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Bank holding company mergers with nonbank financial firms:

Effects on the risk of failure*

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An important issue in the debate over whether bank holding companies (BHCs) should be permitted to enter nonbanking activities is the effect of expanded nonbanking powers on BHC risk. We test this issue empirically by simulating mergers between BHCs and firms in nonbanking financial industries, calculating risk measures for the hypothetical merged firms, and comparing their risk characteristics with those of actual unmerged BHCs. We find that mergers of BHCs with life insurance or property/casualty insurance firms may reduce risk, but that mergers of BHCs with securities firms or real estate firms would likely increase risk.

1. Introduction

The entry of bank holding companies (BHCs) into some financial lines of business outside commercial banking, particularly, entry into investment banking, insurance, and real estate, is being vigorously debated. One of the important issues is the effect that expanded powers in nonbanking activities would have on BHC risk. On the one hand, portfolio diversification theory suggests that expanded powers would reduce the risk of BHC failure. On the other hand, if the sought-after activity is inherently riskier than banking, the benefits from diversification could be overwhelmed, thereby increasing the risk of BHC failure.

The relevance of this issue has been heightened by the recent debacle of the savings and loan industry. Permissible activities for savings and loans were dramatically expanded in the 1980s, and many firms in that industry

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used their new powers in ways that increased risk. The result was increased failures and larger losses for their deposit insurer – the FSLIC – and ultimately for the US taxpayer. Since banking firms have the same system of deposit insurance – with the same inherent tendency to induce moral hazard – there is an understandable concern over potential losses to the bank insurer – the FDIC – if BHCs are permitted to enter risky nonbanking activities.

Some have argued that this concern is overstated because 'firewalls' can be built around BHC banking subsidiaries that would protect them from the adverse effects of risky nonbanking subsidiaries. Federal Reserve Chairman Greenspan (1991), for example, suggests that financial transactions between banking and nonbanking subsidiaries can be quantitatively limited and fully collateralized while achieving the desired synergies in managerial, operational, and marketing areas. We have argued elsewhere [Boyd and Graham (1988)] that 'firewalls' are not likely to provide the desired result. If the activities of banking and nonbanking subsidiaries are not fully separated by law, banking-subsidiary resources most likely will be employed, by some device or other, to aid financially distressed nonbanking subsidiaries. Alternatively, if full legal separation is imposed, any synergism in combining banking and nonbanking activities is eliminated. Market investors can already create portfolios composed of bank, securities, real estate, and insurance company holdings if they want.

Resolution of the issue of the effects of expanded BHC powers on BHC risk is primarily an empirical matter. In this study, we investigate the risk effects of BHC entry into the securities, real estate, and insurance industries. The tests consist of simulating mergers between BHCs and firms in these nonbanking industries, calculating risk measures for the hypothetical merged firms, and comparing their risk characteristics with those of actual unmerged BHCs. The paper proceeds as follows. Section 2 discusses the literature. Section 3 presents methodology: the risk and return measures employed, the sample, and the simulation procedure. Section 4 discusses the risk and return characteristics of the sample firms, and section 5 presents the simulation results. Section 6 summarizes and concludes.

2. Review of the literature

Studies on the effects of nonbanking activities on BHC risk can be placed in two categories: those which look at nonbanking activities already permitted, and those which deal with BHC expansion into currently prohibited activities.

Under the first group we consider the studies of Boyd and Graham (1986), Wall (1987), Brewer (1989), and Liang and Savage (1990). Boyd and Graham examine accounting data for 64 BHCs for 1971–1983 and find no statistically significant relationship between the share of nonbanking assets in BHC portfolios and BHC failure risk. Examining subperiods, however, they find a statistically significant positive relationship between nonbanking share and failure risk during 1971–1977 but not during 1978–1983. The authors argue that the change reflects the imposition of the Fed's 'go-slow policy' in the late 1970s which placed various risk constraints on BHCs' nonbanking activities. Wall, working with accounting data for 267 BHCs for 1976–1984, finds that the probability of failure is greater for nonbanking subsidiaries than for banking subsidiaries. However, due to diversification effects, the risk of BHC failure either does not change or declines a bit as nonbanking activities increase in importance. Brewer, working with accounting and market data for 40 BHCs over 1979–1985, finds a weak negative relationship between nonbanking shares and BHC risk. Liang and Savage, working with accounting data for 298 BHCs for 1987 find that, for BHCs engaged in four nonbanking activities, risk (based on cross-sectional variation in profitability) is greater in their nonbanking than in their banking subsidiaries.

These studies have two shortcomings. First, with the exception of Liang and Savage, they aggregate all nonbanking activities so that the risk of any particular activity cannot be isolated. Second, these studies examine nonbanking activities already permitted and engaged in. The more interesting policy issue is the expansion of powers into prohibited areas. These shortcomings are addressed in a second group of studies which includes Litan (1985), Kwast (1989), Rosen et al. (1989), and Boyd and Graham (1988).

