Are bank shareholders enemies of regulators or a potential source of market discipline?

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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 Tobin's q and an ex ante measure of the failure probability, this paper develops a semi-parametric model for estimating the critical level of bank risk at which put option value starts outweighing charter value. From these estimates, we infer the prevalence of moral hazard. Examining publicly held bank holding companies (BHC) during the tumultuous 1986-92 period, we find that shareholders' risk-taking incentive were confined to a small fraction of highly risky institutions. Furthermore, our analysis shows that the inflection point at which banks begin to tilt in favor of moral hazard increased substantially in 1993-2005. These findings are encouraging to bank regulators and legislators because they indicate that higher capital rules and more rigorous supervision introduced by several legislative initiatives in the 1990s have helped squeeze a lot of the moral hazard incentives out of the banking system.

JEL classifications: G21, G28.

Keywords: Moral hazard; Tobin's q ratio; deposit insurance; bank risk; implied default probability.

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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 pertinent 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 several banking and financial crises experienced in the last two decades across 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, there is renewed interest among policy makers in enacting changes that would encourage more market disclosure and transparency. Directed by the Gramm-Leach-Bliley Act of 1999, the U.S. Treasury and the Federal Reserve Board have explored the possibility of using mandatory subordinated debt as a catalyst to strengthening market discipline. More recently, the new capital adequacy proposals of the Basel Committee for Banking Supervision (Basel II) consider market discipline, along with capital requirements and supervision, as one of the three pillars of support for the banking system (Basel Committee on Banking Supervision (2003)).

In a market discipline framework, debtholders, depositors, and shareholders can apply pressure on banks, raising the funding premium on debt, deposits, and equity. The direct and indirect effects of market discipline have been extensively studied in the academic literature (see survey article by Flannery (1998)). The interest in market discipline has been largely 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 management acts in the interest of shareholders that have voting power. Merton (1977) shows that deposit insurance gives insured banks a put option, that is, the right to sell the bank's assets at the face value of its liabilities. When the deposit insurance premium is fixed or does not fully reflect a bank's risk, the value of the put option increases with the bank's risk, typically, represented by a larger return 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., Keeley (1990), Ritchken et al. (1993), and Park (1997)). In the event of failure, shareholders have to forfeit charter value. Their incentive to preserve 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 and 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 into 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 during the 1980s the rapid deregulation of the banking and thrift sectors, coupled with intense competition from nonbank

institutions, resulted in the deterioration of 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. To measure charter value, Keeley examines the relationship between regulatory changes in bank entry and the market power of bank. As an estimate of market power, Keely uses Tobin's q, defined as the market value of assets divided by the book value of assets.

Using a similar Tobin's q measure, Demsetz, Saidenberg and Strahan (1996) explore more directly the relationship between charter value and bank risk. The authors find a negative relationship between charter value and different stock market measures of risk. Consistent with theoretical predictions, they also discover that banks with higher charter value are motivated to take safer strategies and tend to hold more capital. 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.

This paper differs from the previous empirical studies in that we focus on the tradeoff between 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 using two different but related methods. First, we estimate a bank's probability of failure from historical bank failure records. To verify the

robustness of empirical findings, we also look at the likelihood of default using a contingent claims approach proposed by Merton (1974). Condensing the measure of risk into a single dimension greatly simplifies our analysis. As suggested by Keeley (1990), a bank's option value and charter value can be jointly inferred from Tobin's q ratio (henceforth referred to for brevity as the q ratio) measuring the market value of assets relative to the book value of assets. A negative relationship between the failure probability and the q ratio would mean that the expected loss of charter value outweighs the increase in the option value, and a positive relationship would indicate the opposite.

The next section illustrates that 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 a convex functional relationship between bank risk and market-to-book value without providing an explicit well-defined parametric structure for empirical testing. 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. When we estimate the relationship between the q ratio and risk for the period 1986-1992, we discover that the threshold at which the marginal contribution of the option value starts outweighing the expected loss of charter value is around a 17-percent annual probability of failure (or 22-percent for the implied probability of default). The analysis also reveals that the q ratio for institutions with a strong core deposit base 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.

This estimated point of transition is at a fairly high level with only a very small fraction of bank holding companies (roughly 3 percent) attaining failure scores greater than this threshold level. Among publicly held BHCs, therefore, moral hazard appears to have been confined to a small set of highly risky ones even during this sample period when moral hazard was believed to be prevalent.

The banking crisis led to tighter regulations, including higher capital requirements, risk-sensitive deposit insurance premiums, and prompt corrective action. In addition, many barriers to competition, such as restrictions on intrastate branching, interstate banking, and inter-industry financial affiliations, were removed in the 1990s. These developments may have influenced option value and charter value and hence the relationship between the q ratio and risk. Allen and Rai (1996), for example, show that more rigorous regulation and supervision encourage banks to protect charter value.

To explore this possibility, we estimate the relationship between the q ratio and risk (measured now by the implied default probability) for the period 1993-2005. We find that the implied probability of default inflection point at which banks begin to tilt in favor of moral hazard increased from 0.22 in 1986-1992 to 0.50 in 1993-2005. These findings are encouraging for bank regulators because they demonstrate that tighter regulation and supervision have helped squeeze a lot of the moral hazard incentives out of the banking system.

The rest of the paper is organized as follows. The next section describes the hypothesis to be tested based on the findings of the moral hazard literature. In Section 3, we present a semi-parametric model for estimating the nonlinear relationship between bank risk and the q ratio. Section 4 briefly describes the two methods used in measuring the riskiness of banks. Section 5 presents our empirical findings. The final section summarizes the paper's findings.

2. Option value and the q ratio

2.1. *The effects of option value and charter value on shareholders' wealth*

The moral hazard literature modeling the bank shareholders' incentive to take advantage of deposit insurance (e.g., Keeley, 1990, Ritchken et al., 1993; and Park, 1997) derives an implied U-shaped relationship between shareholders' wealth and risk. When deposit insurance premiums do not reflect bank risk fully, bank shareholders with limited liability can transfer wealth from deposit insurance to themselves by pursuing riskier strategies, namely, lower capital ratios and more volatile asset returns. Gains from this put option value, however, are mitigated by the possibility of losing charter value that cannot be recovered in liquidation. The option value continuously increases with risk, while the charter value is fairly stable in the short run. At a low level of risk, therefore, shareholders' wealth decreases with risk because the value of the option is not large enough to offset the expected loss of charter value. If risk increases sufficiently, however, the value of the option dominates the charter value, and shareholders' wealth increases with risk.

To illustrate the link between this theoretical prediction and our empirical study, we use the analytical framework of Park (1997), which is relatively simple and intuitive. The results of other studies can be applied in a fundamentally similar way. Park (1997) models the maximization of bank shareholders' wealth under the following simplifying assumptions: All agents are risk neutral; all projects have zero net present value; and the cost of debt does not increase with risk thanks to deposit insurance charging fixed premiums. In period 1, bank managers maximize the second-period wealth of shareholders by choosing the capital ratio (ratio of equity to assets) and the portfolio share of the risky asset (two assets in the model: a risky

asset producing a random return and a risk-free asset yielding a certain return). Expected shareholders' wealth in period 2 is defined by

$$E(W_2) = R\ \kappa_1\ A_1 + \beta_2 A_1 + p[\gamma_2 - \beta_2]A_1. \tag{1}$$

The variable R represents the economy-wide gross rate of return on capital (1 plus the net rate of return); κ is the capital ratio; A is the total asset; β is the charter value as a fraction of the lagged asset; p is the probability that the bank fails in the second period; γ is the absolute value of the expected capital ratio conditional on failure, that is, $(|E(\kappa_2 | \kappa_2 < 0)|)$; and subscripts 1 and 2 denote periods 1 and 2.

