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Is There Cyclical Bias in Bank Holding Company Risk Ratings?

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Abstract

This paper examines whether bank holding company (BHC) risk ratings are asymmetrically assigned or biased over business cycles from 1986 to 2003. In a model of ratings determination which accounts for bank characteristics, financial market conditions, past supervisory information, and aggregate macro-economic factors, we find that bank exam ratings exhibit inter-temporal characteristics. First, exam ratings exhibit some evidence of examiner bias for several periods analyzed. When the business cycle turns, examiners sometime depart from standards that they set during the previous phases of the business cycle. However, this bias is not widespread or systematic. Second, exam ratings exhibit some inertia. Our results suggest that examiners rate on the side of not changing (rather than upgrading or downgrading) an institution's exam rating. Third, we find strong and robust evidence of a secular trend towards more stringent examination BHC ratings standards over time.

JEL Classification: G21

Keywords: Bank Holding Company risk ratings, Cyclical bias in bank ratings, Secular trend in bank risk ratings

I. *Introduction*

Outside monitors provide important information that can help stockholders, creditors, regulators and other stakeholders apply market discipline. Private sector rating agencies like Standard and Poor's, Moody's KMV and Fitch provide corporate bond risk ratings so creditors can evaluate the probability of default and the likelihood of repayment. In the banking industry, government examiners are an additional outside monitor but with one important difference: bank examination ratings are not public information, and are known only to supervisors and senior bank management. Still, examination ratings directly influence bank operations and performance because they are used to determine banks' required capital ratios, deposit insurance premiums and in extreme cases, are used to constrain banks' investment decisions. Because of banks' special role in the economy, changes in examination ratings can have important implications for credit availability and general economic activity (Curry, Fissel and Ramirez, 2006).

This paper analyzes one aspect of the bank monitoring process: whether banking holding company risk ratings (BOPEC ratings)[1] are asymmetrically assigned or biased over the business cycles.[2] If examiners are more aggressive with downgrades during downturns and upgrades during upturns and if this carries over from one cycle to another, then this pro-cyclical behavior has

[1] BOPEC is an acronym for the bank holding company examination system which is overseen by the Federal Reserve. It stands for bank (B), other subsidiaries (O), parent organization (P), consolidated earnings (E) and capital (C). Each of these components is rated on an ordinal scale from a 1 to a 5 with one being superior and five nearing failure. An overall composite rating is issued as well. This system was altered by the Federal Reserve in January 2005. However, since our analysis ends at the year 2004, we refer to the system (BOPEC) that was in place at that time.

[2] According to the Federal Reserve System's *Bank Holding Company (BHC) Supervision Manual*, examiners assign bank holding company ratings (BOPEC) based upon the underlying financial characteristics of the firm independent of business cycle movements. "Supervisory ratings should be revised whenever there is strong evidence that the financial condition or risk profile of an institution has significantly changed….It is important that supervisory ratings reflect a current assessment of an institution's financial condition and risk profile". (FRB *BHC Supervision Manual* [Section 4070.3, 1999. p1.].

implications for bank capital levels, bank lending growth and economic activity as noted. We examine hypotheses related to this issue by empirically testing whether bank holding company (BHC) risk ratings are biased cyclically in the sense that assigned ratings are persistently below or above what would be predicted depending upon the condition of the U.S. economy, BHC financial condition and/or financial markets. The null hypothesis states that although ratings may move with the business cycle, risk ratings assigned to BHCs should not have a significantly excess over that predicted by estimated models of past upgrades, downgrades and no changes.[3]

To date, this issue has been largely unexplored in the banking literature. In the only related study that we are familiar, Berger, Kyle, and Scalise (2001) analyze if supervisory officials were particularly harsh with CAMELS rating assignments during the 1989-1992 credit crunch period and whether they become more lenient in their evaluations during 1993-1998 recovery period. Their results show that supervisors may have exacerbated the credit crunch and accelerated the lending boom in bank lending during these periods but the quantitative impact was too small to explain the wide swings in aggregate bank lending to business during the 1990s.

However, there is evidence that suggests bond ratings by private agencies are influenced by business cycle conditions. For example, Altman and Kao (1992) find that agency ratings like Standard & Poor's and Moody's are serially correlated, that is downgrades are more likely to be followed by downgrades than upgrades. Thus, in the aggregate, rating assignments may not be independent. Lucas and Lonski (1992) show that with Moody's ratings, the number of firms downgraded has increasingly exceeded the number of firms upgraded overtime. In recent work, Amato and Furfine (2004) find that initial and newly assigned ratings, as opposed to seasoned ratings

[3] Throughout the study we use the term "rating changes" to refer to the outcome of full scope examinations relative to their previous exams by the Federal Reserve of a BHC. These ratings outcomes are upgrade, no change or

by Standard and Poor's, are related to the macro-economy in a procyclical manner. They show that ratings are relatively better during growth periods and relatively worse during recessions after accounting for specific measures of business and firm risk.

This topic is important because of the implication for the allocation of bank credit and because examiner scrutiny of banking institutions during cyclical downturns has been an issue for bank supervisors in the past. For example, Syron (1991), in responding to charges of a harsh treatment by bank supervisors during the 1990-1991 recession in New England, claims that examiners are historically been more vigilant during recessions. He admits that this disposition may have exacerbated economic conditions at that time. Furthermore, Peek and Rosengren (1995a), while not focusing specifically on bank risk ratings, find that the large declines in the growth rate of bank lending in New England, which may have contributed to the worsening of the 1990-1991 recession, were largely attributable to tough supervisory actions. They conclude that the inability to raise external capital in the face of regulator mandates resulted in a large number of banking institutions shrinking their assets with potentially adverse effects on bank lending. Laeven and Majnoni (2003) also find evidence that strict regulatory actions during economic slowdowns can result in a credit crunch and thus worsen already adverse economic conditions.

An analysis of this issue is also worthy of investigation because of the potential impact that cyclically biased risk ratings may have under the new Basel II framework of capital requirements. Under the new system, risk sensitive capital requirements will increase (decrease) when bank and supervisory estimates of default risk increase (decrease). Lower capital levels during economic expansions caused by risk sensitive requirements may result in capital being too low at the peak of the cycle to deal with the subsequent contraction. In contrast, high capital levels on the downturns

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downgrade.

could result in a reduction in bank lending contributing to deteriorating economic conditions. The concern that the new capital accord may exacerbate business fluctuations is acknowledged by the Basel Committee on Bank Supervision (2002), and others (Altman and Saunders, 2001); (Borio, Furfine and Lowe, 2001).

Simply observing that BOPEC risk ratings move contemporaneously with the business cycle (preponderance of downgrades during recessions and upgrades during expansions) does not necessarily provide evidence that these ratings are biased. Supervisory officials alter ratings in response to changes in default risk of firms as they move through the cycle. The difficult question to answer is what is excessive or unduly restrictive or lax examiner behavior in response to changes in financial condition brought about by shocks in the macro-economy?

To determine if bank supervisors are excessively restrictive or lax at various points along the cycle requires a comparison of actual ratings with expected ratings conditioned upon information available at the time of the examination. This means that a method of determining expected ratings for a banking company must be developed. In this study, we employ benchmark models to determine expected ratings including: (1) a naïve model that assumes that the proportion of new ratings is the same from the prior period; and (2) an econometric model of supervisory rating outcomes for individual banking companies. We use an ordered logistic regression model based upon a sample of over 4,000 newly assigned BHC ratings over the 1986 to 2003 period to forecast expected rating outcomes. This rating determination model is conditioned upon factors such as macro-economic conditions, financial market factors, bank characteristics, and past supervisory information. We use forecasts from a naïve model to compare the forecast results from the estimated models and as a check on the maximum extent of possible bias. We define examiner bias as a significant and persistent deviation of our forecasts of upgrades, downgrades and no changes

from those actually assigned for the periods analyzed.

This paper makes a contribution to the literature. We find some evidence of bias in the application of risk ratings assigned by examiners during the cycles analyzed. In instances, when the business cycle turns, there is some evidence that examiners depart from rating standards that were set during the previous phases of the cycle. However, this result is not widespread or systematic. In addition, we find that exam ratings exhibit some inertia. In these cases, examiners choose not to change ratings rather than upgrading or downgrading institutions.

Our methodology also allows for an analysis of the trend behavior of examination ratings over time. In effect, we address the question if examination standards have weakened or become more stringent since the banking crisis and recession years of the late 1980s and early 1990s and in the post-FDICIA (1991) environment.[4] Using two separate econometric approaches, we find robust evidence to support the notion that BHC examination standards have become more stringent over the period of this study.

