Are Bank Shareholders Enemies of Regulators or a Potential Source of Market Discipline?

Sangkyun Park and Stavros Peristiani*

Abstract: In moral hazard models, bank shareholders have incentives to transfer wealth from the deposit insurer --that is, maximize put option value-- by pursuing riskier strategies. For safe banks with large charter value, however, the risk-taking incentive is outweighed by the possibility of losing charter value. Focusing on the relationship between book value, market value, and a risk measure, this paper develops a semi-parametric model for estimating the critical level of bank risk at which put option value starts to dominate charter value. From these estimates, we infer the extent to which the risk-taking incentive prevailed during 1986-92, a period characterized by serious banking problems and financial turmoil. We find that despite the difficult financial environment, shareholders' risk-taking incentive was confined primarily to a small fraction of highly risky banks.

SANGKYUN PARK is an Economist at the Office of Management and Budget. STAVROS PERISTIANI is a Research Officer in the Research and Market Analysis Group of the Federal Reserve Bank of New York.

*Corresponding author, Main 3 East, Federal Reserve Bank of New York, 33 Liberty Street, New York, NY 10045. E-mail: steve.peristiani@ny.frb.org. We wish to thank Gijoon Hong for excellent research assistance. The views expressed in this paper are those of the authors and do not necessarily represent the views of the Federal Reserve Bank of New York, the Federal Reserve System or the Office of Management and Budget.

1. INTRODUCTION

Many regulators and academic researchers have emphasized market discipline as a means to improve the safety and soundness of the banking system. Perhaps this cannot be more true than in today's complex financial landscape. Because of ever increasing complexity of the banking business, it is difficult to effectively regulate banks solely based on prescribed rules. The importance of market discipline is underscored by the recent banking and financial crises in several emerging markets as well as more industrialized countries worldwide. In many instances, the inability of bank regulators and market forces to effectively discipline financial institutions was deemed as the missing ingredient for ensuring financial stability. Not surprisingly, in the last few years we have been witnessing a renewed interest among policy makers in enacting changes that would encourage more market disclosure and transparency. The new capital adequacy proposals of the Basel Committee for Banking Supervision consider market discipline, along with capital requirements and supervision, as one of the three pillars to support the banking system. Furthermore, directed by the Gramm-Leach-Bliley Act of 1999, the U.S. Treasury and the Federal Reserve Board are considering using mandatory subordinated debt as a catalyst to strengthen market discipline.

The interest in market discipline has largely been stimulated by the moral hazard literature describing the conflict between shareholders and debtholders (or the deposit insurer in the case of insured banks). In a moral hazard framework, bank managers act in the interest of shareholders, who have voting power. Shareholders with limited liability have a put option, that is, have the right to sell the bank's assets at the face value of its liabilities. The value of the put option increases with the bank's risk, typically, reflected by a larger variance of the asset portfolio and a lower capital ratio. If the shareholders of a bank are interested mainly in the put option value, managers may accommodate them by increasing the bank's risk. In this case, shareholders are enemies of bank regulators, and the burden of market discipline falls on the shoulders of debtholders.

Several studies of moral hazard have shown that bank shareholders are also responsive to the bank's charter value or intangible capital (e.g., Marcus (1984), Keeley (1990), Ritchken et al. (1993), and Park (1997)). In the event of failure, shareholders have to forfeit charter value. Their incentive to preserve the charter value should therefore outweigh their desire to increase the put option value when the bank's risk is low or moderate, while the opposite is true at high levels of risk. Consequently, bank shareholders can be allies of regulators or a source of market discipline when a bank is reasonably safe.

The moral hazard theory raises an intriguing empirical question: At what level of risk do shareholders turn to enemies of regulators? Several empirical studies have attempted to shed some light on the relative importance of put option value and charter value. Most notably, Keeley's (1990) study attributes the sharp rise in failure among banks and thrift institutions to the gradual deterioration of bank charter value. Keeley argues that rapid deregulation of the banking and thrift sectors during the 1980s coupled with intense competition from nonbank institutions engendered a deterioration in the charter value of banks and thrifts. As a result of lower charter value, shareholders were compelled to switch to riskier strategies, which in turn brought about the increased incidences of bank failure in this period. Brewer and Mondschean (1994) compare the behavior of low- and high-capital savings and loan associations (S&Ls). Their analysis finds that poorly capitalized S&Ls exhibit a positive relationship between stock market returns and junk bond holdings.   This result indicates that the market may be looking favorably at high-risk strategies for firms whose option value is likely to be higher than charter value. Demsetz, Saidenberg and Strahan (1996) explore more directly the relationship between franchise value and bank risk. The authors find a negative relationship between charter value and different stock market measures of risk. In line with theoretical predictions, they also discover that banks with higher charter values are motivated to take safer strategies and tend to hold more capital.

This paper differs from the previous empirical studies in that we focus on the tradeoff between the put option value and charter value in relation to the level of bank risk. In particular, our analysis aims to highlight the bipolar behavior of bank shareholders -- on one hand, as allies of regulators, protecting their stake in a low-option value institution by penalizing risky strategies, and on the other hand, as enemies of regulators, condoning more risk-taking strategies for institutions whose option value outweighs charter value.

In this paper, we gauge bank risk by the failure probability estimated from actual bank failure records. Condensing the measure of risk into a single dimension greatly simplifies our analysis. The option value and the charter value are jointly inferred from the ratio of the market value of the firm to the book value of its assets (commonly referred to as the Q ratio). A negative relationship between the failure probability and the Q ratio would mean that the expected loss of the charter value outweighs the increase in the option value, and a positive relationship would indicate the opposite. As we will illustrate in the next section, the theoretical relationship between bank risk and the Q ratio is nonlinear and convex, reflecting the changing relative importance of charter value and put option value. Moral hazard theory, however, establishes the functional relationship between bank risk and market-to-book value without the explicit benefit of a structural model with a well defined parametric form. We resolve this challenge by using a semi-parametric spline estimation technique to estimate the link between bank risk and the Q ratio.

The principal findings of our analysis are interesting in several respects. For one, we discover that the threshold at which the marginal contribution of the option value starts outweighing the expected loss of the charter value is around the 17-percent annual probability of failure. This point of transition is at a fairly high level because only a very small fraction of bank holding companies (roughly 3 percent) attain failure scores that are greater than this threshold level. Second, looking at a group of high-charter banks (characterized by a strong core deposits base), we find that the Q ratio for these institutions decreases at a higher level of the failure probability. This result is consistent with the theoretical prediction that banks with more valuable charters are more averse to risk. Overall, our analysis suggests that moral hazard arising from the shareholder-debtholder conflict was confined to a tiny subset of banks. Shareholders are therefore mostly a source of discipline on incompetent and self-serving managers.

The rest of the paper is organized as follows. The next section presents a simple moral hazard model that demonstrates the expected relationship between the failure probability and the Q ratio. In the third section, we estimate the failure probability and its effect on the Q ratio. The final section summarizes the paper's findings.

2. EFFECTS OF FAILURE RISK ON SHAREHOLDERS' WEALTH

A simple two-period model in this section shows the effect of bank risk on the option value and the charter value and the expected relationship between the failure probability and the Q ratio. In the model, the portfolio choice and the capital ratio determine the shareholders' wealth by affecting the put option value and the charter value. In many ways, our framework is very similar to theoretical models developed by Marcus (1984), Keeley (1990), Ritchken et al. (1993), and Park (1997). Nevertheless, this section has two useful purposes. First, it provides the reader a brief overview of the traditional moral hazard framework. More important, this simple theoretical model allows us to formally establish the nonlinear tradeoff between market-to-book value and bank risk.