In this model, the value of the option is $p\gamma_2 A_1$, representing the failure probability times the expected asset shortfall (liability minus asset) in the event of failure. If the bank is perfectly safe (that is, $p=0$), shareholders earn the opportunity cost of capital $(R\kappa_1 A_1)$ and also keep the charter value $(\beta_2\ A_1)$. When $p > 0$ due to risk taking, the combination of the option value and the expected loss of charter value $(p\beta_2\ A_1)$ results in an extra return, which may be positive or negative. Since a riskier strategy results in a higher failure probability and a larger expected loss of equity, $\gamma = 0$ when $p=0$ and it increases continuously at all values of p greater than zero. The charter value β, which is largely determined by exogenous factors, such as customer relation and market structure, is stable in the short run.[1] The sum of the option value and the expected loss of charter value, therefore, is negative at a low level of risk where $\gamma < \beta$ and positive at a high level of risk where $\gamma > \beta$.

[1]It is not necessary to assume that β is fixed. The qualitative results would be the same as long as an increase in p is associated with a smaller increase in β than the increase in γ.

2.2. *Market value versus book value*

The relative importance of the charter value and 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 market value of equity should reflect all components of shareholders' wealth, including tangible capital, option value, and charter value. Consequently, the bank's market value in period 1 is the present value of $E(W_2)$. From (1),

$$MV = \kappa A_1 + \frac{\beta_2 A_1}{R} + \frac{p(\gamma_2 - \beta_2) A_1}{R}. \tag{2}$$

The book value of equity, on the other hand, does not normally include the value of the option and bank charter value. For simplicity, let us assume that the book value of capital is equal to the value of tangible capital.[2]

$$BV = \kappa A_1. \tag{3}$$

A number of empirical studies (e.g., Keeley, 1990; and Demsetz et al., 1997) infer the sum of option value and charter value from the bank's book value and market value. These studies define the q ratio as the sum of the market value of equity and book value of liabilities divided by the book value of assets net of goodwill. The book value of assets excludes the book value of goodwill because it may be influenced by charter value. Since the book value of liability equals the book value of assets (A_1) minus book value of equity (BV), the q ratio can be defined by

[2]Book value may differ from the value of tangible capital because of inaccurate depreciation schedule and delayed loss recognition. Although the depreciation schedule is unlikely to be correlated with the failure probability, the unrecognized loss may be positively related to the failure probability. To compensate for this effect, our empirical model controls for unrecognized loss.

$$q = \frac{MV + (A_1 - BV)}{A_1}. \tag{4}$$

Combining (2), (3), and (4), we obtain

$$q = 1 + \frac{\beta_2}{R} + \frac{p(\gamma_2 - \beta_2)}{R}. \tag{5}$$

The relationship between the q ratio and bank risk shown by (5) is qualitatively the same as the relationship between shareholders' wealth and bank risk shown by equation (1). The first two terms in (5) are fixed. The third term representing the sum of the option value and the expected loss of charter value discounted by R (both as a share of assets), however, is negative at a low level of risk where γ_2 is smaller than β_2. In contrast, this term is positive at a high level of risk where γ_2 is greater than β_2. The failure probability p increases with the asset shortfall or negative equity as a share of assets γ because both variables increase with portfolio risk (share of risky assets) and decreases with the capital ratio. The q ratio should therefore initially decrease with p, but later start increasing with p. Note that the option value $(p\gamma_2)$ increases faster than the expected loss of charter value $(p\beta_2)$ because γ_2 increases with p while β_2 is fixed.

[Insert Figure 1 around here]

Figure 1 plots four simulation examples that illustrate the relationship between the q ratio and the failure probability p, which is a good proxy for bank risk. When charter value is zero, the parameter q increases monotonically with p because in this case only the option value is important (see Panel A in Figure 1). Panels B and C depict a more realistic scenario in which both the option value and the possibility of losing charter value matter. In these examples, q 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 is equal to the marginal expected

gain in the option value. The inflection point of p depends on the magnitude of the charter value, holding other parameters constant. Panel D illustrates the scenario of a bank with very large charter value. Here, it is possible that q 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, q may stop rising or start decreasing again at a high p because negative NPV projects decrease the expected return on assets. A heavy regulatory burden on high-risk banks may also limit the increase in q.

3. A semi-parametric model for estimating the relationship between the q ratio and bank risk

Equation (5) provides a general framework for empirical estimation. Our empirical model estimates the nonlinear and convex relationship between the q ratio, reflecting the bank's book and market value, and bank risk measured by the failure probability. We use the same q ratio employed by Keeley (1990) and Demsetz et al. (1997). 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. The nonlinear relationship between the q

[3]The graphical illustrations provided in Figure 1 assume that the return on the risky asset is uniformly distributed between 0 and $2R$, $R = 1.05$, and $\kappa = 0.05$. To change the level of bank risk, we vary the portfolio share of the risky asset between 0 to1. Varying the capital ratio produces fundamentally the same result. 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 steadily large marginal increases in the failure probability), simulation example D requires a very large charter value $(\beta = 11)$ to generate a steadily declining nonlinear relationship between q and p.

[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.

ratio and its determinants is specified as the following semi-parametric model:

$$q_{ti} = f(P_{t-1,i}) + \beta Z_{t-1,i\bullet} + \varepsilon_{ti}. \tag{6}$$

The key control in our nonlinear regression model is the lagged explanatory variable measuring a bank's risk $P_{t-1,i}$. We assume that the nonlinear relationship between a bank's q ratio and risk is determined by the unknown (non-parametric) function $f(\bullet)$. Admittedly, there are several ways to model the nonlinear relationship between the q ratio and credit risk. In addition to the semi-parametric model, we also consider a simple third-order polynomial form as an alternative specification. The semi-parametric approach, however, offers a more efficient and parsimonious framework for properly capturing the shift in shareholder behavior.[5]

In addition to the non-parametric relationship between the q ratio and risk, the empirical model includes several other variables that may influence the q ratio, defined by the row vector $Z_{ti\bullet}$.[6] To minimize possible endogeneity problems, the explanatory variables in $Z_{ti\bullet}$ are again lagged by one year.[7]

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[5]In the linear case, it is possible to capture the shift in shareholder behavior using an endogenous switching parametric regression model. This crude approach becomes more difficult, however, if the relationships are nonlinear across the two regimes.

[6]In a more general context, it can be argued that the relationships between q and other explanatory factors included in $Z_{ti\bullet}$ are also nonlinear, i.e., $q_{ti} = f(P_{t-1,i}, Z_{ti\bullet}) + \varepsilon_{ti}$. Our focus in this study is the nonlinear association between risk and q. The semi-parametric specification defined by (6) is very convenient because it allows us to estimate the nonlinear impact of risk while at the same time observe the parametric impact of other explanatory factors. Most spline techniques can usually handle a two-dimensional non-parametric form $y = f(x_1, x_2) + \beta Z + \varepsilon$. The spline estimator becomes very difficult and intractable at higher dimensions. Overall, our findings were fairly unchanged when we paired P with another control in the non-parametric function.

[7]Overall, however, the key empirical results are very similar when contemporaneous values are used in the regression estimation.

Tobin's q can be influenced by bank-specific factors, reflecting firm profitability and growth opportunities. The explanatory vector $Z_{ti\bullet}$ includes the variable CORE intended to capture the cross-sectional variation in charter value. Higher CORE ratios represent banks with a more loyal depositor base and therefore a greater capacity to achieve higher net interest margins. The CORE ratio is therefore expected to have a positive effect on the q ratio. The logarithm of total assets (ASSETS) is a very useful control because it can potentially measure the influence of both option value and charter value. Bigger banks may realize a large option value because of "too-big-to fail" policies. They can also achieve a larger charter valuation because of their greater market power and banking expertise. In either case, the sign of the variable is likely to be positive.