The remainder of the paper is broken down as follows. Section II discusses issues raised in the literature pertaining to default risk, business cycles and the assignment of risk ratings by both the private rating agencies and bank supervisors. Section III discusses the sample and data. Section IV presents the model and statistical approach. Section V presents the empirical results and Section VI concludes.

II. *Business Cycles, Credit Default Risk and Risk Ratings*

Empirical studies in the finance literature indicate that credit quality deteriorates and the probability of default (PD) rises during recessions. Fama (1986) and Wilson (1997a,b) find cyclical

PDs especially in the case of economic downturns when PD's increased dramatically. Altman and Brady (2001) show that there is a correlation between default probabilities and macro-economic conditions. Other studies that link default rates and macro variables include Nickel et al (2000), Bangia et al (2002), Pesaran et al. (2003), and Allen and Saunders (2003). These studies show that the likelihood of default is significantly higher during recessionary states along with the volume of credit losses. Other literature finds a correlation between credit spreads on debt instruments and business cycle conditions including Fama and French (1989), Chen (1991), and Stock and Watson (1989).

Figure 1 shows the relationship between credit default risk of BHCs, and the National Bureau of Economic (NBER) defined business cycles over quarterly periods from 1986 to 2003. Default risk is measured by two market-based measures including the probability of insolvency and the distance-to-default for publicly-traded BHCs calculated from the structural models of Merton (1974) and Black and Cox (1973). (See the appendix for the algorithm). As demonstrated, these measures of default risk exhibit a high correlation with changes in the business cycle. The probability of default spikes dramatically prior to and during the 1990-1991 recession while the distance to default narrows as the recession approaches. The pattern reverses itself during periods of recovery and expansion. Both measures appear to be leading indicators of changing risk patterns for BHCs for both the 1990-1991 and 2001-2002 recessions.

These changing patterns over the cycle should be correlated with risk ratings. Figure 2 shows the relationship between the BHC probability of insolvency and the rate of BOPEC downgrades in relation to NBER defined cycles. The number of downgrades is shown as a

[4] "FDICIA" stands for the Federal Deposit Insurance Corporation Improvement Act of 1991. This act ramped up bank supervisory standards and capital requirements.

proportion of the total quarterly ratings assigned for the sample from 1986.q2 to 2003.q4. These aggregate data show a high contemporaneous correlation of 0.73 between the probability of insolvency and the proportion of BOPEC downgrades. This confirms the relationship shown in Figure 2. Newly assigned BOPEC ratings are highly sensitive to changes in financial condition. During recessions, we observe a large increase in the number of downgrades and the opposite behavior during periods of recovery and expansion.

As noted, this close mapping of BOPEC ratings to the changes in default risk does not necessarily indicate evidence of bias in rating assignments. Ratings change in response to changes in financial condition. To evaluate the issue, it is necessary to identify excessively strict or lax examiner behavior in response to changes in insolvency risk as firms move through the cycle. As mentioned, this issue has not been systematically explored in the banking literature. Nevertheless, there is evidence involving agency ratings that suggest bond ratings are influenced by business cycle conditions. In the most recent work, Amato and Furfine (2004) find that initial and newly assigned ratings and rating changes by Standard and Poor's, as opposed to seasoned ratings, are related to the macro-economy in a procyclical manner. They show that ratings are relatively better during growth periods and relatively worse during recessions after accounting for specific measures of business and firm risk. In addition, as previously indicated, others have found evidence of procyclicality and bias associated with agency ratings. Thus, it would behoove us to explore this important issue involving the supervisory behavior of risk rating assignments for financial institutions.

III. *Data*

We use two confidential sources of BHC examination activity: BOPEC risk rating assignments and examination frequency. This information is obtained from the Federal Reserve Board (FRB). Bank holding company inspections normally occur on 12 to 18 month intervals after

FDICIA (1991). Because there is evidence that risk ratings can become outdated quickly between examination cycles (Cole and Gunther,1995), we consider only newly assigned risk ratings by estimating models with mostly one-quarter lags prior to the inspections. Also, we consider only full-scope examinations because other on-site reviews, such as limited-scope exams or visitations, usually fail to generate as much complete information on the financial condition as do full-scope exams. For each exam, we collect data as of the start date, end date, and the date the institution was notified of the rating. To test for examiner bias, we select a benchmark quarter as the one in which the bank's board is informed of the rating.

Data on the financial condition originates from the quarterly Y-9C financial reports collected by the FRB. Data for equity market variables are obtained from the Center for Research in Security Prices (CRSP). CRSP data includes historical information such as daily stock prices, daily returns, equal and value weighted indexes of market returns, dividend information, daily trading volume, and other variables for all organizations that are publicly traded on the national exchanges. We develop a rich database by matching historical CRSP stock price information with quarterly BHC financial data, BOPEC examination ratings and macro-economic data. We calculate all quarterly market variables from the daily stock price and trading information provided by CRSP. The data for the calculation of interest rate spreads on the yield curve are obtained from the FRB constant maturity series from the H.15 Report. The Congressional Budget Office was the source for the GDP gap measure. NBER provides the data for the remaining macro variables.

For the ratings sample, we require that each BHC be a top-tier organization. We focus on top-tier BHCs because they are the legal entity which issues publicly traded equity. We also require that each organization have quarterly financial Y9-C data, CRSP market data and past supervisory ratings. Over the 1986-2003 period, these requirements produce a sample of 787 unique BHCs with

4,041 new inspections, which resulted in 492 BOPEC downgrades, 456 upgrades, and 3,093 inspections with no-rating changes. As long as the BHC was publicly traded, remained on CRSP, and filed quarterly financial reports, the institution remained in the sample. Acquired institutions disappeared from the sample when they no longer filed quarterly financial reports. We analyze separate segments of the business cycle over the duration of the sample data as follows: 1986:2-1991:2 (recessionary period); 1991:3-1995:4 (recovery period); 1996:1-2000:3 (expansionary period); and 2000:4-2003:4 (recessionary period).[5]

IV. *Model and Statistical Approach*

BOPEC rating assignments are the result of inspections of the entire holding company and not just the bank affiliates. We consider the changes in ratings in terms of a time series in which supervisors can choose to change a rating or leave it the same. Therefore, in our approach, unlike that of bank failure models, once a bank is assigned a BOPEC rating, it is not required to remain in that state. We consider that the process that generates risk ratings is the same regardless of the outcome of the evaluation (downgrade, upgrade, or no rating change). This process has three supervisory outcomes and is consistent with an ordered logistic estimation procedure (Maddala,1988). With the exception of an initial BOPEC rating of *1*, from which a holding company can be never be upgraded or an initial BOPEC rating of *5,* from which a holding company can not be downgraded, a firm can be upgraded, downgraded or their rating can remain the same.

We construct regression models that estimate the probability for the three possible outcomes. We specify group *1* for institutions that were downgraded, group *2* for institutions

[5] The selection of the start and end points for the subperiods is based on the NBER's dating of the recessionary periods and the tracking of actual versus potential GDP. We wanted a band of time that was wide enough to account for changes in the credit as well as economic cycles. Just following the strict NBER defined recession markers

whose ratings remained the same; group *3* if institutions were upgraded, thus ordering the regression. In addition, we also use three different models to predict BOPEC rating changes including: (a) the financial accounting model (FA) (which excludes market variables only); (b) the equity market model (EM),(which excludes financial accounting variables only); and (c) the combined model (CM) which include all variables. We choose to experiment with different models because prior literature suggests that the use of multiple models may improve the forecast accuracy of exam rating predictions over the different phases of the business cycle. (Curry, Fissel and Hanweck, 2003).[6] The form of the estimating model is: (1)

$$\text{Prob}(\Delta BOPEC_{it}) = f(\alpha_1 + \alpha_2 + \beta_1 \text{Firm Size}_{\text{it}-1} + \sum_{j=2}^{10} \beta_{2j}(\text{Financial Variables}_{\text{it-1}}) +$$
$$\sum_{j=11}^{16} \beta_{3j}(Market\ Variables_{it-1}) + \sum_{j=17}^{22} \beta_{4j}(\text{Supervisory Variables}_{\text{it}-1}) +$$
$$\beta_5(Linear\,Time\,Trend_t) + \sum_{j=25}^{30} \beta_{6j}(\text{Macrovariables Variables}_{\text{it}-n}) + \varepsilon it)$$

where BOPEC$_{it}$ is the rating change group (1=downgrades, 2=no change and 3=upgrade) for BHC i at time t; n=1 for two macro-variables (C_Spread, GDP GAP); n=2 for the GWTH_EMPL variable; and n=3 for all remaining macro variables; f() is a cumulative probability function such as a logit, β_1 is the slope coefficient for firm size, $\beta_{2\ j=2\ldots10}$ are coefficients for a vector of variables for financial condition based on quarterly accounting information, $\beta_{3\ j=11\ldots17}$ are coefficients for a vector of variables for selected market measures for each BHC$_i$, $\beta_{4\ j=18\ldots23}$ are past supervisory opinions unique to each BHC$_i$, $\beta_{5\ j=24}$ is the linear time trend variable; and $\beta_{6\ j=25\ldots30}$ are coefficients for a

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would be too narrow a band for the analysis since we are also interested in tracking banking cycles not coincident with recessions and changes for periods leading up to and following the recessions.