2.1. Financial Structure of Banks

The liability of banks consists solely of deposits that are fully insured by the government. Since the government-insured deposits are riskless, banks offer the risk-free rate of return on deposits. For simplicity, the insurance premium is assumed to be zero.[1]

In this two-period model, banks invest deposits and their own capital at the beginning of period 1, and the outcome of the investment becomes known at the beginning of period 2. Two investment projects are available for banks; one is risk-free (e.g., short-term Treasury securities), and the other is risky (e.g., loans). All agents are assumed to be risk neutral. The gross rate of return on the risk-free investment is R per period, which is 1 plus the risk-free rate of return. The

[1]Unless the insurance premium fully reflects the riskiness of banks, risk-based premiums would not change the qualitative results. Chan *et al*. (1992) show that "fair" pricing of deposit insurance is not possible under some plausible conditions.

return from the risky project is a random variable that is distributed between 0 and u with the expected value R. Thus, both investments are zero net present value (NPV) projects.

2.2. Probability of Failure

A bank fails if its liability exceeds the asset at the beginning of the second period. For simplicity, liquidation is assumed to be costless. Algebraically, a bank fails if:

$$D \times R \; > \; (1-\alpha)(D+K)R \; + \; \alpha(D+K)\zeta, \tag{1}$$

where D is the amount of deposits in period 1; K is the amount of capital in period 1; ζ is the realized return from the risky investment; and α is the proportion of the bank's assets invested in the risky project. Solving (1) for ζ, we find that the bank fails if:

$$\zeta < \frac{(\alpha-\kappa)R}{\alpha} \equiv \zeta^{*}, \tag{2}$$

where κ is the capital ratio, that is, $\dfrac{K}{(D+K)}$.

Since ζ is a random variable, the probability of failure is defined as:

$$p = \int_{0}^{\zeta^{*}} g(\zeta) \; d\zeta, \tag{3}$$

where $g(\zeta)$ is the probability density function of ζ. It is rather intuitive that this probability increases with α and decreases with κ (see Park, 1997, for a more formal presentation).

2.3. Put Option Value

Limited liability of shareholders produces a put option value. With limited liability, the expected wealth of shareholders is

$$E(W) = \int_0^{\zeta^*} 0 g(\zeta) d\zeta + A \int_{\zeta^*}^{u} [\alpha\zeta + (1-\alpha)R - (1-k)R] g(\zeta) d\zeta, \tag{4}$$

where A represents total asset $(D+K)$. Shareholders with limited liability receive nothing if equity becomes negative $(\zeta \leq \zeta^*)$, otherwise they keep positive equity . Equation (4) can be expressed as:

$$E(W) = \kappa \times A \times R + pA[\![(1-k)R - [(1-\alpha)R + \alpha E(\zeta \mid \zeta < \zeta^*)]]\!]. \tag{5}$$

Here, $E(\zeta \mid \zeta < \zeta^*)$ represents the expected return from the risky project provided that ζ is smaller than ζ^*, i.e., that the bank fails.

Since $(k \times A \times R)$ is the opportunity cost or the intrinsic value of capital, the option value arising from limited liability is defined as:

$$OV = pA[\![(1-k)R - [(1-\alpha)R + \alpha E(\zeta \mid \zeta < \zeta^*)]]\!] \equiv p \times AD. \tag{6}$$

The option value is the failure probability times the expected asset deficiency AD (e.g., liability minus asset) in the event of failure, which equals the expected loss of the deposit insurer. Since both risky and riskless investments are zero net present value (NPV) projects, no one can gain in expected value terms unless someone else loses. Thus, the expected loss of the insurer is the expected gain of bank shareholders. It is a well known result that OV increases with α and decreases with κ (Keeley, 1990; Marcus, 1984; Park, 1997; and Ritchken et al., 1993). Both p and AD increase with α and decrease with κ

2.4. Charter Value

Suppose that a bank has a charter value (intangible capital) deriving from a stable customer base or market power. The charter value, which may be determined by market and regulatory structure, is assumed to be exogenous. The bank retains the charter value only if it survives. The expected wealth of shareholders with charter value can be defined as:

$$\begin{aligned} E(WC) &= \int_0^{\zeta^*} 0 \times g(\zeta)\, d\zeta + A \int_{\zeta^*}^{u} [\alpha\zeta + (1-\alpha)R - (1-\kappa)R]\, g(\zeta)\, d\zeta \\ &\quad + \int_{\zeta^*}^{u} CV g(\zeta)\, d\zeta \;=\; \kappa \times A \times R + pD + (1-p)CV, \end{aligned} \tag{7}$$

where CV is the charter value.

When there is a charter value, the shareholders' gain from a high failure probability resulting from a high α and a low κ is

$$OVC = p(AD - CV). \tag{8}$$

Clearly, OVC is positive only if AD is greater than CV, which is a fixed value. The bank does not fail when the asset is greater than the liability. Thus, AD is 0 when p is 0, and it monotonically increases with p because both p and AD increase with α and decrease with κ Accordingly, OVC is negative at a low value of p and is positive at a sufficiently high p. In other words, the option value is smaller than the expected loss of the charter value at a low p but outweighs the expected loss at a high p. The shareholders' wealth, therefore, decreases with p at first but reverses direction beyond a critical level at which $AD = CV$. This inflection point depends on the relative magnitude of the charter value and the option value.

2.5. Market Value Versus Book Value

The relative importance of the charter value and the option value of a bank can be inferred from the relationship between the failure probability, the market value, and the book value of the bank's capital. The shareholders' wealth consisting of tangible capital $(k \times A \times R)$, the option value, and the charter value should be equal to the market value of the bank's stock. In contrast, the book value of capital does not normally include the option value and the charter value of the bank.

For simplicity, let's assume that the book value of capital is equal to the value of tangible capital.[2] Equations (7) and (8) yield that the difference between the market value (MV) and the book value (BV) of capital is

$$MV - BV = CV + OVC \equiv N. \tag{9}$$

Based on the above analysis, N equals CV when p is zero. If the charter value is zero, N will increase monotonically with p because only the option value counts $(OVC = OV)$ (see Panel A in Figure 1). Panels B and C depict a more realistic scenario where both the charter value and the

[2]The book value may differ from the value of tangible capital because of inaccurate depreciation schedule and delayed loss recognition. Although depreciation schedule is unlikely to be correlated with the failure probability, the unrecognized loss may be positively related to the failure probability. Thus, the empirical section controls for the unrecognized loss.

option value matter. In these examples, N decreases with p at first and begins to rise with p beyond a critical level, which represents the point at which the marginal expected loss of the charter value equals to the marginal expected gain in the option value. The inflection point of p depends on the initial magnitude of the charter value holding other parameters constant. Panel D illustrates the other extreme scenario of a bank with very large charter value. Here, it is possible that N decreases with p in the entire range of observable values, meaning that high-charter institutions have the most to lose from gambling on risky strategies.[3]

The risky investment in the above analysis is a zero NPV project. In reality, an extremely high failure probability may be caused by negative NPV projects.[4] If this is the case, N may stop rising or start decreasing again at a high p because negative NPV projects decrease the shareholders' wealth. A heavy regulatory burden on high-risk banks may also limit the increase in N.

---

[3]The graphical illustrations provided in Figure 1 assume that ζ is uniformly distributed between 0 and $2R$, R=1.05, A=10, and k=0.05. To change the level of bank risk, we vary the value of α between 0 to 1. Our example assumes a uniform distribution for analytical simplicity. Because the uniform distribution assigns an equal chance in the interval between $[0,2R]$ (an extreme case of fat tails and hence very high option values), one of the simulation examples requires a fairly large charter value (150) to generate a steadily declining nonlinear relationship between shareholder wealth and risk.