For the period 1993-2005, we also use the ratio of small business loans (loans to small business and farm borrowers) divided by total assets (SMALL_LOANS) as an additional measure of charter value. Data on small business loans were introduced in the Call Reports in 1991 and became available for most banks by 1993. Small business loans are a good proxy for relationship lending because information is generally more opaque on small businesses and small farms than on other borrowers. When information on some borrowers is opaque, banks with private information on those borrowers can extract some rents because information opaqueness prevents other banks from competing for those borrowers (see Elyasiani and Goldberg (2004) for a survey of the literature on relationship lending). Thus, SMALL_LOANS should positively contribute to charter value and the q ratio.

The variable DELAY is included to capture the effect of delayed loss recognition on the q ratio. Some banks may delay loss recognition to hide financial difficulties. Given that loan delinquencies are serially correlated and partly predictable, a high delinquency rate for a bank

relative to its loan loss provision indicates that the bank may have been delaying loss recognition. By inflating the book value, delayed loss recognition lowers the q ratio.

Changes in the regulatory environment and banking industry market structure are also expected to affect charter value and manager/shareholders risk incentives. The 1956 Douglas Amendment to the Bank Holding Company Act imposed interstate banking and intrastate branching restrictions. Starting in the 1970s, states began to gradually relax these restrictions with most of them allowing some form of branching by the end of 1980s. To control for the structural changes in market power, we first considered a number of traditional measures of power such as the Herfindahl-Hirschman Index (HHI) and market share concentration. These proxies of market power were found to have little explanatory power on bank value. The poor explanatory power of MSA concentration measures is also documented in recent paper by Dick (2006) that analyzes the aftermath of the Riegle-Neal 1994 Nationwide Branching Act on bank market structure. The author shows that although markets have become concentrated at the regional level, nationwide branching deregulation has not affected the structure of metropolitan markets. The median HHI was 1,793 in 1999, only slightly lower than its 1993 median of 1,847. Although dominant banking firms were successful in broad geographic markets, they have been unable to gain market power in urban markets.

Jayaratne and Strahan (1996) propose an alternative way to measure structural variation in markets by looking at state branching regimes. Similarly, we included in the regression specification the binary explanatory variables INTRA_STATE and INTER_STATE, indicating whether the state has introduced intrastate and interstate deregulations, respectively. Branching restrictions should in theory give banks greater market power by limiting competition, thereby increasing profitability. However, Kroszner and Strahan (1999) and Jayaratne and Strahan

[(1996), (1998)] document that branching deregulation had a positive impact on state-level growth, increased economic efficiency, and actually enhanced the ability of technologically efficient banks to compete state-wide or in more distant markets. These dummy variables are not used for the 1993-2005 period because the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 allowed banks to expand nationwide, making the state-level regulations on interstate banking and intrastate branching irrelevant.

As a result of the branching and financial deregulation there was also a significant surge in merger activities among banks throughout our sample period. Although most of these mergers appear to be voluntary transactions, regulators also encouraged the takeover of troubled targets by financially stronger institutions. It is well documented in the financial literature that acquiring firms in the 1980s and 1990s experienced significant negative abnormal returns upon the announcement of the transaction (see, for example, Fuller, Netter, Stegemoller (2002)). It is conceivable therefore those q ratios of banks with a significant expansion agenda would suffer as a result of their merger activities. To control for the impact of mergers, the regression includes the logarithm of the number of banks acquired (plus one) over the year (NUMBER_ACQ). Finally, the specification includes year dummies to capture time variations in macro-economic and stock market conditions.

4. Measuring the riskiness of banks

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 two alternative measures of bank-specific measure of solvency.

4.1. *A logit model of the likelihood of failure at the bank level*

The first approach employs 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 similar as we seek to construct a measure of bank solvency that would accurately describe the current state of the institution. Often models of bank failure focus on longer 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:

$$y^*_{ti} = x_{t-1,i\bullet}\,\gamma + \upsilon_{ti}, \tag{7}$$

where

$$\begin{array}{llll} y_{ti} = 1 & \text{if} & y^*_{ti} \le 0 & \text{(bank failure in t)}, \\ y_{ti} = 0 & \text{if} & y^*_{ti} > 0 & \text{(otherwise)}, \end{array} \tag{8}$$

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} 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 prior to year (t). In particular, a forward-looking estimate of the likelihood of failure can be computed from

$$\hat{P}_{ti} = F(x_{t-1,i\bullet};\hat{\gamma}), \tag{9}$$

where $F(\bullet)$ represents the logistic distribution.

Although ultimately this paper investigates the relationship between charter value and bank risk at the bank holding company level, the 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 1986-92, 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 parents. The estimate of the failure probability for a BHC is simply given by the asset-weighted average score of all its subsidiaries. To salvage poorly performing banks, regulators engineered a large fraction of the bank mergers in the 1980s. To avoid possible sample bias, we eliminated from the logit sample all banks that were taken over during the period (except of course for FDIC-assisted mergers that were counted as failures).[8]

The vector of logit explanatory variables $x_{t-1,i\bullet}$ 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 measures of capital adequacy, asset quality, cost efficiency, profitability, and liquidity.[9] The coefficients in the logit model are generally significant and exhibit the expected sign in most cases. The working paper version of this article (Park and Peristiani (2001))

[8]The 1,200 failures were primarily concentrated in the late 1980s. In 1985, the sample consisted of 13,134 banks of which 131 failed. The average number of yearly failures peaked around 200 between 1986 and 1988. With the large wave of consolidations and failures, the logit regression sample declined to around 10,700 in 1992 (including 100 failures).

[9]In particular, the logit yearly specifications included 16 explanatory variables. Capitalization strength was measured by the equity-to-assets ratio and net loan reserves divided by assets. The bank's asset credit quality and liquidity were measured by several ratios: net charge-offs divided by assets; C&I loans, real estate loans, other real estate loans, government bonds, and liquid assets (all divided by total assets). We proxied profit efficiency by return on assets, and cost efficiency by overhead expenses divided by asset and the non-interest expense ratio. The regression also included state-level employment to control for local macro-economic conditions.

describes in greater details the logistic regressions. As expected, capital adequacy, measured by the equity-to-assets ratio, was very significant indicating that capitalization plays a critical role in determining the ability of bank to survive.

Overall, the logit model generates very accurate and reliable forecasts of failure. The concordant ratio for most of the estimated annual regressions is close to or over 90 percent, meaning that the 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.

4.2. A contingent claims approach

To check the robustness of results, we also employ a contingent claims approach that relies on market data, as opposed to accounting data. In addition to the robustness check, the contingent claims approach is very useful for examining recent periods when few banks failed.

Based on Merton (1974), Crosbie and Bohn (2002) apply the Black-Scholes-Merton (BSM) framework to back out the ex ante implied probability of default during a given time period. In a nutshell, Merton's contingent claims approach is reduced down to two equations:

$$V_{Eti} = V_{Ati}\ N(d_{1ti}) - e^{-rT} L_{ti}\ N(d_{2ti}), \tag{10}$$

and

$$\sigma_{Eti} = \frac{V_{Ati}}{V_{Eti}}\ N(d_{1ti})\ \sigma_{Ati}, \tag{11}$$

where V_{Eti} is the i-th bank's market value of equity (call value) at period (t), V_{Ati} is the market value of assets, and L_{ti} is total liabilities (exercise price). The market value of firm (i) V_{Ai} is assumed to follow a geometric Brownian process with drift μ and volatility σ_{Ati}. The variable σ_{Eti} represents the volatility of the bank's value of equity, and r_t is the risk-free interest rate. As

in the BSM formula, T is time to expiration, $d_{1ti} = [\ln(V_{Ati}/L_{ti}) + T(r_t + 0.5\sigma_{Ati}^2)]/\sigma_{Ati}\sqrt{T}$, $d_{2ti} = d_{1ti} - \sigma_{Ati}\sqrt{T}$, and $N(\bullet)$ is the normal distribution.