Litan conducts two experiments using Internal Revenue Service profit data for several industries over 1962–1981. In one of these experiments he compares the banking industry with each of 15 prohibited nonbanking industries. Litan calculates the coefficient of variation of earnings for each industry and their correlation coefficient with banking. He argues that mergers of banks and nonbanks would be potentially risk-reducing if the coefficient of variation for the nonbanking industry is small relative to banking, and if the correlation coefficient between banking and nonbanking earnings is negative. Results are mixed and depend on the time period. In the other experiment Litan estimates the share of nonbanking assets in a portfolio on an efficient risk-return frontier. Based on data for 1965–1981 he finds that commercial banking comprises the majority share regardless of risk or return level and that the savings and loan industry accounts for the next highest share. The share of the securities industry is never above three percent and real estate developers do not enter the efficient portfolio at any risk or return level.[1]

[1]The results of both these tests must be viewed with caution because of the author's use of aggregate data for each industry rather than individual firm data. Computing risk measures with industry aggregate data results in within-industry averaging. This produces a downward bias to

Kwast examines the potential impact on bank risk of permitting securities powers. He uses bank trading-account activity as a proxy for prohibited securities activity, and his sample consists of all commercial banks with trading-account assets during 1976–1987. Kwast estimates the point of maximum potential diversification by computing the bankruptcy risk for varying portfolio weights of securities and nonsecurities assets. He finds that diversification gains are relatively small. The maximum diversification benefits are attained when the securities share of assets ranges from zero to nine percent.[2]

Rosen et al. examine banks' potential for risk-reducing diversification from entry into direct investment in real estate. Bank profitability data come from call reports of 319 commercial banks from 1980 to 1985. Real estate investment profitability for the same period comes from two sources: real estate investment trusts (REITs) and savings and loan service corporations. The authors estimate the point of maximum potential diversification *a la* Kwast and, like Kwast, find minimal benefits. Service corporation data reveal no diversification potential, while REIT data indicate that the maximum risk reduction is achieved at (no more than) four percent share of real estate assets.

Boyd and Graham examine the risk effects of expanding bank powers into securities, real estate, and insurance. Their method is to simulate a large number of mergers between BHCs and firms in these industries, and compare the resulting bankruptcy risk measures for the simulated firms with those of unmerged BHCs. They employ both accounting and market data from 1971 to 1984. They find that with either accounting or market data, bankruptcy risk falls when BHCs merge with life insurance companies, but rises when BHCs merge with securities or real estate firms.

Although the Boyd–Graham results are not necessarily inconsistent with those of Kwast or of Rosen et al., they are not directly comparable. In the Boyd–Graham merger simulations, firm pairs are chosen at random and the data entirely determine the relative portfolio weights of banking and nonbanking assets. Portfolio weights are not varied, and no attempt is made to ascertain the optimal (risk-minimizing) combination. Kwast and Rosen et al., on the other hand, estimate return distributions for each industry and then solve a portfolio problem in which the choice variable is the ratio of banking to nonbanking assets.

Each method has advantages and disadvantages. The portfolio approach is appealing because it allows an analysis of varying asset combinations and

the estimated volatility of returns by some unknown amount. The object of interest is individual firm risk, not aggregate industry risk.

[2]Kwast's results must be interpreted cautiously because (permitted) trading-account activity is arguably a poor proxy for broader securities powers. Trading-account holdings are composed primarily of US government securities, which are less risky than many other financial claims.

computation of the risk-minimizing portfolio weights. However, these studies assume the existence of homogeneous industries with return distributions which are time-stationary and joint-normal. Neither assumption is appealing and (for the data used in the present study) the normality assumption is often violated.[3] The Boyd–Graham simulation method requires no return distribution assumptions, except existence of the first two moments.

The objective of the present paper is to simultaneously obtain the best features of both approaches. This is done by conducting merger simulations in such a way that a variety of different portfolio weights can be examined for each bank–nonbank industry pair. In addition, the present study extends Boyd and Graham (1988) by substantially enlarging the sample, both in years covered and number of firms included.

3. Methodology

3.1. Measures of profitability and risk

All profitability and risk measures are computed using both accounting and market (stock price) data. Whether accounting or market data provide better measures of risk and return is a debatable issue: Each has advantages and disadvantages. A well-recognized problem with accounting data is the smoothing of profits stemming in part from marking assets and liabilities at historical cost rather than at market value [e.g., Greenawalt and Sinkey (1988)]. This is a particularly undesirable property when estimating measures of volatility as we do here. Stock prices, on the other hand, quickly reflect all material information about a firm as it becomes known; thus, market returns are not smoothed as are accounting returns. However, no one has yet provided a totally satisfactory explanation as to why equity returns are so volatile relative to other economic time-series [e.g., Mehra and Prescott (1985)]. In our study this issue is largely academic because the conclusions are not very sensitive to the kind of data employed.

The accounting profitability measure is the mean rate of return on average accounting equity,

$$\bar{R}=\left\{\sum_{j=1}^{n}\left[2\tilde{\pi}_j/(E_j+E_{j-1})\right]\right\}\Big/ n, \tag{1}$$

where π_j is net accounting income after taxes, E is total accounting equity, and the subscript j is time period. Balance sheet data are end-of-year; thus, $(E_j+E_{j-1})/2$ is average equity in year j. A tilde ($\tilde{}$) is used to denote a random variable, and n is the number of sample years.

[3]For most of the industries studied here the hypothesis of a normal distribution of returns is rejected due to skewness or kurtosis, or both.

The market estimate of mean rate of return on equity is

$$\bar{R}^{\mathrm{m}}=\left\{\sum_{j=1}^{n}[\tilde{P}_j-P_{j-i}+\tilde{D}_j]/P_{j-1}\right\}\Big/n, \tag{2}$$

where P is the price per share of common stock, and D is cash dividends per share, both adjusted for stock splits and stock dividends.