[4]For a bank with positive capital, the failure probability cannot be greater than 0.5 if it invested in a zero NPV project with a symmetric return distribution.

3. A SEMI-PARAMETRIC MODEL FOR DETERMINING MARKET-TO-BOOK VALUE

3.1 An Empirical Model

Equation (9) provides a simple framework for estimating the relationship between charter value, option value, and bank risk. Essentially, the value of a banking firm net of the opportunity cost of capital (extra value) consists of the charter value plus the option value. In reality, neither component of the extra value is observable. Instead, as illustrated quite vividly by the graphical examples (Figure 1), one can infer a certain behavioral association between risk-taking and the two components of bank value. In the more realistic scenario, we hypothesize that both charter value and option value contribute to extra value.

Our empirical model is designed to capture the nonlinear and convex relationship between shareholders' wealth and bank risk. Like Keeley (1990) and Demsetz et al. (1997), we measure the sum of the option value and the charter value by the Q ratio. More specifically, the dependent variable in our analysis is the sum of the market value of equity and the book value of liabilities divided by the book value of assets net of goodwill.[5] The nonlinear relationship between the Q ratio and its determinants are specified as the following semi-parametric model:

$$Q_{ti} = f(p_{ti}) + \beta Z_{ti\bullet} + \varepsilon_{ti}. \tag{10}$$

The key control in our nonlinear regression model is a variable measuring a bank's risk (p_{ti}). We assume that the nonlinear relationship between a bank's Q ratio and risk is determined by the unknown function $f(\cdot)$.

[5]Alternatively, this Q ratio measure equals {1 + (market value of equity - book value of equity) / book value of assets}.

In addition to the non-parametric relationship between the Q ratio and p_{ti}, the empirical model includes other variables that may influence the Q ratio, defined by the vector Z_{ti}. In particular, the vector includes the log of asset size $(ASSET_{ti})$, core deposits as a percent of assets $(CORE_{ti})$, commercial and industrial loans as percent of assets $(CILOANS_{ti})$, delinquent assets as a fraction of loan loss reserves $(DELQT_{ti})$, and year dummies. CORE (loyal depositor base) and CILOANS (lending relationship) are included to capture cross-sectional variation in charter value. The variable CORE is expected to have a positive effect on the Q ratio. The effect of CILOANS, however, is ambiguous. At one level, lending relationships in banking can be viewed as an important contributor to charter value. However, banks lending to businesses face significant risks because commercial and industrial loans are often unsecured. Thus, an excessive concentration of business loans may be viewed as a high-risk strategy and may also be positively correlated with bank risk. The variable ASSET is a useful regressor because it can potentially affect both the option value and the charter value; larger option value for larger banks because of the "too-big-to fail" policy or larger charter value for larger banks because of more market power and banking expertise. In either case, the sign of the variable is likely to be positive. The variable DELQT is included in the model to capture hidden losses that would negatively affect the Q ratio by unduly inflating the book value of equity. Finally, the specification includes year dummies to capture varying stock market conditions over time.

3.2 Measuring Bank Risk by the Likelihood of Failure

The key explanatory factor in our analysis is a measure of bank riskiness p_{ti}. Previous studies have taken different approaches to measuring bank risk relying on stock market based measures of volatility or simply using capital ratios. In this paper, we construct a bank-specific measure of solvency. A number of empirical papers in the literature on market discipline have shown that statistical models can provide accurate ex ante measures of bank solvency (see Gilbert (1987) for a review of the literature). Typically, these studies construct a score of bank riskiness from historical failure information. Using a model of discrete choice, the dependent variable (failure or nonfailure) would be regressed on the financial characteristics of the bank. Recent studies have employed more elaborate econometric methods such as proportional hazard models or survival analysis with competing risks (Cole and Gunther (1995)). Despite the added level of complexity, these sophisticated models provide comparatively similar forecasting results.

In this study, we employ logistic regression to estimate the probability of failure for banks. The premise in market discipline is that market participants (depositors, shareholders, debtholders, and regulators) need to estimate the solvency of the depository institution from publicly available information. Our goal in this paper is somewhat similar in the sense that we seek to construct a measure of bank solvency that would accurately describe the current state of the institution. Often studies of bank failure concentrate on long time horizons because their main concern is evaluating failure prediction models for regulatory purposes. Regulators must recognize the likelihood of failure as early as possible to be able to take preventive or corrective action. In comparison, our framework is focused more on capturing the near-term behavior of the bank. The logistic regression can be defined as:

$$y_{ti}^{\star} = x_{t-1,i\bullet}\gamma + \upsilon_{ti}, \qquad (11)$$

where

$$y_{ti} = 1 \quad if \quad y_{ti}^{\star} \leq 0 \quad (bank\ failure\ in\ t),$$
$$y_{ti} = 0 \quad if \quad y_{ti}^{\star} > 0 \quad (otherwise),$$

such that $x_{t-1,i\bullet}$ is a vector of financial characteristics of the bank in year (t-1). The dependent variable $y_{ti}^{\star}$ can be viewed as a latent index of bank solvency. Note that the logit model is estimated using information as of period $(t-1)$ because in most cases we do not have complete information on bank failures in the current year (t). Based on this model we estimate the financial health of the bank using financial information as of year (t). In particular, a forward-looking estimate of the likelihood of failure can be computed from

$$\hat{p}_{ti} = F(x_{ti\bullet};\hat{\gamma}^{(t-1)}), \tag{12}$$

where $F(\bullet)$ represents the logistic distribution, and the superscript $(t-1)$ simply indicates that model was estimated based on information from the previous year.

The logit model is estimated yearly for the period 1985-92. A large fraction of the bank mergers in the 1980s were engineered by regulators to salvage poorly performing banks. To avoid possible sample bias, we eliminated from our data all banks that were taken over during the period (except of course for FDIC-assisted mergers that were counted as failures). Although ultimately this paper investigates the relationship between charter value and bank riskiness at the bank holding company (BHC) level, our prediction model for bank failure is estimated at the bank level. It is practically impossible to accurately measure failure risk at the holding company level because there were only a handful of publicly traded companies that failed. In contrast, during 1985-92, there were roughly 1,200 bank failures. Thus, it is much easier to construct a score of failure for bank subsidiaries than for their bank holding parent. An estimate of probability of failure for the BHC is simply given by the weighted average of score of all its subsidiaries.[6]

The explanatory variables $x_{t-1,i}$. consists of mainly financial ratios measuring the fundamental risks of financial intermediation, which are typically used by regulators and investors to evaluate the safety and soundness of banks. The set of explanatory variables includes for instance measures of capital adequacy, asset quality, management quality, profitability, and liquidity.

Table 1 presents estimates of the logistic regression for the period 1985-92. Although coefficients are not always significant, they do exhibit the expected sign in most cases. As seen from the table, measures of capital adequacy play a critical role in determining bank failure. More important to our analysis, the logit models generate fairly accurate and reliable forecasts of failure. The concordant ratio for most of the estimated logit regressions is close to or over 90 percent, meaning that model is able to classify correctly most of the observed responses. Moreover, the different logistic regressions across time provide time-consistent forecasts in the sense that the probability of failure for an insolvent bank rises significantly before it is closed by regulators.

---

[6]We use total assets of the bank as weight for calculating the holding company scores. We have also experimented with alternative measures such as assigning to the BHC the score of its lead subsidiary. Overall, the results were very similar.