Equations (10) and (11) correspond to a fairly simplified version of the Moody's KMV model that is currently used by practitioners to measure corporate default risk. As described by Crosbie and Bohn (2002), we can solve this nonlinear two-equation system for $\tilde{V}_A$ and $\tilde{\sigma}_A$ using known values of V_E, σ_E, and D.[10] The implied probability of default for bank at period *t* is given by:

$$\widetilde{IDP}_{ti} = N(-dd_{ti}(\tilde{V}_{Ati}, \tilde{\sigma}_{Ati};\ V_{Eti}, \sigma_{Eti}, L_{ti})). \tag{12}$$

where the distance-to-default is defined as $dd_{ti} = [\ln(V_{Ati}/L_{ti}) + T(r - 0.5\sigma_{Ati}^2)]/\sigma_{Ati}\sqrt{T}$.[11] To compute the implied default probability, we use quarterly measures of volatility and market value of the bank (that is, $T = 1/4$) derived from daily information from the *Center for Research in Securities Prices* (CRSP). The sample is again an unbalanced panel of 337 BHCs with 7,530 quarterly observations spanning the period 1986-92. The implied default probability represents the likelihood that the bank will default in the next quarter. The quarterly horizon $T = 1/4$ was dictated primarily by the availability of information (total liabilities are reported on a quarterly basis). To be consistent with annual logit-derived estimates of probability of failure, however, we use the quarterly measures to compute the yearly average probability of default.

As usual, both the econometric method and the contingent claims method have some shortcomings. In the econometric approach, we measure the riskiness of BHCs by averaging the

[10]To solve the nonlinear system of two unknowns and two equations, we used the SAS PROC MODEL procedure.

[11]Essentially, Moody's KMV assumes that the drift μ is equal to the risk-free rate r. We also derived the implied probability of default by estimating μ from the change in $\log(\tilde{V}_{Ati})$. Overall, both approaches yield very similar findings.

failure probabilities of their subsidiaries because there are only a handful of actual BHC failures during the sample period. This weighted average of the subsidiaries might not capture the full diversification potential of the much larger holding company.[12] In the contingent claims approach, the market value of assets derived from the market value of equity includes both tangible and intangible components, such as charter value and option value. Thus, charter value and option value influence the default probability, although for our purposes, they should not.

These shortcomings are not critical, however. The main purpose of this study is to infer the prevalence of moral hazard behavior. Our main interest is not in the numerical value of failure probabilities but in the percentage of BHCs whose failure probabilities are greater than the threshold level. The bias resulting from averaging the failure probabilities of subsidiaries should be small in our sample because most large BHC organizations are highly concentrated. Specifically, we find that, on average, roughly 90 percent of the assets in our sample of BHCs are located in the core bank. The bias resulting from the inclusion of intangible assets should also be small because on average, the market value of assets is larger than the book value of assets only by 1.6 percent for the sample BHCs.

5. Estimation results

5.1. Data

As noted previously, the data is an unbalanced sample of 337 publicly traded BHCs, with a total of 1,913 bank-year observations spanning the period 1986-92. To calculate the q ratio for

[12]This inability to fully capture holding company diversification benefits is apparent in the higher probabilities of the logit estimates of failure. However, the implied measure of default also does not necessarily correspond to the empirical probability of default (Duffie and Singleton (2003)). Moody's KMV uses a large proprietary database of defaults to adjust the distance-to-default to the actual experience. What is important is that in our framework both the logit estimate and implied default estimates provide a time-consistent indicator of the solvency of banks. For a more detailed discussion of the options-theoretic approach to credit risk measurement, see Chapter 4 of Saunders and Allen (2002).

BHCs, we use market value information from Standard and Poor's COMPUSTAT database. 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.

[Insert Table 1 around here]

Table 1 provides summary statistics of the dependent and explanatory variables of the regression model defined by equation (6). Consistent with other studies of firm value, the q ratio averages close to 1.016. On the surface, the mean probability of failure P_{ti} is fairly high at 0.024. But this result is driven primarily by a handful of failing institutions with very large scores. The median of the probability of failure is 0.0056, meaning that the distribution of the estimates of failure is skewed to the right. The correlation coefficient between the logit-based estimate of probability of bank failure P_{ti} and the implied measure of default IDP_{ti} is around 0.4. This degree of correlation is fairly strong for a cross sectional sample. Although the logit failure model and the contingent claims approach are conceptually similar, they differ in the way they are derived. The logit estimates are based on the actual events of bank-level failure. In contrast, the contingent claims approach extracts the probability of default from stock market perceptions.

5.2. Estimating the nonlinear effect of bank risk

We employ three different approaches to estimate the functional relationship between firm value and bank risk defined by equation (6). The first empirical model asserts that $f(\bullet)$ is a simple linear function of the probability of failure. The second approach specifies $f(\bullet)$ as a third-order polynomial. These two simplifications serve basically as convenient baselines against which we can compare the more efficient 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. Consider for again the q model defined by equation (6), both the polynomial and linear estimators minimize

$$ESS = \frac{1}{N}\sum_{t=1}^{T}\sum_{i=1}^{N}(q_{ti} - f(P_{t-1,i}) - \beta Z_{t-1,i\bullet})^2 . \tag{13}$$

In comparison, the spline approach optimizes the tradeoff between ESS and a measure of the "smoothness" of $f(\bullet)$. 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,

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

Here, the roughness of $f(\bullet)$ is defined by the integral of the square of the second derivative of $f(\bullet)$. 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) and Härdle (1990).

5.3. Results for the period 1986-1992

Table 2 summarizes the coefficient estimates for the q ratio specification. Panels A and B in the table present the estimates for the logit-derived probability of failure and the implied probability of default measures, respectively. The first two columns in the two panels of Table 2 present the least square estimates of the simple parametric versions of the model. In the linear case, the coefficient of the failure probability is negative but statistically insignificant, suggesting that the q ratio keeps on declining at higher levels of bank risk. The inadequacy of the simple

linear model is further underscored by the improvement in the fit of the polynomial model. The polynomial estimates point to a nonlinear relationship between the q ratio and the failure probability.

[Insert Table 2 around here]

Although the third-order 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 (third column in each panel). The strongly significant χ^2 statistics for $f(\bullet)$ presented at the bottom of Table 2 indicate that the spline specification is a very good fit for the data.

Because the spline estimator for $f(\bullet)$ is nonparametric, the best way to demonstrate its contribution is graphically. Figure 2 plots the relationship between the q ratio and the two measures of bank risk. For this graphical exercise, we assume that the remaining parametric explanatory variables are evaluated at their respective averages. For both risk measures, the nonparametric relationship with q is convex. The nonparametric relationship between q and the logistic probability of failure declines with increasing risk, bottoming out at the 17-percent failure probability threshold. The pattern of the nonparametric relationship between the q ratio and the implied probability of default is also very similar, albeit the trough of $f(\mathrm{IDP})$ is slightly higher at around 0.22.[13]

[13]The convex relationship between bank value and risk is robust to several alternative specifications. For example, the cross sectional nature of the sample raises the possibility that there might be a fixed-effect influence in the regression, that is, $q_{ti} = \beta_i + f(P_{t-1,i}) + \beta Z_{t-1,i\bullet} + \varepsilon_{ti}$. In the linear regression case, a simple but somewhat taxing way of accounting for fixed effects is to include as regressors firm dummy indicators. In the spline framework, where the slope of $f(\bullet)$ is estimated in successive neighborhood of points, it is numerically impossible to separately estimate 337 banking firm effects. A more plausible way is to estimate the spline model by demeaning the dependent variable, i.e., $q_{ti} - \overline{q}_i$. To get a more accurate estimate of $\overline{q}_i$, we re-

[Insert Figure 2 around here]

The figure clearly reveals nonlinear patterns that are consistent with theory and our simulation examples. The shape of the empirical spline functions implies that both charter value and put option value matter in the valuation of the bank. Consistent 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. The reversal in the estimated q ratio function allows us to locate the level of risk at which the put option value begins to dominate charter value.

