups of banks are presented in Table 3B. Informational opacity is measured by 1) the percentage of the balance sheet over which the bank may have proprietary information, core deposits

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[21]The result that market power generates performance above a low benchmark but not above a high benchmark is consistent with the finding that banks consume part of their rents from market power through reduced adherence to cost minimization or a "quiet life" (Berger and Hannan 1998).

and small business loans, and 2) proxies for organizational complexity such as an indicator variable revealing whether the bank is in a multi-bank holding company.

Interestingly, the estimates in Table 3B suggest that market power explains winning persistence rather than losing persistence. The estimates of the P(WI.) for high opacity subgroups of banks (columns 1 and 2) are significantly greater than the corresponding estimates for the industry, as predicted by the informational opacity propagation mechanism. Indeed, half of these estimates are 50 percent higher than the industry estimate. Also in support of this mechanism, the WP3 estimates for these subgroups of banks (columns 3 and 4) are all less than the respective industry estimates. Of these estimates, four are significantly less than the respective industry estimate. The P(WI.) and WP3 estimates for the low informational opacity groups (columns 9-12) also coincide in all cases with the predictions of the propagation mechanism, although only one of these estimates is significantly different from the respective industry estimate.

The estimates in Table 3B provide only mixed support for the hypothesis that informational opacity generated losing persistence. Almost none of the P(LI.) and LP3 estimates for the *high* opacity banks are consistent with the informational opacity propagation mechanism: The estimates of the P(LI.) (columns 5 and 6) are generally greater than the corresponding industry estimate, and the LP3 estimates (columns 7 and 8) are generally less than the corresponding industry estimates. However, the P(LI.) and LP3 estimates for the *low* opacity subgroups are consistent with this mechanism. The P(LI.) estimates (columns 13 and 14) are significantly greater than the corresponding industry estimates, and the LP3 estimates (columns 15 and 16) are less than the corresponding industry estimates, although only one of these differences is significantly different.

In sum, the estimates in Table 3B suggest that banks with high percentages of assets over which they have proprietary information (e.g., core deposits or small business loans) or that are organizationally complex (i.e., that are part of a multi-bank holding company) tend to remain the best performers within the distribution of returns. Moreover, this tendency appears to remain in the boom period despite technological advances in data collection and processing.

DID REGIONAL/MACROECONOMIC SHOCKS GENERATE PERSISTENCE THROUGH A PERFORMANCE SOURCE MECHANISM?

We used two different methods to isolate both high (positive) and low (negative) shocks. In the first method, shocks are calculated as deviations from a simple forecasting model based on 3 lags of the relevant variable. Three variables are considered, local market nonperforming loans (measured inversely), gross state product, and gross regional product. In the second method, shocks are calculated as deviations from their cross-section medians.

We group the banks by local, state, and regional shocks. Although we cannot group by national shocks, we use our results to try to infer the effects of national shocks on relative bank performance. If, for example, relative performance is sensitive to shocks to gross state product, then we would expect it to be sensitive to shocks to gross national product as well. We will also discuss the effects of macroeconomic cycles below in our discussion of the interaction between this propagation mechanism and the risk position mechanism.

In Table 3C, the estimates of P(Wl.), P(Ll.), WP3, and LP3 for high (positive) shock and low (negative) shock subgroups suggest that serially correlated shocks are strongly consistent with the propagation mechanism. Shocks may have generated *both* winning and losing persistence. Consider first the estimates for the high (positive) local shock subgroups. As predicted, all P(Wl.) estimates in the pre-boom and boom periods for the high (positive) shock subgroups (columns 1 and 2) are greater than the respective industry estimates (only two were not significantly greater). Also, as predicted by the shocks propagation mechanism, the WP3 estimates for the positive shock subgroups in the pre-boom and boom periods (columns 3 and 4) are generally lower than the respective industry estimates. All of these estimates are significantly different from the respective industry estimates. The P(Ll.) and LP3 estimates for the positive shock subgroups (columns 5 through 8) are generally significant and also almost always consistent with the predictions of the shocks propagation mechanism.

Interestingly, the P(WI.), P(LI.), WP3, and LP3 estimates are much more strongly consistent with the shocks propagation mechanism for the subgroups defined by state and regional shocks than for subgroups defined by local shocks. One possible explanation for this difference is that state and regional shocks may be more serially correlated than local shocks.

The estimates for the low (negative) shock subgroups also support the shocks propagation mechanism. Like the estimates for the positive shock subgroups, these estimates also suggest that state and regional shocks may be more important in generating winning persistence than are local shocks. The P(WI.) estimates for the negative shock subgroups in the pre-boom and boom periods (columns 9 and 10) are all significantly less than the respective industry estimates. Moreover, the P(WI.) estimates for the negative state and regional shock subgroups are the lowest, again suggesting that state and regional shocks may be more serially correlated than local shocks. The WP3 estimates for the negative shock subgroups (columns 11 and 12) support the same conclusion. The LP3 estimates for subgroups defined by negative state and regional shocks are always greater than the respective industry estimates, while only one of these estimates for subgroups defined by local shocks is greater than their respective industry estimates, although none are significantly different from their respective industry estimates. All P(LI.) and LP3 estimates for negative shock subgroups (columns 13 through 16) are consistent with the predictions of the shocks propagation mechanism and a majority are significantly different from the corresponding industry estimates.

On the whole, the evidence presented in Table 3C indicates that bank performance is sensitive to regional/macroeconomic shocks. The lack of statistical significance of some of the persistence estimates during the boom period may be due to the conservative estimates of standard errors used in our significance tests. The fact that the P(WI.) and P(LI.) estimates for the subgroups are almost always significantly different from the respective industry estimates in the predicted direction provides strong evidence that the data are consistent with the shocks propagation mechanism. Further, this sensitivity of relative performance to regional/macroeconomic shocks appears to be just as strong in the recent boom period as in the pre-boom period despite the trend in the industry towards greater geographic diversification and greater use of financial engineering techniques to manage risk.

DID RISK/RETURN POSITIONS GENERATE PERSISTENCE THROUGH A RISK POSITION MECHANISM?

