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Douglas D. Evanoff and Larry D. Wall

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Douglas D. Evanoff, Federal Reserve Bank of Chicago
Larry D. Wall, Federal Reserve Bank of Atlanta

Abstract: Several recent studies have recommended greater reliance on subordinated debt as a tool to discipline bank risk taking. Some of these proposals recommend using sub-debt yield spreads as triggers for supervisory discipline under prompt corrective action (PCA). Currently such action is prompted by capital adequacy measures. This paper provides the first empirical analysis of the relative accuracy of various capital ratios and sub-debt spreads in predicting bank condition, measured as subsequent CAMEL or BOPEC ratings. The results suggest that some of the capital ratios, including the summary measure used to trigger PCA, have almost no predictive power. Sub-debt yield spreads performed slightly better than the best capital measure, the Tier-1 leverage ratio, albeit the difference is not significant. The performance of sub-debt yields satisfies an important prerequisite for using sub-debt as a PCA trigger. However, the prediction errors are relatively high and further work to refine the measures would be desirable.

JEL classification: G28, G21, G14, K23

Key words: bank regulation, subordinated debt, capital adequacy, prompt corrective action

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Please address questions regarding content to Douglas D. Evanoff, Research Officer, Federal Reserve Bank of Chicago, 230 South LaSalle Street, Chicago, Illinois 60604, 312-322-5814, douglas.evanoff@chi.frb.org, or Larry D. Wall, Research Officer, Federal Reserve Bank of Atlanta, 104 Marietta Street, Atlanta, Georgia 30303-2713, 404-521-8931, larry.wall@atl.frb.org.

Sub-Debt Yield Spreads as Bank Risk Measures

The Federal Deposit Insurance Improvement Act of 1991 (FDICIA) contained a number of provisions intended to discourage banks from taking excessive risk, and to protect the deposit insurance fund from losses at failed banks. One important provision of FDICIA is its requirement that the supervisors implement prompt corrective action (PCA).[1] PCA provides a series of optional and mandatory actions by the supervisors as a bank's capital adequacy declines. The intent is to protect the deposit insurance by limiting supervisory forbearance, and thereby reduce the subsidy to risk-taking provided by deposit insurance.

A potential weakness of PCA is its reliance on book value capital adequacy ratios measured using historic costs as required by generally accepted accounting principles (GAAP). As White (1997) indicates: "The GAAP definitions and rules are generally oriented toward backward-looking, cost-based valuations—which are more appropriate for a "stewardship" notion of accounting than for using the accounting information as an indicator of whether a bank may be sliding toward (or may have already reached) true (market value) insolvency…".[2] For example, GAAP does not permit recognition of the effect of interest rate changes on the value of a bank's liabilities or on the value of assets that it intends to hold until maturity.[3]

One alternative to relying on capital adequacy ratios to trigger PCA is to use a market-based measure. A potential advantage of using equity or debt prices is that market participants have an incentive to look through reported accounting figures to the real financial condition of a bank and to price a bank's securities based on their best estimates of the distribution of the security's future cash flows. Thus, security prices have the potential to be a better signal for preventing forbearance than do bank capital adequacy ratios. A possible disadvantage of using market-based measures such as the yields on uninsured debt obligations or equity prices are that these measures are available only for the largest banks. However, the share of assets held by the largest banks is large and increasing. Additionally, these banks pose the greatest danger of systemic risk and the largest risk to the deposit insurance fund.

The market risk measure that has probably received the most attention thus far is subordinated debt (sub-debt) yield spreads.[4] Indeed, the existing empirical evidence provides some support for the use of these spreads. These studies estimate the difference between the yield on sub-debt and the yield on a comparable maturity Treasury security as a function of a number of accounting ratios that are believed to be correlated with the riskiness of the bank. The results, which are summarized in Kwast, et al. (1999), find mixed evidence on the relationship between sub-debt yields and bank risk measures in the early to mid-1980s. Flannery and Sorescu (1996) note that the bailout of all of the creditors of Continental Illinois, and subsequent statements by the Comptroller of the Currency about banks that were "too-big-to-fail," may have led sub-debt investors to believe that they would not suffer credit losses on the debt issues of the largest banks. However, they note that by the late 1980s, the FDIC was imposing losses on sub-debt holders at large failed banks and the least cost resolution provisions passed in 1991 as part of FDICIA strongly suggested that sub-debt holders would remain at risk in future failures.[5] Thus, when Flannery and Sorescu look at the late 1980s and early 1990s, they find that sub-debt yield spreads *are* related to a bank's risk exposure in the manner predicted by theory. Jagtiani, Kaufman and Lemieux (2001) find similar results in the post-FDICIA period. Similarly, Covitz, Hancock and Kwast (2000) find that financially weaker banks are less likely to issue sub-debt, which is consistent with the market charging these banks a risk premium.

While the use of sub-debt as a risk measure is supported by these studies, they are not designed to answer the question of whether sub-debt spreads are better measures of a bank's financial condition than are the current capital adequacy ratios. A strong theoretical case may be made that the credit risk portion of the sub-debt yield spread is a more accurate risk measure, and less likely to be influenced by forbearance, than is the current capital adequacy measure. However, as shown by Hancock and Kwast (2001), non-credit risk factors also appear to influence observed sub-debt prices.

This study takes the first step in evaluating the potential usefulness of sub-debt yield spreads by testing whether these spreads are better predictors of a bank financial condition as proxied by supervisory ratings than are the existing capital ratios. Both the sub-debt yield spreads and the capital adequacy ratios are measured as of the quarter end prior to the assignment of the supervisory rating. Supervisory ratings are typically assigned after an examination, and, hence, may reflect both public and nonpublic information about the bank.

One potential disadvantage of this approach is that information from the examination may leak out before the assignment of the examination rating. This potential bias in favor of sub-debt yield spreads may be offset by the potential for exam findings to be partially reflected in banks' accounting capital in the quarter prior to the assignment of the rating.[6] Another potential problem is that sub-debt yield spreads depend both on the probability that a bank will fail and its loss given failure. On the one hand, almost all of the spread may reflect the probability of failure given that relatively small losses by a bank will result in the debt becoming worthless because of its junior status and the relatively small amount of sub-debt issued. On the other hand, the variation in the loss given default component may be large and more important if market participants believe that the supervisors will follow the spirit of PCA and *try* to close banks before their going-concern value becomes negative.[7] Another potential problem is that whenever the supervisors are exercising forbearance, they also are likely to assign examination ratings that understate the riskiness of the bank. Despite this potential disadvantage, the use of exam ratings as a risk measure may be justified if forbearance, while costly when it occurs, is relatively rare.[8]

Before the empirical analysis, we discuss why using sub-debt yield spreads may be preferred to using alternative market risk measures. The first section, therefore, expands on the discussion of Evanoff and Wall (2000a) concerning the relative merits of sub-debt yield spreads and other possible substitutes for capital adequacy measures. The second section discusses the data and empirical methods. The third section presents the empirical results and the last section provides concluding remarks.

1. Alternative market risk measures

One advantage of obtaining signals from the sub-debt market is that the interests of subordinated creditors are closely aligned with those of the supervisors. Subordinated creditors stand immediately behind equity holders in exposure to loss if a bank fails, but they do not fully share in the up-side gains if a bank's risky strategies succeed. However, credit risk signals may also be extracted from other sources. For example, numerous bank balance sheet variables may be analyzed to identify problem banks. Alternatively, although equity prices may reflect potential gains from a successful gamble, the credit riskiness of the bank may be estimated with models that distinguish the potential for both gain and loss.[9]

Why choose sub-debt yields as a market signal over alternative measures? The natural criteria for evaluating alternative measures is their associated costs and benefits, where benefits are measured in terms of their ability to identify problem banks and costs in terms of the burden imposed on banks solely to obtain a supervisory risk measure. The following sections consider the potential merits of sub-debt-based measures, equity-based measures and combinations of balance sheet variables along these dimensions.