It is interesting to note that roughly 3 percent of the BHC observations in our sample have a failure probability higher than the 17-percent level threshold in P.[14] This finding suggests that shareholders had incentives to encourage managers to pursue riskier strategies in only a handful of cases in this turbulent sample period. Perhaps the most intriguing implication of our empirical analysis is that shareholders are seriously concerned about the possibility of losing charter value. Safer banks are the ones with the 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 bank risk is typically a sharp deterioration in the bank's q ratio. The high threshold level and the

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estimated the spline model using quarterly observations. Overall, we find a similar convex relationship for $f(P)$.

[14]In terms of actual numbers, there were 57 annual observations above the 17-percent threshold, representing 33 unique institutions. The five failed BHCs account for 11 of the 57 annual observations. The deterioration in these institutions becomes apparent and is captured by balance sheet data usually about 2 years before failure. The spline estimate of $f(\bullet)$ is fairly similar when re-estimating the model without these 11 observations.

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.

The remaining parametric explanatory variables have the right sign and are statistically significant in most cases. The strong explanatory power of DELAY suggests that book value is significantly influenced by the timing of loss recognition, over which managers have some discretion.

An interesting result of our regression analysis is that the intrastate branching indicator INTRA_STATE has a significant positive effect on the q ratio, while the interstate banking dummy indicator is insignificant. The positive effect of INTRA_STATE is somewhat surprising, considering that branching deregulation might have reduced banks' market power. These results, however, are consistent with the findings of Jayaratne and Strahan (1996) who document that bank efficiency improves significantly after intrastate branching are relaxed, but the effect of interstate banking expansion is less significant. In particular, they discover significant improvements after intrastate branching restrictions are lifted in nonperforming loans, charge-offs, and loan loss provisions. The authors suggest that these apparent improvements in efficiency have come about because branching deregulation has enabled better performing and more efficient banks to expand at the expense less efficient rivals. In this case, publicly held BHCs might have gained at the expense of small independent banks that had been entrenched in local markets.

[Insert Figure 3 around here]

The significance of CORE indicates a wide variation in charter value across banks. Moral hazard theory predicts that the probability threshold at which put option value 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 value. We divide the sample into two groups of equal size based on CORE (high-CORE and low-CORE banks). As seen from Figure 3, the two sub-samples produce significantly different functional relationships between the failure probability and the q ratio (results are also very similar when we use the implied default measure of bank risk). 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 a weaker core deposit base. Having smaller charter value, these banks have less to lose and are more likely to realize a net benefit 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.

5.3. Moral hazard in the post-crisis period 1993-2005

It is well documented in the banking literature that flat deposit insurance premiums, deregulation, and lax supervision promoted moral hazard among banks and thrifts by increasing option value and reducing charter value in the 1980s (see for example, Barth (1991)). A series of legislations, starting with the Financial Institutions Reform and Recovery Act (FIRREA) of 1989, may have reduced option value and possibly affected the charter value of financial intermediaries. The FIRREA tightened capital requirements, and was followed by the FDIC Improvement Act (FDICIA) of 1991 that introduced risk-based insurance premiums and prompt corrective action in addition to higher capital requirements. Those provisions should in theory diminish more hazard incentives, as higher capital requirements push the option more deeply out

of money, and risk-sensitive deposit insurance premiums and prompt corrective actions reduce the time to expiration.

Furthermore, the Riegle-Neal Interstate Banking and Branching Act of 1994 allowed banks to establish interstate branches through mergers, and the Gramm-Leach-Bliley Act (GLBA) of 1999 (formally known as the Financial Services Modernization Act) removed many restrictions on the affiliation between banks, securities firms, and insurance companies. These major deregulations may have affected charter value, although the direction is unclear. While the two acts may have reduced the market power of banks, they have at the same time created more opportunities for banks, especially for efficient ones. Considering that the market power of banks might have already been substantially eroded by the late 1980s as documented by Keeley (1990), the opportunities to expand into other regions and financial services are likely to have increased charter value.

Ultimately, the efficacy of these major banking legislations would depend on how successful they are in improving the safety and soundness of banks. Have theses legislative initiatives affected the bank value-risk inflection point at which bank shareholders become enemies of regulators? To address this question, we estimate again the relationship between the q ratio and risk defined by equation (6) for the post-crisis period 1993-2005. The Basel Accord and FDICIA have ushered a period of financial stability and calm in the banking industry. In contrast to our earlier period of study that was marred by 1,200 bank closures, there were only a handful of failing banks after 1992, most of them attributed to fraud. The small number and idiosyncratic nature of bank failures in the recent period make it quite difficult to get good logit estimates of the probability of failure. To gauge the riskiness of banks, we fall back on Merton's option

methodology. The obvious advantage of the contingent claims approach is that it is not event driven as we derive an implied probability of default even in the absence of any bank failures.

[Insert Table 3 around here]

Table 3 presents summary statistics for the regression variables for the post-crisis period. In comparison to the more turbulent earlier period, banks are considerably healthier in this recent period, exhibiting lower delinquency ratios, smaller implied probabilities of default, and higher q ratios.

[Insert Figure 4 around here]

More important, Figure 4 plots the relationship between the q ratio and the default probability. The shape of the curve is again convex, but the inflection point is much higher for this period than for the earlier crisis period (0.22 versus 0.50).[15] This finding is consistent with our prior that option value has been significantly reduced. Even at a high failure probability, the option value is small if the bank is expected to be closed without delay (due to more rigorous capital requirements and prompt corrective action) or be punished with a high deposit insurance premium. The substantially higher inflection point shows that charter value has increased in the post-crisis period. This finding is not surprising as nationwide banking and more prudential regulation have helped improve the credit quality of banks. In any case, the higher inflection point for the recent period reinforces our conclusion. Among publicly held BHCs, moral hazard is not prevalent. Even during the tumultuous period of 1986-92, moral hazard incentives were confined to a small subset of BHCs. Higher capital requirements enacted in the early 1990s and

[15]In light of the fact that there were only 10 bank year observations with an implied default probability greater than 0.5., an alternative view is that the convex relationship in Figure 4 is more akin to the theoretical scenario presented in Panel D of Figure 1, depicting the case where banks want to protect their large charter values.

more rigorous banking supervision have effectively eliminated most of these risk-taking incentives.

[Insert Table 4 around here]

As evident in the polynomial specification, the relationship between risk and the q ratio is substantially weaker in the post-crisis period (Table 4). Similarly, the χ^2 test for the spline estimator $f(\text{IPD})$ is only significant at the 10-percent level. This lower significance largely indicates that the market is now less concerned with the riskiness of banks. As in the earlier period, bank size has a positive effect on the q ratio, albeit the effect is now more statistically significant. DELAY continues to show a negative effect on the q ratio with a high statistical significance. The coefficient of CORE remains positive and significant, signifying again the importance of stable and cheaper sources of funding for banks. SMALL_LOANS, an additional measure of charter value, also turns out to be quite significant, suggesting that relationship lending is very important and significantly contributes to charter value. In this period, investors penalized banks with a large number of acquisitions, possibly because there were more unnecessary or inefficient mergers.

6. Conclusion

This paper has empirically examined how the put option value and charter value of banks interact with risk. Our analysis reveals a distinct convex nonlinear relationship between the market-to-book ratio and bank risk. 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 the option value becomes large enough to compensate for the loss of charter value, shareholders elect instead to reward risk-taking to further increase the put option value. The convex relationship between the q ratio and

the likelihood of failure or default allows us to identify the threshold of risk at which the marginal benefit from the option value starts outweighing the expected loss of charter value. Our empirical results show that this risk turning point was quite high even during the turbulent period 1986-1992 and much higher in the recent period 1993-2005. We conclude, therefore, that for publicly held BHCs, the interests of bank shareholders are aligned with those of regulators and debtholders, except for a small subset of extremely risky ones.