Table 3D shows probability and persistence estimates for "high risk" and "low risk" subgroups, identified primarily through portfolio indicators. For example, banks with high percentages of assets in consumer, business, or real estate loans, or banks with foreign deposits might have higher portfolio risk than the rest of the industry. Banks with high equity ratios, securities holdings, or fixed assets might have lower risk profiles than the rest of the industry. We also consider banks with a high degree of off-balance sheet activity to be relatively high risk; in theory, banks may use off-balance sheet activities to hedge risk, but we find that this is not the case.[22]

The probability and persistence estimates in Table 3D generally support the risk position mechanism in the pre-boom period (odd numbered columns). For the high risk subgroups, most of the P(WI.), P(LI.), WP3, and LP3 estimates are consistent with the mechanism and many are statistically different from the industry estimates. However, the estimates for the low risk subgroups are not as strong.

Now consider the boom period estimates (even numbered columns). While the P(WI.) and WP3 estimates for the boom period are consistent with the risk position propagation mechanism; the P(LI.) and LP3 estimates do not appear to support the mechanism (columns 14 and 16). The fact that the P(LI.) and LP3 estimates in the boom period do not support the risk position propagation

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[22]Note that we do not necessarily consider banks with very low values of the loan and off-balance sheet activities as low risk, nor do we consider banks with high equity, securities, or fixed assets as high risk. That is, we consider high values of these variables to be good indicators of risk position, but low values to be imprecise indicators.

mechanism suggests an interaction between this mechanism and the consistently favorable macroeconomic environment in the boom period. In favorable times, we expect safe banks to have very low returns relative to the industry, consistent with a high P(LI.), and to have relatively low performance volatility, consistent with a low LP3. This is precisely what we found. Therefore, the estimates presented suggest that differences in risks across banks continue to strongly affect their relative performance levels.

Interestingly, the analysis of the risk/position mechanism may help validate our measures of risk. We define a "risk strategy profile" as a high degree of investment in a portfolio category. If we find that the cross-section of banks undertaking this strategy are over-represented in both the extreme high and extreme low ends of the performance distribution, then we take this as evidence of a risky strategy. We find that banks with large off-balance sheet activity in the pre-boom and boom periods have P(WI.) and P(LI.) estimates above the corresponding industry estimates. Banks with a high percentage of assets devoted to consumer or business loans or with foreign deposits each meet these conditions in three of four possible cases.

A shift towards these activities identified as risky in the boom period would suggest an overall increase in risk-taking in the banking industry. However, the aggregate data (weighted by gross total assets) only partially support this possibility. The off-balance sheet ratio increased substantially from approximately 10% to 13% during the boom period, whereas consumer loans, business loans, and foreign deposits remained relatively constant.

VI. Conclusion

This paper examines the evolution of the banking industry with respect to its competitiveness, informational opacity, and sensitivity to regional/macroeconomic shocks. To do so, we conduct nonparametric analyses of the time series patterns and sources of the persistence of firm-level rents. The analysis of the time series patterns suggests that persistence at the high end of the performance distribution has markedly different patterns than does persistence at the low end of the distribution. The analysis of the sources of persistence indicates that market power derived from impediments to product market competition affected performance more at the low end of the distribution, whereas market power derived from informational opacity affected performance more at the high end of the distribution. Interestingly, the importance of both these forms of market power has continued in recent years. In addition, regulatory geographic restrictions appear to have had little impact on the performance of banks at either end of the distribution. These findings suggest that the competitiveness of the banking industry has not changed substantially in recent years, despite the many changes in the industry.

We also find that local, state, and regional shocks continue to determine relative performance at both the high and low end of the distribution. Moreover, the recent macroeconomic expansion appears to have had a relatively strong impact on banks with either a high degree of off-balance sheet activity, or a high percentage of assets invested in consumer, business, or real-estate loans. These results suggest that greater geographic diversification and greater use of financial engineering techniques to manage risk in recent years have not greatly reduced the banking industry's sensitivity to regional/macroeconomic shocks.

These findings also suggest reasons for the record profitability of the banking industry in recent years. The finding that market power derived from impediments to product market competition and informational opacity continue to strongly influence relative performance suggests that rents generated by the adoption of new technologies or the offering of new services in recent years may not have dissipated quickly. In absence of market power, these gains would have been passed on to customers in the form of more favorable prices. An additional possible explanation for the recent profitability of the industry is suggested by our finding that the banking industry remains susceptible to regional/macroeconomic shocks. In the boom period, virtually all regions likely had unexpectedly favorable economic conditions, which would boost aggregate profitability. Another potential explanation for the record profitability is that the industry may have expanded into relatively risky activities. We found that banks with high off-balance sheet activity, consumer loans, and business loans, and banks with foreign deposits performed disproportionately in the high and low ends of the distribution, consistent with these activities being risky. We then examined whether the banking industry as a whole increased these risky activities in the boom period and found mixed results, with only off-balance sheet activity increasing substantially.

BIBLIOGRAPHY

Avery, R.A., and M.B. Gordy, 1997, Estimation of a Markov model of loan seasoning with aggregated performance data, Board of Governors of the Federal Reserve Working Paper.

Berger, A.N., and T.H. Hannan, 1998, The efficiency cost of market power in the banking industry: a test of the 'quiet life' and related hypotheses, *Review of Economics and Statistics* 80, 454-465.

Brown, S.J., and W.N. Goetzmann, 1995, Performance persistence, *Journal of Finance* 50, 679-698.

Brown, S. J., W.N. Goetzmann, R.G. Ibbotson, and S.A. Ross, 1992, Survivorship bias in performance studies, *Review of Financial Studies* 5, 553-580.

Carhart, M.M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Cubbin, J., and P. Geroski, 1987, The convergence of profits in the long run: Inter-firm and inter-industry comparisons, *Journal of Industrial Economics* 35 , 427-442.

Goetzmann, W.N., and R.G. Ibbotson, 1994, Do winners repeat? Patterns in mutual fund return behavior, *Journal of Portfolio Management* 20, 9-18.

