# Forecasting Bank Supervisory Ratings using Securities Market Information

John Krainer and Jose A. Lopez

Federal Reserve Bank of San Francisco
Economic Research Department
101 Market Street
San Francisco, CA 94105

Draft date: February 14, 2003

**Abstract:** Approximately once a year, bank supervisors in the United States conduct a comprehensive on-site inspection of a bank holding company and assign it a supervisory rating meant to summarize its overall condition. We develop an empirical forecasting model of these ratings that combines accounting and financial market data. We find that securities market variables, such as stock returns and changes in bond yield spreads, improve the model's in-sample fit. Both equity and debt market variables appear to be useful for explaining upgrades and downgrades. We conclude that stock and bond market investors possess different, but complementary information about bank holding company condition. In an out-of-sample forecasting exercise, we find that the forecast accuracy of the model with both equity and debt variables is little different from the accuracy of a model based on accounting and lagged supervisory data alone.

**Acknowledgments:** The views expressed here are those of the authors and not necessarily those of the Federal Reserve Bank of San Francisco or the Federal Reserve System. We thank Rob Bliss for generously sharing his bank holding company debt database with us. We thank Fred Furlong and seminar participants at the Bank of England for helpful suggestions, and Judy Peng and Ryan Stever for their research assistance.

# Forecasting Bank Supervisory Ratings using Securities Market Information

Draft date: February 14, 2003

**Abstract:** Approximately once a year, bank supervisors in the United States conduct a comprehensive on-site inspection of a bank holding company and assign it a supervisory rating meant to summarize its overall condition. We develop an empirical forecasting model of these ratings that combines accounting and financial market data. We find that securities market variables, such as stock returns and changes in bond yield spreads, improve the model's in-sample fit. Both equity and debt market variables appear to be useful for explaining upgrades and downgrades. We conclude that stock and bond market investors possess different, but complementary information about bank holding company condition. In an out-of-sample forecasting exercise, we find that the forecast accuracy of the model with both equity and debt variables is little different from the accuracy of a model based on accounting and lagged supervisory data alone.

## I. Introduction

Concerns about the real economic damage associated with bank runs have led policymakers in the United States to provide the banking sector with a safety net, chiefly in the form of deposit insurance. In exchange for this safety net, the typical bank or bank holding company (BHC) is subject to much more regulatory oversight than firms in other sectors. The most comprehensive form of banking supervision in the United States is the on-site inspection, where a team of supervisors goes to an institution and assesses its financial condition after analyzing its operations in detail. Supervisors also conduct limited and targeted inspections that focus on specific operational issues, such as information systems.

Between on-site inspections, supervisors conduct what is referred to as off-site monitoring, which largely consists of analyzing data on the institution in question. This type of monitoring is becoming increasingly important as it is recognized that the condition of the modern-day BHC can deteriorate quite rapidly. Indeed, an important part of off-site monitoring in the U.S. is the use of empirical models to forecast supervisory ratings for banks.

The aim of this paper is to investigate the effectiveness of a class of off-site monitoring models in predicting changes in bank holding company (BHC) condition, as measured by the BHC's supervisory rating. We ask whether financial market data can play a useful role as explanatory variables in these models. Finally, we seek to learn which financial market variables appear to be most useful for predicting ratings changes, and under what conditions.

Financial market prices should, in an ideal world, tell supervisors all they need to know about BHC condition and the likelihood of failure. In practice, however, there are a number of real-world frictions that make our question worthy of empirical research. First, perceptions of possible government support for a struggling BHC, and the safety net in general (e.g., the deposit insurance fund in the United States), reduce the incentives of investors to monitor, thus affecting the sensitivity of security prices to changes in BHC asset value. Second, banks specialize in solving problems of asymmetric information. The very nature of this business may make the loans that they hold as assets difficult for outside investors to value. This problem, like the first, would tend to make security prices less sensitive to changes in asset value. Finally, supervisors have access to information that BHCs are not normally required to disclose to investors, raising the question of whether financial market prices can tell supervisors anything that they do not already know.

In spite of these reservations, supervisors are already adopting the use of market data in their monitoring efforts. Supervisors in the United States now have daily access to stock price, debt spread, and asset volatility series on the institutions that they inspect. Yet even with access to this information, there seems to be little consensus on the best way to use the information, which information sources to concentrate on, or whether there are measurable gains in doing so. In our view, the academic literature has yet to resolve these questions. To date, much of the literature has focused on subordinated debt, primarily because the concerns of debt holders are thought to be more closely aligned with those of the supervisors.[1] Curiously, there is less academic research on assessing whether equity markets offer ways to forecast changes in bank condition.[2] Berger and Davies (1998) and Krainer and Lopez (2001) conduct event studies to search for equity market responses to changes in supervisory ratings, and both find evidence of a meaningful response from equity markets even though supervisory ratings are supposed to be private information. Berger, Davies, and Flannery (2000) and Gropp, Vesala, and Vulpes (2001) are among the few studies to use both equity and bond market data to predict changes in condition. We join this literature by examining whether debt market investors or equity market investors are better able to predict changes in BHC condition as measured by the BHC's supervisory rating.

The motivation for such a comparison between different investor information sets arises naturally. If a firm issues both debt and equity, the comparative price sensitivity of the two instruments to changes in underlying asset value will depend on how close the underlying asset value is to the default point. If the market value of the firm's assets are worth less than the face value of the debt, then the seniority of debt over equity implies that changes in asset values will

---

[1] Examples of research in this area include Bliss and Flannery (2001), Evanoff and Wall (2000), Flannery and Sorescu (1996), Hancock and Kwast (2000) as well as Kwast et.al. (1999). See also Gilbert, Meyer and Vaughan (2001) for use of alternative fixed-income instruments.

[2] This is surprising since the private sector has largely embraced the use of equity market information for estimating company default probabilities, a task thought to be ideal for the bond market.

prompt large changes in debt prices and have a relatively smaller impact on equity prices. Debt prices will be much less sensitive to changes in asset values when the firm is far from default because gains (or losses) accrue mainly to the equity holders.

In this paper, we investigate the potential contributions of both equity market and debt market information to the supervisory monitoring of BHCs using an off-site monitoring model. We examine the potential contribution of various equity and debt market indicators of BHC performance for predicting supervisory BHC ratings, known as BOPEC ratings.[3] The contribution of the financial market variables is measured relative to the fit of a model based on supervisory data alone.[4] From the equity markets, we consider two measures based on a decomposition of individual BHC stock returns. The first measure is an abnormal return constructed over a period leading up to the assignment of the supervisory rating. The second measure is a fitted return derived from a two factor model. From the debt markets, we examine the change in a BHC's weighted average bond yield relative to an index composed of bonds with similar ratings and maturities and relative to yield changes in the bonds of BHCs with similar supervisory ratings.

Our empirical results suggest that both equity and debt market information are useful for modeling BOPEC ratings. That is, relative to using just supervisory information, incorporating either equity or debt market information improves the BOM model's pseudo-$R^2$ and significantly improves the model's in-sample fit. Furthermore, the introduction of both sets of market information further improves the in-sample fit, and this result is strongest for BHCs that have issued both sets of securities.

Out of sample, however, there is little evidence of forecasting improvement after incorporating financial market information. That is, the distribution of forecasts of future BOPEC ratings based on supervisory data alone is not statistically different from the set of

---

[3] Note that in this paper we focus on supervisory ratings and not defaults, another key supervisory concern. There exists an extensive literature on bank default dating back to Meyer and Pifer (1970), Sinkey (1975), and Pettway and Sinkey (1980).

[4] Throughout the paper we will use the term "supervisory data" to mean data generated by supervisors as part of the BHC quarterly report or as part of the supervisory process. We do not mean that financial market data are not in the supervisory information set.

forecasts generated by the model augmented with market data. However, we find that while the forecasts are not different in a statistical sense, they are different in an economic sense in that the forecasts based on both supervisory data and market data identify additional BOPEC ratings changes of publicly traded BHCs that were not identified by the benchmark model. Given the supervisory objective function which places significant weight on avoiding bad outcomes, the identification of additional correct BOPEC changes could outweigh the cost of the additional false signals.

The paper proceeds as follows. In section II, we provide a brief overview of the supervisory process for bank holding companies in the U.S. We also provide a brief survey of the academic literature on off-site monitoring models and the use of securities market information for supervisory monitoring. In section III, we estimate a BOPEC Off-site Monitoring model (BOM) for BOPEC ratings using both supervisory and securities market variables. We also examine the various model specifications' out-of-sample performance using a rolling our-quarter sample, as per Krainer and Lopez (2001). Section V concludes.

## II. The U.S. supervisory process and literature review

### II.A. The U.S. supervisory process

The Federal Reserve is the supervisor of bank holding companies (BHCs) in the United States. Full-scope, on-site inspections of BHCs are a key element of this supervisory process. These inspections are generally conducted on an annual basis, particularly for the case of large and complex BHCs.[5] Limited and targeted inspections that may or may not be conducted on-site are also carried out. In this paper, we focus on full-scope, on-site inspections since they provide the most comprehensive supervisory assessments of BHCs.

At the conclusion of an inspection, the supervisors assign the institution a numerical rating called a composite BOPEC rating that summarizes their opinion of the BHC's overall health and financial condition. The BOPEC acronym stands for the five key areas of supervisory

[5] A complex BHC is defined as one with material credit-extending nonbank subsidiaries or debt outstanding to the general public. See DeFerrari and Palmer (2001) for an overview of the supervisory process for large, complex banking organizations.

concern: the condition of the BHC's **B**ank subsidiaries, **O**ther nonbank subsidiaries, **P**arent company, **E**arnings, and **C**apital adequacy. BHCs with the best performance are assigned a BOPEC rating of one, while those with the worst performance are given a BOPEC rating of five. A rating of one or two indicates that the BHC is not considered to be of supervisory concern. Note that BOPEC ratings, as well as all other inspection materials, are highly confidential and are never made publicly available.[6]

Between on-site inspections when private supervisory information cannot be gathered as readily, supervisors monitor BHCs using an off-site monitoring system based on quarterly regulatory reports filed by BHCs and their subsidiary banks. This off-site monitoring system is primarily based on three information sources. The first source, known as the BHC Performance Report, is a detailed summary of their quarterly Y-9C regulatory reporting forms.[7] As of March 1999, the report summarized approximately 800 BHC variables across several years. From this report, certain variables are selected as key performance criteria, and if a BHC fails to meet these criteria in a given quarter, it is noted as an exception that requires further monitoring.

The second source of information for off-site BHC monitoring is the supervisory CAMELS ratings assigned to banks within the holding company. As with BOPEC ratings, CAMELS ratings are assigned after bank examinations. The acronym refers to the six key areas of concern: the bank's Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity to risk. The composite CAMELS rating also ranges in integer value from one to five in decreasing order (i.e., banks that perform best are assigned a rating of one). Since the condition of a BHC is closely related to the condition of its subsidiary banks, the off-site BHC surveillance program includes monitoring recently assigned CAMELS ratings.

As with on-site BHC inspections, on-site bank examinations occur at approximately a yearly frequency, which is long enough for the gathered supervisory information to decay and

---

[6] For an international survey of supervisory bank rating systems, see Sahajwala and Van der Bergh (2000).