[6] In addition, we experiment with different models because it has been shown that models with the best in-sample fits are not always the best out-of-sample predictors (See Pindyck and Rubinfeld, 1976 p. 161).

vector of macro-variables. The dependent variables are ordered so that the regression coefficients should be interpreted as estimating the probability of a BOPEC rating downgrade. The ε_{it} are assumed to have a cumulative logistic function that is similar for each group (Maddala [1988]); α_1 and α_2 are constants estimated for the ordered logit for the three rating groups.

1. Financial and Market Risk Measures

All variables are defined in Table 1. The first independent variable controls for size differences between institutions and is the natural logarithm of total assets (LN_ASSET). To the extent that an institution's size provides for large-scale diversification, economies of scale and scope, access to the capital markets, these factors should reduce the likelihood of experiencing a downgrade. We measure capital adequacy by two ratios: equity to assets (EQ_Asset) and loan-loss reserves to assets (LLR_ASSET). We expect an inverse relationship between these variables and the probability of a downgrade. Credit quality is captured by loans past- due 90 days or more (PD90_ASSET), loans in nonaccrual status (NA_ASSET), and the provision for loan losses-to-assets ratio (LPROV_ASSET). We expect all three variables to be positively related to the likelihood of a downgrade. Charge-offs of delinquent loans (CHARG_ASSET) removes these assets from the balance sheet. The removal of these loans should be negatively related to a downgrade. However, higher levels of charge-offs indicate loan delinquencies which could be positively related to the probability of a downgrade. Thus, the anticipated sign is ambiguous.

We measure profitability by return-on-assets (ROA), which is expected to be negatively related to the likelihood of a downgrade. We posit two measures of liquidity, the ratio of liquid assets to total assets (LIQ_ASSET) and total deposits held in accounts greater than $100,000 (TD100_ASSET). We expect the level of liquid assets ratio to be negatively related to financial distress while we expect a positive relationship between deposits held in accounts greater than

$100,000 and the likelihood of a downgrade, reflecting a more aggressive, volatile funding strategy.

We specify five variables to capture the market appraisal of financial condition. The first two variables, the probability of default (PROB_DEF) and the distance default (DIST_DEF) are equity-based measures of risk based upon the Merton (1974) model. We expect the probability of default to be positively related to receiving a downgrade and negatively related for the distance default. Stock price volatility is captured by the coefficient of variation (COEF_VAR). This variable is expected to be positively related to receiving a downgrade. Market abnormal or excess returns (EX_RETURN) is computed by the difference between the cumulative quarterly returns of all individual stocks and the cumulative quarterly returns of an index of market performance. To this end, the quarterly market excess return is calculated for each stock $i=1\ldots, j$ (MER_i) according to the convention:

$$MERi = \left(\left(\prod_{t=1}^{n} (1 + r_{it})\right) - \left(\prod_{t=1}^{n} (1 + r_{mt})\right)\right) - 1 \qquad (2)$$

where r_{it}=the actual return for stock i on day $t=1,\ldots.n$ and r_{mt} =the return on a market index of day t. The arithmetic average of excess returns for all stocks in each quarterly sample MER= $(1/j)\sum_{t=1}^{j} MER_t$ where j equals the number of banks in the sample. We expect the EX_RETURN measure to be negatively related to downgrades.[7] We expect that (MKT_BK) and trading volume (TURNOVER) to be negatively related to the likelihood of being downgraded and positively related respectively.

[7] We use the CRSP value-weighted index, which covers all publicly traded institutions, as our index of market performance. We choose this CRSP value-weighted index to calculate excess returns, rather an index for the banking industry alone, because it enables us to compare banking company returns with those of the entire market in which all banking company equities compete and to avoid an industry index dominated by a few large companies.

To predict BOPEC rating changes, we include information on previous supervisory inspections. We choose a dummy variable, BOPEC 1 to BOPEC 4 to account for the most recent BHC exam before the current inspection. The omitted BOPEC rating is the one that represents the lowest financial quality, which a BOPEC 5 before 1996.q1 and BOPEC 4 thereafter. We expect that firms with the most favorable ratings are the ones most likely to experience a rating downgrade. Thus, we anticipate a positive relationship.

We include another discrete variable to capture the last rating of the BHCs lead bank ("CAMELS"). Examination ratings at the bank level can lead to changes in ratings at the organizational level. Like the BOPEC ratings, CAMELS ratings for banks carry a value of *1* to *5,* with *1* being the highest and *5* the lowest. We use the rating from the most recent examination of the largest or lead bank before the quarter in which the current inspection of the parent occurs. We assign a value of 1 to a dummy variable (PROB_BK) if the previous rating of the lead bank was a problem-bank rating (*3, 4, or 5)* and a zero if the rating was a *1 or 2*. We expect a positive relationship between a problem bank rating for the lead bank and the likelihood of a BOPEC rating downgrade for the parent.

As mentioned, earlier work shows that examination ratings can decay quickly after an inspections (Cole and Gunther,1995). Thus, a variable is specified that captures the age of the last inspection (INSP_AGE) before the current one. The older the prior rating, the greater the age of the inspection and the more likely that there will be a change in rating. Experience suggests that this is likely to be a downgrade, because more frequently inspected BHCs are most likely to have higher (poorer) past ratings.

2. Business Cycle Influences

We specify several macro-economic variables to capture the turning points in the business

and credit cycle and to evaluate their influences on exam rating changes. The first variable (T-SPREAD) accounts for changes in the term structure of interest rates. Some have shown that the slope of the yield curve is a good predictor of real economic activity (Jorion and Mishkin,(1991), Kozicki (1997), Rudebush and Williams(2007) and Schich (1999). An inverse relationship is anticipated. This variable is lagged 3 quarters in the regression and in basis points units. We include also the yield spread between the BAA and the AAA corporate bonds (C-SPREAD) lagged one quarter in percent. Increasing spreads on corporate bonds reflect the deterioration in credit quality usually associated with downturns and higher levels of default risk. Thus, a positive relationship is the anticipated. Another macro variable included in the model is the gross domestic product gap (GDP_GAP), lagged 1 quarter, which measures the differences between potential and actual GDP. It is assumed that the greater the gap, the greater the likelihood of a downgrade.

We also include three variables used by the NBER to date business cycles all in percent. These include the growth in personal income less transfer payments in real terms (GWTH_ PI); nonfarm employment growth (GWTH_EMPL); and growth in industrial production (GWTH_IP). The GWTH_EMPL variable is lagged two quarters while the GWTH_PI and the GWTH_IP variables are lagged three quarters prior to the benchmark examination quarter. They are measured as annual rates of change. A negative relationship is anticipated between each of these variables and the likelihood of a downgrade.

3. Secular Trend

The presence of a potential secular trend in examiner standards complicates using predictions of BOPEC ratings changes to identify examiner bias. If a trend is toward more stringent examination standards, supervisors will be proportionately downgrading more and upgrading less in later periods than in previous periods simply due to the trend. A forecast using a model developed

in an earlier period may account only partially for this trend and may forecast fewer downgrades and more upgrades than examiners actually made. Some studies have found evidence that agency ratings have become more stringent overtime. As mentioned, Lucas and Lonski (1992) found that the number of firms Moody's downgraded consistently exceeds the number firms upgraded overtime suggesting that either the quality of firms has declined over time or the standards have changed. Also, Blume, Lim and McKinley (1998) show that agency credit ratings have generally worsened overtime after controlling for financial condition. In recent work, however, Amato and Furfine (2004), find no evidence of this in Standard and Poor's ratings. In banking, supervision may have became more strict with the passage of FDICIA (1991) which increased regulatory scrutiny by imposing higher capital standards and prompt corrective action in the wake of the thrift and banking crises of that era.

