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The Demise of Community Banks? Local Economic Shocks Aren't to Blame

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Abstract

A potentially troubling characteristic of the U.S. banking industry is the geographic concentration of many community banks' offices and operations. If geographic concentration of operations exposes banks to local market risk, we should observe a widespread decline in their financial performance following adverse local economic shocks. In addition, geographic diversification should help banks reduce risk significantly.

By analyzing the performance of geographically concentrated U.S. community banks exposed to severe unemployment shocks in the 1990s, I find that banks are not systematically vulnerable to local economic deterioration. Indeed, differences in performance at banks in counties that suffered economic shocks relative to those that did not suffer economic shocks are either statistically insignificant or economically small.

These findings suggest that banks are unlikely to engage in mergers and acquisitions primarily to reduce local market risk because that risk source is already low. This result bodes well for the continued existence of geographically concentrated community banks, though scale and scope economies will continue to reduce their numbers relative to larger banks.

JEL Codes: G1, G2, R1
Key Words: community bank, idiosyncratic risk, market risk, geographic diversification, economic shocks, county unemployment

I. Community Bank Exposure to Local Market Risk

Because of the way that banking laws evolved, many U.S. community banks have geographically concentrated offices and operations. Historically, national and state banking laws prevented banks from branching into other counties and states. Justification for such legislation was to promote sound and stable banking markets by limiting competitive pressures on existing banks and to prevent an excessive concentration of financial power.[1] Such laws, however, potentially left banks vulnerable to local economic downturns. Despite the 1994 Riegle-Neal Act that liberalized branching laws, thousands of small banks with geographically concentrated offices remain. As of June 2001, 4,917 of the 8,116 U.S. commercial banks (61 percent) derived all of their deposits from offices in a single county.[2] Because banks tend to make loans to customers nearby, most banks remain potentially exposed to local economic downturns.

Will independent geographically concentrated U.S. community banks be able to survive in the future financial services industry or will they be acquired or merged out of business by larger, more diversified competitors? Geographically concentrated banks face at least three potential disadvantages that threaten their survival relative to other banks. First, because most of these banks are small (the median asset size of banks operating in a single county in 2001 was $57 million), they operate with relatively high average costs. Several researchers have estimated a bank's minimum efficient scale at roughly $300 million to $500 million in assets, and 95 percent of banks with all deposits in a single county have assets below this threshold.[3] Second, geographically concentrated banks may not be able to achieve the same level of profit efficiencies attained by larger

[1] Berger et. al. (1995), Jayaratne and Strahan, 1997.
[2] Summary of Deposits 2001, Federal Deposit Insurance Corporation.

banks.[4] Profit efficiencies increase revenue by allowing banks to produce or package a wider variety of financial services (such as trust and brokerage products); small banks cannot offer many of these services. Although cost and profit inefficiencies are characteristics of all small banks, geographically concentrated banks face a third potential disadvantage relative to more diversified banks. Specifically, these banks may operate on a less favorable risk-expected return frontier because their geographic concentration of operations potentially exposes them to risks from local economic downturns. If this risk factor is important, community banks will decline even more rapidly than they would if scale effects alone drove mergers and acquisitions.

Geographical concentration is a relative term. A bank may be characterized as geographically concentrated if it operates primarily within a region of the nation, a state, a cluster of counties, or a single county. I define geographically concentrated banks as those with all deposits derived from offices in a single county. A county is a convenient definition of concentration because most banks do operate within a single county, county boundaries are well defined, economic data are readily available at this level of aggregation, and few researchers have studied the vulnerability of banks to county-level downturns.[5]

Portfolio theory suggests that geographically concentrated banks may be riskier than more geographically diversified banks because of heightened credit risk. Credit risk includes idiosyncratic risk and market (systematic) risk. Idiosyncratic credit risk is the potential for default by specific borrowers, driven by firm-specific events unrelated to business cycle conditions. Banks can diversify away idiosyncratic risk by increasing the

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[3] Wheelock (2001), McAllister (1993).
[4] Berger (1999).

number of loan customers. Market risk is the increased default risk associated with a local, regional, national or international economic downturn. Laderman (1991) finds that community banks tend to lend to firms and individuals nearby. In addition, discussions with bank examiners at the Federal Reserve Bank of St. Louis and with community bankers in Arkansas suggest that 75 percent to 90 percent of the loan customers at typical single-county community banks reside within the county. Performance at geographically concentrated banks, therefore, may deteriorate significantly when the local economy suffers a recession or a negative economic shock. I call this risk *local market risk*. Although geographically concentrated banks cannot insulate themselves fully from broader sources of market risk such as a shock to a given state, they can diversify away local market risk by operating across several counties.

Alternatively, banks with geographically concentrated operations may not be particularly vulnerable to local market risk. A few researchers argue that the vulnerability of banks to regional economic markets has declined over the last few decades, either because banks or regional economies have become more diversified. Gunther and Robinson (1999) find that banks faced less risk from variations in regional economic performance in 1996 than in 1985 in part because of industry diversification at the state level. Neely (1997), however, finds that bank earnings are still sensitive to state economic activity. Petersen and Rajan (forthcoming) find that community banks increased their lending to more distant borrowers over the last few decades. In particular, the distance between small firms and lenders grew from an average of 51 miles in the 1970s to 161 miles in the 1990s. The authors attributed most of the gain to improvements in gathering and analyzing information. Banks reduced the importance of

[5] Meyer (2001).

person-to-person contact by relying increasingly on financial statements and credit reports to evaluate potential borrowers. Credit markets have also become more efficient. Banks can engage more easily in financial diversification through loan participations or collateralized mortgage obligations, which offset some of their credit risk. Because of the decreased costs to diversification without geographic expansion, banks may have reduced or eliminated the risk exposures that previous intrastate branching restrictions imposed. The vulnerability of community banks to local economic conditions, then, is an empirical issue.

Relaxation of intrastate and interstate branching restrictions in the 1980s and 1990s has given management at single-county banks the opportunity to geographically diversify. Does such diversification significantly improve the bank's risk-return frontier? Craig and Santos (1997) examine the risk effects of bank acquisitions and conclude that they improve profitability and reduce risk. The risk reduction, however, is not strong enough to be a major force driving acquisitions. Benston et al. (1995) find evidence consistent with the risk-reduction motive for acquisitions, but inconsistent with the deposit subsidy enhancement motive. Their study, however, applies to larger publicly traded banks.

I employ three different techniques to assess the importance of local market risk. First, I regress various bank performance measures on state and local unemployment rates. The results indicate that local market risk is insignificant. I then compare the performance of community banks exposed to an economic shock with a control group of state-aggregate peer banks. The results indicate that the "shock" banks perform slightly worse than their peers. A concern with this technique is that it averages the broader market risk and eliminates the idiosyncratic risk of the peer banks but not the shock banks. Finally, a matched-pairs technique matches each "shock" bank with a similar bank that did not reside in a county that suffered an economic shock (the "no-shock" banks). For each pair of shock and match banks, I compare the deterioration in key performance ratios following the economic shock and find that much of the local market risk disappears.

The weight of the evidence indicates that local market risk is not an important source of bank risk. This finding bodes well for the survival of geographically concentrated community banks. Many geographically concentrated banks may still be at a disadvantage relative to their larger counterparts due to scale and scope inefficiencies and broader sources of market risk, but they do not operate on an inferior risk-return frontier due to local economic shocks. Recent research by Emmons, Gilbert and Yeager (2001) on community bank mergers is consistent with this result. They examine the risk-reduction effects from simulated community bank mergers, and find that bank risk is reduced significantly as merged banks grow larger, but the risk reduction is driven by scale effects, not geographic diversification per se.

II. Regression Analysis

The coefficients obtained from regressing bank performance measures on county and state economic data should shed some light on the relative importance of local and regional market risk. Large and statistically significant coefficients on the county data may indicate high levels of local market risk.

Consistent with Meyer and Yeager (2001), regression analysis shows that local market risk is low at geographically concentrated community banks.[6] To illustrate, I run some simple fixed-effects regressions, regressing quarterly bank performance measures on quarterly seasonally adjusted county and state unemployment rates. Bank performance measures include return on assets (ROA), nonperforming loans (90 days or more past due plus nonaccruing) to total loans, and net charge-offs to total loans. The bank sample includes only geographically concentrated U.S. banks—those banks with all their deposits derived from offices in a single county—because those banks are the most likely to be affected by changing local economic conditions. The data span 1990 through 2001; reliable county unemployment data are unavailable before 1990. The regression equation is the following:

$$BP_{it} = \alpha_i + \sum_{j=0}^{4} (\beta_{1j} \cdot CEcon_{i,t-j} + \beta_{2j} \cdot SEcon_{i,t-j}) + e_{it} \qquad (1)$$

where BP_{it} represents bank i's performance at time t, and the α_i coefficient is the bank-specific intercept term. The variables $CEcon_{it}$ and $SEcon_{it}$ and their four lags represent, respectively, county and state economic data relevant to bank i at time t-j. Economic data are matched with the county and state of the bank's headquarters. Regression results appear in the top panel of Table 1.

The regression results suggest that local market risk is insignificant. A one percentage-point increase in the contemporaneous county unemployment rate increases ROA by one basis point. The sum of the contemporaneous county coefficient and its four lags is zero. Similarly, nonperforming loans rise by a sum of two basis points, and net

[6] See Meyer and Yeager for a thorough econometric analysis, including two-stage least squares, tobit regressions and a variety of robustness checks omitted here.

charge-offs by one basis point, in response to a one percentage-point increase in the county unemployment rate. The standardized coefficients represent the effect that a one standard-deviation change in the unemployment rate has on the bank performance measure, relative to a one standard deviation change in the bank performance measure. The coefficients on county unemployment rates remain low even after this adjustment.