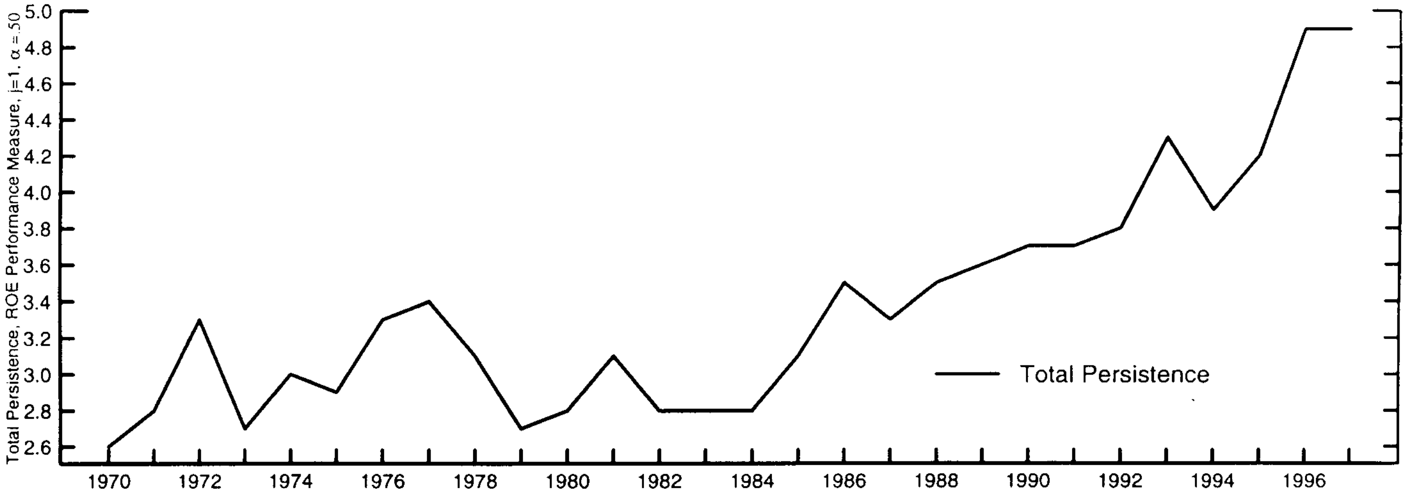
Hendricks, D., J. Patel, and R. Zeckhauser, 1993, Hot hands in mutual funds: The persistence of performance, 1974-1988, *Journal of Finance* 48, 93-130

Mueller, D.C., 1977, The persistence of profits above the norm, *Economica,* 44, 369-380.

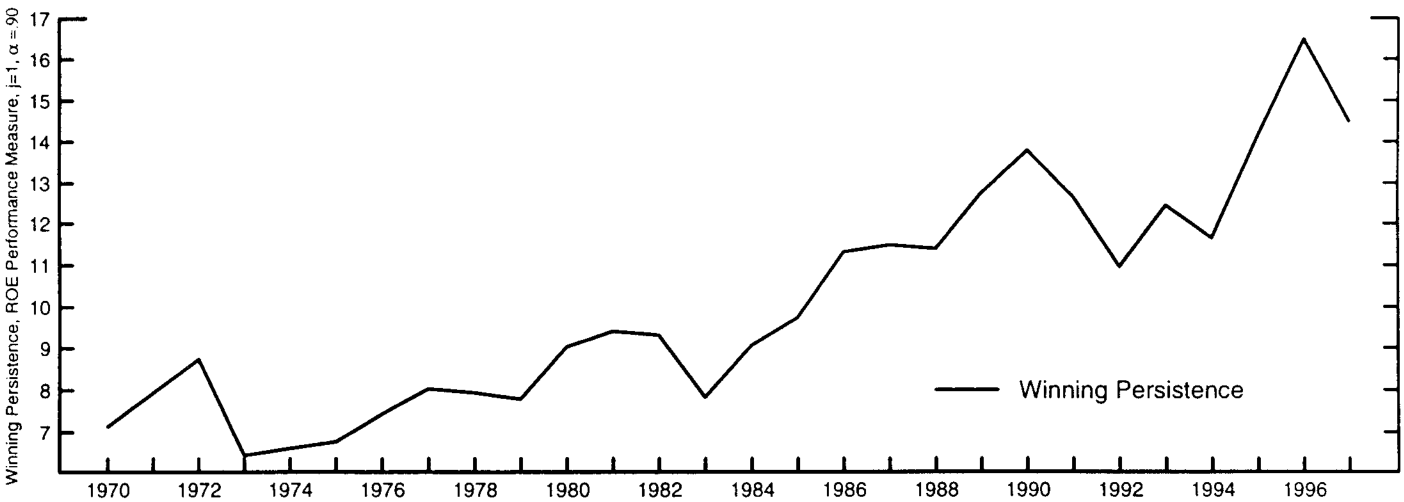
Roland, K., 1997, Profit persistence in large U.S. bank holding companies: An empirical investigation, *OCC* Working Paper.

Waring, G.F., 1996, Industry differences in the persistence of firm-specific returns, *American Economic Review* 78, 246-250.