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. The identification of the threshold probability, for example, can help regulators to determine the timing of corrective action. 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 reaches or goes beyond the turning point where the put option value exceeds the charter value of the firm.

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TABLE 1. Variable definitions and summary statistics, 1986-1992

Symbol	Variable definition	Mean/ Frequency	Max	Min
Dependent variable				
q	Tobin's q ratio: Market value of assets (market value of equity plus book value of liability) divided by book value of assets	1.016	1.387	0.982
Explanatory variables				
P	Logit estimate of probability of failure of the bank holding company	0.024	0.988	4.2×10^{-6}
IDP	Option-derived Implied Probability of Default of the bank holding company	0.011	0.998	0
CORE	Ratio of core deposits to total assets; core deposits is sum of demand deposits, NOW and ATS, other transactions accounts, non-transactions savings deposits, and time deposits less than $100,000	0.696	0.928	0
ASSETS	Total book value of assets (in $ billions)	7.764	230.645	0.072
DELAY	Delinquent loans and lease receivables divided by allowance for loans and lease losses; delinquent loans and leases include past over 90 days and non-accruing loans and leases	1.258	10.059	0
NUMBER _ ACQ	Number of banks (public or non-public) acquired by BHC in a year	0.989	51	0
INTRA _ STATE	Bank is operating in a state having no intra-state branching restrictions	0.871		
INTER _ STATE	Bank is operating in a state allowing interstate banking	0.932		

Number of bank holding companies: 337

Number of yearly observation: 1,913

TABLE 2. The relationship between the q ratio and the probability of failure, 1986-1992
Dependent variable = q ratio (Tobin's market-to-book ratio)

Explanatory variables	A.Logit probability of failure			B.Option-implied probability of default		
	Linear model	Polynomial model	Spline model	Linear model	Polynomial model	Spline model
CONSTANT	0.985*** (71.16)	0.982*** (71.62)	0.967*** (70.85)	0.993*** (71.70)	1.03*** (83.63)	0.993*** (71.70)
P	-0.019 (-1.56)	-0.321*** (-6.21)		-0.067*** (-6.19)	-0.405*** (-6.61)	
P^2		0.914*** (4.79)			0.936*** (4.51)	
P^3		-0.611*** (-3.68)			-0.581*** (-3.54)	
CORE	0.029*** (4.38)	0.019*** (2.95)	0.020 (3.11)	0.016** (2.45)	0.015** (2.21)	0.029*** (4.32)
log(ASSETS)	0.0019*** (2.74)	0.0026*** (3.72)	0.0028*** (4.01)	0.0006 (0.91)	0.00007 (0.11)	0.00082 (1.15)
DELAY	-0.0087*** (-9.12)	-0.0077*** (-8.01)	-0.0075*** (-7.92)	-0.0089*** (-9.13)	-0.0084*** (-8.71)	-0.0082*** (-8.66)
INTRA_STATE	0.011*** (4.26)	0.012*** (4.55)	0.012*** (4.58)	0.011*** (4.35)	0.011*** (4.04)	0.012*** (4.45)
INTER_STATE	-0.0018 (-0.49)	-0.0012 (-0.32)	-0.001 (-0.25)	-0.0013 (-0.37)	-0.0011 (-0.32)	-0.0012 (-0.032)
log(NUNBER_ACQ+1)	-0.0006 (-0.43)	-0.0009 (-0.57)	-0.0011 (-0.72)	-0.0005 (-0.37)	0.0004 (-0.31)	-0.0006 (-0.39)
Sample size	1,913	1,913	1,913	1,902	1,902	1,913
Adjusted R^2	0.152	0.171		0.152	0.163	
	Significance test for spline estimator			Significance for spline estimator		
χ^2 test for $f(\bullet)$			54.36***			40.83***

NOTES: The symbols (*), (**), and (***) indicate significance at the 10-, 5-, and 1-percent level, respectively. Variable definitions and summary statistics are provided in Table 1. In addition to these explanatory variables, the regressions include yearly dummy variables that are not reported. The linear model assumes $f(P_{ti}) = \beta_1 P_{ti}$ and the polynomial version $f(P_{ti}) = \beta_1 P_{ti} + \beta_2 P_{ti}^2 + \beta_3 P_{ti}^3$. The variable $f(P_{ti})$ in the spline mode is an undefined nonparametric function. The semi-parametric model was estimated using the SAS GAM (Generalized Additive Model) procedure.

TABLE 3. Summary statistics, 1993-2005

Symbol	Mean/ Frequency	Max	Min
Dependent variable			
q	1.068	3.462	0.711
Independent variables			
IDP	0.003	0.998	0
CORE	0.646	0.930	0
ASSETS	12.88	1,494.1	0.095
DELAY	0.627	0.930	0
NUMBER _ ACQ	0.299	4.0	0
SMALL _ LOANS	0.114	0.757	0
Number of bank holding companies: 773			
Number of yearly observation: 5,260			

NOTES: Variable definitions are provided in Table 1. SMALL _ LOANS = total amount of loans granted to small business and small farm borrowers divided by total assets. In addition to these explanatory variables, the regressions include yearly dummy variables that are not reported.

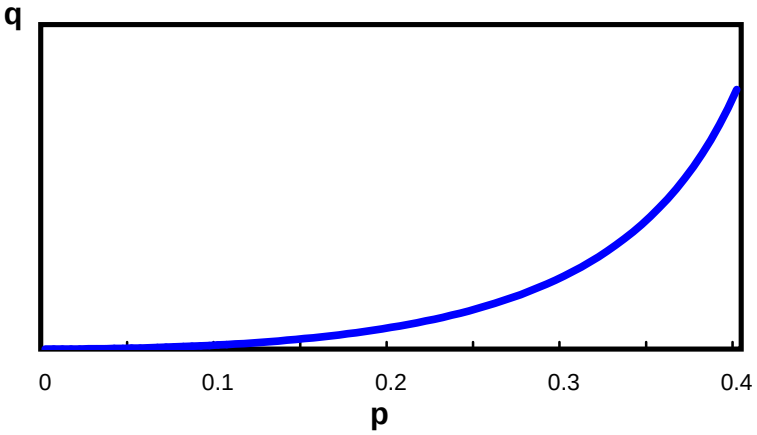
TABLE 4. The relationship between the q ratio and the probability of failure, 1993-2005
Dependent Variable = q ratio (Tobin's market-to-book ratio)

Explanatory variables	Option-implied probability of default		
	Linear model	Polynomial model	Spline model
CONSTANT	0.797*** (46.68)	0.799*** (46.73)	0.799*** (46.81)
IDP	-0.049* (-1.70)	-0.361* (-1.95)	
IDP^2		0.804 (1.14)	
IDP^3		-0.466 (-0.81)	
CORE	0.035*** (4.01)	0.036*** (4.06)	0.036*** (4.06)
log(ASSETS)	0.016*** (17.79)	0.017*** (17.61)	0.016*** (17.64)
DELAY	-0.0088*** (-6.96)	-0.0086*** (-6.82)	-0.0086*** (-6.82)
SMALL_LOANS	0.056*** (3.71)	0.055*** (3.72)	0.055*** (3.76)
$\log(NUNBER_ACQ+1)$	-0.0083*** (-3.63)	-0.0082*** (3.61)	-0.0082*** (-3.61)
Sample size	5,260	5,260	5,260
Adjusted R^2	0.123	0.124	
	Significance test for spline estimator		
χ^2 test for $f(\bullet)$			7.02*

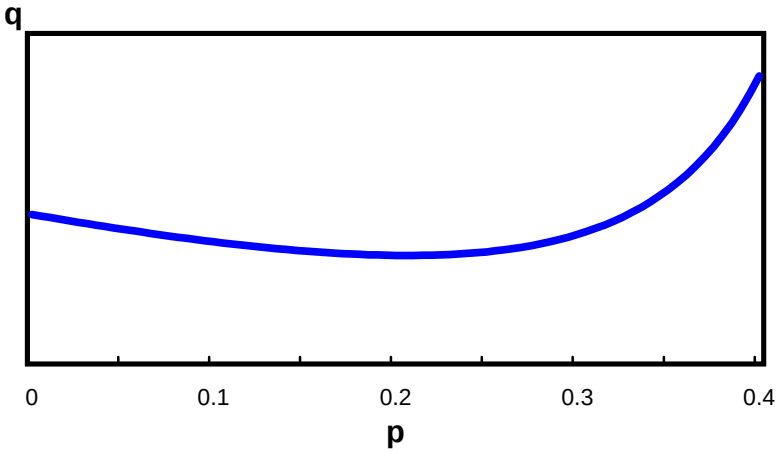
NOTES: The symbols (*), (**), and (***) indicate significance at the 10-, 5-, and 1-percent level, respectively. Variable definitions and summary statistics are provided in Tables 1 and 3. In addition to these explanatory variables, the regressions include yearly dummy variables that are not reported.