[7] For a complete description of the BHC Performance Report, see the user guide at http://www.federalreserve.gov/boarddocs/supmanual/bhcpr/bhcpr_2000_access.pdf

become less representative of the bank's condition.[8] To address this issue, the Federal Reserve instituted an off-site monitoring system for banks, known as the System for Estimating Examiner Ratings (SEER), in 1993. The SEER system actually consists of two separate models that forecast bank failures over a two-year horizon as well as bank CAMELS ratings for the next quarter. The model that we are most interested in here is the latter, which is an ordered logit model with five categories corresponding to the five possible values of the CAMELS rating. The model is estimated every quarter in order to reflect the most recent relationship between the selected financial ratios and the two most recent quarters of CAMELS ratings. Significant changes in a bank's CAMELS rating as forecasted by the SEER model could be sufficient to warrant closer monitoring of the bank. The off-site BHC surveillance program also explicitly monitors the SEER model's forecasted CAMELS ratings.

A third information source is BHC financial market information, when available. Supervisors monitor BHC stock prices (and other financial market variables). If a BHC exhibits irregular stock price movements, it can be noted as an exception that requires further monitoring during the regular surveillance process.[9]

### II.B. Literature review

An extensive academic literature regarding the complementarity of supervisory and market monitoring of BHCs and their banks already exists; see Flannery (1998) for a survey. In broad terms, these studies have examined financial market monitoring of BHCs with respect to their traded equity and their traded debt.

#### II.B.1. Equity market information

Only about 26% of all U.S. BHCs were publicly owned as of the second quarter of 1998, but these BHCs accounted for about 85% of total BHC assets. Given that such a large percentage of BHC assets are traded in the public equity market, it seems reasonable to expect that the equity

---

[8] See Cole and Gunther (1995) as well as Hirtle and Lopez (1999) for further discussion of this issue.

[9] See SR Letters 95-43 and 02-01.

market could provide relevant information on the condition of these assets. Research on this topic has proceeded on two different fronts. First, researchers have questioned whether the supposed opaqueness of bank assets makes it difficult for investors to value bank stocks relative to non-banking stocks. Recent evidence by Flannery *et.al.* (2000) indicates that BHCs appear to be as or more transparent than matched non-bank firms with respect to their equity market microstructure properties, such as trading volume and analyst coverage.

A second branch of the literature assumes that the equity market is capable of valuing BHC assets and looks instead at possible overlaps between the market and supervisory information sets. Specifically, many studies have examined whether equity market variables incorporate private supervisory data. For example, Berger and Davies (1998) use an event study framework to examine whether daily stock prices react to CAMELS rating changes. Even though CAMELS are confidential, they find that BHC stock prices do respond to these changes, implying that supervisory assessments provide valuable information that the equity market can detect.

Berger et. al. (2000) examine the timeliness and accuracy of supervisory and market assessments of the condition of large BHCs. Their study is one of the few that utilizes both equity and bond market information. They find that equity market assessments based on abnormal returns and changes in large shareholdings are not strongly related to supervisory assessments based on BOPEC ratings. Thus, market assessments appear to focus on different aspects of BHC performance than do supervisory assessments. Furthermore, they find that, after accounting for market assessments, supervisory variables do not contribute substantially to the modeling of future indicators of BHC performance, such as changes in nonperforming loans. Overall, their findings suggest that supervisors, bond market participants and equity market participants produce complementary information on BHC performance. Gunther *et.al.* (2001) corroborate this result with their finding that equity-based market signals provide useful information to supplement supervisory assessments.[10]

---

[10] Hall et.al. (2001) find a related result when comparing equity market investors and bank supervisors. Studies by Elmer and Fissel (2001) and Curry et. al. (2001) support this conclusion by finding that equity market variables add value to models of bank failure based on supervisory data.

**II.B.2.  Debt market information**

About 3.5% of all U.S. BHCs as of the second quarter of 1998 had outstanding debt at the BHC or bank level, although these BHCs accounted for 70% of total BHC assets.  Furthermore, almost 3% of all BHCs had both public equity and debt outstanding, and these BHCs accounted for two-thirds of total BHC assets.  Many of the same exercises described above have also been conducted using debt market information, particularly subordinated debt market information. Berger et.al. (2000) find that supervisory and bond market assessments of BHCs are interrelated. DeYoung *et.al.* (2001) find that supervisory information significantly affects contemporaneous and subsequent changes in the spreads on bank debentures.  Specifically, they find that the private supervisory information component of bank CAMELS ratings impacts debenture spreads several months after the CAMELS assignment.

Since the interests of bank subordinated debt holders and bank supervisors are supposedly aligned, several studies have advocated that subordinated debt prices be incorporated into the supervisory process.[11]   Evanoff and Wall (2000) examine this proposition directly by testing the degree to which subordinated debt spreads provide supervisors with additional information.  In their study, they model changes in the supervisory ratings of banks and BHCs with outstanding subordinated debt over the period from 1990 to 1999 as a function of lagged subordinated debt spreads and regulatory capital ratios.  They find that subordinated debt spreads do as well or better than any of the capital ratios at explaining supervisory ratings.  Our paper pursues a similar line of analysis, but also includes equity market variables.

Gropp, Vesala, and Vulpes (2001) examine the ability of equity market variables and subordinated bond spreads for European banks to signal changes in bank financial conditions. Using ordered logit models at several horizons and a proportional hazard model, they find that both equity-based measures of distance-to-default and subordinated debt spreads are useful for detecting changes in bank ratings.  Interestingly, they find that the distance-to-default measure performs less well closer to default and that subordinated debt spreads seem to have signal value

---

[11]  One objection to this proposition is found in Bliss (2000).  He shows supervisory interests may diverge from bondholder interests in that both parties may not necessarily agree on the relative riskiness of different banks or bank portfolios.

only close to default. The authors argue that their empirical results provide support for the use of securities market information in supervisor's early warning models.

### II.C. The BOPEC ratings sample

The core database for our analysis is the supervisory BOPEC ratings assigned over the period from 1990 to the second quarter of 1998. The sample endpoint is dictated by the availability of the bond dataset.[12]

We chose to analyze only BOPEC ratings assigned after an on-site, full-scope inspection. This requirement reflects the concern that limited and targeted inspections produce a less comprehensive supervisory information set than a full inspection. Our sample of BOPEC ratings is further refined to include only inspections of top-tier BHCs with identifiable lead banks, four quarters of available supervisory data and prior BOPEC ratings. We focus on top-tier BHCs since they are typically the legal entity within the banking group that issues publicly-traded equity. The lead bank designation is often provided by banks in their regulatory filings. When such self-reporting is not available, we assign the lead-bank designation to the largest bank within the group. We need the BHCs in our sample to have identifiable lead banks in order to directly link their BOPEC ratings to their lead bank's CAMELS ratings.[13] Finally, we require each BHC to have at least four quarters and a lagged BOPEC rating in order to avoid issues regarding de novo BHCs and new BHCs arising from mergers. In addition, four quarters of supervisory data are required to calculate certain explanatory variables for the model described later.

Table 1 summarizes our sample of inspections. The full sample contains 3,010 complete inspections of 1,034 unique entities for which we know the assigned BOPEC rating, as well as the rating leading into the inspection. Almost 65% of the BHCs in the sample are relatively small, with less than $1 billion in total assets. Slightly more inspections occurred in the first half

---

[12] We are grateful to Rob Bliss for sharing his BHC bond database with us. A complete description of the database is presented in Bliss and Flannery (2001). The last quarter of bond data is the first quarter of 1998, which aligns with the second quarter of 1998 in the BOM model.

[13] Note that this restriction does not imply that we limited the sample to single-bank BHCs. We simply focus on the CAMELS rating for a BHC's lead bank, whether self-identified or identified by asset size.

of the sample than in the second half, reflecting consolidation in the U.S. banking sector.

There are 1,291 inspections of publicly traded BHCs, corresponding to 363 unique entities. Note that publicly-traded BHCs are generally larger than private BHCs, with a greater percentage having total assets ranging between \$1 billion and \$100 billion. Of the 41 inspections of large BHCs (assets greater than \$100 billion), 39 of the BHCs are publicly traded..

With respect to BHCs with outstanding debt issues, this subsample contains 305 BOPEC ratings corresponding to 62 unique BHCs. Again, these BHCs are typically larger than those in the full sample with almost all BHCs having between \$1 billion and \$100 billion in assets.

Finally, there are 279 BOPEC ratings corresponding to 57 unique BHCs that have both public equity and debt outstanding. As expected, these BHCs are also typically larger with almost all having between \$1 billion and \$100 billion in assets.

Tables 2A-2D present the distributions of BOPEC ratings assigned in each year for all BHCs, for BHCs with publicly traded equity, for BHCs with publicly traded bonds, and BHCs with both public equity and debt, respectively. The majority of the ratings fall in the upper two categories, indicating that a BHC's financial condition and risk profile are of little supervisory concern. For the full sample, while the distribution of ratings fluctuates over time, the percentage of ratings in the top two categories for the full sample never falls below 65%. The maximum value is 96.5% in 1998. Note that there are very few inspections culminating in a BOPEC rating of 4 or worse, since both supervisors and bankers actively try to prevent this outcome.

Our sample contains 1,291 BOPEC ratings for publicly-traded BHCs, which represents about 43% of the full sample. These ratings correspond to 397 unique institutions, which implies a slightly higher ratio of BOPEC ratings per unique BHC than for the full sample; i.e., 2.9 for the full sample and 3.3 for the publicly traded sample. That is, BHCs with publicly traded equity are rated more frequently than BHCs without publicly traded equity. However, the ratings distribution for publicly-traded BHCs is quite similar to that of the full sample.

Our sample contains 305 BOPEC ratings for BHCs with publicly-traded debt, which represents about 10% of the full sample. These ratings correspond to 63 unique institutions, which implies a much higher ratio of BOPEC ratings per BHC than for the full sample; i.e., 2.9

for the full sample and 4.8 for this sample. Even so, the evolution of the ratings distribution over time is similar to that of the full sample.

Finally, our sample contains 279 BOPEC ratings for BHCs with publicly-traded equity and debt. This subsample represents just 9% of the full sample, and 22% of the equity subsample, but over 90% of the debt subsample. These rating assignments correspond to 58 unique institutions, which implies a ratio of BOPEC ratings per BHC similar to the ratio for the publicly traded debt subsample (4.8 assignments per BHC). The BOPEC ratings distribution for this subsample differs from that of the full sample; specifically, the BOPEC 1 rating category makes up 35% of this sample relative to just 30% for the full sample. By 1998, all the BHCs in this category were rated BOPEC 2 or better.

Tables 3A-3D present the patterns of changes in the BOPEC ratings in our sample. The most frequent outcome is no change in BOPEC rating, accounting for between 69% and 87% of the annual totals for the full sample and the equity subsample. The pattern of BOPEC upgrades and downgrades fluctuates dramatically over the course of the sample time period. For all four samples, from 1990 through 1992, more downgrades occurred than upgrades, but from 1993 through the end of the sample, the pattern was reversed. The pattern appears to follow the general trends in U.S. banking and macroeconomic conditions during the 1990s.