The risk measure is a statistic indicating the probability of bankruptcy, which we call the Z-score. Define bankruptcy as the situation in which equity is insufficient to offset losses, or $\tilde{\pi}<-E$. Letting $A=$total assets, $\tilde{r}=\tilde{\pi}/A$, and $k=-E/A$, the probability of bankruptcy is then

$$p(\tilde{\pi}<-E)=p(\tilde{r}<k)=\int_{-\infty}^{k}\phi(r)\,\mathrm{d}r, \tag{3}$$

where $p(\cdot)$ is a probability and $\phi(r)$ is the p.d.f. of r. If $\tilde{r}$ is normally distributed, we may rewrite (3) as

$$p(\tilde{r}<k)=\int_{-\infty}^{z}\mathrm{N}(0,1)\,\mathrm{d}z, \tag{4}$$

$$z=(k-\rho)/\sigma, \tag{5}$$

where ρ is the true mean and σ the true standard deviation of the r distribution. Thus, z is the number of standard deviations below the mean by which profits must fall in order to eliminate equity. Even if $\tilde{r}$ is not normally distributed, z is an upper-bound on the probability of bankruptcy, as long as ρ and σ exist. By the Bienaymé–Tchebycheff inequality:

$$p(\tilde{r}\leqq k)\leqq\{\sigma/(\rho-k)\}^2=1/z^2.$$

Here, we use sample estimates for ρ and σ to construct the Z-score – the estimated value of $-z$ (since z is always negative).

The accounting data Z-score is

$$\tilde{Z}=\left\{\sum_{j=1}^{n}[2\tilde{\pi}_j/(A_j+A_{j-1})]/n+\sum_{j=1}^{n}[(E_j+E_{j-1})/(A_j+A_{j-1})]/n\right\}\Big/S_r, \tag{6}$$

where S_r is the estimated standard deviation of r.[4]

[4]Actually, we examine two measures of risk. In addition to the Z-score, we also employ the median standard deviation of the rate of return on equity as an alternative. All conclusions of this study are supported by both risk measures, although for brevity only one is presented.

The market data Z-score is defined as in (6), but with profits, assets, and equity restated in market terms. The market-based estimate of total profits is

$$\tilde{\pi}_j^{\mathrm{m}} = c_j(\tilde{P}_j + \tilde{D}_j) - c_{j-1}P_{j-1}, \tag{7}$$

where c is the number of common shares outstanding, adjusted for stock splits and stock dividends. The market value of total equity is

$$\tilde{E}_j^{\mathrm{m}} = c_j\tilde{P}_j, \tag{8}$$

and total assets on a market basis is,

$$\tilde{A}_j^{\mathrm{m}} = \tilde{E}_j^{\mathrm{m}} + L_j^{\mathrm{a}}, \tag{9}$$

where L^{a}, the accounting value of total debt plus preferred stock, is used as an estimate of market value.

3.2. Merger simulations

We simulate hypothetical mergers between actual BHCs and firms in other financial industries using historical data. One BHC and one firm from a particular nonbanking industry are randomly selected, with replacement. Nonbanking firm data are scaled to produce a predetermined initial portfolio weight; that is, a post-merger ratio of nonbanking to consolidated assets as of the first year that both firms are in the sample. The scaling procedure is as follows. Define A_{b} as total assets of a randomly selected BHC, and A_{n} as total assets of a randomly selected nonbanking firm. Define N as an initial portfolio weight for a particular simulation, $0 \leq N < 1$. Compute the adjustment factor s, where

$$s = \frac{N}{1-N}\frac{A_{\mathrm{b}}}{A_{\mathrm{n}}}. \tag{10}$$

Then, multiply all annual data for the nonbanking firm by the factor s. The effect is to proportionally shrink or blow up the nonbanking firm in order to achieve the desired post-merger ratio of nonbanking to consolidated assets. The initial portfolio ratio, N, is a period-1 condition through which we scale vectors of nonbanking data before merging. The path of growth over time of the nonbanking firm is not disturbed, and therefore the nonbanking share is free to vary with time. As a result, the nonbanking share can, after the first year, differ from the initial ratio. Separate scalings are computed for accounting and market data. Once nonbanking data are scaled, data for the hypothetical firm are generated by summing BHC and nonbanking data for each year that both are in the sample. This aggregation procedure occurs in

Table 1

Risk and return characteristics of the sample firms.[a]

	Median profitability		Median risk		Number of firms in sample	
Industry	Accounting $\bar{R}$	Market $\bar{R}^m$	Accounting Z	Market Z^m	Accounting	Market
Life insurance	11.8%	14.0%	28.1	3.97	30	30
Property/casualty ins.	13.7	18.1	19.7	4.03	16	16
Insurance agent/broker	19.3	15.2	8.6	2.97	20	13
Securities	15.5	16.9	11.8	2.09	27	25
Real estate development	3.5	13.2	6.8	2.01	69	60
Other real estate	1.7	14.3	6.6	2.60	67	50
BHC	13.2	15.9	31.8	3.82	141	137

[a]The sample period is 1971–1987.

Source: Standard & Poor's COMPUSTAT Services, Inc.

historical real time; thus, merged data for year j are created if and only if both firms have data for year j. This procedure defines a merger simulation.

For each nonbanking industry and initial value of N, we simulate 1,000 mergers and compute summary statistics for the newly created BHC–nonbanking combination. The same sample of 1,000 mergers is used for each selected value of N. With N ranging from 0 to 99.99 percent we can trace out the profitability and risk effects of varying asset mix to a high degree of precision.

3.3. The data

The annual data come from Standard & Poor's COMPUSTAT tapes for 1971–1987. Besides BHCs, six financial nonbanking industries are included. The accounting data sample is comprised of 30 life insurance companies, 16 property/casualty insurance firms, 20 insurance agent/brokers, 27 securities firms, 69 real estate development firms, 67 other real estate companies, and 141 BHCs (table 1). Industry classifications are according to Standard & Poor's.[5] The sample firms tend to be the larger ones in their respective

[5]In a recent review article, Benston (1989) criticizes the security industry classifications used in our earlier study [Boyd and Graham (1988)], and summarily dismisses our findings. His criticism needs to be addressed here because, if it were correct, it would apply to the present study as well.