Several problems arise when using regression analysis to identify local market risk. First, regression analysis relies heavily on the quality of local economic data, which tend to be highly volatile because of measurement error. Noisy data bias downward the county economic coefficients, potentially understating the importance of local market risk.

Second, multicollinearity is a serious concern when using quarterly observations because economic data tend to be persistent so that contemporaneous and lagged values are highly correlated. To reduce the collinearity, I regress annual bank performance ratios on annual county and state economic data and one-year lags. The bottom panel of Table 1 presents the fixed-effects regression results using annual data rather than quarterly data. The main conclusion holds; local market risk remains unimportant. Besides the collinearity between the labor data and their lags, state and county labor data are also correlated, regardless of the frequency of the data used in the regression. Indeed, the Bureau of Labor Statistics (BLS) estimates county labor data explicitly from state labor data.[7] Regression analysis, therefore, cannot cleanly separate local and regional market risk.

[7] "Local Area Unemployment Statistics Estimation Methodology," Bureau of Labor Statistics, 2001, http://stats.bls.gov/lau/laumthd.htm.

A third concern with ordinary-least-squares regression analysis is that it assumes a symmetric, linear relationship between bank performance and unemployment rates. That is, a four percentage point increase in unemployment has the same effect on bank performance as a four percentage point decrease in unemployment. Not only might an increase in unemployment rates affect banks differently from a decrease in unemployment rates, but the relationship may be nonlinear. Banks exposed to large county-level economic shocks may deteriorate significantly even as banks exposed to modest economic shocks are unaffected. Including squared values of the county unemployment rates does not help because of the noise in the data; nonlinear terms essentially intensify the noise. Because the time period between 1990 and 2001 was one in which most counties and most banks performed extremely well, ordinary least squares regressions disproportionately account for the strong banks and local economies at the expense of the weak banks and economies. Such a weighting scheme may dampen the county unemployment rate coefficients. In short, regression analysis cannot focus intensely on the subset of banks that we are most interested in analyzing.

III. Defining Economic Shocks and Shock Banks

One way to focus exclusively on banks exposed to large adverse economic shocks is to identify counties that suffered economic shocks and then study only the banks with significant operations in those counties. I define local economic shocks two different ways, using an absolute-change rule and a total-cost rule. The absolute-change rule requires a four percentage point or greater increase in the seasonally adjusted county unemployment rate between the rate in a given quarter and the average rate over the following year. Suppose, for example, that the seasonally adjusted unemployment rate in the fourth quarter of 1991 was 6 percent. The average unemployment rate during 1992 had to be at least 10 percent to qualify as a shock.[8]

Although the absolute-change rule is simple, a four percentage point increase is somewhat arbitrary and has no connection to a natural rate of unemployment. An increase in the unemployment rate from say, two percent to six percent, is treated the same as an increase in the unemployment rate rising from six percent to 10 percent. One could argue, however, that the second scenario would be more difficult for a bank to deal with because the county is farther away from full employment.

The total-cost (TC) rule is based on an assumed natural rate of unemployment of six percent. Using the total-cost rule, a shock is one in which TC exceeds six (not connected to the natural rate), and

$$TC = TC_1 + TC_2 \qquad (1)$$

where $TC_1 = \max [\min [U_{t+1}, 6] - U_t, 0]$

$TC_2 = (\max [U_{t+1}, 6] - 6)^{1.5} - (\max [U_t, 6] - 6)^{1.5}$

U_t = current quarter's unemployment rate

U_{t+1} = average unemployment rate over the next four quarters

Given this definition, the first cost component, TC_1, rises linearly as the unemployment rate rises to 6 percent, the implicit natural rate of unemployment. If U_t is four and U_{t+1} is nine, TC_1 is two (6 – 4). Because of the assumption that the hardships of unemployment on a bank increase as unemployment rises above the natural rate, the second cost

[8] A change in employment is a potential alternative to a change in unemployment rates. An unemployment-based shock definition, however, is more stringent than an employment-based definition because unemployment rates account for the effects of labor force mobility. If a local economy suffers an economic shock and many residents relocate to other areas to take new jobs, the bank may be better off than if many residents remain unemployed in the county. With high labor mobility, the employment decline would be greater than the rise in the unemployment rate because the labor force also declines with the drop in the number unemployed.

component, TC_2, increases exponentially with a rise in the unemployment rate above 6 percent. A rise in the rate from 4 percent to 9 percent results in a value for TC_2 of 5.2 ($(9 - 6)^{1.5}$), for a total cost of 7.2 (2 + 5.2). This change, then, qualifies as an economic shock. Finally, because the first component of TC_2 calculates the cost of unemployment assuming that the initial unemployment rate was 6 percent, the second component of TC_2 subtracts the amount by which the initial unemployment rate exceeds 6 percent. If, for example, the unemployment rate rises from 8 percent to 11 percent, TC_1 is zero, but TC_2 is $(11 - 6)^{1.5} - (8 - 6)^{1.5}$, or 8.35. This increase also qualifies as a shock.

The total-cost definition of a shock has the shortcoming that small changes in the unemployment rate qualify for a shock if they are far enough above the natural rate of unemployment. A change in the unemployment rate from 12 percent to 13.5 percent, for example, qualifies as a shock.

Because both the absolute-change rule and the total-cost rule are somewhat arbitrary, I report the results using both definitions.[9] Figure 1 illustrates for both shock rules the minimum unemployment rate over the following four quarters (the leading unemployment rate) that is required to qualify as a shock given the current unemployment rate in a given quarter. If the current unemployment rate is 9 percent, the leading unemployment rate must be at least 11 percent under the total-cost rule and 13 percent under the absolute-change rule to qualify as a shock. Note that the difference between the current and leading unemployment rates diminishes under the total-cost rule as the current unemployment rate rises.

[9] I also tested a 50 percent change rule on part of the sample, in which the current unemployment rate had to exceed six percent initially and then increase by an average of at least 50 percent over the subsequent four quarters. Results were similar to the absolute-change and total-cost rules.

Despite the measurement error in county unemployment rates, the shock rules should be isolating counties that have suffered serious setbacks because large and persistent changes in the unemployment rate are required under both definitions. The Federal Worker Adjustment and Retraining Notification Act (WARN) provides a limited opportunity to examine whether the shock rules are truly capturing local economic shocks. WARN, which became effective in 1989, requires employers to provide at least 60 days notice of covered plant closings or mass layoffs to affected workers and local governments. Georgia's Department of Labor maintains a web site with a complete series of WARN data that lists the affected county and the date of the layoffs.[10]

The observation that a number of counties that qualify for local economic shocks in this study also appear on the WARN list around the same time period lends credibility to the absolute-change and total-cost rules. Of course, a county may suffer an economic shock but be omitted from the WARN list, or a county may make the WARN list without suffering a true economic shock. Nevertheless, the matched pair analysis described below allows a comparison of the number of shock and "no-shock" (match) counties on the WARN list sometime from one quarter before to three quarters after the quarter of the shock. While seven of nine Georgia shock counties as defined by the absolute change rule appear on the WARN list, only two of fourteen match counties appear on the list. In addition, the number of affected workers as a percentage of the county labor force is six times greater in the shock counties compared with the match counties. Under the total-cost rule, 14 of 26 Georgia shock counties appear on the WARN list, yet only 11 of 30 match counties make the list. The relative number of affected workers in the shock

[10] See http://www.dol.state.ga.us/eshtml/warn.htm. Historical data for a sample of other states were not available.

counties is an average of 3.7 times larger than those in the match counties. Although the differences between the shock and match banks are not statistically significant, the evidence is suggestive that the shock definitions are picking up meaningful slowdowns in local economic activity.

The counties identified suffered economic shocks sometime between the fourth quarter of 1990 and the third quarter of 1999. This time period allows for observations of bank performance four quarters before and two years after the economic shock to give a reasonable time period to compare pre- and post-shock performance.[11] If a county suffered from two or more economic shocks in the 1990s, usually in consecutive quarters, I use the time period of the first shock.

The next step is to identify "shock" banks with geographically concentrated operations in the counties that suffered economic shocks. Using Summary of Deposits data from the Federal Deposit Insurance Corporation (FDIC), I select only those banks that derived all of their deposits from branches in a single county. Because call report data do not report the location of a bank's loan customers, deposit data serve as a proxy. Informal discussions with community bankers and Federal Reserve regulators indicate that typically 75 percent or more of a community bank's loans are to businesses or individuals in the same county. These banks are the ones most likely to be vulnerable to local economic shocks. I exclude banks that had merger activity any time between four quarters before and eight quarters after the quarter of the economic shock because merger banks' financial ratios were likely to be distorted by the merger. Finally, each bank had

[11] If the shock occurred in the fourth quarter of 1990, only three quarters of observations before the shock are available.

to exist over that same 13-quarter time period to adequately measure the bank's performance before and after the shock.

The selection criteria produced 270 banks using the absolute-change rule and 614 banks using the total-cost rule. Summary statistics are reported in Table 2. Under the absolute-change rule, the average bank size four quarters before the economic shock is $46.2 million. The average labor force in the quarter of the shock is 8,425. The average current unemployment rate as of the date of the shock is 7.4 percent, and the leading unemployment rate is 12.1 percent, meaning that the typical shock county has an unemployment-rate increase of 4.7 percentage points. For the 614 shock banks under the total-cost rule, the average asset size is $52.1 million, the average county labor force is 16,874, and the unemployment rate increases from an average of 8.4 percent to 11.4 percent.

IV. Sensitivity of Shock Banks Relative to State Peer Banks

After defining an economic shock and identifying the bank sample, I assess the vulnerability of geographically concentrated banks to local economic shocks by comparing pre- and post-shock bank performance relative to state-aggregated peer banks. The peer banks control for broader levels of market risk. Local market risk may be significant if the shock banks deteriorate relative to peer banks following the economic shocks.