## III. Multivariate analysis using the ordered logit model

Our proposed BOPEC off-site monitoring (BOM) model is an ordered logit model, and is similar in structure to the SEER model for CAMELS ratings. The model assumes that the BOPEC rating assigned to BHC i in quarter t, denoted $BP^*_{it}$, is an unobservable continuous variable based on supervisory variables available in quarter t-2. The $BP^*_{it}$ rating is modeled as

$$BP^*_{it} = \left(\beta + \gamma_E I_{Eit-1} + \gamma_D I_{Dit-1}\right) x_{it-2} + \pi_E z_{Eit-1} + \pi_D z_{Dit-1} + \varepsilon_{it}, \tag{1}$$

where $x_{it-2}$ is a (k×1) vector of explanatory variables unique to BHC i observed two quarters prior to the BOPEC assignment and the indicator variables $I_{Eit-1}$ and $I_{Dit-1}$ represent BHCs with publicly traded equity and debt, respectively, a quarter prior to the BOPEC assignment. We choose to lag the supervisory variables by two quarters because these are often the most recent data available to the holding company inspection team at the time of inspection.[14] The interaction terms allow us to control for possible differences between BHCs with and without public equity and debt. The $z_{Eit-1}$ and $z_{Dit-1}$ terms are vectors of equity and debt market variables, respectively, that correspond to BHC i at time t-1, one quarter before the BOPEC assignment. The supervisory variables and the financial market variables enter into the model with different lags because of the difference since securities market information is available on a more timely basis than is supervisory information. The error term $\varepsilon_{it}$ has a standard logistic distribution.

Since we only observe integer-valued BOPEC ratings, not continuously-valued ratings as in equation (1), we must also estimate four cutpoints denoted $\alpha_j$ such that

$$
(2) \qquad \begin{aligned} BP_{it} &= 1 \text{ if } BP^*_{it} \in (-\infty, \alpha_1]; \\ &= 2 \text{ if } BP^*_{it} \in (\alpha_1, \alpha_2]; \\ &= 3 \text{ if } BP^*_{it} \in (\alpha_2, \alpha_3]; \\ &= 4 \text{ if } BP^*_{it} \in (\alpha_3, \alpha_4]; \\ &= 5 \text{ if } BP^*_{it} \in (\alpha_4, \infty). \end{aligned}
$$

The density function for an assigned BOPEC rating is constructed by defining $Y_{ijt}$ as an indicator variable equal to one if rating j is assigned to BHC i at time t. Since the ratings are ordered, the probability that BHC i is assigned BOPEC rating j is calculated as the difference between the cumulative probabilities of receiving rating j and receiving rating j-1,

$$
(3) \qquad \Pr\left(Y_{ijt} = 1\right) = \Lambda\left[\alpha_j - \left(BP^*_{it} - \varepsilon_{it}\right)\right] - \Lambda\left[\alpha_{j-1} - \left(BP^*_{it} - \varepsilon_{it}\right)\right]
$$

where $\Lambda(x)$ is the cumulative logistic function. In an estimation sample with N ratings, the likelihood function is

[14] See Gunther and Moore (2000).

(4) $$L(\theta) = \prod_{i=1}^{N} \prod_{j=1}^{5} \Pr\left(Y_{ijt} = 1\right)^{Y_{ijt}}.$$

**IIIA.1 Supervisory Variables**

The choice of which supervisory variables to include in $x_{it-2}$ is challenging. No simple behavioral models exist of how supervisors assign BOPEC ratings and, as mentioned, there are more than 800 variables at the supervisors' disposal for this purpose. For this study, we selected nine explanatory variables that are reasonable proxies for the five components of the BOPEC rating. As in Krainer and Lopez (2001), we chose a parsimonious specification that can generate reasonable out-of-sample forecasts. Additionally, we face the practical concern that many fewer BOPEC ratings are available in any given subsample period to be used in a forecasting exercise than are available in our full sample.

We use ten explanatory variables in this study; see Table 4 for summary statistics. The first variable is the natural log of total BHC assets, which is our control variable for BHC size. The next four variables are used to capture the supervisory concerns regarding the BHC's bank subsidiaries, as summarized in the "B" component of the rating. The second variable is the CAMELS rating of the BHC's lead bank. The third variable is the ratio of the BHC's nonperforming loans, nonaccrual loans, and other real estate owned to its total assets. This "problem loans" variable proxies for the health and performance of the BHC's loan portfolio. Note that CAMELS ratings, nonperforming loans and nonaccrual loans variables are all confidential supervisory information. The fourth variable is the ratio of the BHC's allowances (or provisions) for losses on loans and leases to its total loans, another proxy for the health and performance of the BHC's loan portfolio.

The fifth variable is an indicator of whether the BHC has a Section 20 subsidiary, which is a subsidiary that can engage in securities activities that commercial banks were not permitted to engage in before the Gramm-Leach-Bliley Act of 1999. This variable is a proxy for the types of nonbank activities the BHC is engaged in and thus speaks to the "O" component of the BOPEC rating. We also include as the sixth variable the ratio of a BHC's trading assets to its total assets as a proxy of its non-banking activities, whether conducted in banking or non-banking subsidiaries.[15]

The seventh variable is the so-called “double leverage” ratio between the BHC and its lead bank, which is the ratio of the lead bank's equity capital to that of the parent's equity capital. This variable provides a measure of the soundness of the parent BHC, indicating the extent to which the parent's equity capital can be used to buffer against damage to the lead bank's equity capital. We use this variable as a proxy for the condition of the parent BHC as summarized in the “P” component of the BOPEC rating. The eighth variable is the BHC’s return on average assets (ROAA), defined as the ratio of the four-quarter average of the BHC’s net income to the four-quarter average of its assets.  This variable is used to proxy for the “E” component of the BOPEC rating.  The ninth variable is the BHC's ratio of equity capital to its total assets.  This variable is used to proxy for the “C” component of the BOPEC rating.[16]

Finally, we include the lagged BOPEC rating as a tenth supervisory variable.  This variable is meant to capture any persistence in ratings, or serve as a proxy for any omitted variables that themselves have persistence.

We refer to the version of the BOM model based on just the supervisory variables as the core model.  The equity BOM model extends the core model to include the variables from the equity markets.  The debt BOM model extends the core model to include the bond market variables.  Finally, the extended BOM model estimates all of the parameters in the equation.

**IIIA.2: Equity Market Variables**

The equity market variables used in this study are based on observed stock returns over a six-month period that ends one quarter prior to the beginning of the inspection.  Our two variables are motivated by a decomposition of a BHC’s cumulative stock return into systematic and idiosyncratic portions,

---

[15] Note that the trading assets variable as currently reported first became available in the first quarter of 1995. Before then, we proxy for BHC trading assets using the sum of the self-reported replacement cost of interest rate and foreign exchange derivative contracts.

[16] A variety of capital measures have been used in previous studies, such as Evanoff and Wall (2000) and Estrella et al. (2000). We chose a simple measure to facilitate comparison over the entire ten-year period.

(5) $$\sum_{t=-2}^{-1} R_{it} = \sum_{t=-2}^{-1} (a_i + b_{im} R_{mt} + b_{if}\ ff_t) + \sum_{t=-2}^{-1} \varepsilon_{it}\,.$$

The first term on the right-hand-side of equation (5) is a predicted cumulative return based on a two-factor model. The factors are the market return and the change in the federal funds rate. The factor loadings $a_i$, $b_{im}$, and $b_{if}$ are estimated over a 60 month sample period ending 12 months prior to the BHC's inspection. The difference between the actual cumulative return and the predicted cumulative return is a residual, or a cumulative abnormal return. Dividing both sides of the above equation by the standard error of the cumulative abnormal return yields a representation of an "adjusted" cumulative return as a function of an adjusted systematic cumulative return plus a standardized cumulative abnormal return (SCAR).

The motivation behind using stock market data lies in the hope that there is some agreement between stock market investors and supervisors on what constitutes healthy financial condition. Stock market investors are clearly not trying to forecast BOPEC ratings; they are trying to forecast returns. But if the same financial developments that lead to a supervisory ratings change also lead to changes in expected returns, then it is possible that regulators can use stock market signals as indicators of what they themselves might do if they were to inspect the BHC.

The motivation behind using a SCAR in an off-site monitoring model should be apparent. BHC stock price changes that are unusually large in magnitude with respect to general market activity may signal changes in condition that will eventually lead to a ratings change. The SCAR variable is designed specifically for identifying which stock price changes are "unusually large." However, relying exclusively on SCARs for market signals may cause us to miss important information in stock prices. For example, an economy-wide shock that lowers returns for the entire banking sector might not translate into abnormally negative returns for any particular BHC, but could very well be an early indicator for changes in supervisory ratings sector-wide.

For a variety of reasons, these equity market variables are not available for all publicly-traded BHCs over the entire sample period. For example, we cannot generate reliable SCARs when a BHC does not have at least five years of stock return data with which to estimate the two-factor market model. To address this issue, we replaced these missing values with the variable's in-sample mean for the available observations, as per Griliches (1986). We also include fixed effects to account for this data adjustment. This procedure does not affect the model's coefficient estimates for the variables with missing values, but allows us to use the entire sample in our estimation.

**III.A.3: Debt Market Variables**

The debt market variables used in this study are changes in bond yields taken from the Warga/Lehmann Brothers Corporate Bond Database. These are the same data used by Bliss and Flannery (2001).[17] The source of the bond data is Warga / Lehman Brothers Corporate Bond Database. Note that this database includes both subordinated and non-subordinated BHC debt.[18] There are two empirical issues that are unique to bond data. First, in cases where a BHC has multiple outstanding bonds, it is necessary to compress this market information into a single observation. When confronted with this problem, we use a weighted average change in bond yields for the debt market variable, where the weights are the amounts outstanding in the quarter.

Second, as with the stock market variables, we would like to have some measure of what constitutes an abnormal change in yield. We follow Bliss and Flannery and use bond price indices based on term-to-maturity and rating buckets (either using Moody's or S&P ratings to produce two sets of indices). The Bliss and Flannery ratings buckets consist of 11 categories that correspond to Moody's and S&P ratings and three term-to-maturity categories.[19] The Bliss and Flannery indices allow us to study changes in yields relative to an index of similar bonds drawn from all industries.[20] This adjustment allows us to concentrate on changes in yields that are

[17]We thank Rob Bliss for sharing these data with us.

[18] For a discussion of the market for BHC subordinated debt, see Kwast *et.al.* (1999), Hancock and Kwast (2000), Feldman and Schmidt (2000), and Goyal (1998).

[19] The '+' or '-' qualifiers attached to the basic rating definitions are suppressed.. The maturity buckets are less than 5 years, 5-10 years, and greater than 10 years.

[20] In our empirical work to date we used just two of the Bliss and Flannery bond indices. We examined change in average BHC bond yield relative to the index composed of similar rated/term bonds (i.e., all the bonds) as rated by Moody's. We examined both the equally weighted and the amount-outstanding weighted indices. The results were similar, so we report just the results for the amount-outstanding weighted index.

purged of larger, systematic factors. We will also find it useful to subtract out yield changes from the bonds of BHCs with similar supervisory ratings to arrive at a variable more closely related to the abnormal returns used in the stock market data. Indeed, in our empirical work, these "abnormal" changes in bond yields appear to have much more predictive power than the simple changes in yield relative to the all bonds index. In the empirical analysis to follow, we do not use a systematic variable that captures general changes in BHC bond yields. We use only the adjusted yield defined above.

### III.B. Empirical results

We estimate four versions of the BOM model; i.e.,

$$BP_{it}^{*} = \left(\beta + \gamma_E I_{Eit-1} + \gamma_D I_{Dit-1}\right) x_{it-2} + \pi_E z_{Eit-1} + \pi_D z_{Dit-1} + \varepsilon_{it}. \tag{6}$$

For the core model, we set $\gamma_E = \gamma_D = \pi_E = \pi_D = 0$. For the equity BOM model, we set $\gamma_D = \pi_D$ $=0$. For the debt BOM model, we set $\gamma_E = \pi_D = 0$. For the extended BOM model, we do not constrain any of the parameters. The empirical results for the full sample of BOPEC observations are presented in Tables 5A and 5B. Note that while we estimate the model with complete sets of interactions for the supervisory variables, we do not report the coefficients on the interacted variables for purposes of economizing on space.