Fig 1. Charter value and probability of failure: Four simulation examples

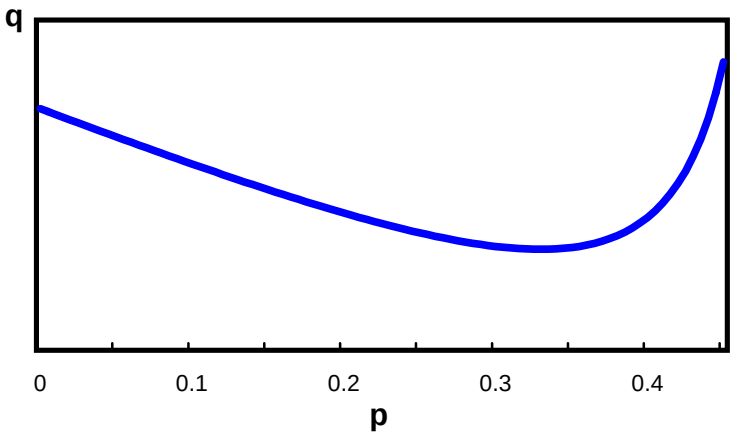
A. Banks With No Charter Value (β=0)



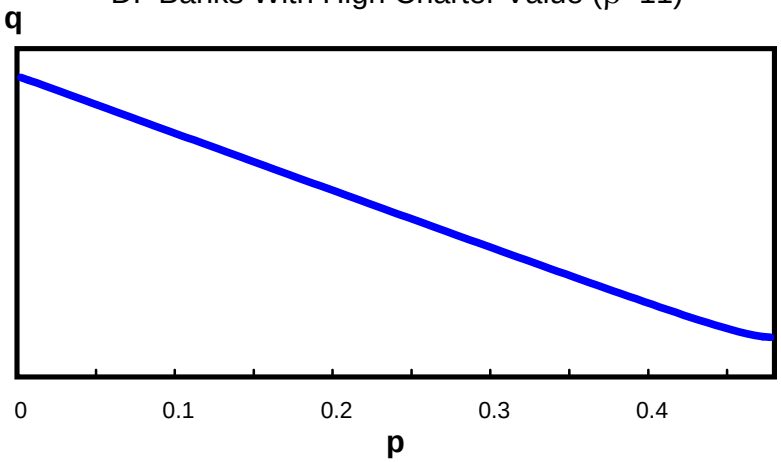
B. Banks With Moderate Charter Value (β=0.05)



C. Banks With Moderate Charter Value (β=0.2)



D. Banks With High Charter Value (β=11)



NOTE: The variable (p) represents the probability of failure and (q) is the ratio of the sum of the market value of equity and the book value of liabilities divided by the book value of assets net of goodwill .

Figure 2. Spline estimates for logit-derived failure and option-implied default probabilities