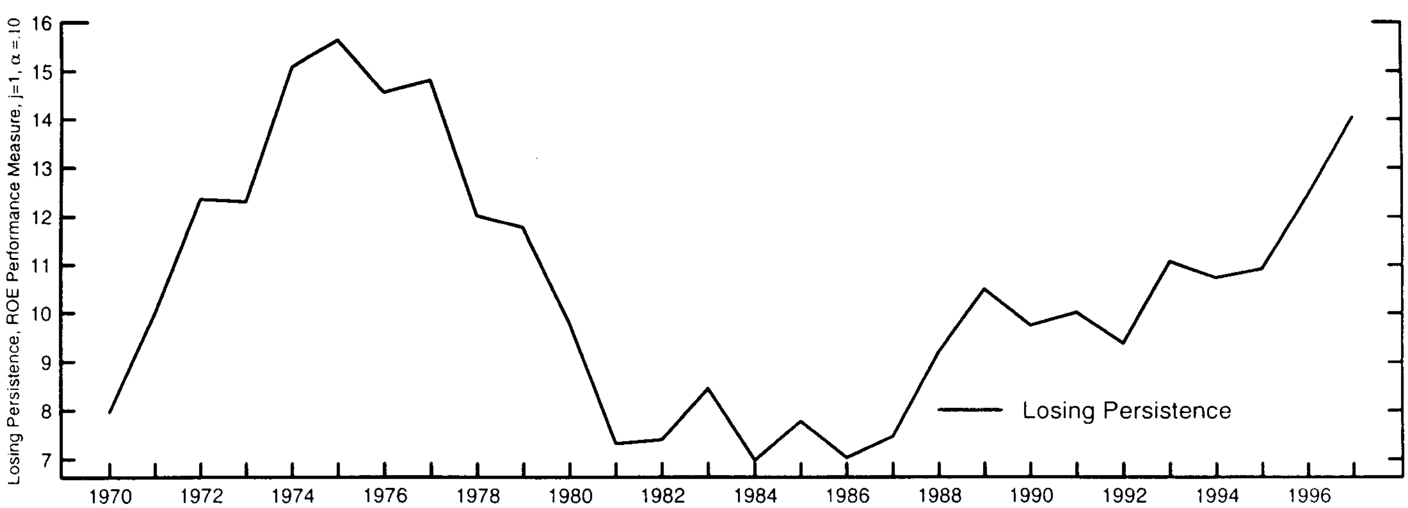
Figure 1 - Nonparametric Persistence Measures for the U.S. Banking Industry
1970 - 1997



Total persistence is the tendency for banks to remain below or above the performance of the median banks rather than to rise above or fall below that bank's performance.



Winning persistence is the tendency for bank performance to remain in the top 10 