We provide two tests for a secular trend in BHC examination standards over the cycles examined. In the first test, we conduct model forecasts and backcasts which compare two recessionary states within the models to evaluate whether standards have changed for these periods. In the second test, we specify a linear time trend (LTT) variable in the full period regression (1986.q2-2003.q4) to account for changing standards. Statistically significant positive or negative coefficients for this variable will indicate trends toward stringency or laxity over the periods examined.

4. Descriptive Statistics

Table 2 displays the sample means and standard deviations for variables used in the regressions for the entire sample period. The sample means `are also broken out by BOPEC rating categories which generally move monotonically with risk ratings. The data show that the best (lower) ratings are associated with the larger firms (LN_ASSET). In addition, BHCs with the poorest (higher)

ratings hold less capital (EQ_ASSET), have greater asset-quality problems (NA_ASSET) (PD90_ASSET), higher loan-loss provisions (LPROV_ASSET), a greater reliance on large time deposits (TD100_ASSET), and significantly weaker earnings (ROA) as expected. Also, the number of days from the last BOPEC inspection (INSP_AGE) generally declines with (higher) poorer ratings, because problem banks are inspected and monitored more frequently than are healthier banks.

The market data follow a similar path, with the weakest-rated firms exhibiting a higher probability of default (PROB_DEF) and a shorter distance to default (DIST_DEF). The data also shows that greater price volatility (COEF_VAR), lower excess returns (EX_RETURN), generally lower market valuations (MKT_BK), and greater share turnover (TURNOVER) are associated with the weakest firms as expected. We use an F-test on mean value equality to statistically test the degree of association between all BOPEC ratings and variables. The degree of association is reflected in the p-values, with all variables being statistically significant at better than the 1 percent level. These tests demonstrate that BHCs with different examination rating levels do have significantly different financial profiles and they do so in the expected ways. The close relationship between these variables and BOPEC ratings indicates that these variables should contain predictive content in the multivariate models of rating changes.

V. *Ordered Logistic Results*

The regression results for the estimating models are presented in tables 3 to 7. Because the primary focus is on predicting examination ratings for out-of- sample periods, the results for the models will be only briefly discussed.

1. Sub-Periods and Overall Regression (1986.q2-2003.q4)

The sample period is broken down into four sub-periods in order to evaluate potential bias in BHC ratings for the different phases of the economic cycle. For each of these sub-periods and for the overall regression, we use the three different estimating models (FA, EM, CM) previously discussed. For the sake of brevity, only the results for the combined model (CM) are discussed and presented in the tables. The results of the other alternative models are available from the authors upon request.

The results for the sub-periods are similar to each other and approximate those for the overall model. However, for the overall model we include the linear trend variable and a more inclusive set of macroeconomic factors. These additional factors are GWTH_PI, GWTH_EMPL, and GWTH_IP. We include these in the overall model because they may show more cyclical variation not evident in the individual period regressions.[8]

We find that institution size is an important determinant BHC ratings. With only a few exceptions, larger sized institutions are generally less likely to be downgraded. Most accounting variables measuring financial condition carry the correct signs and most are significant at high levels for all periods. These results show that the likelihood of a downgrade is highly related to the lagged financial condition of the institution. Three accounting variables are statistically significant and have the correct sign for every sub-period and for the overall period (PD_ASSET, NA_ASSET, ROA). Thus, loan quality and earnings are consistently important over the full period of analysis and for

[8] We conduct extensive robustness checks on the estimating models in response to reviewer comments. First, the original benchmark model was run with three additional macro variables specified as rates of change with 2 to 3-quarter lags. Second, the benchmark model was run with 3 to 2-quarter lag changes in all right-hand-side accounting variables in conjunction with lag changes for the three new macro variables discussed in the previous alternative model. We find that these revised models exhibit a small improved overall fit in comparison to the benchmark model as reflected in the pseudo-R squares and the Akaike Information Criterion. However, these two alternative models show less out-of- sample accuracy and greater inconsistency in some of the estimation results in comparison to the original model. These results are consistent with over-fitting of in-sample data that does not lead

different phases of the business cycle. One interesting finding is that the equity to asset ratio (EQ_ASSET) is statistically significant for only the first and second sub-periods but is significant for the overall regression.

Market variables are also important explanatory factors of rating changes although the results vary between periods. Most carry the correct signs and are significant for at least two of the four periods while the market-to-book ratio (MKT_BK) is significant for three of the four periods. The results for the overall regression show that only the covariance of price (COV_PRICE) is not statistically significant while all others exhibit the hypothesized signs. With the exception of inspection age (INSP_AGE), most supervisory variables are highly related to the probability of rating changes. Past examination ratings and whether or not the BHCs lead bank was a problem bank when the rating was assigned are important determinants of rating changes. Surprisingly, the macro-variables, which generally carry the correct sign, are not generally statistically significant in any of the four sub-periods examined with only one exception.

For the overall regression (table 7), three of the macro-variables (T-SPREAD, GWTH_PI, GWTH_EMPL) are statistically significant with the correct signs. We proxy the time trend by specifying a linear time trend variable (LTT). These results will be discussed in the next section. The fit of the sub-period models range in value from 0.54 to 0.67 as reflected in the Rescaled R^2. For the regression covering the entire period, the R^2 is 0.60.

2. Out-of- Sample Forecast Results

As mentioned, we define examiner bias in the assignment of BOPEC ratings as a significant and persistent deviation of our forecasted changes in upgrades, downgrades and no changes from

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to improvements in out-of-sample forecasting. We therefore report only the original model and use it for the out-of-sample testing.

those actually assigned-- for most periods analyzed. The formal tests for examiner bias are conducted by using our sub-period regression models to perform out-of-sample forecasts which classify companies as downgraded, upgraded or no change. We derive these forecasts by using the three models previously discussed. The model which produces the best out-of- sample classification relative to the actual rating is displayed in table 8. In particular, we estimate models with in-sample data and then use the coefficients to generate one-period ahead forecasts. For example, the 1986-1991 recessionary period is modeled and the coefficients are used to forecast out-of-sample ratings using data from the 1991-1995 recovery period. These forecasts can be considered to be looking back at the previous economic period's variable weightings from examiner attitudes to predict rating changes for the following periods.

Model forecasting errors (actual ratings minus predicted BOPEC ratings expressed as a percentage of total assigned ratings) for each period are computed and displayed in Table 8. If the value of the error is positive, then the actual number of ratings for that category (downgrade, no change, upgrade) exceeds the number predicted by the model and the reverse for a negative sign. We test for bias by inspection of these errors, knowing that the period of comparison is a recession, recovery, expansion or contraction. A bias occurs if examiners significantly downgrade or upgrade more than the model predicts at some level beyond random noise. When going from a recessionary estimation period to a recovery forecast period, a bias would occur if examiners downgrade more or upgrade less than a model predicts. In going from a expansion to a recessionary period, a bias would occur if examiners downgrade less or upgrade more than predicted. No significant and persistent differences between the actual and the predicted ratings indicates a lack of evidence of bias.

A. Naïve Model

Table 8 contains the out-of-sample results according to what we call a "naïve" model (Panel A). We utilize this model as a standard to judge our approach and from which to evaluate the results from our formal tests. This panel projects a simple linear proportion of downgrades, upgrades and no rating changes of the in-sample period to predict ratings for the out-of-sample periods. These "naïve" predictions are then compared with the actual ratings assignments for the periods to check for transitivity of examination procedures and confirmation of our priors. For example, if downgrades compose 30 percent of total ratings over 1986-1991 recessionary period, then applying a factor of 30 percent to the total number of assigned ratings in the 1991-1995 recovery period, we would expect to over predict (negative forecast errors) the number of downgrades assigned. Panel A confirms our expectations by predicting 22.46 percent downgrades when only 10.62 percent were actually assigned exhibiting a forecasting error of -11.84 percent. The model also significantly under predicts the number of upgrades as expected. The results from the naïve model show that out of the six possible cases for the downgrade and upgrade groups, (excluding the no change category), five are accurately classified according to our priors. A binominal proportion test is used to statistically evaluate the differences (errors) between the predicted and actual ratings and all are significantly different.