I identify four ratios to assess bank performance. The focus is primarily on credit quality because, all else equal, geographically concentrated banks are likely to have higher credit risk than more diversified banks. Two ratios that bank examiners routinely use to assess asset quality are nonperforming loans (loans 90 days or more past due and nonaccruing) to total assets, and net chargeoffs (charge-offs less recoveries) to total loans. A third ratio is the bank's failure probability as calculated by the System for Estimating Exam Ratings (SEER), the official early warning system of the Federal Reserve.[12] Each bank's failure probability is estimated using a probit regression technique on key bank ratios. One can think of the failure probability as an overall index of bank risk that ranges between zero and 100 percent. Although the SEER failure probability captures many elements of a bank's risk, it is affected the most by credit quality.[13] Finally, I include return on assets (ROA), which is net income divided by assets. Earnings may capture broader risk effects of local shocks such as liquidity risk that asset quality ratios ignore.

To control for broader market risk factors such as regional and national market risk, I compare changes in the four key bank performance ratios relative to peer bank ratios. The peer ratios for a sample bank in a given county are asset-weighted averages of ratios from banks with less than $250 million in assets with headquarters in the same state as the sample bank, excluding banks with deposits in the same counties as the shock banks. Ninety-nine percent of the sample banks under both shock rules have less than $250 million in assets; therefore, the peer banks are selected to be similar in size so that the peer ratios are not influenced by financial data from larger banks. Subtracting the peer banks' ratios from the sample banks' ratios in a given quarter controls for location and business cycle factors. For example, one bank (Bank A) in Duval County, Texas

[12] See Cole (1995).
[13] The variables in the SEER model include the log of total assets and the ratios to total assets of commercial and industrial loans, residential loans, securities, CDs greater than $100,000, equity capital, loans 30 and 90 days past due, nonaccruing loans and other real estate owned.

suffered an economic shock in the first quarter of 1991 as defined by the absolute-change rule. Its nonperforming loan to total loan ratio in the first quarter of 1990 was 0.16 percent; the same ratio in the first quarter of 1992 was 7.05 percent. In contrast, the nonperforming loan ratio at peer Texas banks was 4.44 percent in the first quarter of 1990 and 2.87 percent in the first quarter of 1992. The change in nonperforming loans between the first quarters of 1990 and 1992 at Bank A relative to peer banks was (7.05 – 2.87) – (0.16 – 4.44), or 8.46 percentage points. In other words, deterioration following an economic shock is relative to the deterioration of peer banks.

To illustrate visually the impact of an economic shock on bank performance, I plot in Figure 2 the average values of the four performance ratios relative to peer banks under each economic shock rule. The figure plots time periods t-4 through t+12 where time period '0' is the quarter of the shock. The vertical axes represent the basis-point difference between the sample bank ratios and peer bank ratios. Clearly loan quality and earnings deteriorate following the economic shock under both shock definitions. Both nonperforming loans and net charge-offs rise while ROA declines after the shock. Failure probabilities, in contrast, show either no trend or they decline following the shock. Although failure probabilities at shock banks are always above peer levels (due to their smaller size), they decline under the total-cost rule and are essentially flat under the absolute-change rule.

An alternative way to assess the impact of the economic shock on bank performance is to compute the differences between the post-shock and pre-shock bank ratios. Specifically, for each performance measure, I compute the average difference between the sample bank and peer bank for the eight quarters following the economic shock (time periods 1 through 8) and subtract from that value the average difference between the sample bank and peer bank for the four quarters prior to the shock (time periods –4 through –1). This timing convention is the “base case.” For example, the average difference in the nonperforming loan to total loan ratio between Bank A in Duval County and peer banks for the eight quarters after the shock is 2.39 percent; the average difference in the nonperforming loan ratios for the four quarters before the shock is -3.30 percent. I conclude, therefore, that the local economic shock in Duval County caused nonperforming loans at Bank A to rise by 5.69 percentage points (2.39 + 3.30) relative to peer banks. I calculate this difference for each bank and then take the average over the entire bank sample. The results are listed in Table 2.

On average, the vulnerability of banks to local market risk appears to be statistically and economically small. Under the absolute-change rule, nonperforming loans rise 12 basis points, net charge-offs rise 16 basis points, and ROA falls 12 basis points. Under the total-cost rule, nonperforming loans rise 15 basis points, net charge-offs increase 17 basis points and ROA decline 8 basis points. Using a one-tailed T-test, the average deterioration in both net charge-offs and ROA is significantly different from zero—usually at the one percent level—under both shock rules. The average increase in nonperforming loans is statistically different from zero only under the total-cost rule.

Post-shock failure probabilities actually decrease relative to pre-shock levels by 13 basis points under the absolute-change rule and by 69 basis points under the total-cost rule. This result is unexpected. I argue that the decline in failure probabilities is due to the convergence of performance in the banking sector in the early 1990s. Many banks had high failure probabilities in the early 1990s, though the asset-weighted failure probability was low. Failure probabilities declined dramatically at the riskiest banks and converged towards zero as banking conditions improved; the standard deviation of failure probabilities, therefore, declined dramatically. Because of the nonlinear aspect of the probit model, small reductions in risk ratios at risky banks translate into large reductions in failure probabilities. On the other hand, large reductions in risk ratios at safe banks translate into small reductions in failure probability. Suppose that a bank with a relatively high pre-shock average failure probability of say, 1.50 percent, experienced a local economic shock in the first quarter of 1991. The pre-shock asset-weighted peer average failure probability was 0.20 percent, a difference of 1.30 percentage points. Although the bank's asset quality was worsening relative to peer banks after the local shock, its asset quality overall was improving, albeit more slowly than peer banks, through the first quarter of 1993. Perhaps the bank's post-shock failure probability declined to 1.0 percent while the asset-weighted peer average declined to 0.10 percent, a difference of 0.90 percentage points. This bank would show that its failure probability improved by 40 basis points (1.30 – 0.90) even though its asset quality relative to peer banks worsened over the time period. This downward bias in failure probabilities was the strongest in the early 1990s and diminished afterwards. Our shock banks draw heavily from the early 1990s, especially under the total-cost rule. Changes in failure probabilities relative to state-averaged peer groups are suspect then because of the shrinking standard deviation of failure probabilities during this time period. Note that this problem disappears under the matched pairs analysis because I compare banks directly without using peer averages.

Although some of the average changes in bank performance ratios are statistically significant, nearly all of the bank-by-bank changes are not statistically different from zero. Because I am concerned only with the cases in which the performance ratios deteriorated relative to peer banks, I conducted one-tailed T-tests on each of the performance ratios. As Table 2 reports in the column titled "Percent Statistically Significant," just 3.70 percent of the banks (10 of 270) under the absolute-change rule experienced statistically significant deterioration in nonperforming loans. The same ratio under the total-cost rule is 4.89 percent. The percent of banks with statistically significant deterioration in any performance ratio never exceed five percent under either shock rule. The low percentages are driven by the large standard deviations of the changes in ratios.

To interpret the relative vulnerability of geographically concentrated banks to local economic shocks, we need a measure of economic significance. Just how big are the differences in performance ratios before and after the economic shocks? The average decline in ROA following the absolute-change rule economic shock was 12 basis points; is this a large decrease?

Bank examination ratings guide the assessments of large changes in bank performance ratios. CAMELS is an acronym that stands for Capital adequacy, Asset quality, Management, Earnings, Liquidity and Sensitivity (to market risk). Each time a bank is examined, regulators assign a composite rating and an individual rating to each of the CAMELS components. CAMELS ratings range from 1 (the safest banks) to 5 (the riskiest banks). Banks with composite ratings of 1 and 2 are considered to exhibit "strong" and "satisfactory" performances, respectively. Banks that fall below a 2 rating may prompt supervisory action, which could include a board resolution, a memorandum of understanding, a written agreement, or a cease and desist order. Hence, regulators consider a drop from a 2 rating to a 3 rating to be a significant change.

Median differences in bank performance ratios between 2- and 3-rated banks serve as benchmarks for evaluating economic significance. To be consistent with the sample, I constructed the benchmarks using examination ratings and performance ratios of all U.S. banks between 1990 and 1999 with less than $250 million in assets. I used only bank performance ratios at the time of the bank examination instead of using all performance ratios for 2- and 3-rated banks to avoid endogeneity issues that might arise if supervisors required 3-rated banks to improve performance. Inclusion of all the ratios would potentially decrease the differences between 2- and 3-rated banks. Table 3 lists the median performance ratios for 2- and 3- rated banks. For banks with a CAMELS asset-rating of 3 (the 'A' rating), the median nonperforming loans are 125 basis points higher and net charge-offs are 35 basis points higher than 2-rated banks. For banks with a CAMELS earnings rating of 3 (the 'E' rating), ROA is 46 basis points lower than 2-rated banks. Finally, the median difference in failure probability between 2- and 3-rated banks is 50 basis points.

Relative to the economic significance benchmarks, the average changes in three of the four bank ratios seem small. Figure 3 plots the average change along with the CAMELS benchmark difference. The only ratio with some evidence of significant deterioration is net charge-offs, which increases by nearly half of the benchmark value under both shock rules. The other ratios increase by only a small fraction of the benchmark.

Although the average change in performance ratios is not economically large, many of the banks do experience significant deterioration in performance. Besides listing the average deterioration in bank ratios, Table 2 also reports the change in ratios by quartile. In particular, under the absolute-change rule, the top quartile of banks experience an increase in nonperforming loans of at least 63 basis points, an increase in net chargeoffs of 42 basis points, and a decline in ROA of 35 basis points. Failure probability, however, increases by just one basis point. The deterioration in ratios is slightly larger under the total-cost rule.