1.1 Benefits: Accuracy in predicting problem banks

If the sole criterion for evaluating the different risk measures were their historical ability to identify problem banks, the best approach would be to use a combination of accounting and market risk measures where the weights on individual variables are determined in an elaborate econometric model.[10] The model could be structured to minimize the cost of the prediction errors. Moreover, such modeling would also produce statistics to indicate the extent of the contribution each variable makes to the prediction of problem banks.

The use of accounting data in such econometric models is subject to two fundamental problems. First, the causes of bank distress and failure may vary over time. For example, a number of large banks failed in the 1980s when they pursued strategies based on continuing high energy prices. Other banks became distressed during this period due to loans to less developed countries, principally Latin American countries. In the early 1990s banks became distressed and in some cases failed due to their real estate lending, especially their commercial real estate activity.

An econometric model that predicted problems based on a particular type of lending might do well for any one of these time periods, but the predictions from applying such a model to a future period may not be very accurate.[11] One advantage of using a simple capital adequacy measure to trigger PCA by supervisors is that regardless of the source of the problem, the consequences of the problem must ultimately appear in the bank's capital account if it is of a magnitude to threaten the bank's viability.

The second problem with relying on econometric models using accounting information is that of banks manipulating the data. At present, banks have an incentive to manage capital because that is the measure used to trigger PCA. If banks know that other accounting variables also play an important role in PCA, they will have an incentive to manage those as well. For example, if a bank knows that non-performing loan ratios are a key measure it has an incentive to work with borrowers before the loan becomes non-performing, or to shift the loan to its market risk portfolio to avoid having to classify it as non-performing.[12] As another example, supervisors often point to rapid asset growth as a signal of likely future problems. If this variable were important in the model, the bank would have an incentive to reduce its measured growth rate, perhaps by becoming more aggressive in selling off loans and emphasizing off-balance sheet activities.

Thus, the use of econometric models that rely on accounting variables are subject to manipulation by banks and forbearance by supervisors; the same problem that motivated Evanoff and Wall (2000a, 2000c) to look for a substitute for capital adequacy measures. Moreover, depending on their specification, these models may also have a tendency to "fight the last war" by identifying banks that would have gotten into trouble during the previous business cycle. Thus, any apparent superiority of econometric models in predicting the future problem banks based on historical accounting data may disappear if used for PCA in the future. In contrast, as noted above, market participants have an incentive to see through bank manipulation of accounting data to assess the true condition of the bank. Thus, the use of market signals extracted from debt yields, equity prices, or both has at least the potential to provide a superior risk measure for the purposes of PCA.

1.2 Costs: Regulatory burden imposed on banks

Although basing PCA on market signals is potentially a better way to deter forbearance, obtaining such signals is likely to impose more costs on banks than is relying on accounting data.[13] Almost all of the required accounting data are currently being reported to the federal bank supervisors.

Both sub-debt and equity prices may be more costly to generate because PCA applies to banks and not to the banks' holding company parents. Yet most publicly traded sub-debt, and virtually all traded equity, is issued by the parent holding company rather than the bank subsidiary. The bank's subsidiary could issue these obligations, but in most cases have not done so under the current system suggesting that bank issuance is perceived to be more costly than having the parent issue the obligation.

One potential solution to the cost issue would be to apply PCA to the holding company parent rather than to the bank subsidiary. However, PCA was initially applied to the bank rather than to the consolidated organization because bank deposits are insured, whereas holding company obligations are not. Expanding PCA to cover the entire holding company would require reversing the general philosophy underlying the recent Gramm-Leach-Bliley (GLB) Act which removed most of the barriers to bank affiliation with other financial services. One of the basic goals of the GLB Act was to allow nonbank financial firms, such as securities and insurance firms, to own banks without subjecting their entire operations to bank-like supervision. Thus, the Act allowed non-traditional financial activities to be conducted within a holding company framework and explicitly limited the ability of the Federal Reserve, the "umbrella supervisor," to supervise the nonbank parts of the organization. While the merits of the philosophy underlying the GLB Act may be debated, applying PCA to the holding company would require major changes in the supervisory status of holding companies; a change that would have to be justified in its own right.

An alternative means to address the cost issue would be to require banks to issue either subordinated debt or equity instruments from which market risk measures could be derived. Kwast et al. (1999) note that while banks sometimes issue publicly traded subordinated debt, most such issues are done by the parent. They report that the issues are made at the holding company level despite the fact that bank sub-debt issues typically sell at lower yields. The explanation provided by market participants to Kwast et al. (1999) for issuance at the holding company level is that doing so provides the parents more discretion in allocating the funds raised by the debt issue. Nevertheless, the fact that some banks issue sub-debt suggests that the cost difference between the two alternatives may not be large.[14]

Although some banks issue sub-debt, virtually no large bank subsidiary has publicly traded stock. We are not aware of any evaluation of why banks do not issue equity, but two related hypotheses are that minority shareholders would supply funds only at a reduced price to reflect the risk that the holding company would divert profits, and the holding company would be concerned that its efforts to exploit synergies may be hindered by minority shareholder law suits.[15] Either effect could discourage issuance at the bank level.

If one shareholder owns a controlling interest in a firm, but less than 100 percent of the equity, the shareholder has an incentive to divert profits to other firms in which he has a larger ownership stake. In a financial holding company this task would be facilitated by the common practice of organizing management structure around customer needs rather than legal charters. This style of organization allows the holding company to maximize the synergy gains from its different subsidiaries, such as by providing wholesale customers with one-stop shopping for deposit, loan, and investment banking products. However, this style also facilitates transfers of profits out of the bank. The holding company may use its allocation of revenue from bundled products, as well as its control over transfer pricing across subsidiaries, to shift profits from the partially owned bank subsidiary to the wholly owned nonbank subsidiaries. Minority shareholders may sue if they perceive that the banking subsidiary's management is not fulfilling its fiduciary responsibilities to all of the shareholders. However, such suits, and the threat of such suits, are likely to raise the cost of co-operation across affiliates.

1.3 Evaluation of alternative risk measures

A combination of accounting variables, equity returns and sub-debt yields are all possible supplements to the capital ratios currently used for PCA. If one's goal is to produce the single best measure of the likelihood of failure then a combination of these variables will almost surely dominate any individual variable. However, if the goal is to find a straightforward risk measure to supplement the capital ratio triggers in PCA in order to deter forbearance then other issues must be considered.

The reason for supplementing the capital triggers in PCA is that supervisors may forbear in forcing banks to recognize losses, with the consequence that the capital measures may be overstated. If the stakes are high enough, banks may also seek to manage other accounting variables, and if the supervisors chose to forbear then banks will not be discouraged from engaging in such management.

A second consideration in deciding on a market measure to augment capital triggers in PCA is the burden placed on banking organizations to generate the measure. The absence of publicly traded equity by bank subsidiaries suggests that the cost of requiring such issues may be significant and theory provides a good reason for believing that the costs would be high. The issuance of sub-debt by some banks and the above discussion suggests that the costs of requiring bank issuance of sub-debt may be significantly less.

Thus, sub-debt yield spreads seem to provide the single best opportunity in the foreseeable future to supplement the capital triggers in PCA. The problem with using accounting measures results from measurement error. Bank initiated, supervisory tolerated financial accounting statement management may create an inherent flaw in the use of these variables for PCA purposes. The problem of having holding companies issue minority shares in their banking subsidiaries results from the potentially high costs. While these issues may turn out to be less of a problem upon closer inspection, any attempt to force such bank issuance until the costs are better understood would seem ill advised.

2. Empirical methodology and data

2.1 Methodology

Our objective in this section is to empirically evaluate whether using market information embedded in sub-debt yield spreads could improve upon current procedures used for prompt corrective action. That is, can debenture spreads outperform the capital ratios that are currently being used to trigger bank supervisory action? Testing this does not require the development of a sophisticated, multivariate statistical model. While these models may add value to the supervisory process, for example, through scheduling examination resources, they may not be all that accurate in forecasting if the determinants of future bank problems differ from those of the past. Additionally, econometric models may be too complex and "black box" in nature to be readily understandable by relevant parties in the bank resolution process: e.g., elected officials, investors, and the courts. More fundamentally, it is not our objective to build a comprehensive failure prediction model, but rather to test the performance of sub-debt relative to the signaling measures *that are currently being utilized* to initiate supervisory action. Thus, as was done for prompt corrective action, our focus is on relatively simple uses of the capital and sub-debt yield spreads. However, even this approach results in a number of complications due mainly to the nature of the data.