Benston says, "Unfortunately, they misclassify 6 of the 11 securities firms because these engage primarily in other activities" (p. 297). That's just not so. In both our 1988 study and this one we employ Standard & Poor's industry classifications (and clearly so indicate). Moreover, we have conducted experiments with both samples, excluding the securities firms Benston believed to have been misclassified. In both cases results are little affected and, if anything, strengthened a bit. We would be glad to provide these results to any interested reader.

industries, and all are publicly traded. Since not all sample firms have data in all periods, we require that each have at least five consecutive years of data.[6]

4. Risk and return characteristics of sample firms

Table 1 shows median risk and return measures for each of the seven industries.[7] In terms of either accounting or market returns on equity, BHCs are roughly in the middle, less profitable than some industries and more profitable than others. The median Z-scores computed with accounting data suggest that BHCs are least risky, followed by life insurance and property/casualty insurance firms. The median Z-scores computed with market data suggest that these three industries are all fairly close in terms of risk. By either Z-score measure the securities, real estate, and insurance agent/broker industries exhibit the highest risk.[8]

These industry median statistics may be of some interest, but they provide little information on the risk effects of combining BHCs with firms from other industries. That depends not only on the distributions of BHC and nonbanking profits, but also on the correlations among them. Our simulation procedure uses actual historical returns. Therefore, the time-series of merged returns automatically account for the actual cross-industry correlations that are in the historical data. We turn next to the simulations.

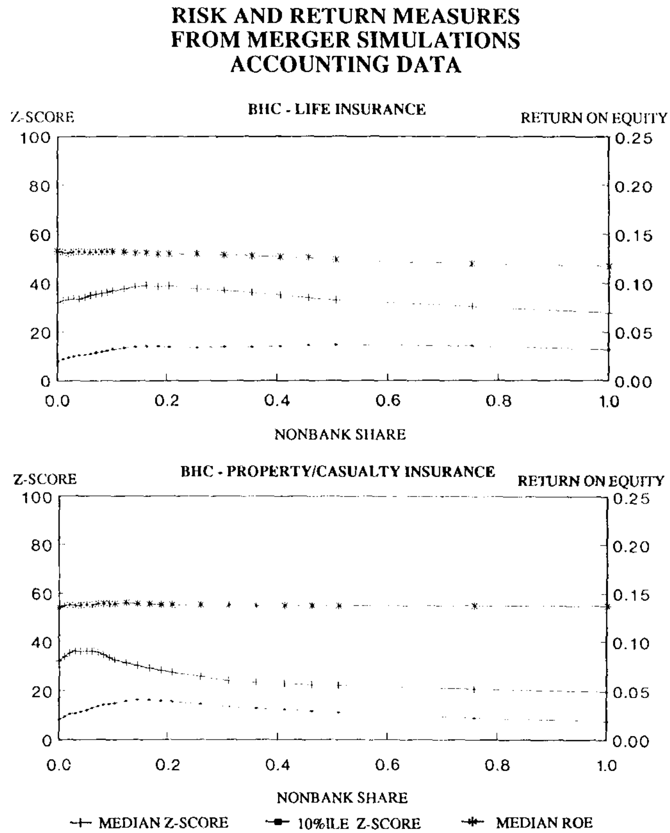
5. Simulation results

Merger simulation results with the accounting data are shown in figs. 1–3 and with the market data in figs. 4–6. The right-hand scale in these figures is the rate of return on equity. The left-hand scale is the Z-score risk measure. The horizontal axis is the median nonbank share, N'. The profitability results merit little comment since merged firm returns are simply a weighted average of individual firm returns. Thus, when a BHC merges with a firm from a

[6]The market data sample is slightly smaller because of our restriction on the minimum number of annual data points. For those BHCs that would have failed except for FDIC assistance, we eliminated all data subsequent to the date when life sustaining government funds were injected. We justify this step because we are studying market behavior. 'Other' real estate includes an amalgam of industry classifications including investment in apartment and nonresidential buildings, dealers, lessors of real property, and real estate agents and managers.

[7]It is important to note that we first compute individual firm statistics and *then* aggregate. Risk measures are never computed using industry average (or total) returns.

[8]The median Z-scores computed with accounting data are so large that, if the distributions of returns were normal, then the Z-scores would imply infinitesimal probabilities of failure. However, these statistics underestimate the true probability of failure for a variety of reasons. First, the return distributions are often not normal. Second, our definition of bankruptcy is too restrictive: it requires a one-period loss that exceeds consolidated equity. Third, smoothing of accounting earnings is undoubtedly taking place, thus giving a downward bias to estimated profits volatility. The Z-scores computed with market data are, of course, much more credible.