I also assess the economic significance of the ratio changes on a bank-by-bank basis by counting the number of times ratio changes are significantly different from zero. For each bank, I divide the post-shock less pre-shock change in each performance ratio by the benchmark differences between CAMELS 2- and 3-rated banks. A ratio of one or greater means that the deterioration is economically significant. The percentages of the banks with economically significant deterioration in a given ratio are listed in Table 2 under the column titled "Percent economically significant." Under the absolute-change rule, banks suffer economically significant deterioration in nonperforming loans 11.5 percent of the time, 30.7 percent for net-chargeoffs, 4.1 percent for failure probabilities, and 18.9 percent for ROA. The ratios are slightly higher under the total-cost rule, reported in the bottom panel of Table 2.

In sum, the evidence is mixed. On average, banks seem to respond modestly to local economic shocks. The changes in performance ratios are most often statistically significant but they are economically small. A fraction of the banks, however, do experience economically significant deterioration after the shock. In particular, nearly 16 percent of banks under the absolute-change rule, and 19 percent of banks under the total-cost rule, have two or more performance measures with economically significant deterioration following the shock. Is the deterioration due to the local shocks or to other factors?

IV.1. Timing Conventions and Survivorship Bias

Before discussing matched-pairs results, I address two potential criticisms of the peer analysis—timing conventions and survivorship bias. By comparing the bank's ratios immediately before and after the unemployment shock, I assume that bank performance reacts contemporaneously to the jump in unemployment. What if the bank deterioration precedes or lags the shock by several quarters?

As robustness checks, I calculated the average difference in pre-shock and post-shock ratios using several different timing conventions. Results appear in Table 4 along with the base case (which calculates the average of the ratios for the eight quarters after the shock less the average of the ratios four quarters before the shock). Because the failure probability ratios continue to move in the unexpected direction, I focus on the other three performance ratios.

To control for the possibility that the economic shock began affecting banks somewhat before or somewhat after the jump in the unemployment rate, I excluded the quarter just before the shock and the quarter just after the shock, which I define in the table as Avg(t+2, t+8) – Avg(t-4, t-2). The average deterioration in the ratios relative to the base case increases by a few basis points at most. For example, under the absolute-change rule, net charge-offs increase 16 basis point in the base case, but 19 basis points when the shocks around the quarter are excluded; the same ratios under the total-cost rule are 17 basis points and 19 basis points, respectively. In addition, the percentages of the ratio changes that are statistically or economically significant also increase slightly.

A second timing convention calculates the ratio deterioration using the first four post-shock quarters and the four pre-shock quarters, or Avg(t+1, t+4) – Avg(t-4, t-1). Perhaps comparing two years of post-shock performance with only one year of pre-shock performance weights the post-shock ratios incorrectly. As Table 4 shows, bank deterioration in this case is much less pronounced, especially for nonperforming loans. Under the base case for the absolute-change rule, nonperforming loans rose an average of 12 basis points, but nonperforming loans actually fell two basis points when post-shock quarters five through eight were eliminated. Under the total cost rule, nonperforming loans increased 15 basis points under the base case, but only 8 basis points when post-shock quarters five through eight were eliminated. Results for the other ratios are similar. These results suggest that bank deterioration may not accelerate until more than one year after the economic shock. Bank loan customers may be able to manage the negative effects from a shock for a time, and the bank may be able to assist by renegotiating contract terms such as reducing required principle payments, but eventually the problem loans must be charged off.

I experimented further with allowing more time for bank deterioration by taking bank ratios from post-shock quarters five through eight, and subtracting the ratios from pre-shock quarters one through four Avg(t+5, t+8) – Avg(t-4, t-1). Consistent with the above results, the deterioration was definitely more pronounced. Under the absolute-change rule, nonperforming loans increased by 25 basis points using this timing convention, compared with 12 basis points in the base case. Under the total-cost rule, nonperforming loans increased to 22 basis points from 15 basis points in the base case. Net chargeoffs and ROA also deteriorated more than the base case under each shock rule.

As a final robustness check on timing conventions, I followed bank performance five to twelve quarters after the shock, and compared the ratios with the four pre-shock quarters Avg(t+5, t+12) – Avg(t-4, t-1). In general, bank deterioration was more pronounced than the base case, but similar to the results posted when using only post-shock quarters five through eight.

It appears that banks tend to deteriorate more during the second year than in the first year following the local economic shock, and the relatively poor performance continues through the third year. Overall, however, the conclusion holds that banks are only modestly affected by local economic shocks. Even under the least favorable timing convention, nonperforming loans increased on average by one-fifth of the CAMELS benchmark of 125 basis points, net chargeoffs rose by two-thirds of the 35 basis point benchmark, and ROA fell by one-third of the 48 basis point benchmark.

Besides timing issues, a second potential criticism of the peer-group analysis is survivorship bias. Local economic shocks may lead geographically concentrated banks to fail, which eliminates them from the sample. Fortunately, banking data allow us to investigate partially the importance of this bias. I obtained a list from the FDIC of every bank that failed between 1990 and 1999 and screened those banks on two criteria: each bank had to have all of its deposits in a single county just before failure, and it had to have its headquarters in a county that suffered an economic shock up to three years before the failure. Although 205 banks passed the deposit screen under the absolute-change rule, just one bank passed both screens. Under the total-cost rule, eleven failed banks met the criteria. The total sample size under each shock rule was 270 and 614, respectively. The available evidence suggests that survivorship bias is not an important factor influencing our results. This analysis, however, does not account for weak performing banks that voluntarily merged out of existence following a local economic shock. Unfortunately, data limitations preclude further analysis of this aspect of survivorship bias.

V. Matched-pairs analysis

Results thus far show that the "average" shock bank performs slightly worse than the average peer bank not exposed to local shocks, but the post-shock performance of geographically concentrated community banks is uneven. Some banks seem to deteriorate significantly while others are unaffected or even improve their performance. In this section, I use matched-pairs analysis to examine the effect of county economic shocks on bank performance. In particular, I match each of the "shock" banks with a similar "no-shock" bank located in a county in the same state that did not suffer a local economic shock. I compare the deterioration of the "shock" banks with the "no-shock" banks using a variety of parametric and nonparametric tests.

Unlike peer group comparisons, the control group in matched-pairs analysis contains idiosyncratic risk. In contrast, peer group comparisons diversify away idiosyncratic risk. Take, for example, two geographically concentrated community banks—banks A and B—located in the same state. Both banks deteriorate for idiosyncratic reasons. In addition, Bank A suffers a local economic shock, which has little separate effect on its performance. When comparing Bank A to the state-averaged peer group, it appears that the local economic shock caused Bank A to deteriorate relative to peer banks because the idiosyncratic risk of Bank B is diversified away when it is averaged into the peer group. Matched pairs analysis, however, compares the performance of Bank A directly to Bank B, and the results would show that the local economic shock at Bank A was unimportant.

Matched pairs analysis also allows for uneven influences of broader levels of market risk. Assume that a state-level economic slowdown affects Bank A more than the average peer bank. Bank A also suffers a local economic shock, which has no separate influence on the bank's performance. In a peer-group comparison, it appears that Bank A deteriorates because of the local economic shock instead of the state-level shock. With matched pairs, however, it is just as likely that Bank B also suffers more than the average peer bank from the state-level slowdown, so that the local economic shock suffered by Bank A is not deemed important. Matched pairs reintroduces the variance into the control group that peer comparisons remove.

To isolate local market risk by controlling for idiosyncratic risk and broader levels of market risk, I pair each of the banks that experience an economic shock with a similar bank from the same state that did not suffer an economic shock. To qualify as a "no-shock" (match) bank under the absolute-change rule, each bank had to derive all its deposits from branches in a single county that had an absolute increase in the unemployment rate of one percentage point or less for the four quarters before and the eight quarters after shock date of the sample bank. Under the total-cost rule, each match bank had to derive all its deposits from branches in a single county that had a total cost calculation of less than two. These requirements eliminate the possibility that a no-shock bank suffered a local economic shock just before or after the quarter in which the matched sample bank suffered the shock. In addition, each match bank had to have 1) the same rural/MSA status as the shock bank, and if both banks were in MSAs, the match bank had to be from a different MSA to ensure that the effects of the local shock did not spill over into the no-shock bank; 2) a composite CAMELS rating within one of the shock bank to roughly equate initial levels of idiosyncratic risk; and 3) no merger activity around the shock date to ensure that the ratios were not distorted by mergers. I then calculate the percentage difference between the labor forces of the shock and no-shock banks as well as the percentage difference in total assets. Given the potential pool of match banks, I choose the one with the smallest sum of the percentage differences in labor force and assets. Not all of the shock banks have suitable matches. Under the absolute-change rule 212 of 270 shock banks have matches, while under the total-cost rule 524 of 614 shock banks have matches. Table 5 presents summary statistics of the shock banks and their matches.

By design, the match banks are similar to the shock banks except for their exposure to rising local unemployment rates. On average, the match banks have a few million dollars more in total assets than the shock banks, and they also come from slightly larger counties. County unemployment rates at the match banks, however, fall on average, from 6.1 percent to 5.8 percent under the absolute-change rule, and from 5.8 percent to 5.7 percent under the total-cost rule. In contrast, county unemployment rates at the shock banks surge by an average of 4.7 percentage points under the absolute-change rule and by 3 percentage points under the total-cost rule.

With a few exceptions, the matched pair results suggest that local economic shocks have small and unsystematic effects on community bank performance. The four panels in Figure 4 plot the average differences in performance ratios between the shock banks and match banks by quarter for the quarters around the economic shock. The charts do illustrate three potentially significant sources of deterioration. First, under the absolute-change rule, nonperforming loans rise from levels close to their matches before the shock to about 40 basis points above their matches five quarters after the shock. Second, failure probabilities under the absolute-change rule increase continuously from well below those of match banks before the shock to levels even with match banks about six to eight quarters after the shock. Third, net charge-offs under the total-cost rule rise consistently after the local shock to levels slightly above match levels.