One way of comparing the accuracy of the two signals would be to contrast the predictive accuracy of the two measures independently:

$$Risk^{t} = a_1 + b_c\,(\text{capital ratio})^{t-1} + e_c \tag{1}$$

$$Risk^{t} = a_2 + b_y\,(\text{sub-debt signal})^{t-1} + e_y \tag{2}$$

An alternative way to conduct the test is to include both measures as explanatory variables:

$$Risk^{t} = a_3 + g_c\,(\text{capital ratio})^{t-1} + g_y\,(\text{sub-debt signal})^{t-1} + e_{cy} \tag{3}$$

and to test the contribution of each risk signal. We use each approach.

Data complications arise from potential problems with all three variables in the model. Perhaps the most difficult issue is that of determining the accuracy of the risk signal realizing that none of the available risk measures are entirely free from error; even the decision to close an insolvent bank may be partially determined by other factors. As the risk measure used in this study we settle on the composite rating assigned to the debt issuer by its federal supervisor: the composite CAMEL for banks and the composite BOPEC for bank holding companies. The supervisory ratings have the advantage of being issued at relatively high frequency and being based on the most comprehensive public and private data available. Nevertheless, the ratings may contain both random error and systematic biases if supervisory forbearance is reflected in the ratings.

An additional measurement issue, and one that has received rather limited attention in the literature, concerns how best to extract the credit risk signal from sub-debt yields. The most common approach in existing empirical work is to adjust for the time value of money by calculating the spread between the yield on a sub-debt issue and the yield on comparable maturity Treasury obligations. Unfortunately, even if sub-debt yield spreads over Treasuries were the best risk measure during our sample period, they may not be in the future as the supply of Treasury obligations decreases. Therefore, in addition to evaluating the traditional spread over Treasuries, as a test for robustness and to capture any peculiarities associated with non-Government debt issues, we also conduct the analysis using the yield spread over corporate bonds. We consider the bank debenture spreads relative to two categories of corporate bonds: Aaa bonds and, in line with the arguments of Evanoff and Wall (2000a), the lowest investment grade bond category (i.e., Baa).[16]

The obvious choice for the capital adequacy measure is the risk-based capital adequacy ratios. These have the virtue of having been internationally endorsed and currently being used as a measure in the regulations implementing PCA. An additional virtue is that the data for calculating the measure is readily available after 1994 for banks and can be estimated from Call Report Data for earlier years.

Thus, the hypothesis that more accurate credit risk measures may be extracted from sub-debt yields than from capital adequacy ratios is tested by evaluating the relative ability of sub-debt yields and risk-based capital measures to predict supervisory ratings. The form of these tests is dictated in part by the data. Supervisory ratings are most accurate at the end of an examination and existing evidence suggests that their accuracy tends to decline over time.[17] The financial data required to generate bank capital ratios are available on a quarterly basis and sub-debt prices (transactions or estimated) are available on a daily basis, but the daily changes in these prices are unlikely to be dominated by changes in credit risk considerations. Given the timing of the data, the empirical tests use the yield spreads and capital ratios as of the end of a quarter to predict the supervisory rating in the following quarter.

2.2 Data

The data are quarterly observations obtained from 1985 to 1999 from four sources. The sub-debt yield data are from Bloomberg. The yield, when available, is obtained for each of the largest 100 banking organizations using the following process: 1) the largest outstanding bond issuance with pricing information on Bloomberg is identified, 2) that bond is tracked for the remainder of the sample, 3) however, if the initial bond matures during the sample period then data are gathered on a replacement bond issue (the largest alternative outstanding bond at the time the initial bond matures) and 4) data for the replacement bond are substituted for the initial bond starting from the issuance of the replacement bond. Yield data from the initial bond must be replaced with data from the replacement bond when the initial bond matures. However, we use data from the replacement bond starting when that bond is issued to reduce the potential problems associated with obtaining pricing data from the relatively illiquid market of maturing bonds and, hence, reduces the noise in the sub-debt yield spread signal. Indeed, Hancock and Kwast (2001) find that market liquidity is important in determining the information content of sub-debt spreads and that more recently issued bonds tend to be more liquid. When sufficient data are available, Bloomberg reports volume-weighted average transaction prices. When debt is not traded, or is thinly traded, "matrix generated" prices based on price quotes from informed market traders are reported.[18]

Yields on Treasury securities and corporate bonds are obtained from the data files at the Board of Governors of the Federal Reserve System's web site. Two risk measures are obtained from these data. The variable *Sub-debt spread over Treasuries* is calculated as the spread of each sub-debt issue over a comparable maturity Treasury security. Treasury yields are linear interpolations of the term structure across 3 month, 6 month, 1 year, 2 year, 3 year, 5 year, 7 year, 10 year and 30 year securities. The variable *Baa less Aaa yield* is the difference between the yield on Moody's Baa bond index and the Aaa bond index. The Moody's bond yield indices contain bonds of a variety of maturity. The variable *Baa less Aaa yield* may provide a measure of market illiquidity if during illiquid periods demand for higher quality bonds increases relative to the demand for lower quality bonds.[19]

The two other yield-spread variables are the spread of bank bonds over roughly maturity-matched corporate bonds rated either Aaa or Baa. Yield indices for Aaa and Baa bonds of various maturities (1-5 years, 5-10 years, and 10 years or more) are constructed from the universe of banks in the Warga-Lehman Brothers Fixed Income Database, for the years 1990 and later.[20] Then the spreads, *Sub-debt spread over Aaa maturity-matched bonds* or *Sub-debt spread over Baa maturity-matched bonds*, are calculated by subtracting the maturity-matched corporate yield from the sub-debt yield.

The capital adequacy ratios are calculated from information on the Report of Condition data (Call Reports) filed by banks and Y-9 data filed by consolidated bank holding companies. The Call Reports did not provide the information required to precisely calculate the banks' risk weighted exposure under the risk-based capital requirements until 1994. Thus, we estimated the risk-weighted exposure using items available in the Call Reports over the earlier period. Four capital adequacy measures are generated: 1) *Total risk based capital ratio*, 2) *Tier 1 Leverage Ratio*, 3*) Tier 1 capital to risk-weighted exposure*, and 4) *PCA capital adequacy status*. The *PCA capital adequacy status* measure takes values from 1 to 5 depending on whether the bank is considered Well Capitalized, Adequately Capitalized, Under Capitalized, Significantly Undercapitalized or Critically Undercapitalized, respectively, under the PCA guidelines. This measure is of particular interest since it is the measure currently being used to trigger PCA.

The supervisory ratings are the composite CAMEL(S) rating for banks or the composite BOPEC rating for bank holding companies obtained from confidential Supervision Department data. Although most of our sample are holding companies (about 70% of firm-quarter observations) we use the more familiar term *CAMEL* as the variable name for the supervisory rating.

The full sample consists of 452 supervisory ratings assigned to banking organizations with outstanding subordinated debt issues. The full sample contains complete information for all variables except *Sub-debt spread over Aaa maturity-matched bonds* and *Sub-debt spread over Baa maturity-matched bonds*, which were not available prior to 1991 or after mid-year 1998. We also evaluate an alternative basis for the debt spread, using a subsample of 321 observations containing the bond spreads over Aaa and Baa indices. The number of banks rated 3 or lower falls from 13 in the full sample to 8 in the restricted sample.

3. Empirical findings

An important preliminary question is the extent to which the various risk measures convey different information. Table 1 provides Spearman rank order correlation coefficients in the upper triangle and Pearson correlation coefficients in the lower triangle to contrast, in a rather general and straightforward manner, the relationship between the *CAMEL*, debt spread, and various capital adequacy measures.