B. Predicted Model (Cycle-to-Cycle Forecasts)

The results for the cycle-to-cycle forecasts are also presented in Table 8 (Panel B). We examine six cases (3 downgrades and 3 upgrades-- excluding the no-change category), for the three distinct in-sample and out-of-sample periods. Of the six cases, we find only 2 instances which exhibit evidence of bias-- where the assigned ratings deviate significantly from the predicted ratings. In particular, using the 1991-1995 (recovery) in-sample model to forecast out-of-sample data for the 1996-2000 (expansionary) period, our model suggests that the 17.99 percent of the exams should

have produced downgrades, but only 7.70 percent produced downgrades. While a negative error is expected, the absolute size difference (-10.29) suggests (but does not prove) that examiners relaxed rating standards in response to the recovery or more plausibly backed off in assigning downgrades during this period in response to harsh criticism by public officials of supervisory actions during the recession years of the early 1990s.[9] Instead of downgrading these banks, the results imply that examiners held exam ratings unchanged. But this temporary examiner optimism was bounded: we cannot find any unusually high frequency of upgrades for these periods.

In the second case, using the 1996-2000 (expansionary) in-sample model to forecast out-of-sample data for the 2000-2003 (recessionary) period, our model suggests that 23.14 percent of the exams should have been upgrades, but only 7.08 percent actually were upgrades. This substantial over prediction of upgrades (-16.06 percent) suggests (but does not prove) that examiners tightened their rating standards in response to the recession and became more stringent in their assessments of financial condition. Instead of upgrading these banks, the results suggest that examiners held exam ratings unchanged. But this temporary examiner pessimism was also bounded. We cannot find any unusually high frequency of downgrades for this period.

The most consistent finding, however, is that the no-change category is significantly under predicted by the models in two out of three periods by wide margins. For example, for the second period analyzed, (table 8 panel B), the difference between the forecasts and actual ratings is 12.72 percentage points, and for the third period, the difference is 20.96 percentage points. This indicates that the actual assignment of these rating changes is significantly greater than predicted. This stickiness in ratings suggests that in marginal cases, there is a heavy dose of examiner inertia against changing exam ratings. Examiner's preferences are on the side of not changing ratings rather than

[9] See Berger, Kyle and Scalise (2001).

upgrading or downgrading banking companies. In summary, we conclude that there is evidence that examiners' carry over attitudes from the previous cycle to the next cycle in the assignment of BOPEC ratings but this evidence of bias is not persistent or widespread during the cycles examined.

C. Secular Trend in Examination Standards

The second part of the analysis tests for secular changes in examination standards. We examine similar economic states and compare the forecasts (and backcasts) with the actual rating assignments (fourth and fifth rows of table 8, panel B). We start by using the model of the in-sample 1986-1991 recessionary period to forecast rating changes for the 2000-2003 recessionary period and the reverse. For the first period of this stringency test, the results show that there are more actual downgrades assigned (10.62 percent) than predicted (3.27 percent). This suggests that examiners were comparatively more restrictive in rating assignments during the 2000-2003 recessionary period relative to the 1986-1991 recessionary period. No significant differences were observed in the upgrade categories however.

We use a backcast method as a robustness check to analyze the reverse situation. We should find if this backcast supports the previous forecast, that the 2000-2003 model should over-predict the 1986-1991 downgrades for the 1986-1991 data and under-predict the number of upgrades. The results indicate that more downgrades were predicted for the 1986-1991 period (42.23 percent) than actually occurred (22.88 percent). This suggests that examiners were comparatively more rigorous with banking companies in the 2000-2003 period than in the banking crisis period of 1986-1991. Conversely, no significant differences were found in the upgrade categories.

In another test for secular changes in examination standards, we approximate the time trend by specifying a linear trend variable (LTT) over the period from 1986.q2 to 2003.q4 (table 7). The linear trend variable is positive and statistically significant at high levels indicating that supervisory

oversight has generally become more restrictive. In robustness checks of this issue, we also specify a logarithmic and quadratic trend variable in separate regressions (not shown). The results for the trend variable in these other specifications are also positive and significant thereby supporting the conclusion that there has been an increase in examination stringency. This finding may be due in part to the passage of FDICIA (1991) which dramatically increased regulatory scrutiny and capital standards over depository institutions in the wake of the thrift and banking crises of that era.

VI. *Conclusion*

This paper analyzes one aspect of the bank risk ratings process: is there asymmetry or bias in how these ratings are assigned by examiners over the business cycle? We define examiner bias as a significant and persistent deviation of our forecasted changes in upgrades and downgrades from those actually assigned-- for most periods analyzed. If bank supervisors grade more harshly during downturns and relatively easier during upturns, then this process may aggravate business fluctuations because of the implications for capital requirements and lending behavior. This issue takes on added importance because of the current Basel II framework of risk sensitive capital requirements. Capital requirements will increase (decrease) if supervisory estimates of default risk increase (decrease) as reflected by changes in supervisory ratings and in turn by supervisors perception of bank credit quality.

To investigate this issue, we use a model of rating determination that controls for macro-economic fluctuations, financial market conditions, bank characteristics and past supervisory information on a sample of over 4,000 newly issued BHC risk ratings over the 1986-2003 period. We find that banking company supervisory ratings exhibit the following inter-temporal characteristics. First, exam ratings show that when the business cycle turns, examiners often depart from the standards that they set during the previous phases of the cycle. This change in examination

standards (bias), however, is not persistent or widespread over the cycles analyzed. Second, BHC examination ratings are sticky. The results suggest that examiners prefer not to change the ratings rather than upgrading or downgrading institutions. Third, we find more convincing and robust evidence of a secular trend toward more stringent examination ratings standards over time. This may be partly in response to the passage of FDICIA (1991) in the early part of our sample period which ramped up capital requirements and bank supervision standards in response to the earlier thrift and banking crises.

Appendix

Distance-to-default is calculated using the structural model of Merton (1974) and Black and Cox (1973). The Merton model shows that the value of a firm's equity can be expressed in terms of a European call option on the assets of the firm owned by the shareholders with a strike value of the promised value of the liabilities of the firm. In the Merton model of the valuation of the equity and debt of the firm, the firm is assumed to have as its liabilities zero coupon debt with a single maturity. The underlying assets are assumed to be stochastic and generated by an Ito process in continuous time. Consistent with this model, the equity value of a firm can be considered as a call option on its assets with a strike price being its total promised debt, B, is:

$$E = V_A N(d_1) - (B)\exp(-R_f T) N(d_2) \qquad \text{(A.1)}$$

where $d_1 = \left[\ln\left(V_A / B\right) + \left(R_f + 0.5\sigma_V^2\right)T\right] \Big/ \sigma_V \sqrt{T}$ and $d_2 = d_1 - \sigma_V \sqrt{T}$

and

E = the market value of equity (stock price times number of shares outstanding),

V_A = the market value of assets,

B = the promised value of bank liabilities discounted at the risk-free rate to time T,

R_f = the risk-free rate with a maturity consistent with the time to asset valuation (bank examination),

T = the time to expiration of the option and time to maturity of the debt,

σ_V = the standard deviation (volatility) of the rate of return on assets,

ln(x) = the natural logarithm of x,

exp(x) = the value e raised to the power of x, and

N(x) = the cumulative standard normal distribution.

Since there are two unknowns to estimate, V_A and σ_V, a second equation is necessary. Ronn and Verma (1986) and Hull (2000, p.630-631) show that by applying Ito's lemma to the stochastic asset value generating process, the following relationship with the observable market value of equity and its volatility can be used as the second equation in our system:

$$\sigma_E E = N(d_1)\sigma_V V_A, \text{ and by rearranging, } \sigma_V = E\sigma_E / V_A N(d_1). \quad \text{(A.2)}$$

where σ_E is the annualized volatility of the return on equity as computed from the market value of equity and all other variables are defined as above.

The observed values needed to estimate V_A and σ_V are the market value of equity (E), book value of liabilities as a proxy for B and the volatility of equity returns (σ_E). E and B are fixed at the end of a period (quarter or month) and σ_E can be estimated in a number of ways. The internal model estimates σ_E using daily equity returns over the most recent prior quarter whereas KMV estimates it from data over the past 3 years. Another method considered relies on the implied volatilities derived from options on the company's stock.

These computed variables can be used to calculate the distance-to-default as $(V-B)/(\sigma_V*V)$, using the variable definitions above. The probability of insolvency is the probability that assets will fall below the value of the debt. If assets are log normally distributed, the probability of insolvency is the cumulative density of assets less than the amount of debt using the measures of assets, V, and volatility,σ_V.