In addition to the graphical exposition, Table 6 lists the results of various parametric and nonparametric tests comparing shock banks with match banks. I report the results for the three most sensitive timing conventions based upon the robustness checks of the peer-comparison results. The first timing convention is the base case; the second timing convention excludes the first four quarters following the economic shock; the third case also excludes the first four post-shock quarters but tracks bank performance for 5 to 12 quarters following the shock.

Differences in means between shock and match banks show some evidence of asset quality deterioration at shock banks. Specifically, nonperforming loans at shock banks increase 36 basis points more than at match banks under the absolute-change rule using the post-shock 5 to 12 quarter timing convention, and the difference is statistically significant at the 5 percent level. None of the other differences, however, are statistically significant under that shock rule, including the 76 basis point rise in failure probabilities. Under the total-cost rule, increases in net charge-offs and nonperforming loans are consistently higher than at match banks across the timing conventions, and the differences are statistically significant at the 5 percent and 10 percent levels, respectively. None of the other differences between shock and no-shock banks are statistically significant. Indeed, failure probabilities actually fall after the shock relative to match banks, and deterioration in ROA is small and insignificant.

In addition to the parametric tests, I conduct a series of nonparametric sign tests to understand better the degree of diversity of responses to local economic shocks. Table 6 reports these results as well. For each of the four bank performance measures, I rank the shock banks from the worst performer to the best performer, and then sum over the four rankings. For example, if Bank A responds the most severely to a local shock by deteriorating the most in each performance measure, its sum of ranks would be four. I independently perform the same ranking procedure for the match banks.

A plot of the sum of ranks for the sample and matched banks helps us to visualize the performance differences between the two groups. Figure 5 plots the sum of ranks for the shock and match banks under the base case. (Results are similar across timing conventions.) I order the banks from each group from lowest to highest by sum of rank and plot on the vertical axis the cumulative percent of the sum of ranks and plot on the horizontal axis the cumulative percent of banks. Similar to a Lorenz curve, the "no effect" line is a 45-degree line in which the cumulative percentage of rank-sums is equivalent to the cumulative percentage of banks in the sample. For example, if performance of all banks were equal so that each bank had the same sum of ranks, then the cumulative percent of the sum of ranks would correspond exactly to the cumulative percent of banks. The impact of the economic shock (or no economic shock) is measured by the degree that the lines bow downward because banks that are affected the most by local economic shocks account for a smaller share of the cumulative sum of ranks. As Figure 5 illustrates, the curves for both the "shock" banks and the matched or "no-shock" banks bow downward. Although the difference is almost indistinguishable, the curve for the no-shock bank actually bows downward slightly more than the curve for the no-shock counties, a result opposite of what we would expect. The chart suggests that the shock banks did not respond much differently to match banks.

Are the sum of ranks of banks in counties that suffered economic shocks and the banks in counties that did not suffer economic shocks statistically different? To answer this question, I conduct a Wilcoxon signed-rank test on the sum of ranks of the sample banks versus the matched banks. In contrast to Figure 5, the signed-rank test requires a ranking of the absolute value of the differences between the shock and match banks. Once the overall rankings of the combined data set are determined, the ranks are given the sign of the original difference of the data. If shock banks deteriorate more than match banks, the sum of the ranks should exceed zero. The null hypothesis, that the sum of ranks is less than or equal to zero, cannot be rejected at any reasonable level of significance. In fact, the mean of most of the sum of ranks is negative and never statistically different from zero, suggesting that the local economic shocks had little impact on banks' performance relative to the match banks.

In addition to the Wilcoxon signed-rank test, I conduct simple sign tests on each of the four performance measures to count the number of times that the bank ratios had the expected signs. I expect the difference between shock and match banks for nonperforming loans, net chargeoffs and failure probabilities to be positive, and ROA to be negative. How many times do these ratio differences have the right sign? Table 6 reports the mean of each of the sign tests for each performance measure. The mean is calculated by subtracting the number of correct signs from half of the sample size. For example, under the absolute-change rule, 212 banks have matches in the base case. If local economic shocks have little effect on bank performance, nonperforming loans should increase more at shock banks than at match banks about half the time, or 106 times. In fact, nonperforming loans increased more at shock banks than at match banks only 91 times. The sign test indicates that nonperforming loans actually decreased at shock banks relative to match banks more times than they increased. Only two of the 24 sign tests under both shock rules are both statistically significant and have the theoretically expected sign.

In sum, local economic shocks do not lead to systematic deterioration of community banks, even when the community banks have geographically concentrated operations. Local shocks do appear to negatively effect some banks some times, especially more than four quarters after the shock. But the shocks seem to have no effect on bank performance the majority of the time. These results are robust to different timing specifications and a host of statistical comparisons.

VI. Conclusion

Whatever the reason, geographically concentrated community banks are not systematically vulnerable to local economic shocks, and whatever vulnerability they faced in the 1990s is likely to decrease even further over time. As banks expand into other economic markets either through mergers and acquisitions, by making loans to more distant borrowers, or by engaging in financial diversification, they will become even less dependent on local economic conditions. Continued economic diversification and integration of local economies will also reduce local market risk.

Anecdotal evidence suggests that economic integration is important in reducing local market risk. Community bankers that I recently questioned at an Arkansas Bankers Association meeting in April 2002 responded that the ability of workers to quickly find new jobs, even if commuting times increased greatly, diminished the impact on bank performance. If workers in a given county are laid off when a plant closes, many of the unemployed can often find jobs in neighboring counties. In addition, new firms are quick to move into buildings vacated by former employers and hire many of the old workers. The Arkansas bankers also commented that consumers tend to protect their cars and houses from default even as they default on other loans. Credit card banks and other nonbank financial institutions hold an increasingly large share of those "other loans." Finally, Jackson (2002) found in banker interviews of some of the banks involved in this study that increased commuting patterns of loan customers and bankers' flexibility in repayment terms eased some banks through plant closings.

One note of caution is that our sample period covers the 1990s, a period of robust economic growth. Banks may have performed as well as they did following local shocks because workers could find jobs in neighboring counties or at new firms in the same counties. If the broader regional economy is in a deep recession, however, local economic shocks may compound the market risk that banks already face. The robust economy of the 1990s is a benefit for this study because it allows us to isolate local economic shocks that are somewhat independent from broader market risk. Our results suggest that local market risk by itself is small.

These findings add to the evidence that small community banks will remain viable in the future financial services industry. Because geographically concentrated community banks are unlikely to reap significant risk-reduction benefits from operating across county lines, many may be content to operate as single county institutions. Of course, scale and scope economies will continue to reduce the number of U.S. community banks; however, recent research by Berger and DeYoung (2001) suggests that there is a limit to these efficiency gains as well. They find that no one type of organizational structure has a sufficient efficiency advantage to drive others out of existence. This result is especially true for small banks that specialize in relationship lending because larger organizations seem to have difficulty effectively managing such banks from a distance. Given the limited scale economies and the small degree of local market risk, relationship banking still has a future.

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Table 1
OLS Regressions with Quarterly Observations

	Return on Assets			Nonperforming Loans			Net Chargeoffs		
Independent variable	Coefficient	t-value	Standardized Coefficient	Coefficient	t-value	Standardized Coefficient	Coefficient	t-value	Standardized Coefficient
County unemployment rate	0.012 *	1.73	0.005	0.017 ***	5.78	0.018	-0.016 ***	-3.67	-0.012
One-quarter lag	-0.006	-1.02	-0.003	0.002	0.66	0.002	0.022 ***	5.81	0.016
Two-quarter lag	0.031 ***	4.92	0.014	0.010 ***	3.92	0.011	-0.018 ***	-4.74	-0.013
Three-quarter lag	-0.063 ***	-10.18	-0.028	-0.022 ***	-8.31	-0.023	0.055 ***	14.46	0.040
Four-quarter lag	0.029 ***	4.30	0.013	0.017 ***	5.89	0.018	-0.034 ***	-8.18	-0.025
Sum of county coefficients	0.002		0.001	0.024		0.026	0.009		0.007
State unemployment rate	-0.152 ***	-5.86	-0.043	0.334 ***	30.70	0.223	0.135 ***	8.46	0.062
One-quarter lag	0.203 ***	4.67	0.057	-0.112 ***	-6.19	-0.075	-0.092 ***	-3.44	-0.042
Two-quarter lag	-0.105 ***	-2.37	-0.030	-0.002	-0.13	-0.002	-0.002	-0.06	-0.001
Three-quarter lag	-0.185 ***	-4.26	-0.052	0.130 ***	7.17	0.086	0.125 ***	4.71	0.057
Four-quarter lag	0.191 ***	7.32	0.053	-0.138 ***	-12.67	-0.090	-0.142 ***	-8.88	-0.064
Sum of state coefficients	-0.049		-0.014	0.211		0.142	0.025		0.012
R-squared	0.001			0.031			0.002		
Number of observations	291,861			291,095			291,072		

OLS Regressions with Annual Observations

	Return on Assets			Nonperforming Loans			Net Chargeoffs		
Independent variable	Coefficient	t-value	Standardized Coefficient	Coefficient	t-value	Standardized Coefficient	Coefficient	t-value	Standardized Coefficient
County unemployment rate	0.005	0.78	0.005	0.014 **	2.28	0.014	0.073	0.55	0.003
One-year lag	-0.008	-1.23	-0.007	0.007	1.13	0.007	-0.053	-0.40	-0.002
Sum of county coefficients	-0.003		-0.003	0.021		0.021	0.021		0.001
State unemployment rate	-0.113 ***	-11.37	-0.082	0.311 ***	34.63	0.244	-0.091	-0.46	-0.003
One-year lag	0.056 ***	5.53	0.039	-0.092 ***	-10.11	-0.070	0.008	0.04	0.000
Sum of state coefficients	-0.058		-0.042	0.219		0.173	-0.083		-0.003
R-squared	0.003			0.045			0.000		
Number of observations	71,913			71,751			71,721		

*, **, *** statistically significant at the .10, .05, and .01 levels, respectively

Table 2
Summary Statistics of Shock Banks and Counties

This table provides summary statistics of the shock banks under both the absolute-change and total-cost shock rules. It also lists the average differences and quartile differences in pre-shock and post-shock performance ratios relative to state-aggregated peer groups. For example, the nonperforming loan to total loan ratio increased by an average of 12 basis points at the shock banks relative to state-aggregated peer groups under the absolute-change rule. The timing convention differences the average of the four quarters before the shock from the eight quarters after the shock. The percent statistically significant is the percent of the total number of sample banks that had significant deterioration in performance ratios. The percent economically significnat is the percent of the total number of sample banks that experienced deterioration in performance ratios equal to or greater than the CAMELS benchmark differences defind in Table 3.