Using the Pearson correlations, as expected, the various capital adequacy ratios are closely associated with each other; the only exception being the *Total risk based capital ratio* and *PCA capital adequacy status*. However, given that both the *CAMEL* and *PCA capital adequacy status* variables are ordinal measures, the more relevant correlations are the Spearman rank order correlations that do not assume the variables are cardinal measures. The *PCA capital adequacy status* is still significantly correlated with both of the Tier 1 measures, but is still not closely associated with the *Total risk based capital ratio*. Apparently the Tier-1 equity capital requirement was generally more binding on the banks that issued sub-debt than was the total capital requirement. Spearman correlations with the bank risk measure (*CAMEL*) are somewhat mixed. *CAMEL* is significantly correlated with the *Sub-*

debt spread over Treasuries, Tier 1 capital to risk-weighted exposure, and the Tier *1 Leverage Ratio,* but not with the *Total risk based capital ratio* or the *PCA capital adequacy status*.

Table 2 provides Spearman rank correlations for the various yield spreads used in the analysis. This includes sub-debt spreads over maturity-matched Treasuries as well as spreads over both maturity-matched and non-maturity-matched corporate bonds. Most of the spread measures are significantly correlated with each other although there are substantial differences in their association with the *CAMEL* measure. Somewhat surprisingly, with one exception, the *Sub-debt spread over Treasuries* is not significantly correlated with the capital measures using either correlation measure. Thus, generally, sub-debt spreads appear to contain different information.

Although the correlations provide some interesting insights, we may obtain more information using a binomial or multinomial choice model. For this purpose we estimate ordered logit models, thus assuming the cumulative distribution function to be logistic.[21] The first subsection below presents the logit analysis for a binomial choice model based on supervisors categorizing banks as either problem banks (*CAMEL* = 3, 4 or 5) or high-rated banks (*CAMEL* = 1 or 2). The second section summarizes results from multinomial choice models using the full range of *CAMEL* ratings. Within each section we present results based on both the full sample with all of our observations and the more restricted sample that contains only observations for which we have spreads over maturity-matched Aaa and Baa indices.

3.1 The binomial choice model: the full sample

While using the full range of *CAMEL* values has the virtue of exploiting all of the information in the data, it also has an important disadvantage in evaluating alternative risk signals for use in triggering supervisory discipline. The overwhelming majority of the banking organizations in our sample, 439 of 452 organizations, were rated 1 or 2 by the supervisory authorities. Thus, the estimation results from using a model to estimate the full range of *CAMEL* values is necessarily going to place great weight on separating the 1 and 2 rated banks. However, the supervisors rarely discipline banks rated 1 or 2, and seldom distinguish between them over safety and soundness concerns. Thus, in this part of our analysis, banking organizations rated 1 or 2 are combined into a single, "high-rated" category to focus on the relative ability of the sub-debt spread and various capital measures to predict banks that should be disciplined. The appropriate form of supervisory discipline is likely to be more severe as the rating falls from 3 to 4 and from 4 to 5. Thus, ideally we would like to retain the 3, 4 and 5 ratings as separate categories. However, given the small number of banks rated 3 and 4, and the absence of 5 rated banks in our sample, we combine the 3 and 4 rated banks into a single "low-rated" category. Thus, if all the regulators are interested in is categorizing banks into two broad groups instead of the finer breakdown, this analysis will capture the potential of the predictive power of alternative explanatory variables within that framework. To test this power we run a number of simple models with each of our predictive variables.

The results from the binomial models are presented in Table 3. Single variable models are presented in the first five columns where *CAMEL* ratings are related to the predicting variable values in the previous period. For example, in column 5 of Table 3 the sub-debt yield at the end of the previous quarter, *Sub-debt spread over Treasuries*, is shown to be positively related to the *CAMEL* rating, and the associated p-value indicates that the parameter estimate is highly significant. Similarly, the criteria for assessing the fit of the model, the Chi-square for covariates and the associated p-value indicates that significant information is being added by inclusion of the spread.

The results are not as good for the single variable models using the current prompt corrective action categories, *PCA capital adequacy status*, or alternative measures of capital adequacy (columns

1-4). While *PCA* c*apital adequacy status* comes in significant at the 10% level in Table 3, the model fit criteria (Chi-square for covariates) indicates that inclusion of this variable adds to the fit of an intercept-only model only at the 10% level of significance. In fact, at the 5% level of significance, the only capital variable in Table 3 that performs statistically significantly better than the intercept-only model is the *Tier 1 Leverage Ratio*.[22] Table 3 also presents evidence on the impact of including alternative capital measures along with the sub-debt spread (columns 6-9).[23] The results suggest that with the possible exception of the *Tier 1 Leverage Ratio*, little additional information is being added by including the alternative capital ratios. Although *PCA capital adequacy status* is significant at the 10% level, it appears to add little predictive power.[24] This weak performance suggests that *PCA capital adequacy status* is not very effective in signaling troubled banks prior to intervention by the supervisors.

At the bottom of each column in the tables is a measure of the correlation between the observed and predicted probabilities of the dependent variable. This correlation index is based on the number of concordant, discordant and tied pairs. Concordance is calculated by first taking all pairs of observations with different rankings. In Table 3, for example, these pairs would consist of each of the high-rated banks (ratings of 1 or 2) being paired with each of the low-rated banks (ratings of 3 or 4). A predicted event probability is then obtained for both observations, say the probability of being low-rated. If the observation that has a low rating has a sufficiently higher probability of being rated as such then the rankings are concordant. If the high-rated bank observation has a higher probability of being low-rated then the observations are discordant. If the probabilities of the low- and high-rated banks are sufficiently close then the pair is categorized as a tie.[25] A summary correlation index, the Goodman-Kruskal Gamma index, is also included for use in making comparisons across models. Generally, the index approaches one as the number of discordant observations goes to zero, and zero as the number of concordant and discordant observations becomes equal.[26]

Of the single variable models presented in Table 3, the one using sub-debt spreads has the highest concordance; and once again the Tier-1 leverage measure is the best performing of the capital measures. Although the "percentage correct" is high for *PCA capital adequacy status*, the high level of "tied" observations suggests the model is not very confident of its assignment of individual observations and the low percentage of correct 3-4 classifications suggests the model is doing very poorly in identifying problem banks. Values for the Gamma index also indicate that the sub-debt spread model is superior to those using alternative capital measures. While the Gamma value is relatively high for the *PCA capital adequacy status* model, the measure is somewhat misleading as it is calculated ignoring the "tied" observations which constitute the bulk of the observations. With the possible exception of the single variable *Tier-1 leverage* model, the rather low concordance found using the alternative capital measures raise concerns about their usefulness to foresee future problem banks.

The logistic models also correctly identify over one-half of the low-rated banks in all of the models that include *Sub-debt spread over Treasuries*. But even in these models there is still a large fraction of banks being misclassified. More problematic, with the possible exception of Tier-1 leverage measure, the models with single variable capital measures do a relatively poor job of capturing the low-rated banks. However this raises an interesting point in deciding how to weight the classification errors. We have estimated the relationship between the alternative risk measures and the *CAMEL* ratings and used those estimates to predict the probability of a bank receiving a certain rating. If one wanted to decrease a particular type of prediction error, for example, supervisors may be more concerned about 'missing' troubled banks, then they could alter the critical probability value to capture more of the targeted firms. There is an obvious tradeoff, however, in that more of the alternative misclassifications would occur. As we stated earlier, our purpose is not to develop a comprehensive bank failure model, but rather to compare the relative predictive power of sub-debt versus capital adequacy models using the same predictive criteria. Based on these criteria, the sub-debt-based models seem to dominate most of the capital-based models; particularly the *PCA capital adequacy status* measure actually being used today.