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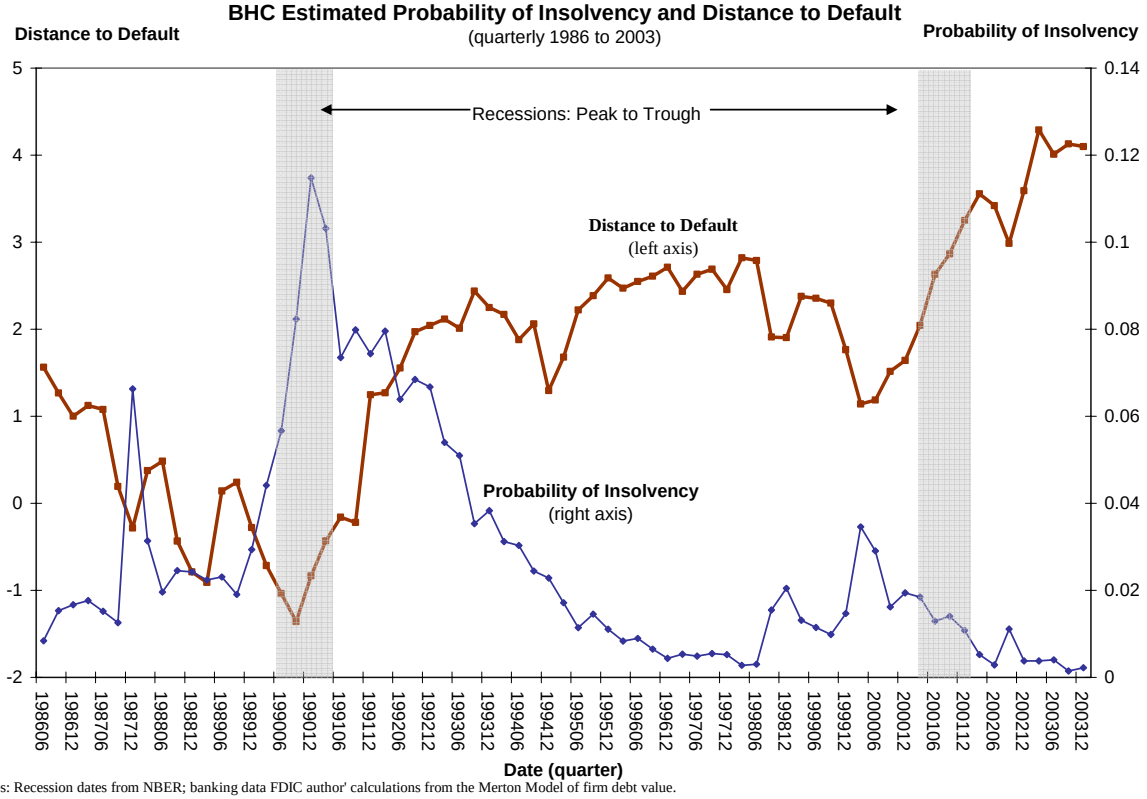
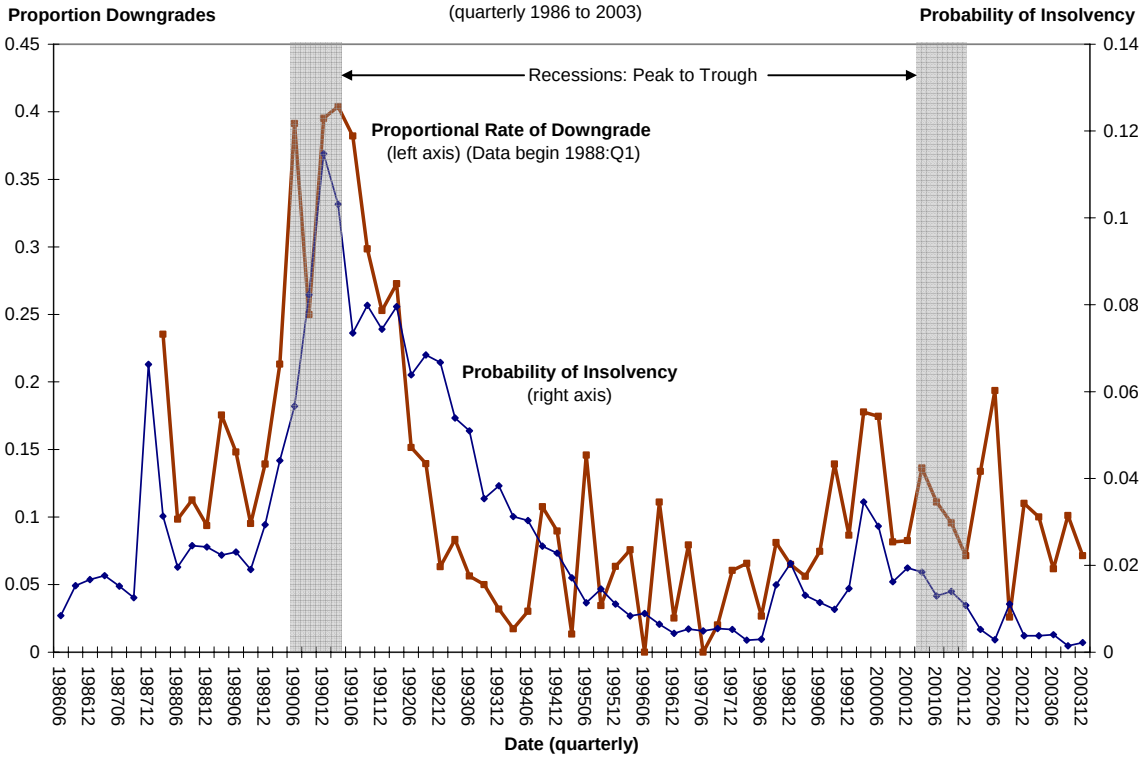
Figure 1
BHC Estimated Probability of Insolvency and Distance to Default
(quarterly 1986 to 2003)



Sources: Recession dates from NBER; banking data FDIC author' calculations from the Merton Model of firm debt value.

Figure 2
BHC Estimated Probability of Insolvency and Rate of BOPEC Downgrades
(quarterly 1986 to 2003)



Sources: Recession dates from NBER; banking data FDIC author' calculations from the Merton Model of firm debt value.

Table 1

Definition of Variables

Variable	Description	Source
	Size of Institution	
LN_ASSET	Natural logarithm of total assets	FDIC
	Financial Accounting Variables	
EQ_ASSET	Equity to Total Assets	FDIC
LLR_ASSET	Loan-Loss Reserves to Total Assets	FDIC
PD90_ASSET	Loans Past Due 90 days to Total Assets	FDIC
NA_ASSET	Nonaccrual Loans to Total Assets	FDIC
LPROV_ASSET	Loan-Loss Provisons to Total Assets	FDIC
CHARG_ASSET	Chargeoffs to Total Assets	FDIC
ROA	Annual Return on Assets	FDIC
LIQ_ASSET	Liquid Assets to Total Assets	FDIC
TD100_ASSET	Time Deposits>$100,000 to Total Assets	FDIC
	Financial Market Variables	
PROB_DEF	Probability of Default	Calculated by Authors
DIST_DEF	Distance to Default	Calculated by Authors
COVAR_PRICE	Coefficient of Variation of Price (%)	CRSP
EX_RETURN	Abnormal or Excess Quarterly Returns (value weighted) (%)	CRSP
STD_RETURN	Std. Deviation of Quarterly Returns (%)	CRSP
MKT_BK	Market Value of Firm to Book Value of Firm	CRSP
TURNOVER	Quarterly Turnover of Shares (%)	CRSP
	Supervisory Variables	
BOPEC-1	Dummy Variable: BOPEC rating of 1 before most recent inspection	Federal Reserve
BOPEC-2	Dummy Variable: BOPEC rating of 2 before most recent inspection	Federal Reserve
BOPEC-3	Dummy Variable: BOPEC rating of 3 before most recent inspection	Federal Reserve
BOPEC-4	Dummy Variable: BOPEC rating of 4 before most recent inspection	Federal Reserve
PROB_BK	Dummy Variable: CAMELS rating of lead bank before current	Federal Reserve
	inspection: 1=prior rating of 3, 4, 5: 0=1 or 2 rating	Federal Reserve
INSP_AGE	Time from prior holding company inspection to current inspection (days)	Federal Reserve
	Time Trend Variable	
LTT	Linear Time Trend Variable: an integer value which counts from 1....n for the number of quarters in the data over the 1986.q2 to 2003.q4 period.	Authors' Calculation
	Macro Economic Variables	
T_SPREAD	Spread on 5 year vs. 1 year Treasury Securities (basis points)	Federal Reserve
C_SPREAD	Spread on Aaa vs. Baa Corporate Securities (basis points)	Federal Reserve
GDP GAP	Potential GDP-Actual GDP/Potential GDP (%)	BEA
GWTH_PI	Growth in Personal Real Income (%)	NBER
GWTH_EMPL	Growth in Employment (%)	NBER
GWTH_IP	Growth in Industrial Production (%)	NBER