4. EFFECT OF THE FAILURE PROBABILITY ON THE MARKET-TO-BOOK RATIO

4.1 Data

Our data is an unbalanced sample of 337 publicly traded BHCs, with a total of 1,902 bank-year observations spanning the period 1986-92. To calculate the Q ratio for BHCs, we use market value information from Standard and Poor's COMPUSTAT database. As noted previously, an estimate of the failure probability is produced at the bank level using information from the *Consolidated Report of Condition and Income for Banks (Call Reports)*, which is available at the Board of Governors. The remaining information was obtained from the *Consolidated Financial Statement for Bank Holding Companies* (FR Y-9C), also available from the Board of Governors.

Table 2 provides summary statistics of the regression variables explaining the Q ratio defined by equation (10). In line with other studies of firm value, our Q ratio averages close to 1.016. On the surface, the mean probability of failure in a given year is fairly high at 0.023. But this of course is driven primarily by a handful of failing institutions with very large scores. The median of the probability of failure is roughly 0.0056, meaning that the distribution of the estimates of failure is skewed to the right.

4.1 The Nonlinear Effect of Bank Risk

We employ three different approaches to estimating the functional relationship between firm value and bank risk defined by equation (10). The first empirical model asserts that $f(p_{ti})$ is a simple linear function of the probability of failure. The second approach specifies $f(p_{ti})$ as a third-order polynomial. These two simplifications of our empirical model serve basically as convenient baselines against which we can compare the more complex spline estimator. In contrast to linear specifications that minimize the error sum of squares of the model, the semi-parametric spline estimator optimizes the error sum of squares as well as the "smoothness" of the functional solution. More specifically, both the polynomial and linear estimators minimize

$$ESS = \frac{1}{N}\sum_{t=1}^{T}\sum_{i=1}^{N}(Q_{ti} - f(p_{ti}) - \beta Z_{ti\cdot})^2. \tag{13}$$

In comparison, the spline approach optimizes the tradeoff between ESS and a measure of the "smoothness" of $f(p_{ti})$. In its simplest form, the minimization criterion can be defined as the sum of ESS plus a second component representing the penalty of roughness times the smoothing parameter λ. Specifically,

$$\frac{1}{N}\sum_{t=1}^{T}\sum_{i=1}^{N}(Q_{ti} - f(p_{ti}) - \beta Z_{ti\bullet})^2 + \lambda\int_a^b (f^{(2)}(p))^2 dp. \tag{14}$$

Here, the roughness of $f(\cdot)$ is defined by the integral of the square of the second derivative of $f(\cdot)$. The parameter λ determines the tradeoff between smoothness and goodness of fit. An excellent survey of the spline models, describing methods of estimation and other applications, is given in Wahba (1990).

The first two columns of Table 3 present least square estimates of the simple parametric versions of the model. In the linear case, the estimate coefficient value of p_{ti} is negative, suggesting that the Q ratio continues to decline at higher levels of bank risk. The inadequacy of the simple linear model is further underscored by the notable improvement in the fit of the polynomial model. All of the three terms turn out to be statistically significant at the 1 percent level. The estimates reveal a fairly strong nonlinear relationship between the Q ratio and the failure probability.

Although the third-order degree polynomial provides a fairly good fit, a major limitation of this approach is that it imposes an arbitrary functional specification. The spline model resolves the estimation problem by evaluating both the nonparametric and parametric facets of the model. In the third column, the root mean square error of the spline model is now slightly larger than the polynomial model because this approach optimizes a different and broader criterion.

Because the spline estimator for $f(p_{ti})$ is nonparametric, the best way to demonstrate its contribution is through a graph. Figure 2 plots the relationship between the Q ratio and the probability of failure $f(p_{ti})$, assuming that the remaining parametric explanatory variables are evaluated at their mean. The figure clearly reveals a nonlinear pattern that is consistent with theory and our simulation examples. The shape of the empirical spline function implies that both charter value and put option value matter in the valuation of the bank. In line with a couple of our theoretical simulation scenarios presented in Figure 1 (specifically Panels B and C), we observe that at first the Q ratio declines with the increasing likelihood of failure. The Q ratio gradually reaches a minimum after which it reverses direction and begins to rise again. The reversal in the estimated Q ratio function allows us to locate the level of riskiness at which the put option value of the insurance subsidy begins to dominate the loss of charter value.

Based on our full sample of BHCs, our results indicate that the critical threshold of transition is around a yearly probability of failure of 0.17.[7] It is interesting to note that roughly 3 percent of the bank observations in our sample have a failure probability higher than the 17-percent level threshold. This result suggests that shareholders had incentives to encourage managers to pursue riskier strategies in only a handful of cases during the sample period. The identification of the threshold probability also has an important implication for prompt corrective action. In 1991, the FDIC Improvement Act (FDICIA) has introduced a range of prompt corrective action rules requiring mandatory closure of banks failing to meet certain regulatory standards. The primary objective of these prompt corrective action criteria is to minimize the damages from insolvency. Interestingly, implicit in the prompt corrective action rules implemented by FDICIA is the belief that bank regulators can close down a failing bank before it goes beyond the turning point where the put option value exceeds the franchise value of the firm.

Perhaps the most intriguing implication of our empirical analysis is that risk is quite detrimental to charter value. Safer banks are the ones with most to lose from higher risk. As illustrated by Figure 2, investors are initially averse to risk-taking as any significant sign of deteriorating financial conditions is readily disciplined. The aftermath of a more conspicuous jump in the likelihood of failure (say from around zero to 0.05) is typically a sharp deterioration in the bank's Q ratio to typically below one. The high threshold level and the strong negative relationship between bank risk and shareholders' wealth for safe banks signify that regulators can count on bank shareholders as a source of market discipline to a large extent.

---

[7]This probability threshold is pertinent only for the annualized logit regression model. As will be shown later, the risk metric will be different for quarterly logistic regressions or for some other appropriate sample design variation.

The remaining parametric explanatory variables have the right sign and are usually statistically significant. The strong explanatory power of DELQT may reflect bank managers' incentives to delay the recognition of losses and to inflate the book value of capital. The significance of CORE indicates a wide variation in charter value across banks.

Moral hazard theory predicts that the probability threshold at which the put option overtakes charter value would be higher for banks with greater charter value. Given its empirical significance, CORE seems to be a good proxy for charter value. Banks with higher core deposit ratios are more likely to have greater charter values. We divide the sample into two groups of equal size based on CORE (high-CORE and low-CORE banks). The two sub-samples produce significantly different functional relationships between the failure probability and the Q ratio. The probability transition threshold is smaller for low-CORE banks than that for their high-CORE counterparts. This outcome affirms that the desire to take on more risk was probably stronger among BHCs with weaker core deposit base. Having smaller charter values, these banks have less to lose and are more likely to realize the marginal benefits of insurance subsidy from taking on more risk. Perhaps as important is our finding that the nonlinear relationship between risk and the Q ratio for high-CORE banks exhibits limited marginal benefits from greater risk as it rises at much lower trajectory. Shareholders of high-CORE banks are therefore more reluctant to accept riskier strategies that deplete charter value.

4.2 Robustness of Results

The surge in failures during the latter half of the 1980s was primarily concentrated in smaller banks and thrifts. In reality, only a very small fraction of publicly traded bank holding companies have actually failed in United States during this period, although several of the weaker banks found refuge by merging with healthier institutions. Specifically, our panel of BHCs includes only three failures. In part, our analysis has dealt with the rarity in BHC defaults by estimating riskiness at the bank subsidiary level. Overall, we found that the likelihood of failure for BHCs is quite small. Roughly 90 percent of bank observations had a probability of failure less than 0.04. Put another way, the estimated semi-parametric function was determined to a great length by a small fraction of bank observations with significant probabilities of failure.