3.2 The binomial choice model: the restricted sample with spreads over corporate bond yields

Using the restricted data set permits the analysis to be extended to look at spreads over Aaa and Baa bonds of roughly comparable maturity. A basic finding from the results presented in Table 4 is that based on measures of concordance or the ability to predict poor-rated banks the *Sub-debt spread over Baa maturity-matched bonds* is a slightly better predictor of bank risk than is the corresponding spread over Aaa bonds.[27] Therefore, in the discussion that follows we emphasize the results found using the spread over the Baa bond. As with the larger sample and the more traditional yield spreads discussed above, the *Sub-debt spread over Baa maturity-matched bonds* is also significant in explaining risk differences and when used as a single variable model correctly predicts bank risk in a manner similar, or perhaps slightly superior, to that found using alternative debt spreads. However, the results in the second column show that *Baa less Aaa yield* (the difference between the yield on Baa and Aaa rated debt) enters statistically significantly and improves the predictive accuracy of the model—albeit, not the ability to predict problem banks. The statistically significant positive coefficient on this variable suggests a higher probability of banks being down-rated when overall market risk is high. The results from combining the capital adequacy variables with the debt spreads are consistent with those obtained using the spreads over Treasuries; i.e., only the *Tier 1 Leverage Ratio* is statistically significant when included as an explanatory variable with *Sub-debt spread over Baa maturity-matched bonds*. Moreover, the combination of the *Sub-debt spread over Baa maturity-matched bonds* and *Baa less Aaa yield* appears to be substantially better than the combination of *Sub-debt spread over Baa maturity-matched bonds* and the *Tier 1 Leverage Ratio* in terms of the Gamma measure.

3.3 Tests for robustness

We have tried to keep the specifications relatively simple, since the current procedure used to initiate supervisory action is tied to a relatively simple model. However, concerns about data quality lead us to conduct a number of robustness checks with alternative subsamples and yield spreads. Since the "CAMEL" data can be obtained from either the bank or the holding company, depending on where the debt is issued, we account for potential systematic differences by including a binary variable to account for this difference. The coefficient was not significantly different from zero in any of the auxiliary runs and none of the basic results reported above were affected by the inclusion of this variable. Additionally, to see if market disruptions may affect the analysis we allowed for varying effects through time by introducing fixed time effects. The fixed effects have relatively little impact on the findings. Across the various specifications, the time effects are insignificant for most years except for 1992 when the results indicate that ratings are systematically higher. None of the other variables or the basic results of the analysis are significantly affected by the inclusion of these time variables. We also generated estimates excluding matrix-generated prices; a price generating practice somewhat common for certain infrequently traded issues. Again, the basic findings were not affected. Finally, we reestimated the models for which the results are presented in Table 4 using spreads based on non-maturity-adjusted corporate bond yields (i.e., *Sub-debt spread over Baa non-maturity-matched bonds* and *Sub-debt spread over Aaa non-maturity-matched bonds*). This basis for calculating the spread is generally thought to be inferior to the maturity-adjusted measure and could perhaps result in relatively large random error in the estimated spreads. However, this is one additional piece of information that we evaluate to see if we find significant differences in the estimates. While the estimates obviously differed for the non-maturity-adjusted yield spreads, the basic findings remained unchanged. Thus, the findings discussed above are relatively robust to changes in model specification.

3.4 The multinomial choice model

We next report, in more summary fashion, the findings based on the full range of *CAMEL* ratings. That is, we estimate ordered logit models based on all the *CAMEL* ratings instead of just the "good-bank" and "problem-bank" categories. Based on this ordering we again run a number of relatively simple models to evaluate the marginal impact of debt spreads relative to that of the alternative capital adequacy measures. These results are presented in Table 5 and are summarized below.

Generally the results are similar and sometimes stronger for the full set of *CAMEL* ratings. The variable *PCA capital adequacy status* is insignificant, but the other three capital adequacy measures are statistically significant. The debt spread, *Sub-debt spread over Treasuries*, always enters significantly whether in a single variable model or in conjunction with the other explanatory variables, whereas the single variable models using the alternative capital adequacy measures typically perform less satisfactorily. What is most revealing from the single variable results is the poor performance of the capital adequacy measure used for triggering prompt corrective action (column 6). Not only do the criteria for measuring model fit indicate that the measure adds very little to an intercept-only model, but the concordance measure indicates that the model was essentially unable to distinguish between banks in the various risk ratings. However, while the single variable models for the alternative capital ratios (columns 7-9) do not fit the data as well as does the sub-debt spread, each variable is significant in explaining variations in the bank risk measure.

When the alternative capital ratios are used as additional explanatory variables along with the sub-debt spread they add relatively little to the predictive power of the model (columns 2-5). However, again, the most glaring result from the analysis is the relatively poor performance of the capital adequacy measure presently used to trigger prompt corrective action.

Finally, using the restricted data set permits analysis of the more detailed *CAMEL* ratings to be extended to look at spreads over Aaa and Baa bonds of roughly comparable maturity. The logit results from this analysis are not presented in the tables but may be summarized as follows. As with the binomial logit results, the spread over Baa rated bonds again produces more accurate predictions than does the spread over Aaa rated bonds. The logit results also show that the variable *Baa less Aaa yield* is statistically significant in models with *Sub-debt spread over Aaa maturity-matched bonds* and in models with *Sub-debt spread over Baa maturity-matched bonds*. The capital adequacy variables, except *PCA capital adequacy status*, did about as well as the combination of the *Sub-debt spread over Baa maturity-matched bonds* and *Baa less Aaa yield* in terms of statistical significance and predictive accuracy. *PCA capital adequacy status* was statistically insignificant with very low predictive accuracy

4. Conclusion

As banking organizations have become more complex, greater reliance on market discipline has become attractive to many policy analysts. Although additional market discipline could be obtained in a variety of ways, increased reliance on subordinated debt has attracted considerable interest because sub-debt is widely perceived to be outside the federal safety net. This paper focuses on one way in which sub-debt may help generate increased discipline: using risk measures obtained from sub-debt pricing to trigger supervisory action. In particular, the PCA provisions of the FDIC Improvement Act of 1991 already use bank capital adequacy ratios to trigger supervisory action, and some recent proposals recommend that sub-debt yields also be used as triggers for PCA. This paper provides an empirical evaluation of the absolute and relative accuracy of the risk measures derived from capital adequacy ratios and sub-debt prices.

There is no error free measure of the true riskiness of a banking organization. The measure used in this study is the examiners' overall rating of each banking organization's financial condition; termed the BOPEC rating for bank holding companies and the CAMEL rating for banks. The tests evaluate the ability of four capital adequacy measures and sub-debt yield spreads at the end of a quarter to predict the rating that will be assigned by the examiners in the following quarter. The purpose in predicting supervisory ratings using lagged capital adequacy ratios and sub-debt yields spreads is to reduce the extent to which the capital and sub-debt measures are merely reflecting the findings of the bank examiners.

The results suggest that sub-debt yield spreads do as well or better at predicting supervisory ratings than any of the capitalization ratios. This result satisfies an important pre-requisite for using sub-debt as a PCA trigger. In part, this result is obtained because most of the capital measures, including the risk-based measures, were poor predictors of future supervisory ratings. Indeed, the results suggest the surprising result that a bank's capital adequacy status under PCA in one quarter is virtually uncorrelated with the examination rating that the bank will receive the next quarter.

Sub-debt yield spreads are not significantly better than one of the capitalization ratios, the Tier-1 leverage ratio. However, when the bank examination ratings are divided into two categories, high-rated and low-rated banks, both of these risk measures misclassify a large fraction of the observations. Whether the current proposal to improve the capital adequacy measures--the Basel Committee on Bank Supervision internal models proposal for risk measurement--would result in a significant improvement in practice almost surely cannot be evaluated using these tests for many years to come.[28] Moreover, Evanoff and Wall (2000b) argue that the Basel proposals may create an incentive for banks to systematically underestimate their risk exposure. On the other hand, practical opportunities may exist for improved measures of sub-debt yield spreads both now and in the future. One direction for improving upon a potential sub-debt risk measure would be to better match sub-debt issues with corporate bond indices of comparable maturity, e.g., calculating a yield spread using a sub-debt issue with seven years to maturity and a portfolio of Baa corporate bonds with seven years until maturity. Another direction, as suggested by Hancock and Kwast (2001) would be to collect improved measures of sub-debt prices and yields. This may be done in part, as they show, by judicious choice of bonds and data sources. Finally, it may also be the case that *if* a sub-debt proposal is adopted then changes in the marketplace will lead to better pricing. More regular and possibly more frequent issues might lead to greater market depth. Moreover, the increased supervisory attention to sub-debt yields may lead to greater transparency of transaction prices.