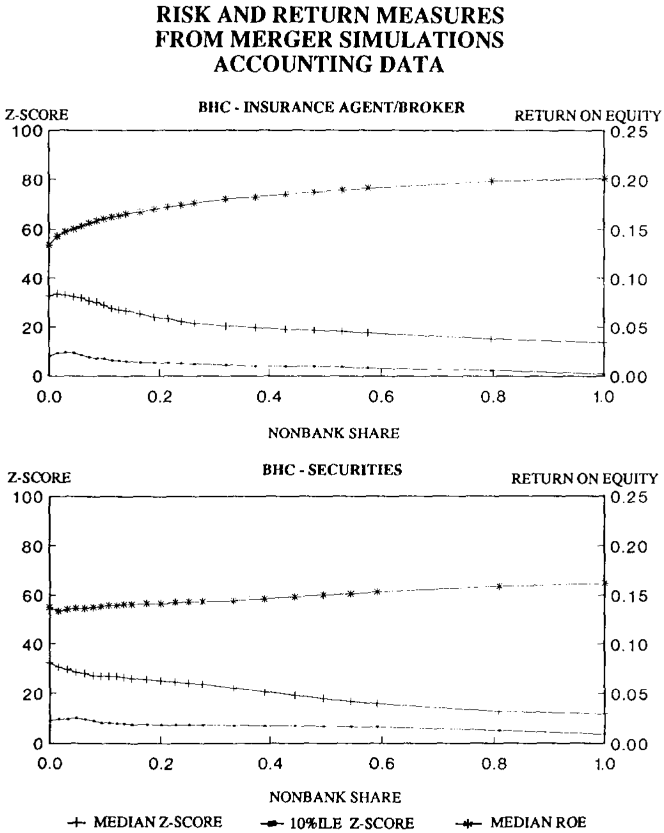


The median Z-score and tenth percentile Z-score (left scale) and the median rate of return on equity [ROE] (right scale) are from a random sample of 1000 hypothetical mergers of a BHC and a nonbank firm from a given industry. The same set of 1000 mergers is used in each of 24 simulations with differing initial portfolio weights (N) of the nonbank firms.

Fig. 1

more (less) profitable industry, the rate of return on equity increases (decreases) with the nonbank share of assets.

We use two statistics to summarize each distribution of Z-scores: a measure of central tendency and a measure of high-risk outcomes. The first measure is the 50th percentile (median) Z-score resulting from 1,000 simulated mergers for a particular industry pair and initial portfolio weight, N. This measure is employed to represent the riskiness of a typical merger combination. The second measure is the 10th percentile Z-score from the same distribution. The idea is to represent the riskiness of the weaker randomly selected combinations – those in the left tail of the distribution. In all cases, we checked Z-scores at the 5th and 15th percentile and the results



The median Z-score and tenth percentile Z-score (left scale) and the median rate of return on equity (ROE) (right scale) are from a random sample of 1000 hypothetical mergers of a BHC and a nonbank firm from a given industry. The same set of 1000 mergers is used in each of 24 simulations with differing initial portfolio weights (N) of the nonbank firms.

Fig. 2

were comparable to those at the 10th. The right tail of the Z-score distribution is of no particular interest. In all cases these lines are relatively smooth, suggesting that 1,000 simulations are sufficient to produce stable results. We refer to these lines as 'Risk–Portfolio Weight' (RPW) functions, and let RPW_{50} denote the median Z-score and RPW_{10} denote the 10th percentile.

5.1. Accounting data results

Simulations with accounting data (figs. 1–3) indicate that mergers between BHCs and firms in four nonbanking industries increase BHC risk of failure at virtually any portfolio weight. The four industries are: securities, real

**RISK AND RETURN MEASURES
FROM MERGER SIMULATIONS
ACCOUNTING DATA**

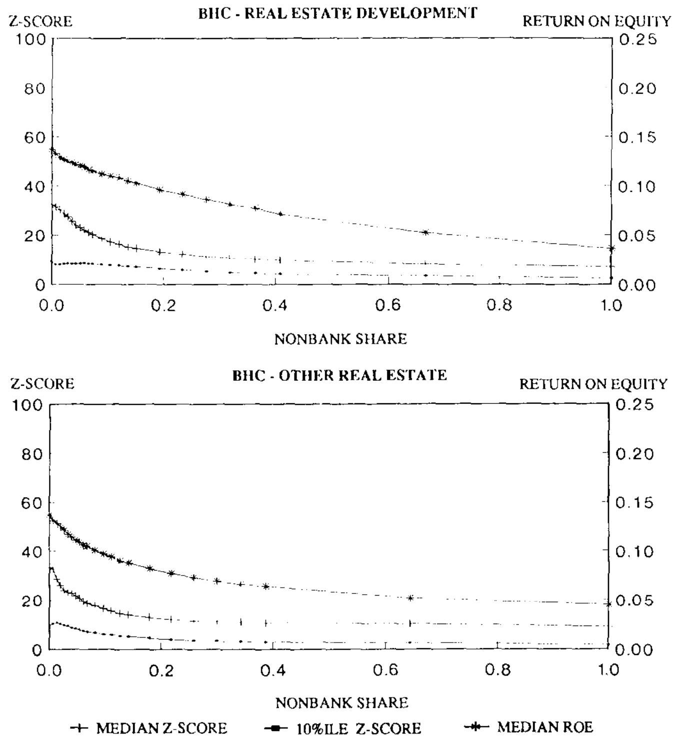


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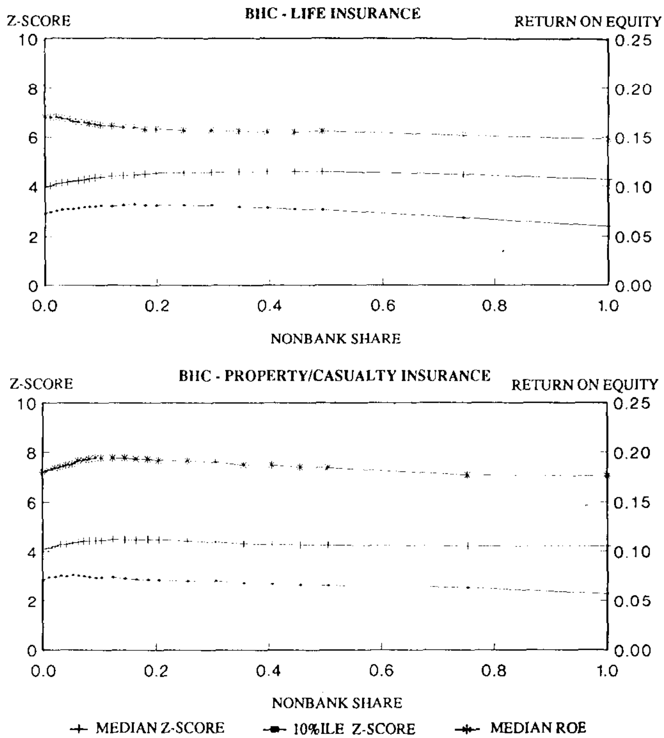
Fig. 3

estate development, other real estate, and insurance agent/brokers. For these combinations, both RPW functions decline monotonically (or nearly so), with N'. Specifically, with respect to the RPW_{50} function, three industries exhibit maxima at $N'=0$. The fourth industry, insurance agent/brokers, has an interior maximum at less than two percent nonbank share. With respect to the RPW_{10} function, real estate development declines monotonically with N', and the other three industries reach interior maxima between one and five percent nonbank share.[9]