Absolute Change Rule

	Average		1st quartile	Median	3rd quartile	Percent statistically significant	Percent economically significant
Bank Assets (000s)	46,177		23,427	38,005	58,952		
Labor Force	8,425		3,911	6,265	9,056		
Leading Unemp Rate	12.1		10.0	11.7	13.6		
Current Unemp Rate	7.4		5.3	6.9	8.8		
Absolute Change	4.7		4.2	4.5	5.0		
Post-shock less pre-shock value of:							
Nonperforming Loans (%)	0.12		-0.56	0.10	0.63	3.70	11.48
Net Chargoffs (%)	0.16	**	-0.20	0.09	0.42	4.44	30.74
Failure Probability (%)	-0.13		-0.14	0.00	0.01	3.33	4.07
ROA (%)	-0.12	***	-0.35	-0.10	0.13	3.33	18.89
Other Statistics							
Number of banks:	270						
Number in MSA:	8						

Total Cost Rule

	Average		1st quartile	Median	3rd quartile	Percent statistically significant	Percent economically significant
Bank Assets (000s)	52,069		24,872	42,391	66,885		
Labor Force	16,874		5,061	8,803	15,579		
Leading Unemp Rate	11.4		10.0	10.9	11.9		
Current Unemp Rate	8.4		6.5	8.1	9.5		
Total Cost	7.7		6.3	7.1	8.6		
Post-shock less pre-shock value of:							
Nonperforming Loans (%)	0.15	**	-0.49	0.14	0.76	4.89	15.47
Net Chargoffs (%)	0.17	***	-0.16	0.13	0.48	2.93	33.22
Failure Probability (%)	-0.69	***	-0.11	0.00	0.01	0.98	3.91
ROA (%)	-0.08	***	-0.38	-0.10	0.14	1.95	20.52
Other Statistics							
Number of banks:	614						
Number in MSA:	64						

Table 3
CAMELS Benchmarks for Economic significance

This table computes benchmarks for economic significance by calculating the median differences in performance ratios between CAMELS 2-rated banks and CAMELS 3-rated banks. The sample includes all U.S. banks between 1990 and 1999 with less than $250 million in assets. The results suggest that a 125 basis point increase in nonperforming loans and a 35 basis point increase in net chargeoffs are economically significant changes in asset quality. In addition, a 46 basis point decline in ROA and a 50 basis point increase in failure probability are economically significant changes in earnings and overall risk, respectively.

		Performance Ratio (%)	
CAMELS 'A' Rating	**Number of Observations**	**Nonperforming Loans to Total Loans**	**Net Chargeoffs to Total Loans**
2	40,925	1.08	0.13
3	12,499	2.34	0.48
Difference		*1.25*	*0.35*

CAMELS Composite Rating	**Number of Observations**	**Performance Ratio (%) Failure Probability**
2	56,338	0.05
3	10,542	0.55
Difference		*0.50*

CAMELS 'E' Rating	**Number of Observations**	**Performance Ratio (%) ROA**
2	46,598	1.04
3	16,542	0.58
Difference		*-0.46*

Table 4
Robustness Checks Using Different Timing Intervals

This table lists the average post-shock less pre-shock differences in bank performance ratios relative to state-aggregated peer groups under five different timing conventions. The first is the base case, which calculates the average ratio eight quarters after the economic shock and subtracts from that the average ratio four quarters prior to the shock. The second timing convention excludes the quarter directly before and the quarter directly after the shock. A third convention uses only the first four quarters after the shock instead of using the first eight quarters. The fourth convention excludes the first four quarters following a shock and uses only post-shock quarters five through eight. The final timing convention also excludes the first four quarters following the shock, but uses post-shock quarters five through twelve. The last two timing conventions that exclude the first four post-shock quarters show the most deterioration in bank performance relative to peer groups. The evidence indicates that banks do not feel the full effect of the shock until a year or more after the shock.

Absolute Change Rule

	Nonperforming Loans	Net Charge-offs	Failure Probability	ROA
Base case: Avg (t + 1, t + 8) - Avg (t - 4, t - 1)				
Average difference between pre- and post-shock ratios	0.12	0.16 **	-0.13	-0.12 ***
Percent statistically significant:	3.70	4.44	3.33	3.33
Percent economically significant:	11.48	30.74	4.07	18.89
Avg (t + 2, t + 8) - Avg (t - 4, t - 2)				
Average difference between pre- and post-shock ratios	0.14	0.19 **	-0.14	-0.13 ***
Percent statistically significant:	3.70	4.07	3.70	3.33
Percent economically significant:	12.96	32.22	4.07	20.74
Avg (t + 1, t + 4) - Avg (t - 4, t - 1)				
Average difference between pre- and post-shock ratios	-0.02	0.09 *	-0.14 ***	-0.08
Percent statistically significant:	2.96	5.19	4.07	4.81
Percent economically significant:	11.11	27.78	4.07	14.81
Avg (t + 5, t + 8) - Avg (t - 4, t - 1)				
Average difference between pre- and post-shock ratios	0.25 *	0.22 **	-0.12	-0.16 ***
Percent statistically significant:	3.33	2.96	2.22	1.48
Percent economically significant:	14.07	29.26	4.44	22.96
Avg (t + 5, t + 12) - Avg (t - 4, t - 1)				
Average difference between pre- and post-shock ratios	0.33 ***	0.22 **	-0.20	-0.15 ***
Percent statistically significant:	3.35	1.67	4.18	1.26
Percent economically significant:	17.15	32.64	5.86	21.34

Total Cost Rule

	Nonperforming Loans	Net Charge-offs	Failure Probability	ROA
Base case: Avg (t + 1, t + 8) - Avg (t - 4, t - 1)				
Average difference between pre- and post-shock ratios	0.15 **	0.17 ***	-0.69 ***	-0.08 ***
Percent statistically significant:	4.89	2.93	0.98	1.95
Percent economically significant:	15.47	33.22	3.91	20.52
Avg (t + 2, t + 8) - Avg (t - 4, t - 2)				
Average difference between pre- and post-shock ratios	0.16 **	0.19 ***	-0.81 ***	-0.11 ***
Percent statistically significant:	4.23	1.95	0.81	2.44
Percent economically significant:	16.78	35.99	3.91	21.66
Avg (t + 1, t + 4) - Avg (t - 4, t - 1)				
Average difference between pre- and post-shock ratios	0.08 *	0.11 ***	-0.57 ***	-0.07 ***
Percent statistically significant:	4.40	4.07	0.65	3.91
Percent economically significant:	13.84	29.48	4.23	18.08
Avg (t + 5, t + 8) - Avg (t - 4, t - 1)				
Average difference between pre- and post-shock ratios	0.22 ***	0.23 ***	-0.80 ***	-0.09 **
Percent statistically significant:	4.72	2.61	0.81	1.14
Percent economically significant:	18.57	36.81	3.75	23.62
Avg (t + 5, t + 12) - Avg (t - 4, t - 1)				
Average difference between pre- and post-shock ratios	0.20 ***	0.21 ***	-0.83 ***	-0.10 ***
Percent statistically significant:	4.21	2.63	0.70	1.75
Percent economically significant:	17.72	36.67	3.51	22.81

Table 5

Summary Statistics of Shock Banks and Matches

This table lists summary statistics and changes relative to peer groups under the bas case for the shock banks with successful matches and the match banks. On average, the match banks are a few million dollars bigger, and they are headquartered in counties with slightly larger labor forces. While shock banks experienced large increases in unemployment rates, match banks had either small increases in unempoyment rates or decreases in unemployment rates.

Absolute Change Rule

	Shock Banks Successfully Matched				Match Banks			
	Average	Median	%statistically significant	%economically significant	Average	Median	%statistically significant	%economically significant
Bank Assets (000s)	46,282	37,472			48,928	39,123		
Labor Force	8,090	6,265			11,019	7,642		
Leading Unemp Rate	12.2	12.0			5.8	5.2		
Current Unemp Rate	7.5	7.1			6.1	5.4		
Absolute Change	4.7	4.5			0.1	0.0		
Number of banks:	212				212			
Number in MSA:	7				7			

Total Cost Rule

	Shock Banks Successfully Matched				Match Banks			
	Average	Median	%statistically significant	%economically significant	Average	Median	%statistically significant	%economically significant
Bank Assets (000s)	50,876	41,604			55,398	41,362		
Labor Force	17,243	8,543			23,091	10,366		
Leading Unemp Rate	11.4	10.9			5.7	5.6		
Current Unemp Rate	8.4	8.0			5.8	5.6		
Total Cost	7.7	7.1			0.3	0.0		
Number of banks:	524				524			
Number in MSA:	64				64			

Table 6
Matched Pairs Analysis

This table displays the results of T-tests under the null hypothesis that the deterioration of the shock banks was greater than or equal to the deterioration of the match banks. The T-tests are run under the base case and the two timing conventions that exclude the first four quarters after the shock. The results show that, in general, shock banks and match banks behaved similarly under the absolute-change rule. Under the total-cost rule asset quality deteriorated significantly more at the shock banks, but changes in ROA and failure probability were not statistically different. The sign tests indicate that shock banks did not deteriorate significantly more times than they improved relative to match banks following the economic shock.