Endnotes

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[1] The prompt corrective provisions are in Section 131 of the Federal Deposit Insurance Corporation Improvement Act of 1991 and they are codified at 12 U.S.C. 1831o. The federal bank regulatory agencies have each adopted regulations to implement PCA. For example, the Federal Reserve's implementation may be found at 12 C.F.R. 208.40-45. PCA is based on an earlier proposal called structured early intervention and resolution (SEIR) by Benston and Kaufman (1988).

[2] White (1997) advocates the use of market value accounting (MVA) as the solution to the problems of using GAAP. While MVA may reduce some of the problems, it may only exacerbate others. For example, MVA would make the measurement of capital even more dependent on the judgement of bankers that do not want to be disciplined, and on supervisors that may be hesitant to impose discipline.

[3] Kane (1985, chapter 4) documents the extent of the mismeasurment of changes in asset values due to interest rate movements in the thrift industry over the 1970s and early 1980s.

[4] A variety of recent papers have discussed the potential for increased reliance on sub-debt to discipline banks including Benink and Schmidt (2000), Calomiris (1997, 1998), Ferguson (1999), Kwast et al. (1999), Meyer (1999), and Moskow (1998). The use of sub-debt yield spreads as a trigger for PCA is endorsed by the U. S. Shadow Financial Regulatory Committee (2000). Evanoff and Wall (2000a, 2000c) provide a specific proposal on how the signals from sub-debt markets may be used as supplements to the existing capital ratios used in PCA.

[5] Indeed, Benston and Kaufman (1998) find that losses have been imposed.

[6] One example in which examination findings may become known is in cases where the supervisors delay assigning a *CAMEL* rating if they find problems. However, to the extent this exists, it most likely results in a bias toward finding a relationship between risk and the capital measures. This results because as the supervisors 'work' with the problem bank they most likely require adjustments to loan loss allocations, to asset valuations and to the resulting capital ratios. When the rating is assigned, it comes after the adjustments when the capital measure should more accurately reflect the true condition of the bank. Similarly, to the extent that the financial data have been revised there exists a potential bias in favor of the capital ratios. The financial accounting reports filed with the bank supervisors are revised after the initial filing if deficiencies are found in the original data. Gunther and Moore (2000) evaluate the impact of changes in reported accounting information on the accuracy of models designed to provide an early warning of impending problems at the bank. They find that the use of revised data does significantly improve the predictive ability of these early warning models. We are also employing the most up-to-date data available, including revisions.

[7] Going concern value is the value of the bank's assets net of its liabilities in the hands of its existing managers. This value may be reduce if the bank is resolved by the FDIC because of the direct costs of resolution and any discount in the price paid by an acquirer.

[8] Moreover, it is possible to compare the relative ability of capital adequacy ratios and yield spreads to predict a subset of exam ratings that may not be biased by forbearance. Examiners assign banks to one of five categories, numbered 1 through 5. Banks that are rated 1 or 2 are highly unlikely to be subject to supervisory discipline for safety and soundness reasons, whereas banks rated 3, 4 or 5 will almost surely be subject to discipline, with the disciplinary measures increasing in severity as the numeric exam rating increases. Thus, forbearance is most likely to be associated with a biased examination rating if a bank should have been rated 3, 4 or 5. Supervisors have far less incentive to assign a "1" rating to a bank that should have been rated a "2." Thus, the tests of the relative ability of yield spreads and capital adequacy to predict banks that should be disciplined are supplemented by tests of their relative ability to discriminate between banks rated "1" and those rated "2".

[9] See Pettway and Sinkey (1980) for an example of the use of equity returns to identify banks that are likely to fail. While the vast event study literature in finance suggests that equity is a sensitive indicator of changes in the expected value of returns, how accurately the variability of the bank returns can be extracted from options on its equity has received less attention.

[10] For example, see the analysis of Cole and Gunther (1998) in predicting bank failures and that of Shumway (2001) for predicting the failure of nonfinancial firms.

[11] Gilbert, Meyer, and Vaughan (1999) make this point in the context of using econometric models to identify agricultural banks (which are almost all small banks) at risk of failure in the 1980s.

[12] Jones (2000) suggests that banks are manipulating their risk as measured under the 1988 Basel Supervisors Accord. The analysis of Gunther and Moore (2000) suggests that banks may already manage a variety of other variables to obscure potential problems.

[13] This is not to suggest that the supervisors should not be willing to impose any costs on banks. By definition, binding regulation imposes costs on banks and bank supervisors already impose a large number of binding regulations on banks.

[14] Moreover, the recent trend may be towards more issuance of sub-debt by banks. Jagtiani, Kaufman and Lemieux (2001) examine sub-debt issued by the 100 largest banks and their bank holding company (BHC) parents in 1997. They report that "the few bank bonds issued prior to 1992 had matured by 1997." However, after applying all of their sample selection criteria they found 19 banks and 39 BHCs had qualifying sub-debt issues. Thus, while more banking organizations issue debt through the BHC, a substantial number also issue sub-debt through their bank subsidiaries.

[15] The issuance of subsidiary shares with control rights in equity carve-outs is examined in a series of studies; see for example Allen and McConnell (1998). Similarly the issuance of shares that are intended to track the performance of a subsidiary without granting control rights is examined by several papers including D'Souza and Jacob (2000) and Billett and Vijh (2000). Studies in both literatures find

statistically significant abnormal returns for the parent's stock upon the announcement of a carve-out or issuance of tracking stock. However, these literatures focus on firms that voluntarily choose to engage in such transactions, presumably because such transactions were expected to produce benefits for the managers and/or shareholders of the parent. Thus, any favorable results of these studies may not extend to a regulatory policy of forcing bank holding companies to engage in carve-outs or to issue tracking stock. That significant costs may arise from such transactions may be inferred from the relatively small number of firms that engage in carve-outs and that issue tracking stock. Moreover, some of the firms that engage in such transactions subsequently revert back to a simpler structure by either divesting the subsidiary or buying out the shareholders in the subsidiary. Klein, Rosenfeld and Beranek (1991) examine firms that undo carve-outs by either repurchasing the stock or selling the subsidiaries. Billett and Vijh (2000) report that three of the firms in their universe of 28 tracking stocks had undone or were reported to be in the process of undoing their tracking stock.

[16] Critics of sub-debt proposals have argued that such programs will be procyclical in that they will restrict bank behavior during economic slowdowns [see Kwast et al. (1999) Appendix D]. Evanoff and Wall (2000a) argue that utilizing spreads over corporate bonds may partially address this "problem" although, by its very nature, any form of regulation can be expected to be somewhat procyclical.

[17] See Cole and Gunther (1998) and Berger, Davies and Flannery (2000).

[18] Prices are weighted averages based on a minimum of two price sources and they must be within an "acceptable" tight range.

[19] Kwast et al. (1999) report statements from market participants that the sub-debt market became highly illiquid in the wake of the East Asia financial crisis, Russian bond default and failure of Long Term Capital Management in late 1998. In part based on this concern, Evanoff and Wall (2000c) provide for the suspension of using sub-debt yields if the market becomes sufficiently illiquid.

[20] The data are indices created for Bliss and Flannery (2001), and kindly provided, by Robert Bliss and Mark Flannery.

[21] Similar findings were generated using an ordered probit model.

[22] The superior performance of Tier-1 leverage, relative to alternative capital measures, was also found in Estrella, Park and Peristiani (2000).

[23] This is similar to the methodology of Smirlock, Gilligan, and Marshall (1984) and Smirlock (1985).

[24] This statement is based on changes in the Gamma measure going from the single variable model using the sub-debt spread to the two variable model including the PCA capital adequacy measure. We also note that it is not the measure of association between the actual and predicted values that is being

optimized (the Gamma measure) as seen in the decrease in the Gamma value as some of the capital adequacy measures are added to the single variable spread models.