The skewness in the distribution of failure scores raises a concern that our results may not be robust to outlying observations. To address this issue, we re-estimated the spline model using a jack-knife methodology. The jack-knife approach estimates the semi-parametric model by omitting one observation from the sample at each iteration. Our objective here is not necessarily to calculate the jack-knife estimate but instead to investigate if our findings are robust to outliers. In particular, we want to find if there are any influential observations in our sample that can drastically change the observed relationship between the Q ratio and risk. Figure 4 plots the range for all possible jack-knife estimates of the semi-parametric relationship. This exercise demonstrates that the relationship between market-to-book value and the risk of failure is very robust and not influenced by any single observation. The range of the jack-knife estimates is broader at higher scores of failure because observations in that zone have a larger impact on the direction of $f(p_{ti})$.

As a further test of robustness, we also estimated the semi-parametric model using quarterly data. One apparent benefit of the quarterly sample is that it allows for a better mapping of the market-to-book value and the risk of failure. Indeed, the quarterly sample provides more information, especially for the intermediate range of probabilities of failure (typically, between 0.1 and 0.3). Unfortunately, the quarterly approach also complicates logistic estimation because the ratio of failures to nonfailures is altered. To obtain quarterly scores of failure, we chose to pool all four quarters in a year before we applied again logit estimation. Although the number of failures is the same as those listed at the bottom of Table 1, the number of nonfailures has roughly quadruple, meaning that the relative frequency of failure has declined. Despite these differences, quarterly estimates of the semi-parametric model of the Q ratio yield essentially very similar findings, declining first with increasing likelihood of failure but rising after a point. Because the odds ratio is lower in the quarterly framework, the transition threshold at which the put option value overtakes losses in charter value is now around 0.11.[8]

5. CONCLUSION

This paper has empirically examined how the put option value and the charter value of banks interact with risk. Our analysis reveals a distinct convex nonlinear relationship between the market-to-book ratio and the risk of failure. The paper's theoretical framework attributes the observed convex relationship to bank shareholders' disparate affinity for risk. Initially, shareholders penalize riskier strategies to preserve charter value. But once option value becomes large enough to compensate for the loss of charter value, shareholders elect instead to reward risk to further increase the put option value of the bank. The convex relationship between the Q ratio and the likelihood of failure allows us to identify the threshold failure probability at which the

---

[8] In our quarterly approach, banks that fail in the latter quarters of the year (say the fourth and third quarters) have to be treated as nonfailing in the earlier quarters. The increase in nonfailures lowers the odds ratio of the event of failure, resulting in a lower transition point.

marginal benefit from the option value outweighs the expected loss of charter value. Based on our empirical analysis, we find that this risk turning point is quite high for most banks. We conclude, therefore, that during the period 1986-92, the interests of bank shareholders were aligned with those of regulators and debtholders, except for a small subset of extremely risky banks.

Based on this finding, regulators may be able to extract a useful signal about bank risk from stock price movements, especially in conjunction with the book value of banks. However, the banking sector has undergone a considerable change since the period of our study. The enactment of the 1994 Riegle-Neal Act has allowed BHCs to expand nationwide. More recently, the repeal of Glass-Steagall Act has removed many industry barriers to competition. Increased competition may have lowered charter value, encouraging a less prudent behavior with regard to risk among banks. At the same time, however, the put option value may have also decreased because of other regulatory changes that promote prompt corrective action and risk-based deposit insurance premiums. Thus, the net effect on the risk-taking incentives of bank shareholders is unclear. Taken together, the evidence that the threshold failure probability was fairly high even among banks with a relatively low charter value suggests that, even if banks have become less prudent, the behavior of shareholders to encourage risky strategies may still be an exception than a rule.

REFERENCES

Brewer, Elijah, and Thomas Mondschean. "An Empirical Test of the Incentive Effects of Deposit Insurance: The Case of Junk Bonds at Savings and Loan Associations" *Journal of Money, Credit and Banking*, (February 1994), 146-64.

Chan, Y. S., Stewart I. Greenbaum, and Anjan V. Thakor. "Is Fairly Priced Deposit Insurance Possible?" *Journal of Finance*, (1992), 227-245.

Cole, Rebel A. and Jeffery W. Gunther. "Separating the Likelihood and Timing of Bank Failure," *Journal of Banking and Finance*, (September 1995), 1073-89.

Demsetz, Rebecca S., Marc R. Saidenberg, and Philip E. Strahan. "Banks with Something to Lose: The Disciplinary Role of Franchise Value," FRBNY *Economic Policy Review*, (October 1996), 1-14.

Gilbert, Alton R. "Market Discipline of Bank Risk: Theory and Evidence," *Economic Review*, Federal Reserve Bank of St. Louis (January/February 1990), 3-17.

Keeley, Michael C. "Deposit Insurance, Risk, and Market Power in Banking," *American Economic Review*, (December 1990), 1183-1200.

Marcus, Alan J. "Deregulation and Bank Financial Policy," *Journal of Banking and Finance*, (1984), 557-565.

Park, Sangkyun. "Risk-Taking Behavior of Banks Under Regulation," *Journal of Banking and Finance*, (1997), 491-507.

Ritchken, Peter, James B. Thomson, Ramon P. DeGennnaro and Along Li. "On Flexibility, Capital Structure and Investment Decisions for Insured Banks," *Journal of Banking and Finance*, (1993), 1133-1146.

Wahba, Grace. *Spline Models for Observational Data*. Society for Industrial and Applied Mathematics: Philadelphia, PA, 1990.

TABLE 1. A logit model of bank failure, 1986-1992 (Wald χ^2 statistics in parentheses)
Dependent variable is the event of failure (y=1 for failure, y=0 for nonfailure)