In the full sample, the coefficients on the financial market variables are statistically significant at conventional levels. The equity market variables have negative signs, which is to be expected; positive values for both abnormal and predicted returns tend to be associated with lower (better) BOPEC ratings. For the debt market variable, the positive sign is also in line with expectations. Higher yield spreads relative to a ratings-specific composite are associated with higher (worse) BOPEC ratings.

The likelihood ratio results indicate that incorporating securities market information improves the core BOM model's in-sample fit. The likelihood ratio test statistic for the equity market BOM model relative to the core BOM model is 57.0, which has a p-value of 0.0% under the $\chi^2(3)$ distribution. The likelihood ratio test statistic for the debt market BOM model relative to the core BOM model is 6.6, which has a p-value of 10.0% for the $\chi^2(2)$ distribution. Finally, the likelihood ratio test statistic for the equity-debt BOM model relative to the simple BOM model is 106.6, which has a p-value of 0.0% under the $\chi^2(5)$ distribution.

Clearly, the results indicate that using some type of securities market information in the BOM model is appropriate. However, again using likelihood ratio statistics, we find that using both sources is better than using either one alone. The likelihood ratio test statistic for the equity-debt BOM model relative to the equity BOM model is 49.6, which has a p-value of 0.0% for the $\chi^2(2)$ distribution. The likelihood ratio test statistic for the equity-debt BOM model relative to the debt BOM model is 113.2, which has a p-value of 0.0% for the $\chi^2(3)$ distribution. Hence, both sources of market information are shown to be useful complements to the chosen supervisory information set.

### III.C. The relative importance of debt and equity information

As mentioned in the introduction, one of the primary motivations for using both equity and debt market data in a monitoring model is that no single information source is likely to dominate the other in all states of the world. For example, the residual claim feature of equity suggests that equity market investors would be good at predicting upgrades, or predicting changes in supervisory ratings when asset values are relatively far from the default point. Debt market investors, by contrast might be more likely to predict downgrades, or predict changes in supervisory ratings when asset values are relatively close to the default point.

In this section, we study whether debt market and equity market variables have differential ability to predict certain types of inspection outcomes. In Tables 6A and 6B, we present the results from the estimation of upgrade and downgrade models. Unlike the analysis in the previous section, the models used here are ordinary logit models where the dependent variables are indicator variables of whether an upgrade or downgrade takes place or not at the inspection. Interestingly, both sets of financial market variables have strong statistical significance in both the upgrade and the downgrade models. This same basic result carries over when we analyze transitions between the of-concern list (BOPEC 3-5) and the not-of-concern list (BOPEC 1-2). Debt market signals appear to anticipate both upgrades and downgrades over regulatory thresholds. Interestingly for the case of equity market variables, only the SCAR consistently anticipates threshold transitions. For the case of upgrades to BOPEC 2 or better, the systematic return variable is not statistically significant.

Debt and equity securities have payoffs that are nonlinear functions of the underlying value of a firm's assets. To investigate more closely whether these nonlinearities are important for the relative significance of debt market and equity market signals, we conduct a simple exercise of estimating a version of the BOM model that allows for the financial market variables to have differential effects on supervisory ratings, depending on the market value of the BHC's assets. For this exercise we use a model of a firm's asset value that is widely used in the literature.[21] As per Ronn and Verma (1986), we model asset value as a geometric Brownian motion. The firm's equity can be modeled as a call option,

$$E = AN\left(\frac{\ln\left(A/D\right)+\left(s_A^2/2\right)}{s_A}\right) - DN\left(\frac{\ln\left(A/D\right)+\left(s_A^2/2\right)}{s_A} - s_A\right), \tag{7}$$

where E is the market value of equity, A is the market value of assets, D is the book value of debt, $s_A$ is the volatility (standard deviation) of changes in asset value, and N(x) is the standard normal cumulative density function. Neither the market value of assets nor the volatility are directly observable in the data. A second equation linking asset volatility to equity volatility completes the model,

$$s_A = \frac{E}{AN\left(\frac{\ln(A/D)+(s_A^2/2)}{s_A}\right)} s_E . \tag{8}$$

Essentially, the asset volatility is a de-levered equity volatility. Our distance-to-default is simply the market value of assets minus the book value of liabilities (both in logs), all scaled by the estimated asset volatility.

[21] Gropp, Vesala and Vulpes (2001) use a similar measure.

Working within the BOM framework, we create indicator variables that take the value one if a BHC's distance-to-default is in a certain percentile of the overall distribution of distance-to-default, and zero otherwise. We then interact this indicator variable with the market signals. Since this exercise requires us to restrict the sample to include just BHCs with publicly traded securities, we include the lagged BOPEC rating as the lone supervisory variable in the model. Formally, the model is,

(9) $$BP_{it} = \beta BP_{i,t-2} + (\pi + \alpha I_{n,i,t-1})Z_{i,t-1} + \varepsilon_{i,t}$$

where Z is the financial market variable in question and $I_{nit-1}$ is equal to one if BHC i's distance-to-default is in the nth percentile at time t-1, and zero otherwise.

The results from this exercise are in Tables 7A and 7B. In Table 7A, the regressions are based on 1,266 inspections for BHCs with publicly traded equity. For this exercise, we restrict our attention purely to the SCAR. In Table 7B, the regressions are based on 282 inspections of firms with publicly traded equity and debt. In 7B, we restrict our attention purely to the adjusted bond yield.

Our main object of interest is whether the coefficients on the financial market variables are different in magnitude depending on how close the BHC is to its default point. For example, for the case of debt market information, we expect the coefficients to be positive–large abnormal changes in yields should signal increases in the BOPEC rating, or downgrades. But we would also expect the coefficient to be larger in magnitude if the BHC is closer to default. Additionally, all other things held constant, we might expect the stock market signal to have a larger impact on the BOPEC assignment the farther away the BHC is from default.

In Table 7A we see that when we allow for a differing impact of the SCAR variable on assigned BOPEC ratings, SCARs are associated with a larger impact on ratings for BHCs defined to be far from default. The coefficients are of the expected signs and are significantly different from zero at the conventional levels. This is true for most definitions of what it means to be close or not close to default. Close to default, the coefficients on the SCAR variable are not significantly different from zero. Note that the choice of which percentile to use in the definition of the indicator variable $I_{nit-1}$ has no impact on the overall fit of the model. The pseudo-$R^2$ in each model is 0.31.

In Table 7B we see strong evidence of the impact of distance-to-default on the coefficient estimate on the bond market variable. For BHCs in the bottom 20$^{th}$ percentile of the distance-to-default distribution, the coefficient on the adjusted yield variable is almost three times as large as adjusted yield coefficient associated with BHCs further from default. Both coefficients are of the expected sign and statistically significant, with p-values of 0.00. As the definition of close to default becomes more inclusive, however, the close-to-default coefficient ceases to be significant. When close to default is defined as in the belonging to the bottom 80$^{th}$ percentile (i.e., virtually all BHCs are in this category), then the close-to-default coefficient is significant again and the far-from-default coefficient is not significantly different from zero. As in the exercise with the SCAR variable in Table 7A, the choice of which percentile to use in the definition of the indicator variable $I_{nit-1}$ has no impact on the overall fit of the model. The pseudo-$R^2$ in each model is 0.41.

In summary, we detect an asymmetric contribution of debt and equity market signals to explaining BOPEC ratings that depends on how close the BHC is to its default point. The coefficients on the equity market signals are largest in magnitude for the case of BHCs defined to be far from default. Coefficients on the adjusted yield spreads are much larger in magnitude for BHCs defined to be very close to default.

### III.D. Out-of-sample performance

For supervisors, the true test of usefulness of an empirical model is whether the model has any predictive power out of sample. As in Krainer and Lopez (2001), we evaluate the model's forecasting ability by estimating a series of rolling logits and compare the model's predicted BOPEC ratings to the realized BOPECs. Specifically, we estimate various specifications of the model using four quarters of data and then use the estimated coefficients to predict BOPEC ratings awarded in the next quarter. Clearly, the subsamples available for estimation in any given period will be small relative to the full sample. However, we accept this small sample size because this type of exercise would, presumably, simulate the way market data would be used if supervisors were to adopt it formally.

Our measure of whether the model forecasts well or not is to ask how often model predictions are borne out. For example, if the model generates a signal suggesting an upgrade, what percentage of the time will an upgrade actually take place? The upgrade (downgrade) predictions in the tables are based on forecasted ratings that are a full rating better (worse) than the current rating. For the core model, an upgrade signal received four quarter prior to inspection materializes into an actual upgrade 52% of the time (Table 8A). Consequently, an upgrade signal at four quarters prior is incorrect 48% of the time–35% of the time the actual outcome of the inspection is no change in rating, and 13% of the time the actual outcome is a downgrade. By one quarter prior to the inspection, the upgrade signal is accurate 90% of the time. The model appears to be just as effective at picking up downgrades. Four quarters prior to the inspection, a downgrade signal is accurate 69% of the time, improving to 90% accuracy one quarter prior to the inspection.

These results are quite promising. In the full sample, the unconditional probabilities of upgrades, downgrades, and no change at the inspection are 22%, 12%, and 66%, respectively. Thus, the conditioning information in the model is clearly useful relative to the unconditional probabilities. This notion is formalized by the Pearson tests (contained in the right-most column), which test whether the conditional probabilities generated by the model are statistically different from the unconditional probabilities.

Model accuracy is little changed after incorporating financial market data. In Table 8B we see that when the debt market variable is added, the model's forecasting accuracy is actually a little worse than the accuracy of the simple model with only supervisory variables. An upgrade signal four quarters prior to the inspection is correct 46% of the time, compared to 52% of the time for the core model. A downgrade signal four quarters prior to the eventual inspection results in an actual downgrade 63% of the time, compared with 69% for the core model.

With the equity market data (Table 8C), the results are somewhat better for the case of upgrades. Signal accuracy increases from 62% four quarters prior to inspection to 91% accuracy within one quarter of the inspection. This compares to 52% and 90%, respectively, for the core model. For downgrades, forecast accuracy improves from 56% to 82% as the inspection approaches, not quite as good an improvement in accuracy as observed in the core model. Forecasting accuracy of the extended model with both equity and debt market variables is nearly indistinguishable from the accuracy of the core model (Table 8D).

In summary, the forecasting accuracy of the extended models looks very similar. This is formalized by the Pearson statistics reported in the rightmost columns of Tables 8B-8C, where we test whether the probabilities of BOPEC rating changes generated by the extended models are statistically different from the conditional probabilities generated by the core model. By and large, the extended models fail to generate forecasts that are different from the core model forecasts at conventional levels of significance.

### III.E. Information in the Forecasts

The forecasts of BOPEC ratings at upcoming inspections do not appear to be appreciably different across the core and the extended models. This result, however, does not mean that the individual BOPEC rating changes correctly forecasted by the two models are the same. The forecasting literature has shown that combining forecasts from different models can improve certain aspects of forecast accuracy. That appears to be the case here, since the two models signal BOPEC changes for different, although overlapping, sets of BHCs. Hence, another way to gauge the contribution of equity market information is to examine the additional forecast signals for public BHCs as generated by the extended model relative to the core model's signals. Seen in this light, the marginal benefit of adding these additional signals to the signals from the core model is notable.[22]

In Table 9A we focus exclusively on downgrades. We define a downgrade signal as a forecasted BOPEC rating that is greater than the current rating by one or more. Using signals generated by both the core and the extended models, we ask what is the percentage increase in correct signals when financial market data are used in the BOM model? For the complete model with bond yields and stock return data, the extended model produces 9% more correct signals at the four quarter horizon over and above those produced by the core model. By the 1 quarter horizon, the model produces 37% more signals. All the extended models show an increasing rate of marginal usefulness as the inspection grows near. All of these additional correct forecasts are

[22] It must be acknowledged these differences in the set of correct forecasts of ratings changes could be evidence of parameter instability in our model.

for ratings changes at BHCs with publicly traded securities.