percent of the distribution rather than to rise into the top 10 percent.



Losing persistence is the tendency for bank performance to remain in the bottom 10 percent of the distribution rather than fall into the bottom 10 percent.

Figure 2-Normalized Persistence Measures for the US Banking Industry

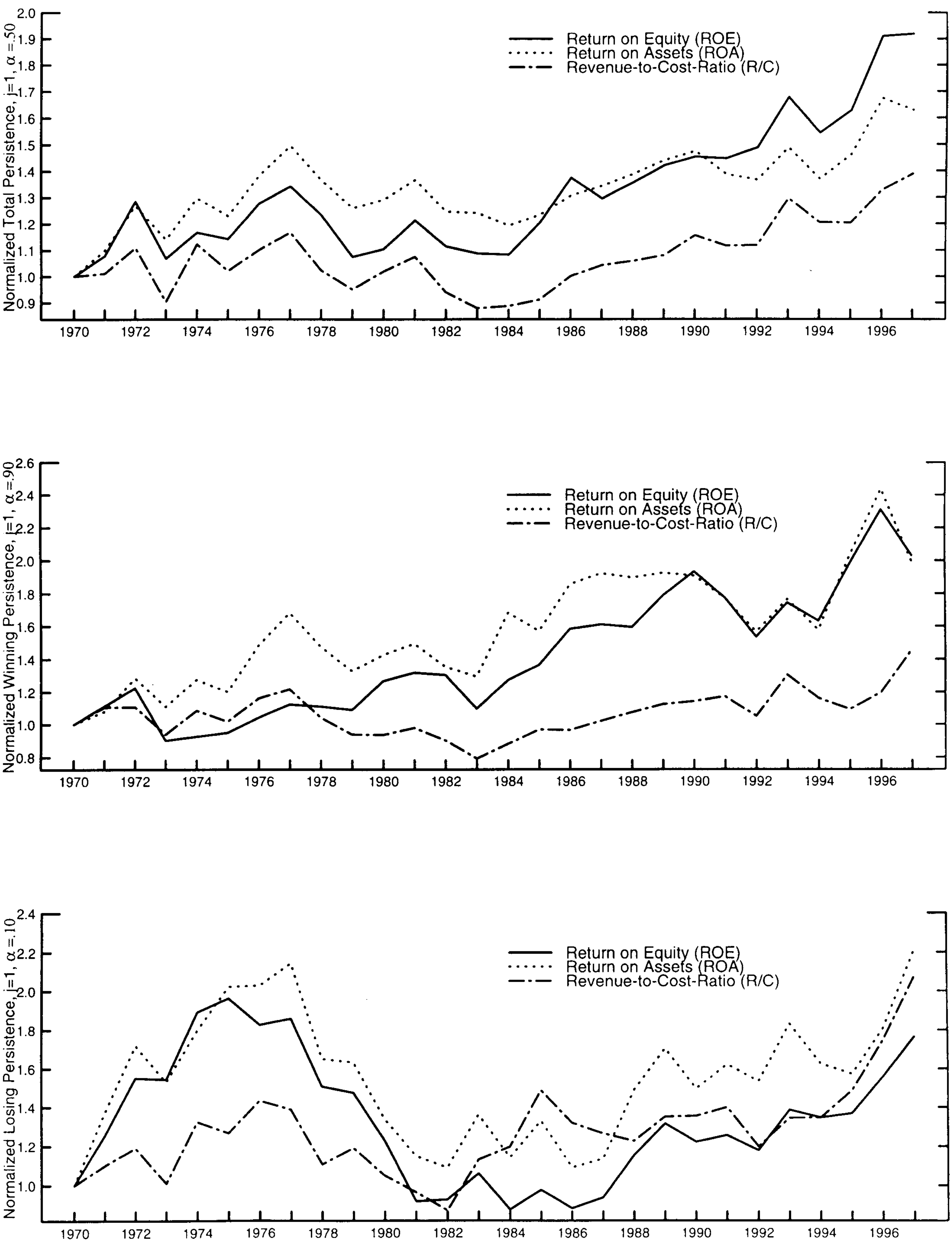
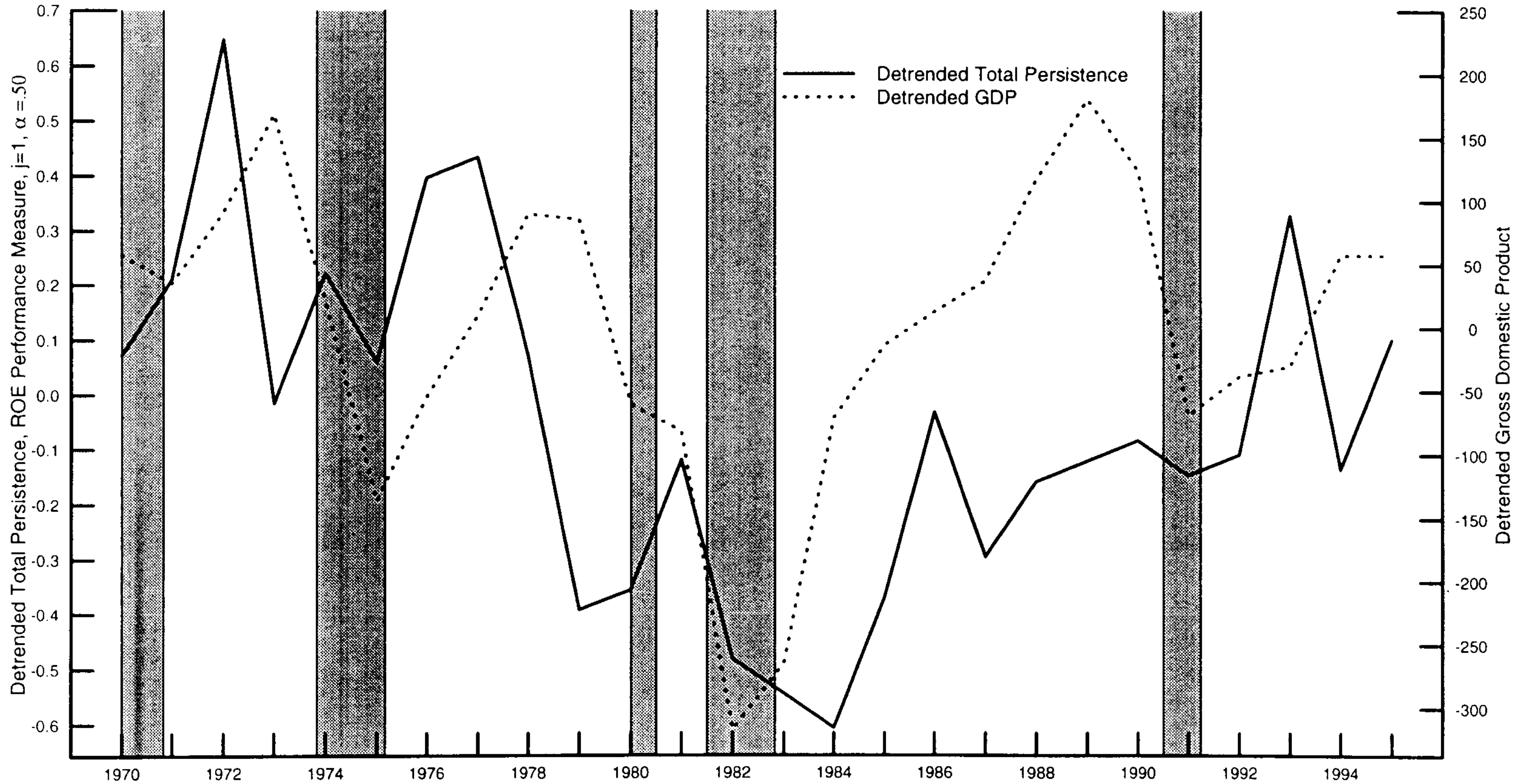