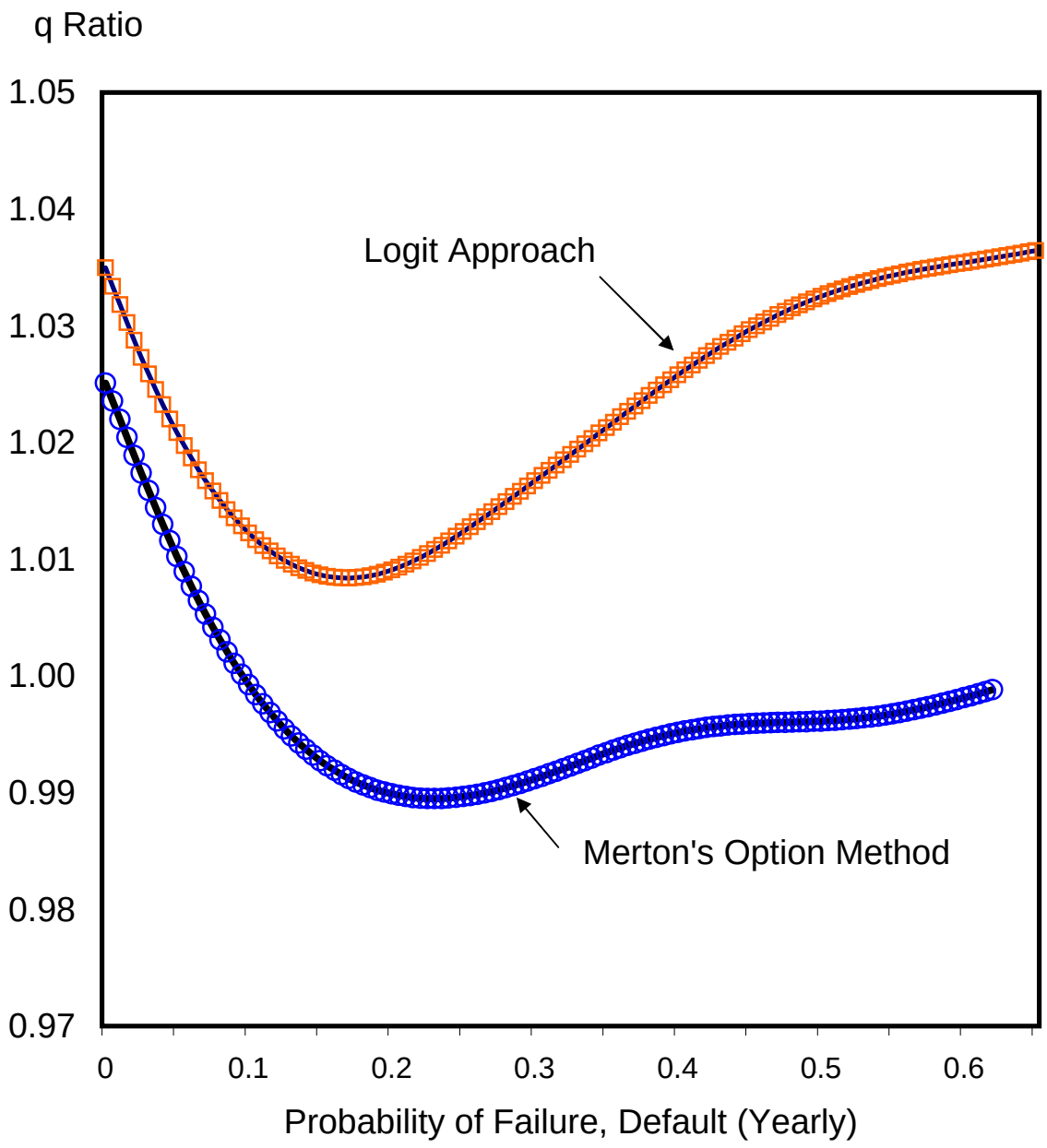


Figure 3. Spline estimates for low- and high-Core deposit banks

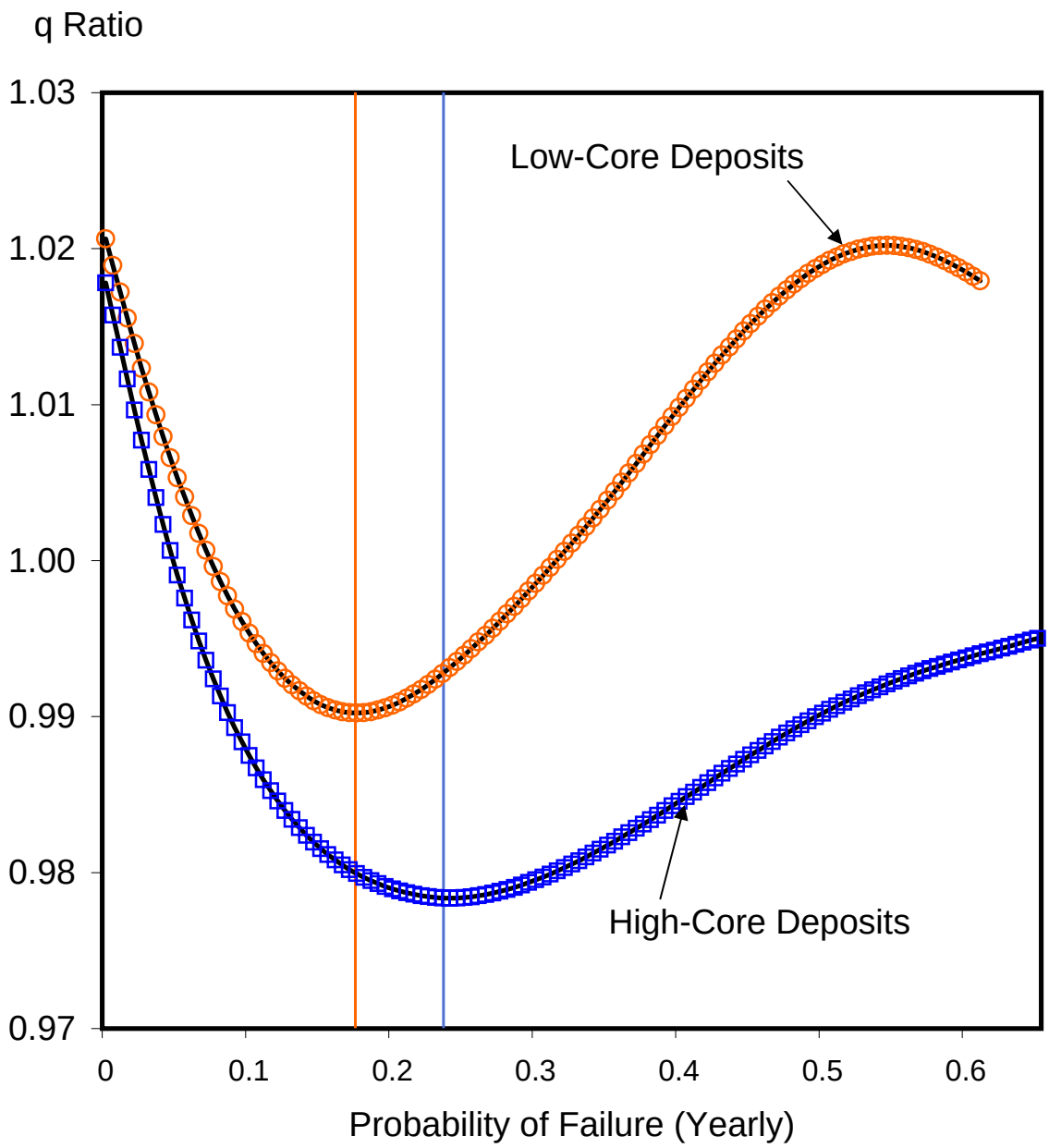
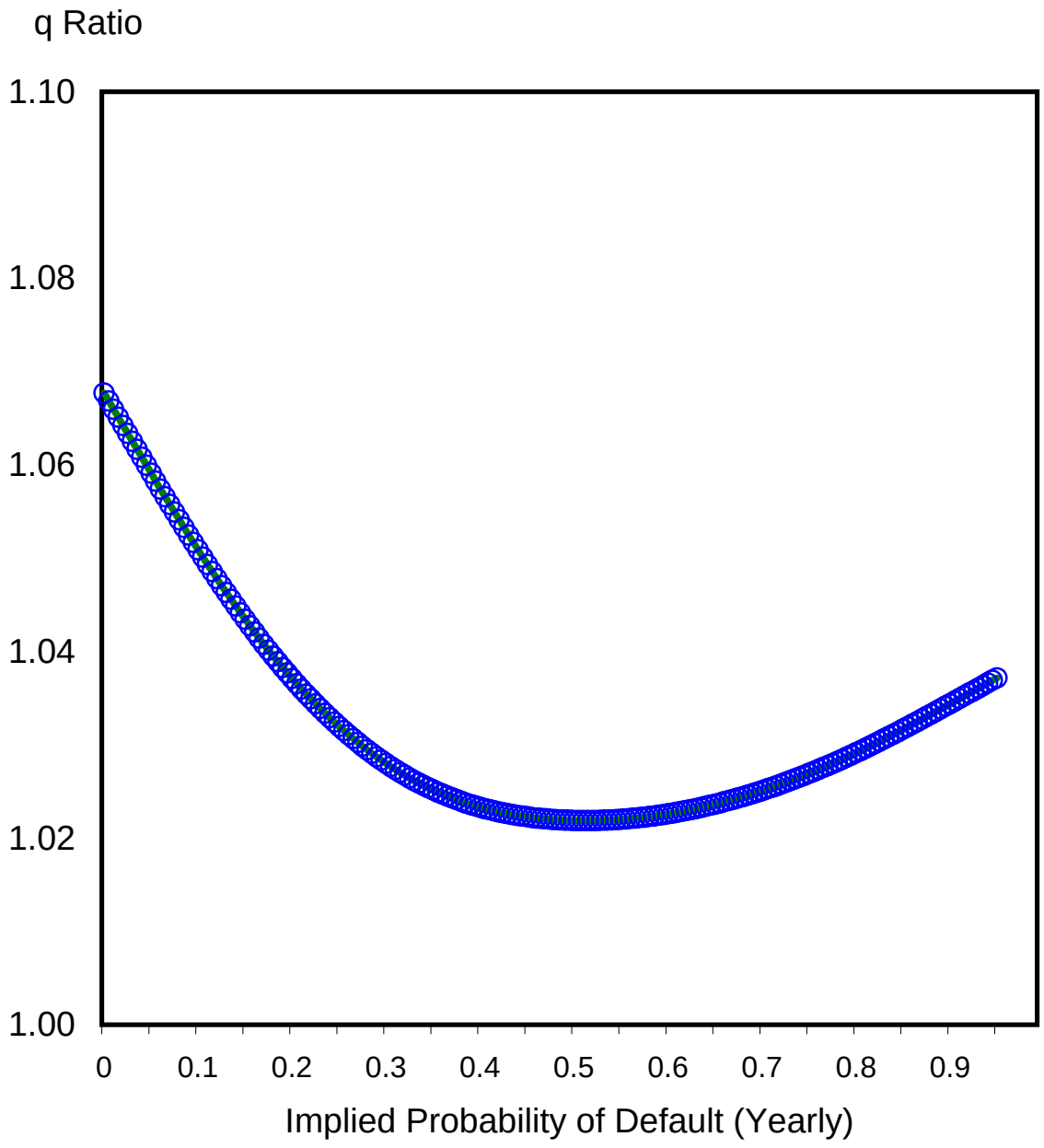



Figure 4. Spline estimates for implied default probabilities, 1993-2005