One other interesting point in Table 9A is the similarity between the marginal contributions of the debt and equity model and the equity market alone model. Evidently, in this particular forecasting framework, most of the additional signals a supervisor can extract from financial market data come from the equity markets. This result contrasts with the in-sample results and may be due to the relatively small number of BHCs with publicly traded debt in any given subsample period.

Of course, the extended model produces incorrect signals over and above those produced by the core model. Given that Table 9A shows that the extended model helps to identify additional BOPEC ratings changes, these mistakes may be responsible for our earlier result that the forecast accuracy of the core and extended models is virtually the same. We look at this tradeoff more closely in table 9B, where we express the ratio of correct signals to incorrect signals. For example, in the case of the debt and equity model at the four quarter horizon, the model produces 1 extra correct signal at the cost of 4 incorrect downgrade signals. By the 1 quarter horizon, however, the accuracy dramatically improves. The extended model produces 4 extra correct signals at the cost of only one extra incorrect signal. The model extended by debt and equity and the model extended by equity market data alone behave quite similarly. Interestingly, the correct signal / incorrect signal tradeoff for the model extended with debt market information is quite good. By one quarter out, the extended model produces 6 correct signals for every incorrect signal. However, the drawback to this model is that it produces relatively fewer signals over and above the core model.

## IV. Conclusion

In conclusion, our empirical results indicate that both equity and debt market information are useful in improving the in-sample fit of our proposed BOM model for BOPEC ratings. Both types of financial market information appear to be useful in explaining both upgrades and downgrades. Moreover, we are able to detect nonlinearities in the impact of financial market variables on BOPEC ratings. Close to default, the estimated effect of changes in yield spreads on BOPEC ratings is larger in magnitude for than it is for BHCs far from default, and vice-versa for equity market data.

When we turn to out-of-sample forecasting, however, evidence for the usefulness of market information is disappointingly weak. We adopt a methodology of estimating the BOM model's coefficients on a rolling subsample of data and then forecasting BOPEC ratings into the future. We find the forecast accuracy of the models extended by financial market data is not much different than the accuracy of the core model based on supervisory data alone.

Finally, while the out-of-sample forecasting accuracy of the core and extended models is similar, we note that the actual forecasts are quite different. That is, the core model correctly identifies one set of BOPEC ratings changes, while the extended model correctly identifies another set of ratings changes. We show that the extended model correctly identifies additional ratings changes for publicly traded BHCs over and above the correct forecasts in the core model. These additional correct forecasts can be achieved at a relatively modest cost of additional incorrect signals.

## References

Basel Committee on Banking Supervision, 2001. "The New Basel Accord." Consultative Paper, Bank for International Settlements. (http://www.bis.org/publ/bcbsca.htm)

Berger, A. N., and Davies, S. M., 1998. "The Information Content of Bank Examinations," *Journal of Financial Services Research*, 14, 117-144.

Berger, A.N., Davies, S.M., and Flannery, M.J., 2000. "Comparing Market and Supervisory Assessments of Bank Performance: Who Knows What When?," *Journal of Money, Credit and Banking*, 32, 641-667.

Bliss, R., 2000. "The Pitfalls in Inferring Risk from Financial Market Data," Manuscript, Economic Research Department, Federal Reserve Bank of Chicago.

Bliss, R. and Flannery, M., 2001. "Market Discipline in the Governance of U.S. Bank Holding Companies: Monitoring versus Influence," in R. Mishkin, ed. Prudential Supervision: Why Is It Important and What are the Issues?. NBER. Forthcoming.

Board of Governors of the Federal Reserve System, 1995. Supervisory Letter 95-43: Revised Bank Holding Company Surveillance Procedures. http://www.federalreserve.gov/boarddocs/SRLETTERS/1995/sr9543.htm.

Board of Governors of the Federal Reserve System, 2002. Supervisory Letter 02-01: Revisions to Bank Holding Company Supervision Procedures for Organizations with Total Consolidated Assets of $5 Billion or Less. http://www.federalreserve.gov/boarddocs/SRLETTERS/2002/sr0201.htm

Campbell, J., Lo, A., and MacKinlay, A., 1997. The Econometrics of Financial Markets. Princeton University Press.

Cole, R.A., Cornyn, B.G. and Gunther, J.W., 1995. "FIMS: A New Monitoring System for Banking Institutions," *Federal Reserve Bulletin*, January, 1-15.

Cole, R.A. and Gunther, J.W., 1998. "Predicting Bank Failures: A Comparison of On- and Off-Site Monitoring Systems;" *Journal of Financial Services Research*, 13, 103-17.

Curry, T.J., Elmer, P.J. and Fissel, G., 2001. "Regulator Use of Market-Related Data to Improve the Identification of Bank Financial Health," Manuscript, Federal Deposit Insurance Corporation.

DeFerrari, L, and Palmer, D., 2001. "Supervision of Large Complex Banking Organizations." *Federal Reserve Bulletin*, February, 47-57.

DeYoung, R., Flannery, M., Lang, M., and Sorescu, S., 2001. "The Information Content Bank Exam Ratings and Subordinated Debt Prices." *Journal of Money, Credit, and Banking*, forthcoming.

Elmer, P.J. and Fissel, G., 2001. "Forecasting Bank Failure from Momentum Patterns in Stock Returns," Manuscript, Federal Deposit Insurance Corporation.

Estrella, A., Park, S. and Peristiani, S., 2000. "Capital Ratios as Predictors of Bank Failure", *Federal Reserve Bank of New York Economic Policy Review*, July, 33-52.

Evanoff, D., and Wall, L., 2000. "Sub-debt Yield Spreads as Bank Risk Measures." Working paper #2000-24, Federal Reserve Bank of Atlanta.

Feldman, R. and Schmidt, J., 2000. "Granger Tests of Subordinated Debt Spreads and KMV Expected Default Frequencies," Manuscript, Banking Supervision and Regulation Department, Federal Reserve Bank of Minneapolis.

Flannery, M., 1998. "Using Market Information in Prudential Bank Supervision," *Journal of Money, Credit, and Banking*, August, Part I, 273-305.

Flannery, M.J., 2001. "The Faces of 'Market Discipline'," Manuscript, University of Florida.

Flannery, M., Kwan, S., and Nimalendran, M., 2000. "Market Evidence on the Opaqueness of Banking Firms' Assets," Manuscript, Federal Reserve Bank of San Francisco.

Flannery, M., and Sorescu, S., 1996. "Evidence of Bank Market Discipline in Subordinated Debenture Yields: 1983-1991." *Journal of Finance*, 51, 1347-1377.

Gilbert, A., Meyer, A. and Vaughn, M., 2001. "Can Feedback from the Jumbo CD Market Improve Off-Site Surveillance of Small Banks?," Manuscript, Economic Research Department, Federal Reserve Bank of St. Louis.

Goyal, V.K., 1998. "Market Discipline of Bank Risk: Evidence from Subordinated Debt Contracts," Manuscript, Department of Finance, Hong Kong University of Science and Technology.

Griliches, Z., 1986. "Economic Data Issues," in Griliches, Z. and Intriligator, M.D., eds. Handbook of Econometrics, Volume III. Elsevier Science Publishers BV.

Gropp, R., Vesala, J. and Vulpes, G., 2002. "Equity and Bond Market Signals as Leading Indicators of Bank Fragility," Manuscript, European Central Bank.

Gunther, J.W., Levonian, M.E. and Moore, R.R., 2001. "Can the Stock Market Tell Bank

Supervisors Anything They Don't Already Know?," *Federal Reserve Bank of Dallas Economic and Financial Review*, Second Quarter, 2-9.

Gunther, J.W. and Moore, R.R., 2000. "Early Warning Models in Real Time," Financial Industry Studies Working Paper #1-00, Federal Reserve Bank of Dallas.

Hall, J.R., King, T.B., Meyer, A.P. and Vaughn, M.D., 2001. "What Can Bank Supervisors Learn from the Equity Markets? A Comparison of the Factors Affecting Market-Based Risk Measures and BOPEC Scores," Manuscript, Federal Reserve Bank of St. Louis.

Hancock, D., and Kwast, M., 2000. "Using Subordinated Debt to Monitor Bank Holding Companies: Is it Feasible?" Manuscript, Board of Governors of the Federal Reserve System.

Hirtle, B. and Lopez, J.A., 1999. "Supervisory Information and the Frequency of Bank Examinations," *Federal Reserve Bank of New York Economic Policy Review*, April, 1-20.

Krainer, J. and Lopez, J.A., 2001. "Incorporating Equity Market Information into Supervisory Monitoring Models," Federal Reserve Bank of San Francisco Working Paper #2001-14.

Kwast, M., et. al., 1999. "Using Subordinated Debt as an Instrument of Market Discipline: Report of the Study Group on Subordinated Notes and Debentures." Federal Reserve System Staff Study # 172, Board of Governors of the Federal Reserve System.

Merton, R., 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance*. 29, 449-470.

Meyer, P. and Pifer, H., 1970. "Prediction of Bank Failures," *Journal of Finance*, 25, 853-868.

Pettway, R.H. and Sinkey, J.F., 1980. "Establishing On-Site Bank Examination Priorities: An Early-Warning System using Accounting and Market Information," *Journal of Finance*, 35, 137-150.

Sinkey, J.E., 1975. "A Multivariate Statistical Analysis of the Characteristics of Problem Banks," *Journal of Finance*, 20, 21-36.

Sahajwala, R. and Van der Bergh, P., 2000. "Supervisory Risk Assessment and Early Warning Systems," Basel Committee on Banking Supervision Working Paper No. 4, Bank for International Settlements.

**Table 1. Asset size of the BHCs in the BOPEC sample**

| | 1990-1998 | 1990-1994 | 1995-1998 |
|---|---|---|---|
| Total inspections | 3,010 | 1,735 | 1,275 |
| Asset Size: | | | |
| Assets > $100B | 41 | 13 | 28 |
| $1B < assets < $100B | 1,019 | 594 | 425 |
| Assets<$1B | 1,950 | 1,128 | 822 |
| Inspections of publicly-traded BHCs | 1,291 | 741 | 550 |
| Asset Size: | | | |
| Assets > $100B | 39 | 13 | 26 |
| $1B < assets < $100B | 807 | 487 | 320 |
| Assets<$1B | 445 | 241 | 204 |
| Inspections of BHCs holding debt | 305 | 172 | 133 |
| Asset Size: | | | |
| Assets > $100B | 37 | 11 | 26 |
| $1B < assets < $100B | 266 | 161 | 105 |
| Assets<$1B | 2 | 0 | 2 |
| Inspections of publicly-traded BHCs holding debt | 279 | 161 | 118 |
| Asset Size: | | | |
| Assets > $100B | 36 | 11 | 25 |
| $1B < assets < $100B | 243 | 150 | 93 |
| Assets<$1B | 0 | 0 | 0 |

**Note**: The data sample spans the period from the beginning of 1990 to the second quarter of 1998. The definition of a bank holding company used in this table is the definition used in constructing our dataset; i.e., a top-tier BHC with an identifiable lead bank and four quarters of available regulatory reporting data.