Table 2
Descriptive Statistics:1986.q2-2003.q4
(Means by BOPEC Ratings for New Examinations)
(Quarterly)[1]

			BOPEC Rating					
Variable	**Mean**	**Std. Dev.**	**1**	**2**	**3**	**4**	**5**	**p value[2]**
Size of Institution					Mean			
LN_ASSET	14.80	1.83	14.97	14.81	14.55	14.40	14.14	0.01
Financial Accounting Variables								
EQ_ASSET	8.02	2.27	9.01	7.98	6.91	5.69	2.61	0.01
LLR_ASSET	1.12	0.62	0.92	1.02	1.51	2.25	2.89	0.01
PD90_ASSET	0.20	0.28	0.13	0.18	0.32	0.40	0.69	0.01
NA_ASSET	0.84	1.13	0.34	0.62	1.77	3.21	5.05	0.01
LPROV_ASSET	0.28	0.46	0.14	0.21	0.50	1.09	1.53	0.01
CHARG_ASSET	0.30	0.44	0.15	0.23	0.52	1.06	1.58	0.01
ROA	0.90	0.90	1.29	1.01	0.37	-0.68	-2.41	0.01
LIQ_ASSET	20.58	13.54	24.72	20.97	12.84	10.43	7.83	0.01
TD100_ASSET	9.81	6.12	9.11	10.03	10.65	9.66	12.75	0.01
Financial Market Variables								
PROB_DEF	0.02	0.09	0.00	0.01	0.04	0.15	0.39	0.01
DIST_DEF	1.75	2.86	2.81	1.99	-0.20	-1.53	-5.89	0.01
COEF_VAR	5.83	4.84	5.04	5.25	7.43	10.21	18.48	0.01
EX_RETURN	0.02	0.17	0.02	0.02	0.03	-0.04	-0.18	0.01
MKT_BK	1.62	1.11	2.03	1.58	0.98	0.72	1.45	0.01
TURNOVER	11.94	12.24	9.48	11.77	16.79	18.15	17.15	0.01
Supervisory Variables								
INSP_AGE (days)	465.32	291.18	505.08	469.27	390.76	355.92	344.17	0.01
BOPEC-1	0.33	0.47						
BOPEC-2	0.51	0.50						
BOPEC-3	0.11	0.31			(NA)			
BOPEC-4	0.05	0.21						
PROB_BK	0.16	0.37						
Macro Economic Variables								
T_SPREAD	92.30	72.88			(NA)			
C_SPREAD	87.80	22.40						
GDP_GAP	0.44	1.79						
GWTH_PI	0.60	0.99						
GWTH_EMPL	0.34	0.41						
GWTH_IP	0.69	1.03						
Number of Observations		4,104	1,335	2,075	438	204	52	

[1]Data are for the quarter of the BOPEC rating change.

[2] p values are determined by an F test on mean value equality. "NA" not applicable.

Table 3
Ordered Logistic Regressions: 1986q.2–1991.q2

This table presents ordered logistic regression results for a sample of 791 new bank holding company inspections. The ordering is BOPEC downgrades, no change in ratings, and BOPEC upgrades. All independent variables are defined in table 1. A single, double, or triple "*" indiciates significance at the 10%, 5%, or 1% level, respectively.

Variable	(Anticipated Sign)	Coefficient	t-statistic
Intercept 1		-2.285	0.691
Intercept 2		5.233	1.572
Size of Institution			
LN_ASSET	–	-0.545	4.544 ***
Financial Accounting Variables			
EQ_ASSET	–	-0.437	4.646 ***
LLR_ASSET	–	-0.716	2.453 **
PD90_ASSET	+	0.853	2.319 **
NA_ASSET	+	1.123	6.012 ***
LPROV_ASSET	+	0.589	1.607
CHARG_ASSET	–	0.048	0.138
ROA	–	-0.661	3.246 ***
LIQ_ASSET	–	-0.071	2.252 **
TD100_ASSET	+	0.023	1.270
Financial Market Variables			
PROB_DEF	+	-3.688	2.361 **
DIST_DEF	–	-0.027	0.937
COVAR_PRICE	+	0.089	2.951 ***
EX_RETURN	–	-1.774	2.345 **
MKT_BK	–	-0.185	2.772 ***
TURNOVER	+	0.028	2.157 **
Supervisory Variables			
BOPEC-1	+	14.088	9.674 ***
BOPEC-2	+	9.872	7.909 ***
BOPEC-3	+	4.974	4.416 ***
BOPEC-4	+	1.740	1.650 *
PROB_BK	+	3.710	9.708 ***
INSP_AGE	+	0.000	0.915
Macro Variables			
T_SPREAD	–	-0.006	1.420
C-SPREAD	+	-0.003	0.109
GDP GAP	+	0.163	0.606
AIC		655.262	
Rescaled R^2		0.671	
χ^2 Likelihood Ratio (df = 25)		580.853	***

Table 4
Ordered Logistic Regressions: 1991.q3–1995.q4

This table presents ordered logistic regression results for a sample of 1,055 new bank holding company inspections. The ordering is BOPEC downgrades, no change in ratings, and BOPEC upgrades. All independent variables are defined in table 1. A single, double, or triple "*" indiciates significance at the 10%, 5%, or 1% level, respectively.

Variable	(Anticipated Sign)	Coefficient	t-statistic
Intercept 1		-12.984	6.311 ***
Intercept 2		-5.836	2.959 ***
Size of Institution			
LN_ASSET	–	-0.186	2.324 **
Financial Accounting Variables			
EQ_ASSET	–	-0.320	4.886 ***
LLR_ASSET	–	0.259	1.360
PD90_ASSET	+	1.191	3.037 ***
NA_ASSET	+	0.865	6.200 ***
LPROV_ASSET	+	0.653	1.533
CHARG_ASSET	–	0.357	0.993
ROA	–	-0.936	4.545 ***
LIQ_ASSET	–	-0.010	0.878
TD100_ASSET	+	0.065	3.059 ***
Financial Market Variables			
PROB_DEF	+	1.993	1.822 *
DIST_DEF	–	-0.082	1.793 *
COVAR_PRICE	+	-0.007	0.261
EX_RETURN	–	0.602	0.954
MKT_BK	–	-0.855	3.274 ***
TURNOVER	+	0.003	0.319
Supervisory Variables			
BOPEC-1	+	18.612	13.992 ***
BOPEC-2	+	14.415	13.029 ***
BOPEC-3	+	8.900	9.803 ***
BOPEC-4	+	4.280	5.500 ***
PROB_BK	+	3.561	9.316 ***
INSP_AGE	+	0.000	0.062
Macro Variables			
T_SPREAD	–	-0.007	3.056 ***
C-SPREAD	+	0.014	1.013
GDP GAP	+	-0.239	1.038
AIC		965.073	
Rescaled R^2		0.669	
χ^2 Likelihood Ratio (df = 25)		815.465	***

Table 5
Ordered Logistic Regressions: 1996.q1–2000.q3

This table presents ordered logistic regression results for a sample of 1,156 new bank holding company inspections. The ordering is BOPEC downgrades, no change in ratings, and BOPEC upgrades. All independent variables are defined in table 1. A single, double, or triple "*" indiciates significance at the 10%, 5%, or 1% level, respectively.