Independent Variables	1985	1986	1987	1988	1989	1990	1991	1992
Constant	-7.9243* (2.90)	-1.9709 (0.83)	-3.8655 (1.38)	5.8327*** (10.31)	3.8782 (2.24)	0.3865 (0.01)	5.7293** (5.47)	-0.5185 (0.04)
Equity/assets	-0.1873*** (20.24)	-0.2393*** (42.33)	-0.2781*** (50.33)	-0.2891*** (62.30)	-0.4439*** (94.16)	-0.4729*** (106.13)	-0.5043*** (84.40)	-0.2656*** (32.64)
Net loan reserves/assets	-0.0995*** (7.99)	-0.1248*** (18.24)	-0.1408*** (17.81)	-0.1389*** (14.17)	-0.0283 (1.00)	-0.0663** (5.54)	-0.0152 (0.09)	-0.1639*** (9.65)
Net charge-offs/ assets	0.0544 (1.33)	-0.0100 (0.08)	-0.0872** (3.88)	0.0332 (0.57)	0.0666** (4.73)	-0.2437*** (10.97)	-0.1458* (3.50)	0.000706 (0.05)
Total loans/ assets	0.0632 (1.84)	0.00338 (0.02)	0.0303 (0.86)	-0.0738*** (16.33)	-0.0403 (2.56)	0.000974 (0.00)	-0.0553** (5.19)	-0.0296 (1.18)
C&I loans/ assets	0.0238*** (13.83)	0.0294*** (27.80)	0.0164*** (8.16)	0.0291*** (23.84)	0.0188*** (7.23)	0.0335*** (24.65)	0.0368*** (27.70)	0.0246*** (8.67)
Real estate loans/assets	0.0111 (1.53)	0.0012 (0.02)	0.0141** (4.23)	0.0256*** (12.49)	0.0332*** (18.20)	0.0263*** (12.01)	0.0236*** (8.52)	0.0299*** (16.21)
Other real estate loans/assets	0.0644 (0.53)	0.1213** (5.82)	0.1853*** (12.71)	0.1017*** (6.82)	0.0954** (4.25)	0.1159** (5.59)	0.0722 (2.28)	0.0863* (3.31)
Earned income (loans)/assets	0.9706*** (69.91)	1.0263*** (86.72)	0.4448*** (7.97)	0.8176*** (20.38)	0.6766*** (10.57)	0.9687*** 18.57	-0.3050 (0.70)	0.5521** (6.60)
Government bonds/assets	0.0159 (0.98)	0.00245 (0.04)	-0.0678*** (38.64)	-0.0969*** (65.59)	-0.0320** (5.94)	-0.00991 (0.31)	-0.0412*** (7.72)	0.00609 (0.11)
Overhead expenses/assets	0.4689** (5.03)	0.7970*** (37.83)	0.8972*** (11.63)	0.1354 (0.30)	1.0647*** (12.98)	0.8263*** (49.61)	-0.0344 (0.01)	0.7437*** (7.93)
Noninterest expenses/ revenue	0.00548* (3.80)	0.00891 (2.63)	-0.00523 (0.28)	.000490 (0.10)	-0.009 (0.62)	-0.0121 (1.50)	0.00492 (0.13)	0.0174*** (14.11)
Credit to insiders/assets	0.0608** (4.24)	0.0771** (4.65)	0.00215 (0.00)	-0.0126 (0.10)	0.1150*** (12.70)	0.0295 (0.20)	-0.0307 (0.10)	0.1269 (2.32)
Return on assets	-0.12** (4.10)	-0.1311** (5.81)	-0.1006 (2.53)	-0.0709 (1.31)	-0.1513** (5.09)	-0.3722*** 16.30	-0.4555*** (19.80)	-0.0671 (1.06)
Liquid assets/ assets	-0.0092 (0.04)	-0.0451* (3.58)	0.0383 (1.37)	-0.0623*** (10.33)	-0.0461* (3.14)	-0.0486 (1.73)	-0.0493* (3.80)	-0.0782** (6.23)
Core deposits/ assets	-0.037*** (14.43)	-0.0494*** (37.58)	-0.0529*** (51.73)	-0.0520*** (49.30)	-0.0331*** (13.17)	-0.0308*** (10.32)	-0.0629*** (39.21)	-0.0176* (3.43)
State employment growth	-0.1084* (3.12)	-0.1963*** (14.80)	-0.3102*** (67.73)	-0.3671*** (76.66)	-0.6479*** (20.35)	-0.4936*** (25.68)	-0.1055* (3.13)	0.1647** (5.35)

TABLE 1 continued

Likelihood ratio test for H_0:γ=0	411.4***	733.2***	706.9***	944.2***	744.3***	582.1***	552.8***	299.4***
Number of banks	13,134	12,741	12,391	12,052	11,685	11,706	11,257	10,704
Failures	131	197	196	198	155	123	112	96
Concordant ratio (percent)	89.6	93.5	93.9	96.9	96.3	95.1	96.7	89.5
Discordant ratio (percent)	7.6	5.5	5.1	2.7	2.9	3.5	2.7	7.8

NOTES: The symbols (*), (**), and (***) indicate significance at the 10, 5, and 1 percent level, respectively. All explanatory variables are measures as percent. The logistic model is defined by equation 11 in the paper.

TABLE 2. Variable Definitions and Summary Statistics, 1986-92

Symbol	Variable Definition	Mean	Max	Min
Dependent Variable				
Q_{ti}	Q ratio: Market value of equity minus book value equity divided by bank value of assets.	1.016	1.387	0.892
Explanatory Variables				
p_{ti}	Probability of failure of the bank holding company.	0.023	0.988	4.2×10^{-6}
$CORE_{ti}$	Ratio of core deposits as fraction of total assets; core deposits is sum of demand deposits, NOW and ATS, other transactions accounts, nontransactions savings deposits, and time deposits less than \$100,000.	0.702	0.928	0
$ASSETS_{ti}$	Total book value of assets (in $ billions).	7.764	230.645	0.072
$DELQT_{ti}$	Delinquent loans and lease receivables divided by allowance for loans and lease losses; delinquent loans and leases includes past over 90 days and non-accruing loans and leases.	1.190	10.059	0
$CILOANS_{ti}$	Commercial and industrial loans to U.S. addressees divided by total assets	0.149	0.529	0
Additional Descriptive Variables				
	Market value of equity (as a fraction of total assets)	0.086	0.461	0.007
	Book value of equity (as a as fraction of total assets)	0.072	0.179	-0.078

Number of bank holding companies: 337

Number of yearly observation: 1,902

TABLE 3. Estimating the relationship between the Q ratio and the probability of failure, 1986-92
Dependent Variable = Q ratio (Market-to-Book Ratio)

Symbol	Linear Model	Polynomial Model	Spline Model
CONSTANT	1.013*** (80.40)	1.008*** (80.93)	1.015*** (80.85)
p_{ti}	-0.031** (2.58)	-0.343*** (-6.52)	
p_{ti}^2		0.962*** (4.94)	
p_{ti}^3		-0.653*** (-3.83)	
$CORE_{ti}$	0.016** (2.13)	0.007 (0.93)	0.013* (1.87)
$ASSETS_{ti}$	0.0013** (1.99)	0.0019*** (3.09)	0.0013** (2.08)
$DELQT_{ti}$	-0.0087*** (-8.67)	-0.0073*** (-7.15)	-0.0087*** (-8.59)
$CILOANS_{ti}$	-0.0012 (-0.10)	0.0095 (0.77)	-0.0014 (-0.12)
Sample size	1,902	1,902	1,902
Root MSE	0.0378	0.0374	0.0374
Adjusted R^2	0.132	0.150	
Summary Statistics for Spline Estimation			
Chi-square test for $f(p_{ti})$			36.41***
Smoothing penalty			0.976
$log10(n\times\lambda)$			-2.426

NOTES: The symbols (*), (**), and (***) indicate significance at the 10, 5, and 1 percent level, respectively. Variable definitions are provided in Table 2. In addition to these explanatory variables, the regressions include yearly dummy variables that are not reported in the table. The effect of the probability of failure in the linear model is simply defined as $f(p_{ti})=\beta_1 p_{ti}$ The third-order polynomial model assumes $f(p_{ti})=\beta_1 p_{ti}+\beta_2 p_{ti}^2+\beta_3 p_{ti}^3$. Finally, in the spline model, $f(p_{ti})$ is an undefined nonparametric function.