Figure 3

US Banking Industry Total Persistence and the Macroeconomy

1970 - 1995



Recessions as identified by the National Bureau of Economic Research are indicated by shading. Time series were detrended using a linear time trend.

Figure 4 - Persistence Estimates for the US Banking Industry:
The Effect of Different Lag Lengths

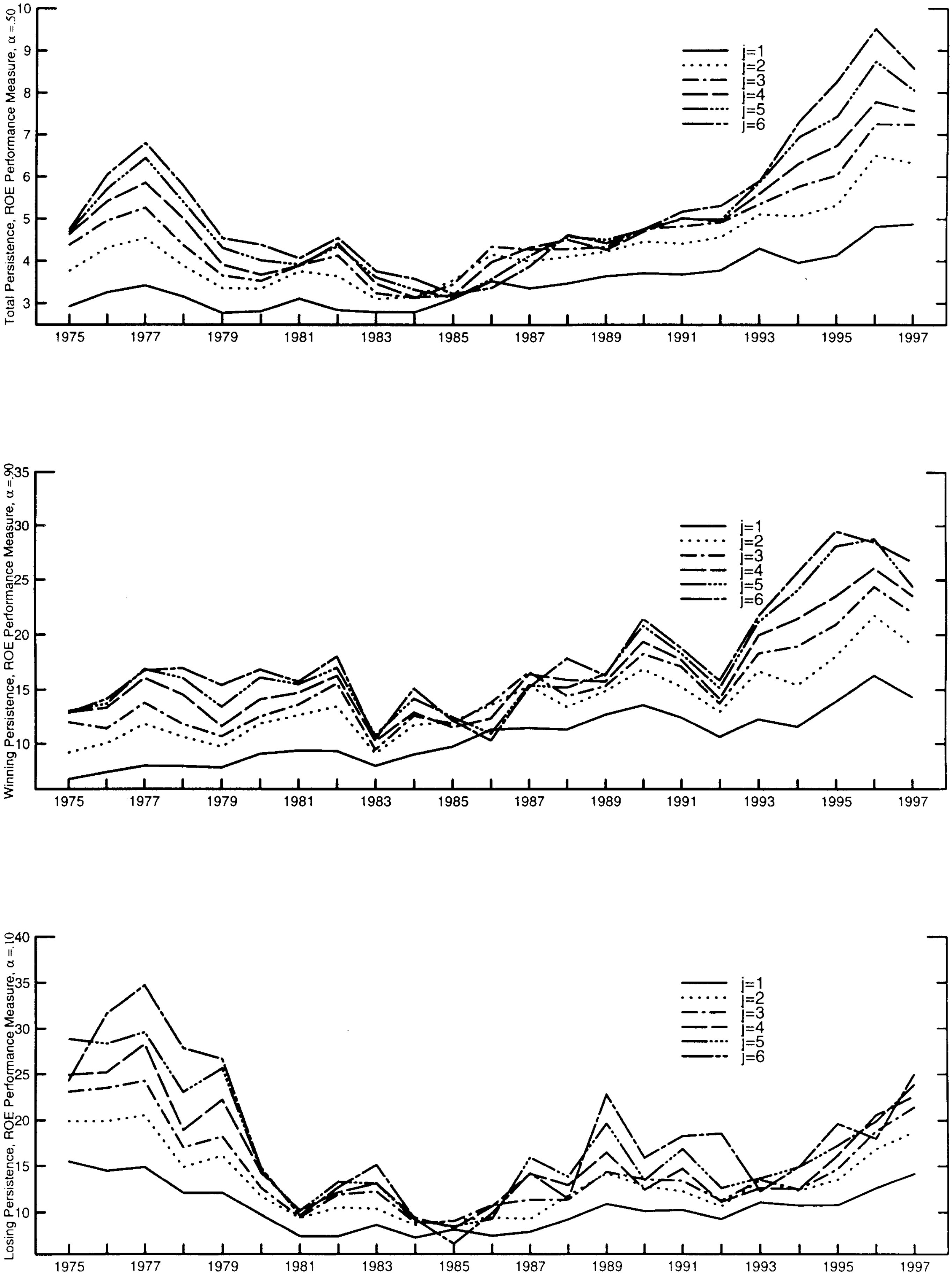


Table 1 - US Banking Industry Persistence Estimates for Three Performance Measures For j=1

Year	Rate of Return on Equity (ROE)			Rate of Return on Assets (ROA)			Revenue-to-Cost Ratio (R/C)		
	Winning Persistence $\alpha = .90$	Total Persistence $\alpha = .50$	Losing Persistence $\alpha = .10$	Winning Persistence $\alpha = .90$	Total Persistence $\alpha = .50$	Losing Persistence $\alpha = .10$	Winning Persistence $\alpha = .90$	Total Persistence $\alpha = .50$	Losing Persistence $\alpha = .10$
1970	7.13	2.56	7.96	6.69	2.61	6.33	16.80	4.17	10.89
1971	7.94	2.76	9.99	7.23	2.87	8.69	18.59	4.22	12.00
1972	8.74	3.28	12.36	8.61	3.31	10.87	18.65	4.63	12.98
1973	6.44	2.73	12.30	7.44	2.97	9.70	15.81	3.76	11.02
1974	6.62	2.98	15.07	8.54	3.38	11.39	18.24	4.68	14.44
1975	6.77	2.92	15.63	8.03	3.21	12.81	17.11	4.26	13.82
1976	7.43	3.26	14.56	9.93	3.61	12.86	19.53	4.60	15.64
1977	8.03	3.43	14.80	11.24	3.90	13.57	20.44	4.87	15.17
1978	7.93	3.15	12.02	9.87	3.56	10.45	17.51	4.27	12.07
1979	7.78	2.75	11.76	8.88	3.28	10.35	15.81	3.96	12.99
1980	9.04	2.82	9.79	9.53	3.37	8.50	15.75	4.25	11.45
1981	9.40	3.10	7.32	9.99	3.56	7.29	16.46	4.49	10.52
1982	9.31	2.85	7.39	9.06	3.25	6.92	15.18	3.92	9.50
1983	7.83	2.78	8.45	8.66	3.24	8.63	13.31	3.66	12.33
1984	9.07	2.77	6.98	11.24	3.11	7.24	14.81	3.70	13.07
1985	9.73	3.08	7.78	10.50	3.22	8.44	16.26	3.80	16.24
1986	11.30	3.51	7.03	12.42	3.41	6.92	16.24	4.18	14.40
1987	11.48	3.31	7.46	12.87	3.50	7.18	17.15	4.35	13.80
1988	11.38	3.47	9.20	12.68	3.62	9.44	18.05	4.41	13.39
1989	12.75	3.63	10.50	12.88	3.75	10.80	18.90	4.51	14.75
1990	13.78	3.72	9.75	12.75	3.84	9.49	19.20	4.82	14.80
1991	12.63	3.70	10.01	11.83	3.61	10.28	19.71	4.65	15.29
1992	10.95	3.80	9.38	10.47	3.56	9.72	17.67	4.66	13.08
1993	12.44	4.29	11.07	11.80	3.88	11.60	21.90	5.40	14.66
1994	11.65	3.94	10.74	10.55	3.57	10.28	19.52	5.02	14.71
1995	14.15	4.16	10.92	13.61	3.81	9.97	18.35	5.02	16.23
1996	16.48	4.88	12.42	16.30	4.36	11.44	20.12	5.53	19.05
1997	14.48	4.90	14.04	13.34	4.25	13.94	24.51	5.79	22.53

Note: Benchmarks for winning persistence, total persistence, and losing persistence were the top decile bank, the median bank, and the bottom decile bank, respectively. One lagged period was used (i.e., j=1). Using a two-sided test, all persistence estimates are significantly different from one at the 1% confidence level.

Table 2
Testable Implications of the Propagation Mechanisms

Performance Source Mechanism:

Implications regarding the probability of winning and losing for subgroups relative to the industry as a whole

High Source Subgroup $P(W \mid .)^{.90}$	>	Industry $P(W \mid .)^{.90}$
High Source Subgroup $P(L \mid .)^{.10}$	<	Industry $P(L \mid .)^{.10}$
Low Source Subgroup $P(W \mid .)^{.90}$	<	Industry $P(W \mid .)^{.90}$
Low Source Subgroup $P(L \mid .)^{.10}$	>	Industry $P(L \mid .)^{.10}$

Implications regarding winning and losing persistence for subgroups relative to the industry as a whole

High Source Subgroup $WP3^{.90}$	<	Industry $WP3^{.90}$
High Source Subgroup $LP3^{.10}$	>	Industry $LP3^{.10}$
Low Source Subgroup $WP3^{.90}$	>	Industry $WP3^{.90}$
Low Source Subgroup $LP3^{.10}$	<	Industry $LP3^{.10}$

Risk Position Mechanism:

Implications regarding the probability of winning and losing for subgroups relative to the industry as a whole

High Risk Subgroup $P(W \mid .)^{.90}$	>	Industry $P(W \mid .)^{.90}$
High Risk Subgroup $P(L \mid .)^{.10}$	>	Industry $P(L \mid .)^{.10}$
Low Risk Subgroup $P(W \mid .)^{.90}$	<	Industry $P(W \mid .)^{.90}$
Low Risk Subgroup $P(L \mid .)^{.10}$	<	Industry $P(L \mid .)^{.10}$

Implications regarding winning and losing persistence for subgroups relative to the industry as a whole

High Risk Subgroup $WP3^{.90}$	<	Industry $WP3^{.90}$
High Risk Subgroup $LP3^{.10}$	<	Industry $LP3^{.10}$
Low Risk Subgroup $WP3^{.90}$	>	Industry $WP3^{.90}$
Low Risk Subgroup $LP3^{.10}$	>	Industry $LP3^{.10}$

Table 3A

Is There Evidence for a Market Power Performance Source Mechanism Derived From Regulatory Restrictions or Other Impediments to Competition?