**Table 2A. All BOPEC ratings in the sample**

| | BOPEC Rating | | | | | % of total | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 - 5 | Total | 1 | 2 | 3 | 4 - 5 |
| 1990 | 46 | 135 | 54 | 27 | 262 | 16% | 52% | 21% | 10% |
| 1991 | 48 | 140 | 76 | 36 | 300 | 16% | 47% | 25% | 12% |
| 1992 | 55 | 194 | 75 | 52 | 376 | 15% | 52% | 20% | 14% |
| 1993 | 96 | 216 | 56 | 28 | 396 | 24% | 55% | 14% | 7% |
| 1994 | 136 | 211 | 32 | 22 | 401 | 34% | 53% | 8% | 5% |
| 1995 | 143 | 210 | 31 | 18 | 402 | 36% | 52% | 8% | 5% |
| 1996 | 194 | 195 | 21 | 3 | 413 | 47% | 47% | 5% | 1% |
| 1997 | 176 | 178 | 16 | 1 | 371 | 47% | 48% | 4% | 0% |
| 1998 | 42 | 44 | 3 | 0 | 89 | 47% | 49% | 3% | 0% |
| Total | 936 | 1,523 | 364 | 187 | 3,010 | 31% | 51% | 12% | 6% |

**Note**: The data sample spans the period from the beginning of 1990 to the second quarter of 1998.

**Table 2B. All BOPEC ratings for the publicly traded BHCs in the sample**

| | BOPEC Rating | | | | | % of total | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 - 5 | Total | 1 | 2 | 3 | 4 - 5 |
| 1990 | 22 | 69 | 17 | 10 | 118 | 17% | 58% | 14% | 8% |
| 1991 | 22 | 61 | 30 | 14 | 127 | 17% | 48% | 24% | 11% |
| 1992 | 35 | 71 | 26 | 22 | 154 | 28% | 46% | 17% | 14% |
| 1993 | 49 | 85 | 20 | 12 | 166 | 30% | 51% | 12% | 7% |
| 1994 | 67 | 88 | 13 | 8 | 176 | 38% | 50% | 7% | 5% |
| 1995 | 64 | 97 | 15 | 5 | 181 | 35% | 53% | 8% | 3% |
| 1996 | 84 | 85 | 6 | 0 | 175 | 48% | 49% | 3% | 0% |
| 1997 | 69 | 72 | 1 | 1 | 143 | 48% | 50% | 1% | 1% |
| 1998 | 25 | 26 | 0 | 0 | 51 | 49% | 51% | 0% | 0% |
| Total | 437 | 654 | 128 | 72 | 1,291 | 34% | 51% | 10% | 6% |

**Note**: The data sample spans the period from the beginning of 1990 to the second quarter of 1998.

**Table 2C. All BOPEC ratings for the BHCs with publicly traded bonds in the sample**

| | BOPEC Rating | | | | | % of total | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 - 5 | Total | 1 | 2 | 3 | 4 - 5 |
| 1990 | 6 | 17 | 5 | 3 | 31 | 19% | 55% | 16% | 10% |
| 1991 | 3 | 10 | 9 | 6 | 28 | 11% | 36% | 32% | 21% |
| 1992 | 6 | 15 | 9 | 6 | 36 | 17% | 42% | 25% | 17% |
| 1993 | 8 | 25 | 1 | 2 | 36 | 22% | 69% | 3% | 6% |
| 1994 | 17 | 22 | 2 | 0 | 41 | 41% | 54% | 5% | 0% |
| 1995 | 17 | 24 | 0 | 0 | 41 | 41% | 59% | 0% | 0% |
| 1996 | 21 | 15 | 0 | 0 | 36 | 58% | 42% | 0% | 0% |
| 1997 | 19 | 16 | 0 | 0 | 35 | 54% | 46% | 0% | 0% |
| 1998 | 13 | 8 | 0 | 0 | 21 | 62% | 38% | 0% | 0% |
| Total | 110 | 152 | 26 | 17 | 305 | 36% | 50% | 0% | 6% |

**Note**: The data sample spans the period from the beginning of 1990 to the second quarter of 1998.

**Table 2D. All BOPEC ratings for BHCs with public equity and bonds in the sample**

| | BOPEC Rating | | | | | % of total | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 - 5 | Total | 1 | 2 | 3 | 4 - 5 |
| 1990 | 6 | 16 | 5 | 2 | 29 | 21% | 55% | 17% | 7% |
| 1991 | 3 | 9 | 8 | 6 | 26 | 12% | 35% | 31% | 23% |
| 1992 | 6 | 14 | 9 | 5 | 34 | 18% | 41% | 26% | 15% |
| 1993 | 8 | 23 | 1 | 2 | 34 | 24% | 68% | 3% | 6% |
| 1994 | 17 | 19 | 2 | 0 | 38 | 45% | 50% | 5% | 0% |
| 1995 | 16 | 20 | 0 | 0 | 36 | 44% | 56% | 0% | 0% |
| 1996 | 18 | 12 | 0 | 0 | 30 | 60% | 40% | 0% | 0% |
| 1997 | 19 | 14 | 0 | 0 | 33 | 58% | 42% | 0% | 0% |
| 1998 | 13 | 6 | 0 | 0 | 19 | 68% | 32% | 0% | 0% |
| Total | 106 | 133 | 25 | 15 | 279 | 38% | 48% | 9% | 5% |

**Note**: The data sample spans the period from the beginning of 1990 to the second quarter of 1998.

**Table 3A. All BOPEC rating changes in the sample**

| | Change in BOPEC rating | | | | % of total | | |
|---|---|---|---|---|---|---|---|
| | Upgrade | No change | Downgrade | Total | Upgrade | No change | Downgrade |
| 1990 | 21 | 184 | 57 | 262 | 8% | 70% | 22% |
| 1991 | 33 | 172 | 93 | 300 | 11% | 57% | 31% |
| 1992 | 73 | 231 | 72 | 376 | 19% | 61% | 19% |
| 1993 | 111 | 265 | 20 | 396 | 28% | 67% | 5% |
| 1994 | 107 | 263 | 31 | 401 | 27% | 66% | 8% |
| 1995 | 113 | 260 | 29 | 402 | 28% | 65% | 7% |
| 1996 | 102 | 289 | 22 | 413 | 25% | 70% | 5% |
| 1997 | 85 | 264 | 22 | 371 | 23% | 71% | 6% |
| 1998 | 13 | 73 | 3 | 89 | 15% | 82% | 3% |
| Total | 660 | 2,001 | 349 | 3,010 | 22% | 66% | 12% |

**Note**: The data sample spans the period from the beginning of 1990 to the second quarter of 1998.

**Table 3B. All BOPEC rating changes for the publicly traded BHCs in the sample**

| | Change in BOPEC rating | | | | % of total | | |
|---|---|---|---|---|---|---|---|
| | Upgrade | No change | Downgrade | Total | Upgrade | No change | Downgrade |
| 1990 | 8 | 76 | 34 | 118 | 7% | 64% | 29% |
| 1991 | 8 | 79 | 40 | 127 | 6% | 62% | 31% |
| 1992 | 28 | 98 | 28 | 154 | 18% | 64% | 18% |
| 1993 | 53 | 105 | 8 | 166 | 32% | 63% | 5% |
| 1994 | 43 | 121 | 12 | 176 | 24% | 69% | 7% |
| 1995 | 48 | 118 | 15 | 181 | 27% | 65% | 8% |
| 1996 | 40 | 124 | 11 | 175 | 23% | 71% | 6% |
| 1997 | 26 | 109 | 8 | 143 | 18% | 76% | 6% |
| 1998 | 7 | 43 | 1 | 51 | 14% | 84% | 2% |
| Total | 261 | 873 | 157 | 1,291 | 20% | 68% | 12% |

**Note**: The data sample spans the period from the beginning of 1990 to the second quarter of 1998.

**Table 3C. All BOPEC rating changes for the BHCs holding debt in the sample**

| | Change in BOPEC rating | | | | % of total | | |
|---|---|---|---|---|---|---|---|
| | Upgrade | No change | Downgrade | Total | Upgrade | No change | Downgrade |
| 1990 | 3 | 20 | 8 | 31 | 10% | 65% | 26% |
| 1991 | 3 | 15 | 10 | 28 | 11% | 54% | 36% |
| 1992 | 3 | 28 | 5 | 36 | 8% | 78% | 14% |
| 1993 | 16 | 20 | 0 | 36 | 44% | 56% | 0% |
| 1994 | 7 | 34 | 0 | 41 | 17% | 83% | 0% |
| 1995 | 6 | 33 | 2 | 41 | 15% | 80% | 5% |
| 1996 | 7 | 28 | 1 | 36 | 19% | 78% | 3% |
| 1997 | 4 | 29 | 2 | 35 | 11% | 83% | 6% |
| 1998 | 3 | 17 | 1 | 21 | 14% | 81% | 5% |
| Total | 52 | 224 | 29 | 305 | 17% | 73% | 10% |

**Note**: The data sample spans the period from the beginning of 1990 to the second quarter of 1998.

**Table 3D. All BOPEC ratings for BHCs with public equity and bonds in the sample**

| | Change in BOPEC rating | | | | % of total | | |
|---|---|---|---|---|---|---|---|
| | Upgrade | No change | Downgrade | Total | Upgrade | No change | Downgrade |
| 1990 | 3 | 19 | 7 | 29 | 10% | 66% | 24% |
| 1991 | 2 | 15 | 9 | 26 | 8% | 58% | 35% |
| 1992 | 3 | 27 | 4 | 34 | 9% | 79% | 12% |
| 1993 | 15 | 19 | 0 | 34 | 44% | 56% | 0% |
| 1994 | 7 | 31 | 0 | 38 | 18% | 82% | 0% |
| 1995 | 6 | 28 | 2 | 36 | 17% | 78% | 6% |
| 1996 | 6 | 23 | 1 | 30 | 21% | 77% | 3% |
| 1997 | 4 | 27 | 2 | 33 | 12% | 82% | 6% |
| 1998 | 3 | 15 | 1 | 19 | 16% | 79% | 5% |
| Total | 49 | 204 | 26 | 279 | 18% | 73% | 9% |

**Note**: The data sample spans the period from the beginning of 1990 to the second quarter of 1998.

**Table 4: Summary Statistics for Financial Statement and Supervisory Variables**

| | Mean | Std. Dev. | 25 pctile | Median | 75 pctile |
|---|---|---|---|---|---|
| Assets | $6,336 million | $23,700 million | $250 million | $493 million | $2,068 million |
| CAMELS rating | 1.94 | 0.80 | 1 | 2 | 3 |
| Nonperforming loans / assets | 1.97% | 1.87% | 0.87% | 1.47% | 2.41% |
| Allowances for loan losses / assets | 0.41% | 0.69% | 0.09% | 0.21% | 0.44% |
| Section 20 subsidiary | 0.04 | 0.19 | 0.00 | 0.00 | 0.00 |
| Trading assets / assets | 1.10% | 42.27% | 0.0% | 0.0% | 0.0% |
| Double leverage | 55.24% | 108.34% | 7.29% | 43.27% | 98.21% |
| Return on average assets | 0.82% | 0.97% | 0.66% | 0.98% | 1.22% |
| Equity capital / assets | 8.18% | 2.47% | 6.71% | 7.88% | 9.26% |

**Table 5a: Full Sample Results**

| | Core BOM model | | Extended BOM–equity variables | |
|---|---|---|---|---|
| | coefficients | p-value | coefficients | p-value |
| lagged BOPEC | 1.292 | 0.00 | 1.363 | 0.00 |
| CAMELS | 1.223 | 0.00 | 1.266 | 0.00 |
| Total assets | -0.247 | 0.00 | -0.160 | 0.03 |
| Problem loans | 48.050 | 0.00 | 48.837 | 0.00 |
| Allowances | 56.676 | 0.00 | 57.266 | 0.00 |
| Trading assets | 0.004 | 0.49 | 0.008 | 0.19 |
| Section 20 | 1.819 | 0.00 | 2.203 | 0.00 |
| Double leverage | 0.054 | 0.25 | 0.059 | 0.16 |
| ROA | -1.015 | 0.00 | -1.000 | 0.00 |
| Equity capital | -22.103 | 0.00 | -21.446 | 0.00 |
| SCAR | | | -0.529 | 0.00 |
| Systematic return | | | -0.828 | 0.00 |
| | | | | |
| Observations | 3,010 | | 3,010 | |
| Log likelihood | -1,843.1 | | -1,814.6 | |
| Wald $\chi^2$(j) | 1,155.6 | | 1,124.7 | |
| pseudo $R^2$ | 0.47 | | 0.48 | |

**Note:** Model is $BOPEC_{it} = \beta X_{it-2} + \gamma Z_{it-1} + \varepsilon_{it}$, where X is a vector of supervisory variables and Z is a vector of financial market variables. SCAR is the 6-month standardized abnormal return, systematic return is the 6-month cumulative return predicted by a two factor model, standardized by the standard error of the cumulative abnormal return. The sample period ranges from 1990.Q1 to 1998.Q2. Model estimated with robust standard errors and adjustments for clustered observations.