[9]The reader may observe that in figs. 1–6 the Z-scores statistics at the vertical axis are not exactly the same for each industry combination, nor are they exactly equal to the median Z-score for the unmerged BHC industry reported in table 1. There are two reasons. First, these Z-

RISK AND RETURN MEASURES
FROM MERGER SIMULATIONS
MARKET DATA

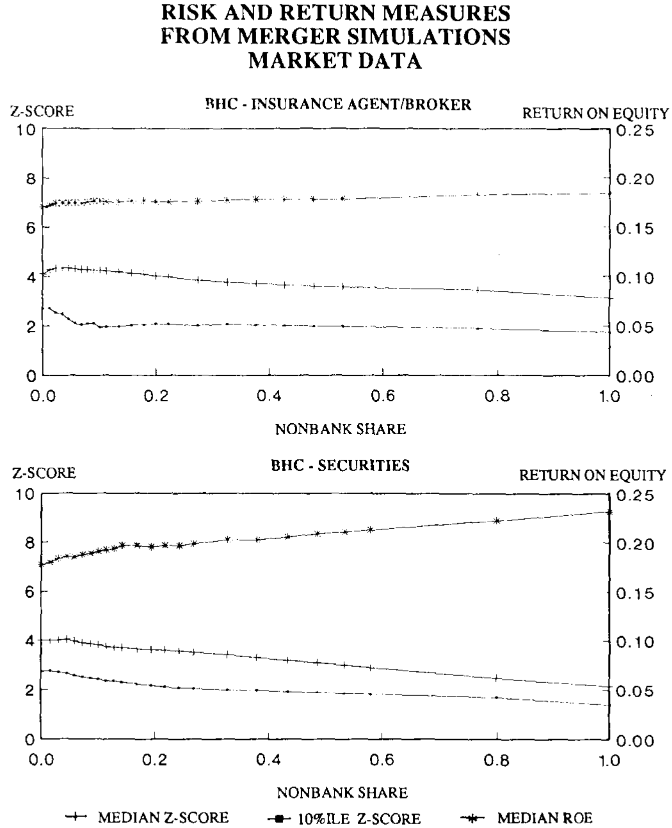


The median Z-score and tenth percentile Z-score (left scale) and the median rate of return on equity [ROE] (right scale) are from a random sample of 1000 hypothetical mergers of a BHC and a nonbank firm from a given industry. The same set of 1000 mergers is used in each of 24 simulations with differing initial portfolio weights (N) of the nonbank firms.

Fig. 4

Simulated BHC mergers with firms in two industries, life insurance and property/casualty insurance, suggest that with the right portfolio weights, risk reducing diversification is possible. The RPW_{50} for life insurance attains an interior maximum at 16 to 20 percent nonbank share and remains above the $N'=0$ level out to approximately 60 percent nonbank share. Property/

scores are the medians of 1,000 randomly selected BHCs, and not the median Z-score of the entire set of BHCs, each represented once. Second, our methodology requires that merged firms have at least five consecutive years of data; therefore, some combinations are not admissible. With N set at zero, the resulting (merged) sample of 1,000 BHCs has characteristics which are slightly different than that of the set of BHCs from which the merger sample is drawn. For the same reasons we should not expect the Z-scores, at the point where N' is (near) 100 percent, to exactly equal the Z-scores of the unmerged nonbanking industries.



The median Z-score and tenth percentile Z-score (left scale) and the median rate of return on equity [ROE] (right scale) are from a random sample of 1000 hypothetical mergers of a BHC and a nonbank firm from a given industry. The same set of 1000 mergers is used in each of 24 simulations with differing initial portfolio weights (N) of the nonbank firms.

Fig. 5

casualty insurance's RPW_{50} reaches an interior maximum at three to six percent nonbank share but falls below the vertical axis ($N'=0$) level at about 11 percent nonbank share. The RPW_{10} functions for both industries exhibit interior maxima and remain above the vertical axis ($N'=0$) level beyond 75 percent nonbank share.

5.2. *Market data results*

RPW functions based on market data (figs. 4–6) have shapes that are quite similar to those using accounting data, except that market RPW functions