Classification Variables for Subgroups	HIGH MARKET POWER							
	Winning α=.90				Losing α=.10			
	P(WL)		WP3		P(LL)		LP3	
	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Conventional Local Market Power Measures								
Herfindahl index of local market concentration	0.078* ✓	0.062	10.7* ✓	21.8	0.038* ✓	0.041* ✓	14.6 ✓	16.0 ✓
Bank's share of local market deposits	0.075* ✓	0.071* ✓	11.4* ✓	20.3 ✓	0.028* ✓	0.028* ✓	14.4	18.3 ✓
Rural/Metropolitan Area indicator variable	0.065*	0.051*	12.3 ✓	26.0	0.038* ✓	0.043* ✓	14.4	17.1 ✓
Geographic Regulatory Restrictions								
Unit banking indicator variable	0.090* ✓	--	9.7* ✓	--	0.052*	--	12.3*	--
Limited branching state indicator variable	0.057*	0.065 ✓	15.5*	22.1	0.044* ✓	0.051 ✓	16.7* ✓	15.0
Statewide branching state indicator variable	--	--	--	--	--	--	--	--
Multibank Holding Company limits on expansion indicator variable	0.070 ✓	0.065 ✓	12.6 ✓	19.0 ✓	0.052*	0.046* ✓	10.3*	15.0
Proportion of nation's banking assets that can potentially enter the state	0.067	0.048* ✓	12.2 ✓	26.2	0.045* ✓	0.046* ✓	17.7* ✓	15.6 ✓
Industry Comparison	**0.068**	**0.065**	**13.1**	**21.0**	**0.049**	**0.054**	**14.4**	**15.4**

Classification Variables for Subgroups	LOW MARKET POWER							
	Winning α=.90				Losing α=.10			
	P(WL)		WP3		P(LL)		LP3	
	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Conventional Local Market Power Measures								
Herfindahl index of local market concentration	0.076*	0.08*	14.2 ✓	18.4	0.066* ✓	0.062* ✓	12.5* ✓	14.0 ✓
Bank's share of local market deposits	0.076*	0.072*	14.0 ✓	19.0	0.086* ✓	0.096* ✓	11.5* ✓	11.9* ✓
Rural/Metropolitan Area indicator variable	0.072*	0.084*	14.2 ✓	16.5	0.068* ✓	0.071* ✓	12.5* ✓	13.9 ✓
Geographic Regulatory Restrictions								
Unit banking indicator variable	--	--	--	--	--	--	--	--
Limited branching state indicator variable	--	--	--	--	--	--	--	--
Statewide branching state indicator variable	0.066 ✓	0.063 ✓	15.1 ✓	20.8	0.063* ✓	0.057 ✓	11.3* ✓	15.4 ✓
Multibank Holding Company limits on expansion indicator variable	--	--	--	--	--	--	--	--
Proportion of nation's banking assets that can potentially enter the state	0.071*	0.084*	11.9*	14.9*	0.051* ✓	0.052	15.8	15.1 ✓
Industry Comparison	**0.068**	**0.065**	**13.1**	**21.0**	**0.049**	**0.054**	**14.4**	**15.4**

Note: A ✓ indicates that the bank subgroup estimates relative to the industry estimates are consistent with the propogation mechanism. A "*" indicates that the subgroup estimate is significantly different from the respective industry estimate at the 95% confidence level.

Table 3B

Is There Evidence for a Market Power Performance Source Mechanism Derived From Informational Opacity?

Classification Variables for Subgroups	HIGH OPACITY								LOW OPACITY							
	Winning α=.90				Losing α=.10				Winning α=.90				Losing α=.10			
	P(WL)		WP3		P(LL)		LP3		P(WL)		WP3		P(LL)		LP3	
	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Proprietary Information																
Core deposits relative to gross total assets	0.079* ✓	0.076* ✓	10.8* ✓	19.4 ✓	.030* ✓	0.044* ✓	13.4	17.3 ✓	0.058* ✓	0.065 ✓	16.8* ✓	23.6 ✓	0.100* ✓	0.079* ✓	9.5* ✓	12.8 ✓
Small business loans relative to gross total assets	--	0.071* ✓	--	15.7 ✓	--	0.064*	--	14.3	--	0.061 ✓	--	27.3 ✓	--	0.063* ✓	--	14.5 ✓
Organizational Complexity																
Bank holding company indicator variable	0.085* ✓	0.078* ✓	12.2 ✓	18.5 ✓	0.049	0.045* ✓	13.8	17.0 ✓	--	--	--	--	--	--	--	--
Multilayer bank holding company indicator variable	0.122* ✓	0.137* ✓	9.4* ✓	10.9* ✓	0.060*	0.070*	10.0	10.5	--	--	--	--	--	--	--	--
Out-of-state bank holding company indicator variable	0.108* ✓	0.112* ✓	11.0 ✓	11.4* ✓	0.066*	.120*	10.2	8.4*	--	--	--	--	--	--	--	--
Trading asset account indicator variable	0.075 ✓	0.125* ✓	12.1 ✓	8.0 ✓	0.063*	0.083*	8.0	17.8 ✓	--	--	--	--	--	--	--	--
Industry Comparison	**0.068**	**0.065**	**13.1**	**21.0**	**0.049**	**0.054**	**14.4**	**15.4**	**0.068**	**0.065**	**13.1**	**21.0**	**0.049**	**0.054**	**14.4**	**15.4**

Note: A ✓ indicates that the bank subgroup estimates relative to the industry estimates are consistent with the propogation mechanism. A "*" indicates that the subgroup estimate is significantly different from the respective industry estimate at the 95% confidence level.