Figure 1. Charter Value and Risk: Four Simulation Examples

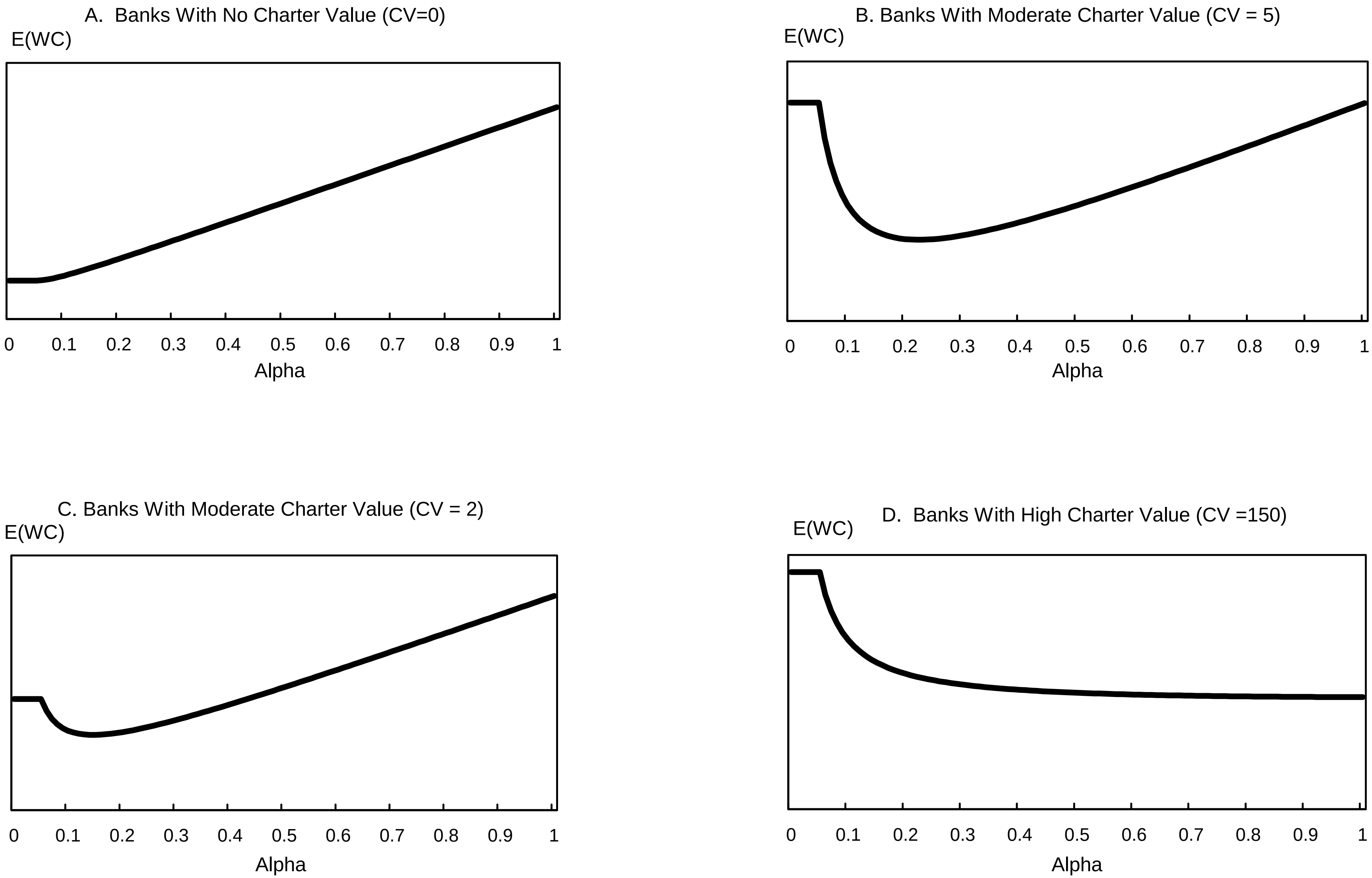


Figure 2. A Semi-Parametric Estimate of the Nonlinear Relationship Between the Q Ratio and Failure Probability