Absolute-Change Rule

	Base Case			Avg (t + 5, t + 8) - Avg (t - 1, t - 4)			Avg (t + 5, t + 12) - Avg (t - 1, t - 4)		
Difference	Mean	t-Value	Pr > |t|	Mean	t-Value	Pr > |t|	Mean	t-Value	Pr > |t|
Nonperforming Loans	0.01	0.07	0.947	0.15	1.41	0.159	0.36 **	2.11	0.037
Net Chargeoffs	-0.03	-0.33	0.742	0.05	0.79	0.429	0.01	0.11	0.910
Failure Probability	0.39	1.24	0.218	0.55	0.44	0.657	0.76	1.65	0.101
ROA	-0.04	-0.66	0.511	-0.07	-1.05	0.294	-0.06	-1.02	0.310
Sign Tests Ho: $X_S > X_M$	Mean	z-value	Pr > |z|	Mean	z-value	Pr > |z|	Mean	z-value	Pr > |z|
Wilcoxon Signed-Rank	-57.61	-0.03	0.487	-2.31	0.00	0.499	-57.66	-0.04	0.484
Nonperforming Loans	-15 **	-2.06	0.020	-15 **	-2.06	0.020	-5.5	-0.81	0.208
Net Chargeoffs	5	0.69	0.246	1	0.14	0.445	-3.5	-0.52	0.302
Failure Probability	-15 **	-2.06	0.020	-9	-1.24	0.108	-4.5	-0.67	0.253
ROA	5	0.69	0.246	7	0.96	0.168	-1.5	-0.22	0.412
N	212			212			183		

Total Cost Rule

	Base Case			Avg (t + 5, t + 8) - Avg (t - 1, t - 4)			Avg (t + 5, t + 12) - Avg (t - 1, t - 4)		
Difference	Mean	t-Value	Pr > |t|	Mean	t-Value	Pr > |t|	Mean	t-Value	Pr > |t|
Nonperforming Loans	0.15 *	1.73	0.084	0.18 *	1.68	0.094	0.19 *	1.79	0.074
Net Chargeoffs	0.17 **	2.44	0.015	0.24 **	2.77	0.006	0.23 **	2.69	0.007
Failure Probability	-0.22	-0.86	0.392	-0.16	-0.56	0.579	0.01	0.02	0.985
ROA	-0.03	-0.56	0.575	-0.05	-0.84	0.403	-0.08	-1.4	0.161
Sign Tests Ho: $X_S > X_M$	Mean	z-value	Pr > |z|	Mean	z-value	Pr > |z|	Mean	z-value	Pr > |z|
Wilcoxon Signed-Rank	0.25	0.00	0.500	-1.81	0.00	0.500	-82.78	-0.01	0.495
Nonperforming Loans	11	0.96	0.168	14	1.22	0.111	22 **	2.00	0.023
Net Chargeoffs	8	0.70	0.242	17	1.49	0.069	14	1.27	0.102
Failure Probability	-24 **	-2.10	0.018	-28 **	-2.45	0.007	-14	-1.27	0.102
ROA	13	1.14	0.128	19 **	1.66	0.048	10	0.91	0.182
N	524			524			484		

Figure 1
Leading Unemployment Rate Necessary to Qualify as a Shock

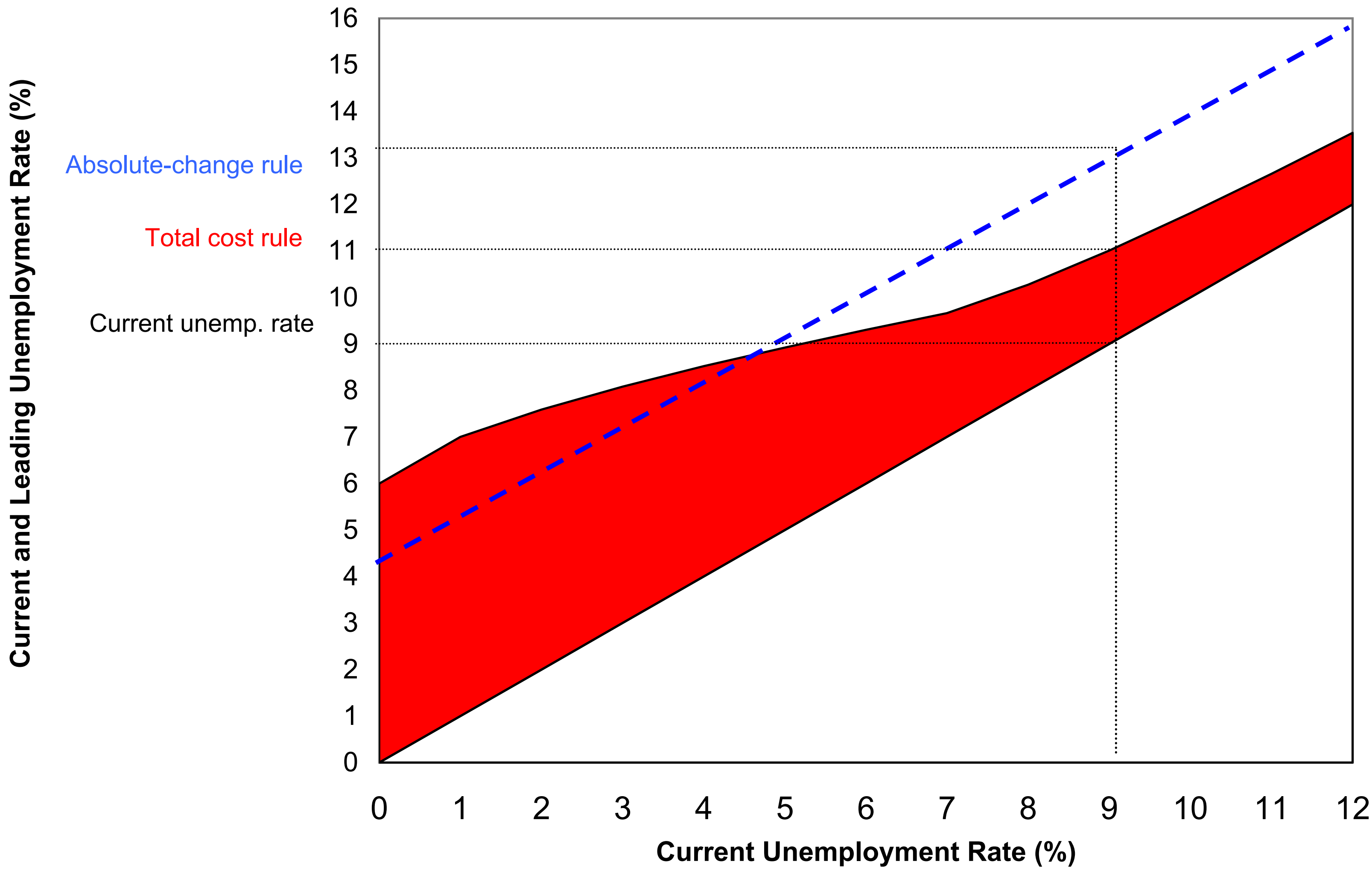

Figure 1 plots the minimum leading unemployment rate necessary to quality as an economic shock given the current unemployment rate. With a current unemployment rate of 9 percent, the unemployment rate would have to rise to 13 percent under the absolute-change rule and to 11 percent under the total-cost rule. The shaded area shows how the difference between the required leading unemployment rate and the current unemployment rate changes as the current unemployment rate rises.

Figure 2
Average Bank Performance Ratios by Quarter Around the Economic Shock
(Basis point difference between the sample bank ratios and peer bank ratios)