Table 3C

Is There Evidence for the Regional/Macroeconomic Shocks Performance Source Mechanism?

Classification Variables for Subgroups	HIGH (POSITIVE) SHOCKS								LOW (NEGATIVE) SHOCKS							
	Winning Persistence α=.90				Losing Persistence α=.10				Winning Persistence α=.90				Losing Persistence α=.10			
	P(WL)		WP3		P(LL)		LP3		P(WL)		WP3		P(LL)		LP3	
	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Local Shocks																
Shocks to nonperforming loans in the local market	0.069 ✓	0.078* ✓	12.3 ✓	16.8 ✓	0.046* ✓	0.046* ✓	16.7* ✓	16.2 ✓	0.065* ✓	0.051* ✓	12.4	24.7 ✓	0.053 ✓	0.071* ✓	14.3 ✓	13.2 ✓
Growth of nonperforming loans in the local market	0.072* ✓	0.064	13.0 ✓	25.2	0.039* ✓	0.045* ✓	17.4* ✓	15.6 ✓	0.061* ✓	0.060* ✓	12.7	20.3	0.065* ✓	0.071* ✓	11.0* ✓	14.9 ✓
State Shocks																
Shocks to gross state product	0.083* ✓	0.095* ✓	10.9* ✓	14.8* ✓	0.044* ✓	0.043* ✓	17.2* ✓	14.1	0.059* ✓	0.050* ✓	14.0 ✓	26.2 ✓	0.054* ✓	0.066* ✓	14.3 ✓	15.0 ✓
Growth of gross state product	0.118* ✓	0.108* ✓	8.2* ✓	12.5* ✓	0.044* ✓	0.042* ✓	15.1 ✓	13.7	0.046* ✓	0.045* ✓	17.6* ✓	27.8 ✓	0.057* ✓	0.075* ✓	13.2 ✓	13.4 ✓
Regional Shocks																
Shocks to gross regional product	0.078* ✓	0.087* ✓	11.4* ✓	16.9 ✓	0.043* ✓	0.049 ✓	16.7* ✓	16.1 ✓	0.060* ✓	0.043* ✓	13.8 ✓	28.1 ✓	0.052* ✓	0.063* ✓	15.1	16.0
Growth of gross regional product	0.095* ✓	0.084* ✓	9.8* ✓	16.6 ✓	0.041* ✓	0.052 ✓	16.4 ✓	14.2	0.052* ✓	0.045* ✓	15.8* ✓	26.7 ✓	0.056* ✓	0.06* ✓	12.6 ✓	14.0 ✓
Industry Comparison	**0.068**	**0.065**	**13.1**	**21.0**	**0.049**	**0.054**	**14.4**	**15.4**	**0.068**	**0.065**	**13.1**	**21.0**	**0.049**	**0.054**	**14.4**	**15.4**

Note: A ✓ indicates that the bank subgroup estimates relative to the industry estimates are consistent with the propogation mechanism. A "*" indicates that the subgroup estimate is significantly different from the respective industry estimate at the 95% confidence level.

Table 3D

Is There Evidence for a Risk Position Mechansim?

Classification Variables for Subgroups	HIGH RISK								LOW RISK							
	Winning α=.90				Losing α=.10				Winning α=.90				Losing α=.10			
	P(WL)		WP3		P(LL)		LP3		P(WL)		WP3		P(LL)		LP3	
	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom	Pre-Boom	Boom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Balance Sheet Indicators																
Consumer loans relative to gross total assets	0.082* ✓	0.096* ✓	12.3 ✓	17.8 ✓	0.063* ✓	0.041*	12.5 ✓	17.1	--	--	--	--	--	--	--	--
Business loans relative to gross total assets	0.079* ✓	0.055*	11.1* ✓	19.2 ✓	0.063* ✓	0.059* ✓	10.3* ✓	13.4 ✓	--	--	--	--	--	--	--	--
Real estate loans relative to gross total assets	0.060*	0.085* ✓	16.1*	18.9 ✓	0.046*	0.051	13.6 ✓	19.3	--	--	--	--	--	--	--	--
Foreign deposits indicator	0.061	0.108* ✓	15.5	11.2 ✓	0.082* ✓	0.138* ✓	6.7 ✓	12.0 ✓	--	--	--	--	--	--	--	--
Equity capital relative to gross total assets	--	--	--	--	--	--	--	--	0.028* ✓	0.013* ✓	24.0* ✓	82.3* ✓	0.058*	0.076*	20.2* ✓	13.3
Securities holdings relative to gross total assets	--	--	--	--	--	--	--	--	0.066 ✓	0.036* ✓	12.5	27.3 ✓	0.026* ✓	0.063*	23.4* ✓	13.0
Fixed assets relative to gross total assets	--	--	--	--	--	--	--	--	0.050* ✓	0.066	15.1 ✓	17.8	0.099*	0.080*	9.6*	11.0*
Off-Balance Sheet Indicators																
Size of off-balance sheet transactions relative to gross total assets	0.072* ✓	0.090* ✓	12.1 ✓	15.0* ✓	0.052* ✓	0.061* ✓	14.9	15.9	--	--	--	--	--	--	--	--
Industry Comparison	**0.068**	**0.065**	**13.1**	**21.0**	**0.049**	**0.054**	**14.4**	**15.4**	**0.068**	**0.065**	**13.1**	**21.0**	**0.049**	**0.054**	**14.4**	**15.4**

Note: A ✓ indicates that the bank subgroup estimates relative to the industry estimates are consistent with the propogation mechanism. A "*" indicates that the subgroup estimate is significantly different from the respective industry estimate at the 95% confidence level.
We do not necessarily consider banks with very low values of the loan and off-balance sheet activities as low risk, nor do we consider banks with high equity, securities, or fixed assets as high risk. That is, we consider high values of these variables to be good indicators of risk position, but low values to be imprecise indicators