**Table 5b: Full Sample Results**

| | Extended BOM–debt variables | | Extended BOM–equity and debt variables | |
|---|---|---|---|---|
| | coefficients | p-value | coefficients | p-value |
| lagged BOPEC | 1.340 | 0.00 | 1.368 | 0.00 |
| CAMELS | 1.105 | 0.00 | 1.294 | 0.00 |
| Total assets | -0.133 | 0.01 | -0.177 | 0.02 |
| Problem loans | 46.220 | 0.00 | 49.882 | 0.00 |
| Allowances | 70.835 | 0.00 | 59.132 | 0.00 |
| Trading assets | -0.002 | 0.77 | 0.008 | 0.20 |
| Section 20 | -0.199 | 0.68 | 1.302 | 0.05 |
| Double leverage | 0.042 | 0.49 | 0.064 | 0.13 |
| ROA | -0.932 | 0.00 | -1.003 | 0.00 |
| Equity capital | -25.775 | 0.00 | -21.508 | 0.00 |
| SCAR | | | -0.506 | 0.00 |
| Systematic return | | | -0.798 | 0.00 |
| Adjusted yield | 3.407 | 0.00 | 3.152 | 0.00 |
| | | | | |
| Observations | 3,010 | | 3,010 | |
| Log likelihood | -1,846.4 | | -1,789.8 | |
| Wald $\chi^2$(j) | 1,075.2 | | 1,1977.3 | |
| pseudo $R^2$ | 0.47 | | 0.49 | |

**Note:** Model is $BOPEC_{it} = \beta X_{it-2} + \gamma Z_{it-1} + \varepsilon_{it}$, where X is a vector of supervisory variables and Z is a vector of financial market variables. SCAR is the 6-month standardized abnormal return, systematic return is the 6-month cumulative return predicted by a two factor model, standardized by the standard error of the cumulative abnormal return, and adjusted yield is the change in yield spread minus the change in yield spread for all similarly rated BHCs. The sample period ranges from 1990.Q1 to 1998.Q2. Model estimated with robust standard errors and adjustments for clustered observations.

**Table 6A: Upgrade and Downgrade Models**

| | Upgrade model | | Downgrade model | |
|---|---|---|---|---|
| | coefficient | p-value | coefficient | p-value |
| Lagged BOPEC | 4.071 | 0.00 | -2.830 | 0.00 |
| CAMELS | -1.579 | 0.00 | 1.006 | 0.00 |
| ln(assets) | 0.120 | 0.21 | -0.316 | 0.00 |
| Problem loans | -53.710 | 0.00 | 44.610 | 0.00 |
| Allowances | -88.448 | 0.00 | 53.816 | 0.00 |
| Section 20 | -9.594 | 0.00 | 0.368 | 0.71 |
| Trading assets | -45.052 | 0.37 | -3.123 | 0.89 |
| Double Leverage | -9.594 | 0.00 | -0.62 | 0.73 |
| ROA | 1.174 | 0.00 | -0.427 | 0.15 |
| Equity capital | 13.280 | 0.00 | -17.631 | 0.01 |
| SCAR | 0.387 | 0.00 | -0.758 | 0.00 |
| Predicted return | 0.926 | 0.00 | -0.978 | 0.00 |
| Adjusted yield | -3.348 | 0.04 | 4.124 | 0.00 |
| | | | | |
| Observations | 3,010 | | 3,010 | |
| Log likelihood | -940.9 | | -680.7 | |
| Wald $\chi^2$(j) | 747.6 | | 348.8 | |
| pseudo $R^2$ | 0.41 | | 0.37 | |

**Note:** Model is Pr(BOPEC change at time t)= $\beta X_{it-2} + \gamma Z_{it-1} + \varepsilon_{it}$, where X is a vector of supervisory variables and Z is a vector of financial market variables. SCAR is the 6-month standardized abnormal return, systematic return is the 6-month cumulative return predicted by a two factor model, standardized by the standard error of the cumulative abnormal return, and adjusted yield is the change in yield spread minus the change in yield spread for all similarly rated BHCs. The sample period ranges from 1990.Q1 to 1998.Q2. In the full sample of 3,010 observations, 22% are upgrades and 12% are downgrades.

**Table 6B: Upgrade and Downgrade Past Thresholds**

| | Upgrade to 2 or better | | Downgrade to 3 or worse | |
|---|---|---|---|---|
| | **coefficient** | **p-value** | **coefficient** | **p-value** |
| Lagged BOPEC | 3.474 | 0.00 | -2.172 | 0.00 |
| CAMELS | -0.440 | 0.06 | 0.757 | 0.00 |
| ln(assets) | -0.011 | 0.94 | -0.464 | 0.00 |
| Problem loans | -56.092 | 0.00 | 40.391 | 0.00 |
| Allowances | -102.534 | 0.01 | 52.274 | 0.00 |
| Section 20 | -8.237 | 0.00 | 2.803 | 0.00 |
| Trading assets | -0.247 | 0.04 | -0.185 | 0.00 |
| Double Leverage | -0.055 | 0.07 | -0.028 | 0.88 |
| ROA | 1.329 | 0.00 | -0.074 | 0.77 |
| Equity capital | 1.313 | 0.75 | -25.755 | 0.00 |
| SCAR | 0.345 | 0.01 | -0.816 | 0.00 |
| Predicted return | -0.485 | 0.16 | -1.554 | 0.00 |
| Adjusted yield | -4.021 | 0.05 | 2.559 | 0.01 |
| | | | | |
| Observations | 3,010 | | 3,010 | |
| Log likelihood | -496.3 | | -408.7 | |
| Wald $\chi^2$(j) | 806.6 | | 300.1 | |
| pseudo $R^2$ | 0.42 | | 0.33 | |

**Note:** Model is Pr(BOPEC change over threshold at time t)= $\beta X_{it-2} + \gamma Z_{it-1} + \varepsilon_{it}$, where X is a vector of supervisory variables and Z is a vector of financial market variables. SCAR is the 6-month standardized abnormal return, systematic return is the 6-month cumulative return predicted by a two factor model, standardized by the standard error of the cumulative abnormal return, and adjusted yield is the change in yield spread minus the change in yield spread for all similarly rated BHCs. The sample period ranges from 1990.Q1 to 1998.Q2. In the full sample of 3,010 observations, 8% are upgrades from three or worse to two or better, and 5% are downgrades to three or worse from two or better.

**Table 6C: Marginal effects in upgrade and downgrade models**

| | SCAR | Systematic return | Adjusted yield |
|---|---|---|---|
| Upgrade | 0.021 | 0.051 | -0.185 |
| (p-value) | (0.02) | (0.02) | (0.09) |
| | | | |
| Upgrade above threshold | 0.005 | -0.007 | -0.059 |
| (p-value) | (0.01) | (0.16) | (0.06) |
| | | | |
| Downgrade | -0.027 | -0.035 | 0.149 |
| (p-value) | (0.00) | (0.00) | (0.00) |
| | | | |
| Downgrade below threshold | -0.011 | -0.022 | 0.036 |
| (p-value) | (0.00) | (0.00) | (0.00) |

**Note:** Model is Pr(BOPEC change at time t)= $\beta X_{it-1} + \gamma Z_{it-1} + \varepsilon_{it}$, where X is a vector of supervisory variables and Z is a vector of financial market variables. SCAR is the 6-month standardized abnormal return, systematic return is the 6-month cumulative return predicted by a two factor model, standardized by the standard error of the cumulative abnormal return, and adjusted yield is the change in yield spread minus the change in yield spread for all similarly rated BHCs. The sample period ranges from 1990.Q1 to 1998.Q2. Marginal effect is the change in probability BOPEC change given a change in financial market variable. All derivatives are calculated with explanatory variables at their mean values.

**Table 7A: BOM with distance-to-default interactions on SCARs**

| | far from default | p-value far from default | close to default | p-value close to default | log likelihood | pseudo $R^2$ |
|---|---|---|---|---|---|---|
| 10th pctile | -0.421 | 0.00 | 0.137 | 0.48 | -972.3 | 0.31 |
| 20th pctile | -0.406 | 0.00 | 0.022 | 0.89 | -972.7 | 0.31 |
| 30th pctile | -0.423 | 0.00 | 0.054 | 0.71 | -972.6 | 0.31 |
| 40th pctile | -0.431 | 0.00 | 0.058 | 0.67 | -972.7 | 0.31 |
| 50th pctile | -0.418 | 0.00 | 0.030 | 0.84 | -972.7 | 0.31 |
| 60th pctile | -0.313 | 0.00 | -0.114 | 0.42 | -972.4 | 0.31 |
| 70th pctile | -0.271 | 0.04 | -0.155 | 0.32 | 972.5 | 0.31 |
| 80th pctile | -0.286 | 0.09 | -0.126 | 0.49 | -972.5 | 0.31 |
| 90th pctile | -0.197 | 0.41 | -0.214 | 0.40 | -972.4 | 0.31 |

**Note:** Model is $BOPEC_{it} = \beta * BOPEC_{it-2} + (\pi + \alpha I_{n,t-1})*Z_{it-1} + \varepsilon_{it}$, where $Z_{it-1}$ is the six month SCAR at time t-1 and $I_{n,t-1}$ equals 1 if distance-to-default is in the nth percentile at time t-1, and zero otherwise. This model is estimated separately for the n= 10th to 90th percentiles. The coefficients in the "far from default" column correspond to $\pi$. The coefficients in the "close to default" column correspond to $(\pi+\alpha)$. All models are estimated with a sample of 1,266 observations.