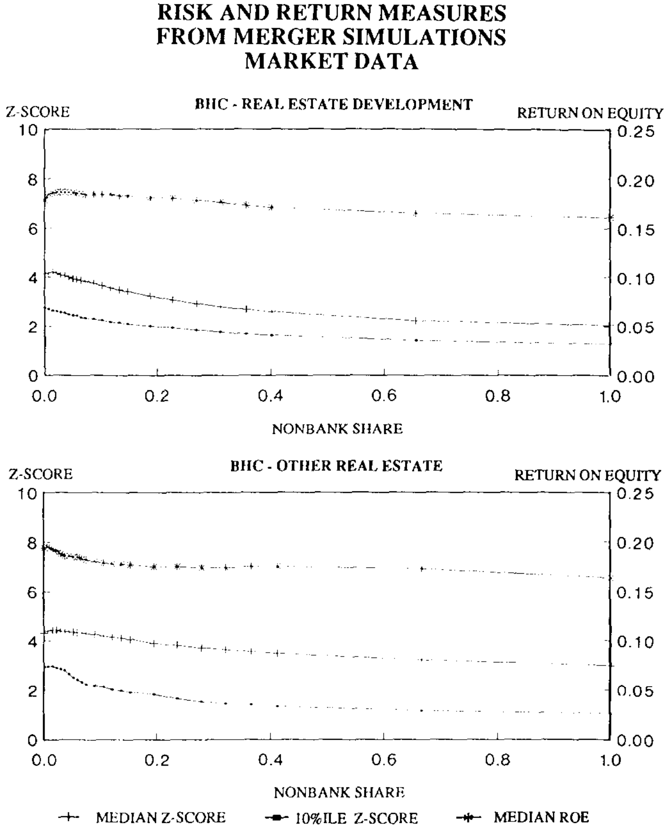


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Fig. 6

tend to be flatter. This characteristic indicates that market data risk outcomes are less sensitive to choice of portfolio weight.

According to the market data, BHC combinations with three industries increase risk at almost any portfolio weight. These are combinations with securities, real estate development, and other real estate firms. For these three industry combinations, both the RPW_{50} and RPW_{10} functions decline essentially monotonically with N'. In the case of BHC–securities mergers, RPW_{50} is flat between zero and five percent nonbank share and then declines. With the two BHC–real estate combinations, the RPW_{50} functions rise very slightly and reach maxima at one to two percent nonbank share. The RPW_{10} functions for these three combinations have their maxima at a nonbank share less than two percent. Thus, the risk-minimizing combinations for these three industries are very near $N'=0$. Moreover, it is quite possible that the near-vertical-axis interior maxima reflect nothing more than noise in the simulation results (see Appendix 1).

BHC mergers with insurance agent/brokers using market data produce slightly more favorable results than those with accounting data. The RPW_{50} has an interior maximum at about five percent nonbank share and falls below the $N'=0$ level at about a 16 percent nonbank share. However, the RPW_{10} declines monotonically from the vertical axis.

BHC mergers with life insurance and property/casualty insurance firms using market data reinforce the results obtained with accounting data. The RPW_{50} functions for both life insurance and property/casualty insurance combinations are higher than the $N'=0$ level for all nonzero values of N'. Interior maxima are observed at about the 40 percent nonbank level for life insurance combinations and at 12–20 percent for property/casualty insurance. The RPW_{10} functions for life insurance and property/casualty insurance combinations remain above the $N'=0$ level out to 50 percent and 20 percent nonbank shares, respectively.[10]

5.3. *Sources of potential bias in the simulations*

There are a number of sources of potential bias in the merger simulations. Some are arguably unfavorable to mergers, making them appear to be more risky or less profitable than is actually the case. Others operate in the other direction, however.

1. We have considered only pairwise mergers, those between one BHC and one firm from another industry. It can be argued that we have overlooked greater potential diversification which would be realized if BHCs were to combine with firms from *several* nonbank industries simultaneously.

This is true, but the six nonbanking industries included in this study allow for 63 possible combinations (one BHC plus one or more nonbanks), even before portfolio weights are allowed to vary. This is a large number of combinations. If we were to consider all of them, there is the possibility of finding one or more that appeared particularly good, merely by chance. And from a policy perspective, pairwise combinations are most relevant, since these are what the authorities must evaluate in actual BHC merger applications.

[10]One interesting property of the simulation results merits further comment. In figs. 4 and 6, the median ROE functions exhibit interior maxima. It can be proved that as sample size increases without limit, mean ROE must be monotonic in N', and in fact that is true in all cases. Obviously, what we are observing is attributable to skewed distributions of returns for some of the merger combinations. As discussed in the text, however, with our methodology this presents no particular problem.

2. Our procedure ignores the possibility of scale and scope economies in combining banking and nonbanking activities. Arguably, this feature biases the simulations, making the merged results look unrealistically bad.

Several studies have detected little evidence of scope economies in combinations of banking and nonbanking firms [e.g., Rhoades and Boczar (1977)]. And the consensus seems to be that scale economies in banking firms are exhausted at a rather modest size.[11] Some studies even find evidence of diseconomies of scale at very large banking firms [e.g., Humphrey (1990)].

3. There is a widely-recognized problem in using COMPUSTAT data for some research purposes, the so-called 'survivor bias'. Firms which are acquired, failed, or have their securities delisted, are often dropped from COMPUSTAT. Therefore, firms included in the database are not necessarily representative of their industries, but are the stronger ones which have 'survived'. This is potentially a problem for studies such as this one which investigate measures of profitability and risk.

In the present instance we are primarily interested in the *relative* riskiness of different lines of business. Thus, if the survivor bias were equally present in all industries studied, it would not be too troubling. A priori, that is unlikely to be the case. The special regulatory treatment afforded to banking firms often keeps failing firms in that industry afloat. In fact, nine of the sample BHCs received financial assistance from the FDIC, without which, presumably, they would have failed (five during the sample period, 1971–1987, and four in 1988). This treatment is extraordinary and its implications are clear. The sample BHCs are, in all likelihood, more truly representative of their industry than are the nonbank firms which have no regulatory safety net to prevent failures.