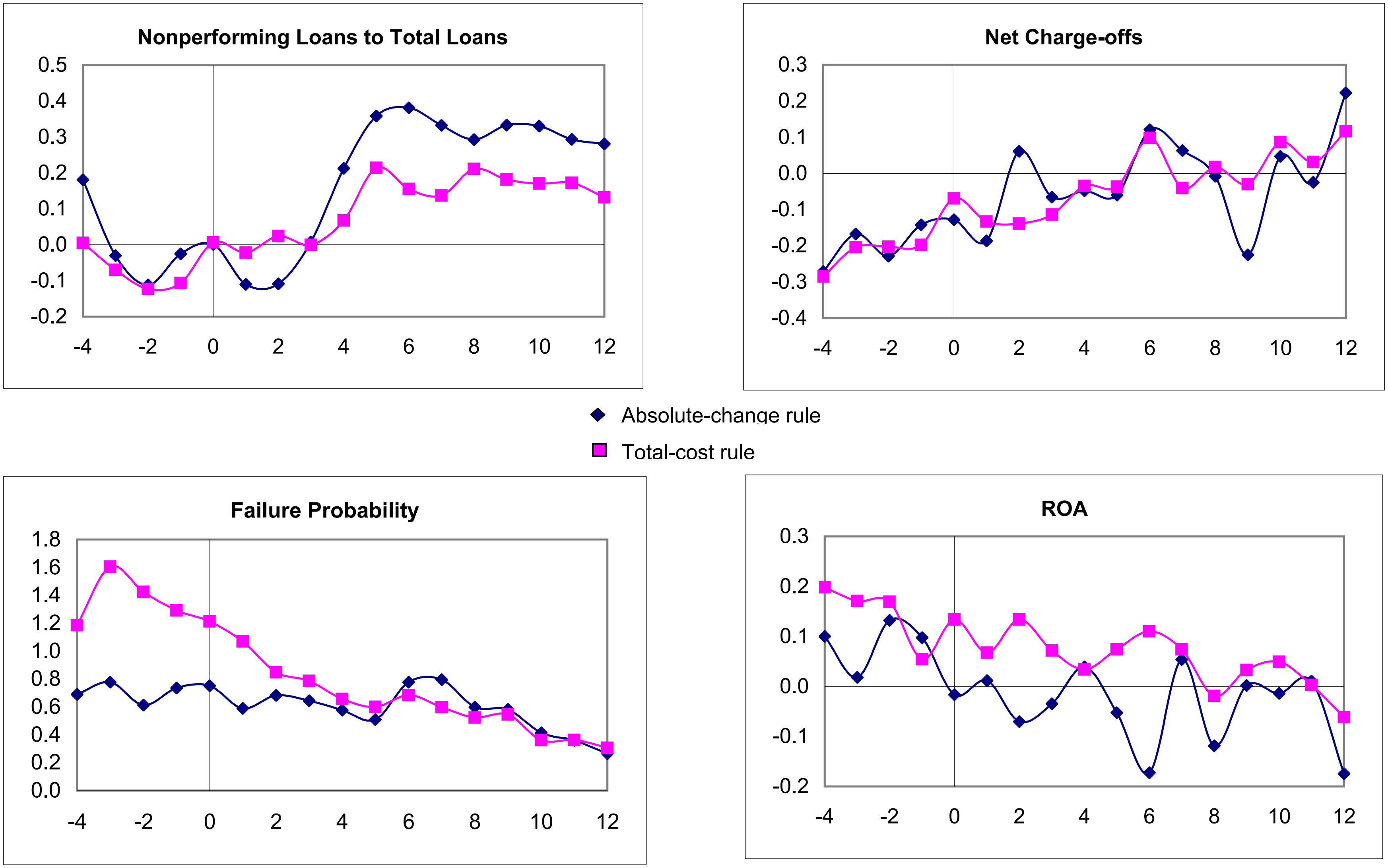

Figure 3

Average Basis-Point Difference Between Post-shock and Pre-shock Bank Ratios

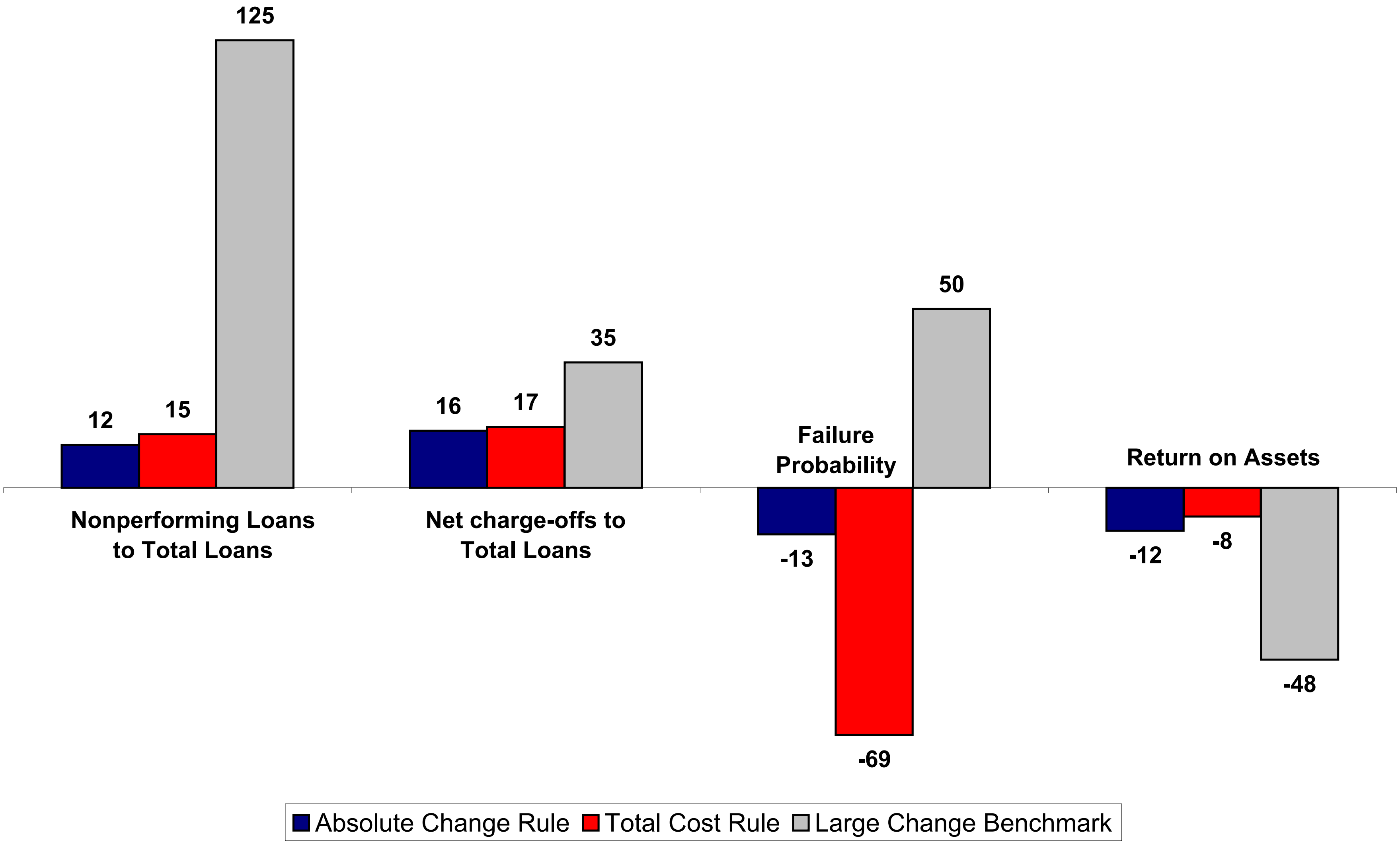

Figure 4
Average Bank Performance Ratios by Quarter Around the Economic Shock
(Basis point difference between the sample bank ratios and match bank ratios)

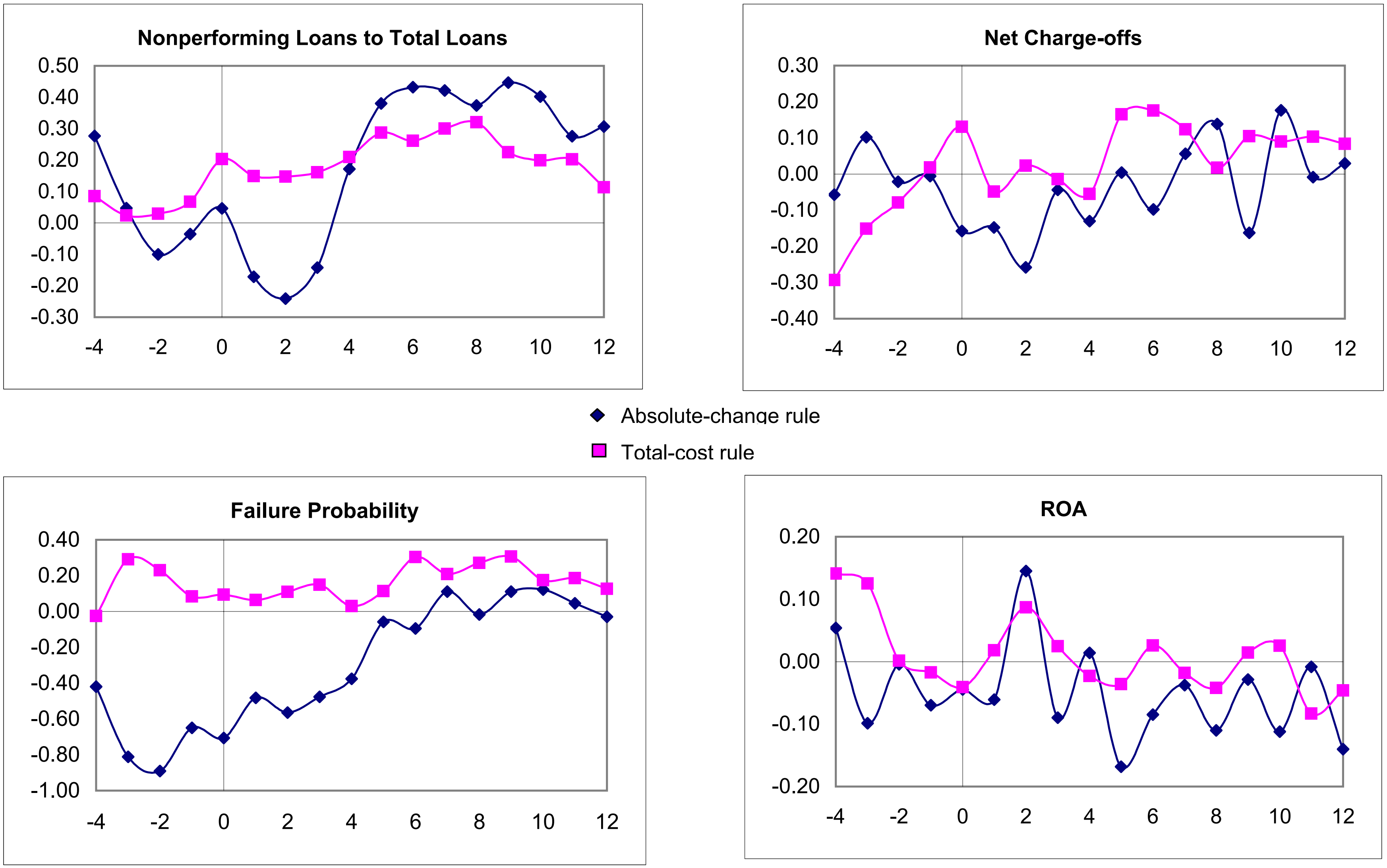

Figure 5

Sum of Ranks Depiction of Economic Shocks Under the Absolute-Change Rule