**Table 7B: BOM with distance-to-default interactions on adjusted yields**

| | far from default | p-value far from default | close to default | p-value close to default | log likelihood | pseudo $R^2$ |
|---|---|---|---|---|---|---|
| $10^{th}$ pctile | 2.781 | 0.00 | 7.196 | 0.00 | -184.4 | 0.41 |
| $20^{th}$ pctile | 2.781 | 0.00 | 7.196 | 0.01 | -184.4 | 0.41 |
| $30^{th}$ pctile | 2.516 | 0.00 | 1.261 | 0.63 | -184.9 | 0.41 |
| $40^{th}$ pctile | 2.563 | 0.00 | 1.009 | 0.71 | -184.9 | 0.41 |
| $50^{th}$ pctile | 2.670 | 0.00 | 0.672 | 0.81 | -185.0 | 0.41 |
| $60^{th}$ pctile | 1.800 | 0.02 | 1.601 | 0.30 | -184.7 | 0.41 |
| $70^{th}$ pctile | 1.786 | 0.02 | 1.597 | 0.34 | -184.7 | 0.41 |
| $80^{th}$ pctile | -0.723 | 0.75 | 3.863 | 0.10 | -184.4 | 0.41 |
| $90^{th}$ pctile | -2.831 | 0.39 | 5.918 | 0.08 | -184.3 | 0.41 |

**Note:** Model is $BOPEC_{it} = \beta * BOPEC_{it-2} + (\pi + \alpha I_{n,t-1})*Z_{it-1} + \varepsilon_{it}$, where $Z_{it-1}$ is the adjusted three-month change in yield at time t-1 and $I_{n,t-1}$ equals 1 if distance-to-default is in the nth percentile at time t-1, and zero otherwise. This model is estimated separately for the n= $10^{th}$ to $90^{th}$ percentiles. The coefficients in the "far from default" column correspond to $\pi$. The coefficients in the "close to default" column correspond to $(\pi + \alpha)$. All models are estimated with a sample of 282 observations.

**Table 8A: Forecast Accuracy of Core BOM**

**Actual Inspection Outcome**

| **Signal at -4 quarters** | **# signals** | **upgrade %** | **no change %** | **downgrade %** | **Pearson statistic** |
|---|---|---|---|---|---|
| upgrade | 23 | 52% | 35% | 13% | |
| no change | 2,885 | 22% | 67% | 67% | |
| downgrade | 32 | 3% | 7% | 69% | 153.0* |
| **Signal at -3 quarters** | | | | | |
| upgrade | 29 | 66% | 21% | 14% | |
| no change | 2,880 | 22% | 67% | 11% | |
| downgrade | 31 | 0% | 16% | 84% | 263.0* |
| **Signal at -2 quarters** | | | | | |
| upgrade | 45 | 80% | 13% | 7% | |
| no change | 2,854 | 21% | 68% | 11% | |
| downgrade | 41 | 0% | 10% | 90% | 472.2* |
| **Signal at -1 quarters** | | | | | |
| upgrade | 60 | 90% | 8% | 2% | |
| no change | 2,832 | 21% | 69% | 11% | |
| downgrade | 48 | 0% | 10% | 90% | 635.6* |

**Note:** This table presents the forecast accuracy results based on conditioning on the adjusted BOPEC forecasts from the core BOM model at different horizons. A forecast signal is the difference between the forecasted BOPEC and the previously assigned BOPEC rating. Thus, signals of less than -1 and greater than 1 are forecasts of upgrades and downgrades, respectively. The cells in bold indicate the outcome expected, conditional on the signal. The Pearson goodness-of-fit statistic tests the null hypothesis that the distribution of BOPEC outcomes conditional on the Core model forecasts is not different from the in-sample probabilities of upgrade, no change, and downgrade (the unconditional distribution). The statistic is distributed $\chi^2(10)$. A * denotes significance at the 5% level.
**Note:** Percentages in rows may not sum to 100% due to rounding.

**Table 8B: Forecast accuracy of Extended BOM with debt market variables**

| Actual Inspection Outcome | | | | | | |
|---|---|---|---|---|---|---|
| **Signal at -4 quarters** | **# obs.** | **upgrade %** | **no change %** | **downgrade %** | **Pearson statistic I** | **Pearson statistic II** |
| upgrade | 28 | 46% | 43% | 11% | | |
| no change | 2,877 | 22% | 67% | 11% | | |
| downgrade | 35 | 3% | 34% | 63% | 130.6* | 2.6 |
| **Signal at -3 quarters** | | | | | | |
| upgrade | 31 | 58% | 29% | 13% | | |
| no change | 2,874 | 21% | 67% | 11% | | |
| downgrade | 35 | 0% | 20% | 80% | 248.7* | 3.3 |
| **Signal at -2 quarters** | | | | | | |
| upgrade | 48 | 77% | 15% | 8% | | |
| no change | 2,851 | 21% | 68% | 11% | | |
| downgrade | 41 | 0% | 10% | 90% | 466.5* | 12.9* |
| **Signal at -1 quarters** | | | | | | |
| upgrade | 63 | 87% | 10% | 3% | | |
| no change | 2,824 | 21% | 69% | 10% | | |
| downgrade | 53 | 2% | 9% | 89% | 661.2* | 6.5* |

**Note:** This table presents the forecast accuracy results based on conditioning on the adjusted BOPEC forecasts from the core BOM model at different horizons. A forecast signal is the difference between the forecasted BOPEC and the previously assigned BOPEC rating. Thus, signals of less than -1 and greater than 1 are forecasts of upgrades and downgrades, respectively. The cells in bold indicate the outcome expected, conditional on the signal. The Pearson goodness-of-fit statistic I tests the null hypothesis that the distribution of BOPEC outcomes conditional on the Core model forecasts is not different from the in-sample probabilities of upgrade, no change, and downgrade (the unconditional distribution). The statistic is distributed $\chi^2(10)$. The Pearson goodness-of-fit statistic II tests the null hypothesis that the distribution of BOPEC outcomes conditional on the Extended model forecasts is not different from the distribution of outcomes forecasted by the Core model. The statistic is distributed $\chi^2(2)$. A * denotes significance at the 5% level.
**Note:** Percentages in rows may not sum to 100% due to rounding.

**Table 8C: Forecast accuracy of Extended BOM with equity market variables**

| Actual Inspection Outcome | | | | | | |
|---|---|---|---|---|---|---|
| **Signal at -4 quarters** | **# obs.** | **upgrade %** | **no change %** | **downgrade %** | **Pearson statistic I** | **Pearson statistic II** |
| upgrade | 26 | 62% | 27% | 12% | | |
| no change | 2,875 | 22% | 67% | 11% | | |
| downgrade | 39 | 0% | 44% | 56% | 139.2* | 10.3* |
| **Signal at -3 quarters** | | | | | | |
| upgrade | 31 | 71% | 19% | 10% | | |
| no change | 2,870 | 22% | 68% | 11% | | |
| downgrade | 39 | 0% | 15% | 85% | 336.5* | 1.1 |
| **Signal at -2 quarters** | | | | | | |
| upgrade | 49 | 84% | 12% | 4% | | |
| no change | 2,832 | 21% | 69% | 10% | | |
| downgrade | 59 | 0% | 10% | 90% | 637.6* | 3.1 |
| **Signal at -1 quarters** | | | | | | |
| upgrade | 69 | 91% | 7% | 2% | | |
| no change | 2,803 | 21% | 69% | 10% | | |
| downgrade | 68 | 0% | 18% | 82% | 748.2* | 9.1* |

**Note:** This table presents the forecast accuracy results based on conditioning on the adjusted BOPEC forecasts from the core BOM model at different horizons. A forecast signal is the difference between the forecasted BOPEC and the previously assigned BOPEC rating. Thus, signals of less than -1 and greater than 1 are forecasts of upgrades and downgrades, respectively. The cells in bold indicate the outcome expected, conditional on the signal. The Pearson goodness-of-fit statistic I tests the null hypothesis that the distribution of BOPEC outcomes conditional on the Core model forecasts is not different from the in-sample probabilities of upgrade, no change, and downgrade (the unconditional distribution). The statistic is distributed $\chi^2(10)$. The Pearson goodness-of-fit statistic II tests the null hypothesis that the distribution of BOPEC outcomes conditional on the Extended model forecasts is not different from the distribution of outcomes forecasted by the Core model. The statistic is distributed $\chi^2(3)$. A * denotes significance at the 5% level.
**Note:** Percentages in rows may not sum to 100% due to rounding.

**Table 8D: Forecast accuracy of Extended BOM with debt and equity market variables**

| Actual Inspection Outcome | | | | | | |
|---|---|---|---|---|---|---|
| **Signal at -4 quarters** | **# obs.** | **upgrade %** | **no change %** | **downgrade %** | **Pearson statistic I** | **Pearson statistic II** |
| upgrade | 28 | 54% | 36% | 11% | | |
| no change | 2,876 | 22% | 67% | 11% | | |
| downgrade | 36 | 0% | 42% | 58% | 125.4* | 6.5 |
| **Signal at -3 quarters** | | | | | | |
| upgrade | 34 | 65% | 27% | 9% | | |
| no change | 2,865 | 22% | 68% | 11% | | |
| downgrade | 41 | 6% | 20% | 81% | 301.3* | 2.3 |
| **Signal at -2 quarters** | | | | | | |
| upgrade | 54 | 80% | 13% | 7% | | |
| no change | 2,827 | 21% | 69% | 10% | | |
| downgrade | 59 | 0% | 10% | 90% | 636.8* | 11.6* |
| **Signal at -1 quarters** | | | | | | |
| upgrade | 69 | 90% | 7% | 3% | | |
| no change | 2,807 | 21% | 69% | 10% | | |
| downgrade | 64 | 2% | 13% | 86% | 757.8* | 6.9 |

**Note:** This table presents the forecast accuracy results based on conditioning on the adjusted BOPEC forecasts from the core BOM model at different horizons. A forecast signal is the difference between the forecasted BOPEC and the previously assigned BOPEC rating. Thus, signals of less than -1 and greater than 1 are forecasts of upgrades and downgrades, respectively. The cells in bold indicate the outcome expected, conditional on the signal. The Pearson goodness-of-fit statistic I tests the null hypothesis that the distribution of BOPEC outcomes conditional on the Core model forecasts is not different from the in-sample probabilities of upgrade, no change, and downgrade (the unconditional distribution). The statistic is distributed $\chi^2(10)$. The Pearson goodness-of-fit statistic II tests the null hypothesis that the distribution of BOPEC outcomes conditional on the Extended model forecasts is not different from the distribution of outcomes forecasted by the Core model. The statistic is distributed $\chi^2(5)$. A * denotes significance at the 5% level.
**Note:** Percentages in rows may not sum to 100% due to rounding.

**Table 9A. Percentage increase of correct downgrade forecasts captured by the extended BOM model over the core BOM model**

| | Debt + equity | Debt | Equity |
|---|---|---|---|
| 4 quarters | 9% | 9% | 14% |
| 3 quarters | 38% | 15% | 38% |
| 2 quarters | 51% | 5% | 51% |
| 1 quarters | 37% | 10% | 37% |

**Note:** Downgrade signal is defined as forecasted rating - current rating > 1. Table reports number of downgrades correctly signaled by Extended model and not identified by Core model, expressed as a percentage of downgrades correctly identified by Core model.

**Table 9B. Tradeoff of correct downgrade forecasts for mistakes in the extended BOM model**

| | Debt + equity | Debt | Equity |
|---|---|---|---|
| 4 quarters | 1 / 4 | 2 / 3 | 3 / 10 |
| 3 quarters | 5 / 2 | 2 / 1 | 5 / 1 |
| 2 quarters | 19 / 3 | 2 / 0 | 19 / 3 |
| 1 quarters | 4 / 1 | 6 / 1 | 16 / 7 |

**Note:** A cell entry *x / y* implies that the Extended BOM model identifies *x* additional downgrades over the Core model, at the rate of *y* additional incorrect downgrade signals.