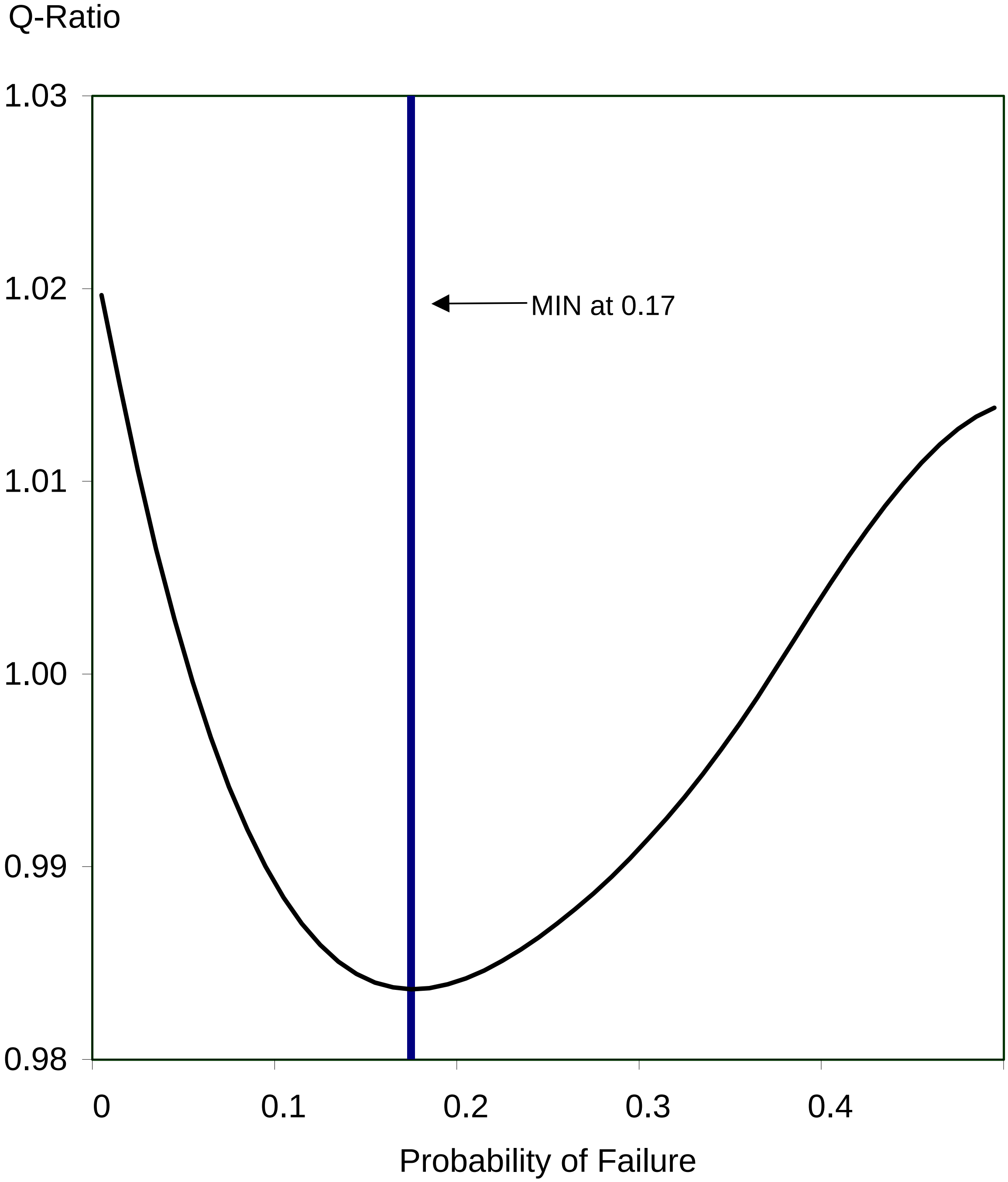


Figure 3. Spline Estimates for Low- and High-Core Deposit Banks

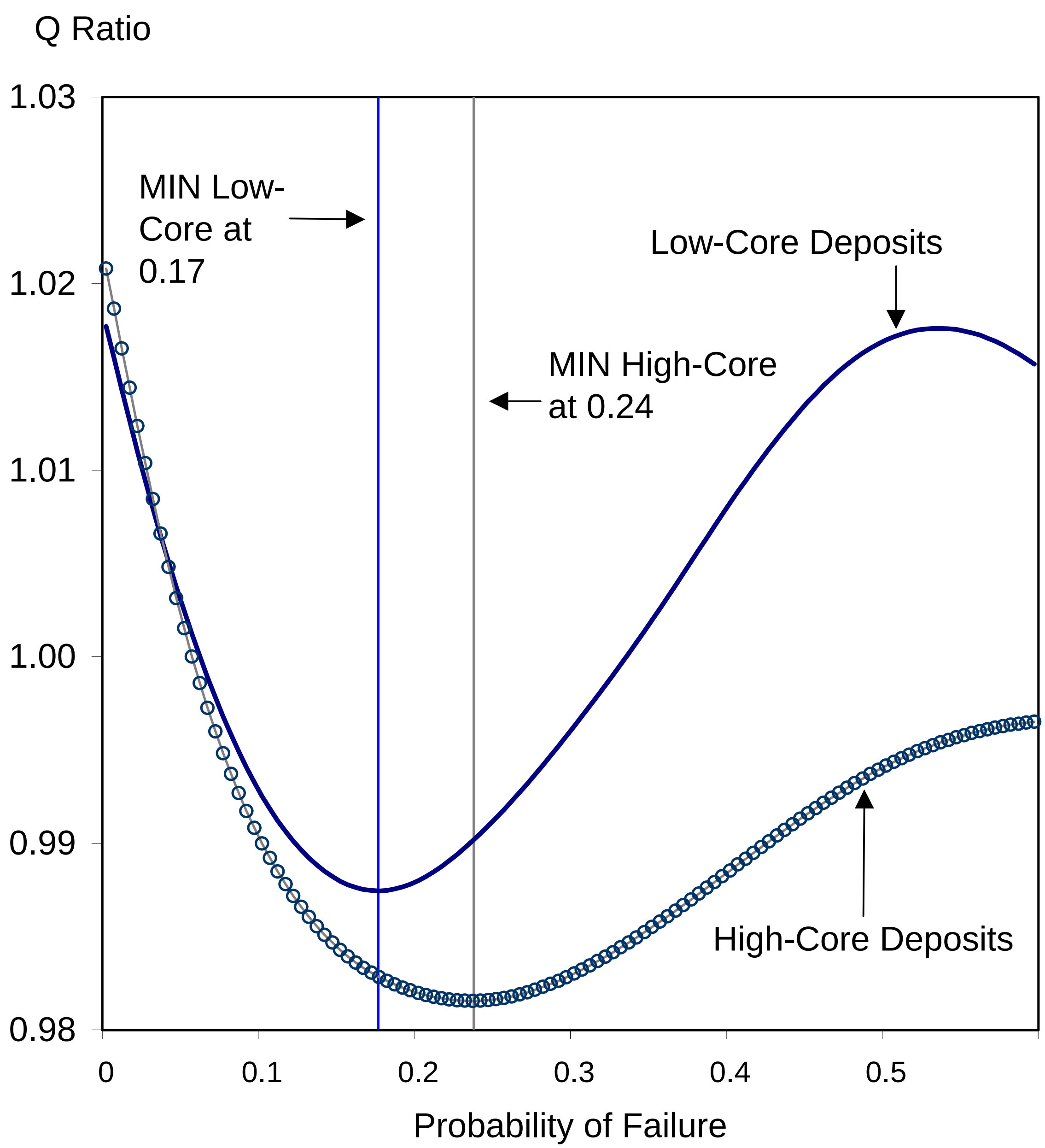
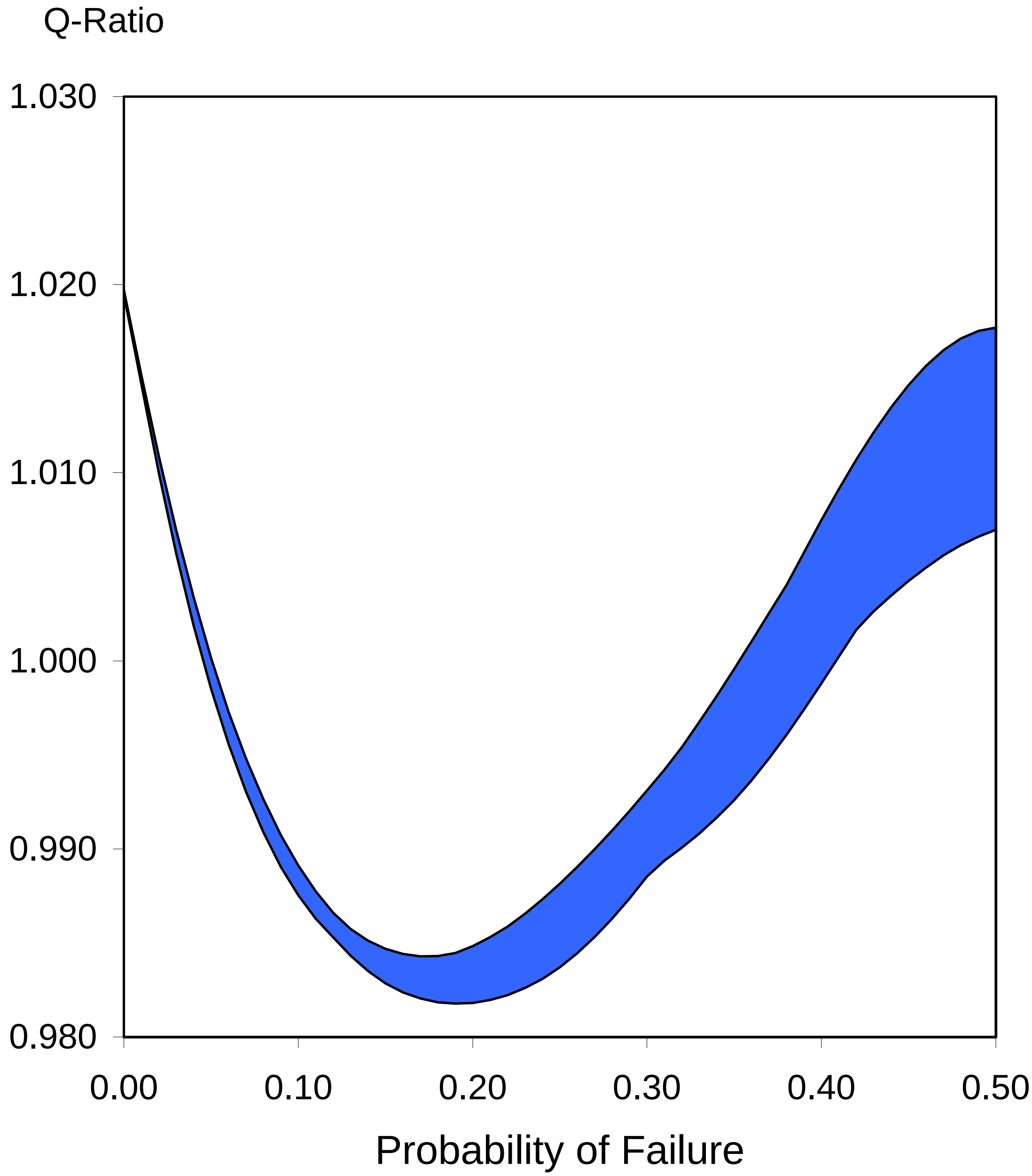


Figure 4. Range of All Nonlinear Jacknife Estimates



Footnote: Shaded area represents all possible Jacknife estimates.