Variable	(Anticipated Sign)	Coefficient	t-statistic
Intercept 1		-15.471	5.836 ***
Intercept 2		-7.265	2.874 ***
Size of Institution			
LN_ASSET	–	-0.081	1.135
Financial Accounting Variables			
EQ_ASSET	–	-0.096	1.546
LLR_ASSET	–	-0.157	0.485
PD90_ASSET	+	3.410	5.953 ***
NA_ASSET	+	0.881	2.921 ***
LPROV_ASSET	+	2.599	2.651 ***
CHARG_ASSET	–	-1.440	1.950 *
ROA	–	-1.584	5.308 ***
LIQ_ASSET	–	-0.010	1.030
TD100_ASSET	+	0.037	2.054 **
Financial Market Variables			
PROB_DEF	+	1.234	0.293
DIST_DEF	–	-0.326	3.141 ***
COVAR_PRICE	+	-0.019	1.043
EX_RETURN	–	-1.820	2.676 ***
MKT_BK	–	0.126	0.924
TURNOVER	+	0.009	0.749
Supervisory Variables			
BOPEC-1	+	16.968	7.890 ***
BOPEC-2	+	12.404	6.206 ***
BOPEC-3	+	6.538	3.363 ***
PROB_BK	+	6.240	9.152 ***
INSP_AGE	+	-0.001	3.065 ***
Macro Variables			
T_SPREAD	–	0.003	0.533
C-SPREAD	+	0.006	0.494
GDP GAP	+	-0.071	0.708
AIC		892.261	
Rescaled R^2		0.536	
χ^2 Likelihood Ratio (df = 24)		541.628	***

Table 6
Ordered Logistic Regressions: 2000.q4-2003.q4

This table presents ordered logistic regression results for a sample of 1,102 new bank holding company inspections. The ordering is BOPEC downgrades, no change in ratings, and BOPEC upgrades. All independent variables are defined in table 1. A single, double, or triple "*" indiciates significance at the 10%, 5%, or 1% level, respectively.

Variable	(Anticipated Sign)	Coefficient	t-statistic
Intercept 1		-15.609	7.139 ***
Intercept 2		-7.252	3.563 ***
Size of Institution			
LN_ASSET	–	-0.027	0.374
Financial Accounting Variables			
EQ_ASSET	–	-0.076	1.448
LLR_ASSET	–	-0.093	0.234
PD90_ASSET	+	1.029	2.162 **
NA_ASSET	+	1.058	3.840 ***
LPROV_ASSET	+	1.998	2.526 **
CHARG_ASSET	–	-0.724	0.939
ROA	–	-1.201	4.997 ***
LIQ_ASSET	–	-0.005	0.559
TD100_ASSET	+	0.002	0.149
Financial Market Variables			
PROB_DEF	+	4.862	2.021 **
DIST_DEF	–	0.125	1.477
COVAR_PRICE	+	0.057	1.487
EX_RETURN	–	-0.849	1.290
MKT_BK	–	-0.294	1.928 *
TURNOVER	+	0.019	1.819 *
Supervisory Variables			
BOPEC-1	+	14.797	9.227 ***
BOPEC-2	+	10.088	7.373 ***
BOPEC-3	+	4.432	3.410 ***
PROB_BK	+	5.492	10.023 ***
INSP_AGE	+	0.001	0.987
Macro Variables			
T_SPREAD	–	-0.004	1.377
C-SPREAD	+	0.014	1.305
GDP GAP	+	-0.023	0.209
AIC		830.644	
Rescaled R^2		0.539	
χ^2 Likelihood Ratio (df = 24)		512.522	***

Table 7

Ordered Logistic Regressions: 1986.q2-2003.q4

This table presents ordered logistic regression results for a sample of 4,104 new bank holding company inspections. The ordering is BOPEC downgrades, no change in ratings, and BOPEC upgrades. All independent variables are defined in table 1. A single, double, or triple "*" indiciates significance at the 10%, 5%, or 1% level, respectively.

Variable	(Anticipated Sign)	Coefficient	t-statistic
Intercept 1		-14.028	14.628 ***
Intercept 2		-6.710	7.420 ***
Size of Institution			
LN_ASSET	–	-0.114	3.184 ***
Financial Accounting Variables			
EQ_ASSET	–	-0.151	5.206 ***
LLR_ASSET	–	-0.192	1.596
PD90_ASSET	+	1.557	7.578 ***
NA_ASSET	+	0.830	9.765 ***
LPROV_ASSET	+	0.781	3.411 ***
CHARG_ASSET	–	0.083	0.393
ROA	–	-0.991	9.424 ***
LIQ_ASSET	–	-0.006	1.195
TD100_ASSET	+	0.027	3.260 ***
Financial Market Variables			
PROB_DEF	+	1.623	2.220 **
DIST_DEF	–	-0.099	4.344 ***
COVAR_PRICE	+	0.010	0.850
EX_RETURN	–	-0.980	3.286 ***
MKT_BK	–	0.176	3.947 ***
TURNOVER	+	0.008	1.727 *
Supervisory Variables			
BOPEC-1	+	16.082	21.765 ***
BOPEC-2	+	12.167	18.823 ***
BOPEC-3	+	6.966	12.080 ***
BOPEC-4	+	2.817	5.303 ***
PROB_BK	+	4.200	19.766 ***
INSP_AGE	+	-0.003	1.860 *
Time Trend Variable			
LTT	+	0.014	3.318 ***
Macro Variables			
T_SPREAD	–	-0.025	2.341 ***
C-SPREAD	+	0.005	1.612
GDP GAP	+	-0.063	1.076
GWTH_PI	–	-0.150	2.560 **
GWTH_EMPL	–	-0.685	2.336 **
GWTH_IP	–	0.056	0.776
AIC		3379.992	
Rescaled R^2		0.599	
χ^2 Likelihood Ratio (df = 28)		65.683	***

TABLE 8

Binomial proportion tests are used to identify the significance of the differences. *,**, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

A. Naïve Panel

NAÏVE CLASSIFICATION TESTS

Naïve ratings changes are computed from the proportion of ratings changes during the in-sample period, and are then applied to the out-of-sample period.

				DIFFERENCES (ACTUAL - NAÏVE)											
				Downgrade				No Change				Upgrade			
In-Sample Period		Out-Sample Period		Actual % of Total Actual	Naive % of Total Actual	Difference % of Total Actual[1]		Actual % of Total Actual	Naive % of Total Actual	Difference % of Total Actual[1]		Actual % of Total Actual	Naive % of Total Actual	Difference % of Total Actual[1]	
Cycle-to-Cycle Forecast															
198606-199106	Recessionary	199109-199512	Recovery	10.62	22.46	-11.84	***	69.00	71.56	-2.55	**	20.38	5.98	14.40	***
199109-199512	Recovery	199603-200009	Expansionary	7.70	10.93	-3.24	***	81.83	68.45	13.39	***	10.47	20.62	-10.15	***
199603-200009	Expansionary	200012-200312	Recessionary	10.62	8.06	2.55	***	82.30	80.65	1.66		7.08	11.29	-4.21	***
Recession Forecast & Backcast: Stringency Test															
198606-199106	Recessionary	200012-200312	Recessionary	10.62	22.46	-11.84	***	82.30	71.56	10.75	***	7.08	5.98	1.10	
200012-200312	Recessionary	198606-199106	Recessionary	22.88	10.18	12.71	***	71.18	82.61	-11.44	***	5.94	7.21	-1.27	

[1]Binomial test where H0: Predicted Ratings = Actual Ratings.

B. Predicted Panel

OUT-Of-SAMPLE CLASSIFICATION TESTS

The predicted values are taken from the regression that most closely matches the actual number of BOPEC rating changes.

				DIFFERENCES (ACTUAL - PREDICTED)																
				Downgrade					No Change					Upgrade						
In-Sample Period		Out-Sample Period		Actual % of Total Actual	Predicted % of Total Actual	Closest Regression[1]	Difference % of Total Actual[2]		Actual % of Total Actual	Predicted % of Total Actual	Closest Regression[1]	Difference % of Total Actual[2]		Actual % of Total Actual	Predicted % of Total Actual	Closest Regression[1]	Difference % of Total Actual[2]		Total Actual Exams
Cycle-to-Cycle Forecast																				
198606-199106	Recessionary	199109-199512	Recovery	10.62	10.71	FA	-0.09		69.00	69.19	EM	-0.19		20.38	21.42	EM	-1.04		1,055
199109-199512	Recovery	199603-200009	Expansionary	7.70	17.99	EM	-10.29	***	81.83	69.12	CM	12.72	***	10.47	9.17	CM	1.30		1,156
199603-200009	Expansionary	200012-200312	Recessionary	10.62	11.16	EM	-0.54		82.30	61.34	CM	20.96	***	7.08	23.14	CM	-16.06	***	1,102
Recession Forecast & Backcast: Stringency Test																				
198606-199106	Recessionary	200012-200312	Recessionary	10.62	3.27	FA	7.35	***	82.30	71.42	EM	10.89	***	7.08	7.80	EM	-0.73		1,102
200012-200312	Recessionary	198606-199106	Recessionary	22.88	42.23	EM	-19.34	***	71.18	49.81	EM	21.37	***	5.94	4.93	FA	1.01		791

[1]FA represents the Financial Accounting regression model, EM represents the Equity Market regression model, and CM represents the Combined regression model.

[2]Binomial test where H0: Predicted Ratings = Actual Ratings.