[25] To classify observations as ties the SAS Logistic routine uses probability buckets of length 0.002. A similar procedure is followed below when the observations are split into more than two risk categories. The procedure is still valid for two reasons. First, the dependent variable is an ordered variable; a higher rating implies a riskier bank. Second, the logistic regression estimates a single set of coefficients for each of the categories, with only the intercept coefficient varying across the categories.

[26] If nc is the number of concordant pairs and nd the number discordant pairs then the Goodman-Kruskal Gamma = $(nc-nd) / (nc+nd)$. See Goodman and Kruskal (1972).

[27] The predictive powers using this spread, however, does not seem to be significantly greater than those found using the more traditional spread over similar maturity Treasuries for the same sample. We also conducted similar analysis using the PCA capital adequacy status measure. The results were similar to those found using the larger sample with the *PCA capital adequacy measure* typically being less significant than before.

[28] The latest work of the Basel Committee on Banking Supervision may be found at the Bank for International Settlements (BIS) publications web page: http://www.bis.org/publ/index.htm.

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Table 1: Simple correlation coefficients for risk measures, debt spreads and capital measures

Upper triangle: Spearman rank correlation coefficients (in italics)
Lower triangle: Pearson correlation coefficients

	CAMEL rating	Sub-debt spread over Treasuries	Total risk based capital ratio	Tier 1 leverage ratio	Tier 1 capital to risk-weighted exposure	PCA capital adequacy status
CAMEL rating	1.00000 (0.0)	*0.24425* (*0.0001*)	*-0.07205* (*0.1216*)	*-0.18704* (*0.0001*)	*-0.18071* (*0.0001*)	*0.02752* (*0.5595*)
Sub-debt spread over Treasuries	0.23468 (0.0001)	1.00000 (0.0)	*-0.09616* (*0.0410*)	*-0.05855* (*0.2141*)	*-0.06355* (*0.1774*)	*-0.00260* (*0.9560*)
Total risk based capital ratio	-0.10798 (0.0217)	-0.03511 (0.4565)	1.00000 (0.0)	*0.33874* (*0.0001*)	*0.79073* (*0.0001*)	*-0.03941* (*0.4032*)
Tier 1 leverage ratio	-0.18085 (0.0001)	-0.05159 (0.2737)	0.16782 (0.0003)	1.00000 (0.0)	*0.44107* (*0.0001*)	*-0.31793* (*0.0001*)
Tier 1 capital to risk-weighted exposure	-0.18659 (0.0001)	-0.02788 (0.5544)	0.79455 (0.0001)	0.43523 (0.0001)	1.00000 (0.0)	*-0.09612* (*0.0411*)
PCA capital adequacy status	0.05528 (0.2408)	0.00008 (0.9987)	-0.03647 (0.4393)	-0.41675 (0.0001)	-0.12158 (0.0097)	1.00000 (0.0)

The significance probability of the correlation is provided in parentheses beneath the coefficients.
Number of observations = 452

Table 2: Spearman rank correlation coefficients for alternative debt yield spreads

	CAMEL rating	Sub-debt spread over Treasuries	Sub-debt spread over Baa maturity-matched bonds	Sub-debt spread over Aaa maturity-matched bonds	Sub-debt spread over Baa non-maturity-matched bonds	Sub-debt spread over Aaa non-maturity-matched bonds
CAMEL rating	1.00000 (0.0)	0.38625 (0.0001)	0.22675 (0.0001)	0.14890 (0.0075)	0.06101 (0.2758)	0.10893 (0.0512)
Sub-debt spread over Treasuries		1.00000 (0.0)	0.18492 (0.0009)	0.30346 (0.0001)	0.45425 (0.0001)	0.54412 (0.0001)
Sub-debt spread over Baa maturity-matched bonds			1.00000 (0.0)	0.58027 (0.0001)	-0.05867 (0.2947)	-0.04777 (0.3937)
Sub-debt spread over Aaa maturity-matched bonds				1.00000 (0.0)	0.42259 (0.0001)	0.47618 (0.0001)
Sub-debt spread over Baa non-maturity-matched bonds					1.00000 (0.0)	0.96330 (0.0001)
Sub-debt spread over Aaa N*on*-maturity-matched bonds						1.00000 (0.0)

The significance probability of the correlation is provided in parentheses beneath the coefficients.
Number of observations = 321.

Table 3: Binomial model predicting CAMEL ratings as a function of capital ratios and debenture spreads over the Treasury rate

Variable	Parameter Estimate (1)	Parameter Estimate (2)	Parameter Estimate (3)	Parameter Estimate (4)	Parameter Estimate (5)	Parameter Estimate (6)	Parameter Estimate (7)	Parameter Estimate (8)	Parameter Estimate (9)
Intercept	-5.2195 (0.0001)	-3.0839 (0.1008)	1.2028 (0.5061)	-1.3070 (0.4499)	-4.5877 (0.0001)	-6.3409 (0.0001)	-4.2802 (0.0268)	-0.0959 (0.9611)	-2.4323 (0.1641)
Sub-debt spread over Treasuries					1.1047 (0.0038)	1.1159 (0.0035)	1.1032 (0.0039)	1.0205 (0.0088)	1.1135 (0.0039)
PCA capital adequacy status	1.5700 (0.0525)					1.6056 (0.0519)			
Total risk based capital ratio		-0.0352 (0.8155)					-0.0247 (0.8695)		
Tier 1 leverage ratio			-0.7052 (0.0119)					-0.6876 (0.0198)	
Tier 1 capital to risk-weighted exposure				-0.2622 (0.2083)					-0.2570 (0.2127)
Association of Predicted Probabilities and Observed Responses									
Concordant	14.8%	43.2%	65.9%	54.8%	76.8%	77.9%	74.9%	75.0%	73.4%
Discordant	3.1%	35.4%	30.8%	40.3%	19.0%	17.9%	20.3%	22.5%	23.1%
Tied	82.1%	21.4%	3.3%	4.9%	4.2%	4.2%	4.8%	2.5%	3.5%
Gamma	0.656	0.099	0.363	0.152	0.604	0.625	0.574	0.539	0.521
% Correct	94.0%	23.2%	55.3%	38.9%	58.0%	70.1%	59.1%	63.3%	58.2%
% 3 - 4 Correct	15.4%	0%	69.2%	53.8%	69.2%	69.2%	61.5%	76.9%	61.5%
% 1 - 2 Correct	96.4%	23.9%	54.9%	38.5%	57.6%	70.2%	59.0%	62.9%	58.1%
Chi-square for covariates (p - value)	2.259 (0.0967)	0.058 (0.8098)	6.402 (0.0114)	1.797 (0.1801)	6.475 (0.0109)	9.283 (0.0096)	6.504 (0.0387)	12.049 (0.0024)	8.198 (0.0166)

The dependent variable takes a value of 0 for CAMEL (or BOPEC) ratings 1 and 2, and a value of 1 for ratings 3 and higher. The PCA capital adequacy status ranges from 1 for the best capitalized banks (well capitalized) to 5 for the least well capitalized (critically undercapitalized). The *p*-values for the maximum likelihood parameter estimates are in parentheses below the coefficients. The "Chi-square for covariates" statistic is based on the log likelihood statistic, and tests the marginal explanatory power of the independent variables relative to a model with only a constant term. The associated p-values are included in parentheses.

Concordance is a measure of the correlation between the observed and predicted probabilities of the dependent variable. A pair of observations is said to be concordant if, based on the model, the observation that has a particular rating has a sufficiently higher probability of receiving that rating than does the other observation. A pair is discordant if the reverse is true. A pair is tied if the probability interval between the two observations is sufficiently small, 0.002. A correlation index, the Goodman-Kruskal Gamma index, is also included for assessing the predictive power of the model and for making comparisons across models. If *nc* is the number of concordant pairs and *nd* the number of discordant pairs, then the Goodman-Kruskal Gamma = (*nc* - *nd*) / (*nc* + *nd*). See Goodman and Kruskal (1972). Generally, the index approaches zero as independence between the two measures increases. Number of observations = 452.