Working in the opposite direction, our treatment of FDIC-assisted BHCs probably tends to overstate their profitability, and understate their risk. Data for these firms are deleted from the sample in the first year in which they received FDIC assistance, and thereafter. We wanted to keep these firms in the sample as long as possible so as to minimize survivor bias. But operating results in a year with massive governmental intervention are not useful. The problem is that failing BHCs tend to defer losses as long as possible. Thus, their profits for the last sample year or so are undoubtedly overstated. In effect, the survivor bias is attenuated for BHCs, but end-of-sample profits are overstated for the weakest among them.[12]

We do not think the bias from this source can be great. Less than four percent of sample BHCs received FDIC assistance during the sample period (five out of 141 firms). And for these only the last few years of operating

[11]See Clarke (1988) for an excellent review of this literature.

[12]We thank an anonymous referee for pointing out this problem with the data.

results would have been affected (out of an 18-year overall sample period). Finally, the data suggest that Z-scores for the assisted firms are considerably lower than for the other BHCs, even though the Z-scores are computed with strictly preintervention data (see Appendix 2).

4. It could be argued that our procedure of matching firms at random is unfair, in that BHCs could do better than choosing their merger partners at random.

While seemingly plausible, this argument misses the fact that each industry has a limited number of members. Nonbank merger candidates with the best risk/return characteristics would be expected to command the highest acquisition premia. These premia reduce their expected profitability (and post-merger Z-scores) in a way our study does not take into account. Finally, while it is likely that (with the advantage of hindsight) we could construct some very successful mergers, it is unclear what would be learned from such an exercise.

5. Substantial biases work in the opposite direction, favoring the simulated mergers vis-à-vis reality.

For example, the simulations unrealistically ignore acquisition premia and out-of-pocket merger costs. Both can be substantial and they are completely omitted in the simulations. Moreover, the simulations assume that acquisitions are entirely equity financed. That is not the common practice in BHC acquisitions, however, which usually employ the issuance of some debt. Allowing for leveraged acquisitions would considerably complicate our simulation procedure. But it would undoubtedly produce riskier post-merger operating results.

Quantitatively, we suspect that the biases produced by ignoring acquisition premia and acquisition debt are quite large relative to the other sources of bias. Thus, we think it most unlikely that real-world mergers would produce systematically more favorable results than those simulated.

6. Conclusion

If the objective of public policy is to minimize the risk of bank failure, then our results suggest that BHCs should be permitted to acquire life and property/casualty insurance firms, but be prohibited from acquiring securities and real estate firms. As discussed above, however, the simulations could well understate the potential risk of BHC mergers with firms in all these lines of business. Thus, even the finding of risk-mitigating effects of BHC–insurance combinations must be taken cautiously. Moreover, most of the simulations indicate that risk is greater for mergers involving high proportions of nonbanking assets. Since any deregulation measure is likely to permit large nonbanking firms to purchase small banks, the likelihood of risk-reducing mergers is further diminished.

We are on firmer ground in reaching conclusions about the *relative* effects of BHC combinations with firms in the other lines of business. Our tests unambiguously suggest that BHC mergers with life and property/casualty insurance firms are less risky than BHC mergers with securities firms, insurance agent/brokers, and real estate firms. This conclusion holds quite generally. It holds whether Z-scores are computed with accounting or with market data. It holds if we use as our risk measure the median standard deviation of the rate of return on equity (not shown) instead of median Z. Perhaps most surprisingly, this conclusion holds for essentially all positive post-merger fractions of nonbanking assets. These findings are in accord with Boyd and Graham (1988). They are also largely in agreement with those of Kwast (1989) with respect to BHC mergers with securities firms, and with those of Rosen et al. (1988) with respect to BHC mergers with real estate firms.

Appendix 1

Several industry combinations exhibit RPW functions with interior maxima when N' is close to, but not exactly, zero. These are shown below, along with the approximate maximizing value of N' and the percentage increase in Z over that obtained with $N'=0$.

Nonbank industry	RPW function	Data	Nonbank share at maximum RPW	% Increase in RPW from $N'=0$
Insurance agent/broker	RPW_{50}	Accounting	0.015	2.6
Insurance agent/broker	RPW_{10}	Accounting	0.029	19.8
Securities	RPW_{10}	Accounting	0.048	11.5
Securities	RPW_{50}	Market	0.045	0.2
Securities	RPW_{10}	Market	0.015	0.4
Real estate development	RPW_{50}	Market	0.014	1.2
Other real estate	RPW_{10}	Accounting	0.014	12.8
Other real estate	RPW_{50}	Market	0.022	3.0
Other real estate	RPW_{10}	Market	0.015	1.0

We would tend to dismiss these interior maxima as insignificantly different from those obtained at $N'=0$ from an economic standpoint. They are obtained when N' is close to zero, and the difference in Z-scores is usually small. In fact, they could reflect nothing more than noise in the simulation procedure.

Appendix 2

In 1988 four additional BHCs in the sample had been reorganized by the FDIC, with financial assistance, bringing the total to nine. As can be seen by comparing columns (1) and (2) below, the assisted group does exhibit lower Z-scores than do the others, even though these Z-scores are computed strictly with preintervention data.

Columns (3) and (4) show Z-scores for the sample BHCs grouped according to their bond ratings in early 1988. The sample firms with better bond ratings also tended to exhibit higher Z-scores. This comparison is complicated by the fact that some of the 'best' sample BHCs (stable earnings growth, well capitalized, etc.), are smaller ones which did not issue long term debt and thus were not rated. In sum, the data do support our view that Z-score is a useful, albeit imperfect, risk indicator.

	Full sample (1)	Failed BHCs (2)	Bonds rated A3 or better (3)	Bonds rated B or worse (4)
Number of firms	141	9	54	22
Mean accounting Z-score	43	13	40	21
Median accounting Z-score	32	8	32	16
Mean market Z-score	4.0	2.9	4.0	3.8
Median market Z-score	3.8	2.7	4.1	3.5

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