Table 4: Binomial model predicting bifurcated CAMEL ratings as a function of capital ratios and debenture spreads over Baa and Aaa bond indices

Variable	Parameter Estimate (1)	Parameter Estimate (2)	Parameter Estimate (3)	Parameter Estimate (4)	Parameter Estimate (5)	Parameter Estimate (6)	Parameter Estimate (7)	Parameter Estimate (8)	Parameter Estimate (9)	Parameter Estimate (10)
Intercept	-3.9322 (0.0001)	-8.9797 (0.0001)	-3.4383 (0.0602)	2.6748 (0.2626)	-1.8384 (0.3854)	-4.0496 (0.0001)	-6.4383 (0.0001)	-4.3577 (0.0460)	2.0470 (0.3857)	-1.6701 (0.4461)
Sub-debt spread over Baa maturity-matched bonds	1.7941 (0.0343)	1.9189 (0.0097)	1.8077 (0.0330)	1.7573 (0.0413)	1.7792 (0.0367)					
Sub-debt spread over Aaa maturity-matched bonds						1.0045 (0.0476)	0.3293 (0.6047)	1.0067 (0.0471)	0.8125 (0.1063)	1.0395 (0.0433)
Baa less Aaa yield		6.9990 (0.0015)					3.7040 (0.0639)			
Total risk based capital ratio			0.0554 (0.7694)					0.0241 (0.8848)		
Tier 1 leverage ratio				-1.0069 (0.0087)					-0.9200 (0.0142)	
Tier 1 capital to risk-weighted exposure					-0.2434 (0.3265)					-0.2792 (0.2843)
					Association of Predicted Probabilities and Observed Responses					
Concordant	73.3%	88.9%	74.3%	80.2%	63.8%	58.9%	84.0%	58.2%	76.6%	61.0%
Discordant	24.0%	10.2%	23.5%	17.7%	31.9%	36.1%	12.3%	36.5%	21.3%	35.1%
Tied	2.8%	1.0%	2.2%	2.0%	4.3%	4.9%	3.7%	5.3%	2.1%	3.9%
Gamma	0.507	0.794	0.519	0.638	0.332	0.240	0.745	0.229	0.564	0.270
% Correct	64.8%	78.2%	64.8%	72.9%	66.4%	66.7%	84.1%	66.7%	69.5%	63.6%
% 3 - 4 Correct	75.0%	62.5%	62.5%	62.5%	50.0%	37.5%	50.0%	25.0%	50.0%	37.5%
% 1 - 2 Correct	64.5%	78.6%	64.9%	73.2%	66.8%	67.4%	85.0%	67.7%	70.0%	64.2%
Chi-square for covariates (p - value)	4.083 (0.0433)	12.818 (0.0016)	4.164 (0.1247)	11.529 (0.0031)	5.122 (0.0772)	3.088 (0.0789)	5.921 (0.0518)	3.108 (0.2114)	9.408 (0.0091)	4.343 (0.1140)

The dependent variable takes a value of 0 for CAMEL (or BOPEC) ratings 1 and 2, and a value of 1 for ratings 3 and higher. The *p*-values for the maximum likelihood parameter estimates are in parentheses below the coefficients. The "Chi-square for covariates" statistic is based on the log likelihood statistic, and tests the marginal explanatory power of the independent variables relative to a model with only a constant term. The associated p-values are included in parentheses.

Concordance is a measure of the correlation between the observed and predicted probabilities of the dependent variable. A pair of observations is said to be concordant if, based on the model, the observation that has a particular rating has a sufficiently higher probability of receiving that rating than does the other observation. A pair is discordant if the reverse is true. A pair is tied if the probability interval between the two observations is sufficiently small, 0.002. A correlation index, the Goodman-Kruskal Gamma index, is also included for assessing the predictive power of the model and for making comparisons across models. If *nc* is the number of concordant pairs and *nd* the number of discordant pairs, then the Goodman-Kruskal Gamma = (*nc* - *nd*) / (*nc* + *nd*). See Goodman and Kruskal (1972). Generally, the index approaches zero as independence between the two measures increases. Number of observations = 321.

Table 5: Ordered logit model predicting the full range of CAMEL ratings as a function of capital ratios and debenture spreads

Variable	Parameter Estimate (1)	Parameter Estimate (2)	Parameter Estimate (3)	Parameter Estimate (4)	Parameter Estimate (5)	Parameter Estimate (6)	Parameter Estimate (7)	Parameter Estimate (8)	Parameter Estimate (9)
Intercept1	-6.1568 (0.0001)	-6.5308 (0.0001)	-4.9173 (0.0001)	-3.7823 (0.0001)	-4.1632 (0.0001)	-5.3244 (0.0001)	-3.7125 (0.0001)	-3.0276 (0.0001)	-2.5769 (0.0026)
Intercept2	-4.6532 (0.0001)	-5.0256 (0.0001)	-3.4137 (0.0001)	-2.2678 (0.0023)	-2.6555 (0.0001)	-3.8346 (0.0001)	-2.2232 (0.0007)	-1.5346 (0.0080)	-1.0808 (0.1180)
Intercept3	-0.8463 (0.0001)	-1.2153 (0.0289)	0.4066 (0.5306)	1.6096 (0.0208)	1.2118 (0.0358)	-0.1896 (0.7079)	1.4357 (0.0190)	2.1696 (0.0001)	2.6252 (0.0001)
Sub-debt spread over Treasuries	1.1838 (0.0001)	1.1878 (0.0001)	1.1739 (0.0001)	1.1717 (0.0001)	1.1904 (0.0001)				
PCA capital adequacy status		0.3532 (0.4707)				0.3027 (0.5272)			
Total risk based capital ratio			-0.1000 (0.0411)				-0.1055 (0.0304)		
Tier 1 leverage ratio				-0.3463 (0.0002)				-0.2343 (0.0001)	
Tier 1 capital to risk-weighted exposure					-0.2361 (0.0001)				-0.3543 (0.0001)
	Association of Predicted Probabilities and Observed Responses								
Concordant	47.8%	48.2%	50.4%	52.3%	56.2%	4.6%	27.1%	48.1%	46.0%
Discordant	24.0%	24.6%	24.1%	26.1%	24.0%	3.6%	20.8 %	28.1%	28.4%
Tied	28.2%	27.2%	25.5%	21.6%	19.8%	91.8%	52.1%	23.9%	25.5%
Gamma	0.332	0.325	0.353	0.334	0.402	0.126	0.130	0.263	0.236
Chi-square for covariates (p - value)	23.425 (0.0001)	23.910 (0.0001)	27.796 (0.0001)	37.435 (0.0001)	38.874 (0.0001)	0.372 (0.5419)	4.952 (0.0261)	15.742 (0.0001)	14.949 (0.0001)

The dependent variable takes a value of 0 for CAMEL (or BOPEC) ratings 1 and 2, and a value of 1 for ratings 3 and higher. The PCA capital adequacy status ranges from 1 for the best capitalized banks (well capitalized) to 5 for the least well capitalized (critically undercapitalized). The *p*-values for the maximum likelihood parameter estimates are in parentheses below the coefficients. The "Chi-square for covariates" statistic is based on the log likelihood statistic, and tests the marginal explanatory power of the independent variables relative to a model with only a constant term. The associated p-values are included in parentheses.

Concordance is a measure of the correlation between the observed and predicted probabilities of the dependent variable. A pair of observations is said to be concordant if, based on the model, the observation that has a particular rating has a sufficiently higher probability of receiving that rating than does the other observation. A pair is discordant if the reverse is true. A pair is tied if the probability interval between the two observations is sufficiently small, 0.002. A correlation index, the Goodman-Kruskal Gamma index, is also included for assessing the predictive power of the model and for making comparisons across models. If *nc* is the number of concordant pairs and *nd* the number of discordant pairs, then the Goodman-Kruskal Gamma = (*nc* - *nd*) / (*nc* + *nd*). See Goodman and Kruskal (1972). Generally, the index approaches zero as independence between the two measures increases. Number of observations = 452.