# Modeling Bank Senior Unsecured Ratings: A Reasoned Structured Approach to Bank Credit Assessment*

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This paper studies the impact of bank-specific financial indicators and macroeconomic variables on bank senior unsecured ratings by Moody's. Controlling for bank financial characteristics, we find significant evidence of procyclicality in bank ratings stemming from lagged interaction effects between the real output gap and the credit gap. In particular, macroeconomic slowdowns that follow credit booms tend to imply lower ratings. Similarly, when credit expansion above a trend is followed by strong economic performance, bank ratings tend to increase. Bank ratings also appear to correlate positively with the slope of the yield curve and tend to increase with sovereign ratings, market share of lending, and bank size. Given the ongoing debate on the importance, timeliness, and information content of credit ratings in general—and those assigned to banks in particular—the paper addresses a topic that is of great importance to central banks, regulators, and risk managers.

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## 1. Introduction

Bank credit ratings are metrics of bank creditworthiness that market participants focus on. Among other types of ratings (e.g., ratings of short-term debt, subordinated debt, or bank financial strength ratings), senior unsecured ratings attract particular attention due to their wide use in financial covenants and regulatory rules, defining portfolio allocation mandates for asset managers, triggers in securitization transactions, and the risk weighting for assets under the standardized approach of Basel II. Changes in those ratings are likely to shape market sentiment, and adverse changes may exacerbate any difficulties faced by banks during periods of stress. Bank senior unsecured ratings could come to a sharper focus in periods when banks are facing challenging financial conditions. Such periods may coincide with heightened macroeconomic uncertainty, as market participants may reassess financial risks and possibly retrench from certain types of financing.

Recent downgrades of banks were attributed by rating agencies to more difficult economic conditions, in conjunction with a deterioration in asset quality and reduction in the fair value of certain types of financial instruments. From a policy perspective, procyclicality in bank ratings would be an undesirable outcome.[1] At the very least, a deterioration in bank ratings that coincides with an economic downturn might impart a blow to confidence in the sector at a time when it is vulnerable to negative sentiment due to heightened macroeconomic uncertainty. That could eventually have implications for the real economy if tightening lending criteria to banks, in response to lower ratings, would exacerbate tight credit conditions in the economy.

Analysis on how bank senior unsecured ratings respond to bank-specific financial indicators and macroeconomic developments would be useful both to market participants and to policymakers. Considering in particular how ratings respond to fluctuations in macroeconomic and financial conditions could add to the debate about factors that may amplify fluctuations in the credit cycle and the

[1] In line with Amato and Furfine (2004), ratings are considered *procyclical* if they tend to be higher when the economy expands and lower during economic downturns, after controlling for firm-specific factors.

real economy. This paper offers a positive economic analysis of factors that may have an impact on bank senior unsecured ratings, avoiding normative implications of the rating process. Following Amato and Furfine (2004) and Blume, Lim, and MacKinlay (1998), we use an ordered probit framework to predict future ratings based on currently available information.

Explanatory variables for the empirical model include key financial indicators from banks' published accounts and measures of domestic economic activity and general financial conditions. As a modeling choice, we focus on the rating approach by one rating agency only (i.e., Moody's) given our familiarity with their rating policies and the availability of sufficient data to estimate the empirical model. Consequently, our results may not necessarily hold for other rating agencies and do not offer a judgment on Moody's rating performance relative to other agencies.

We take an informed approach to Moody's credit assessment of banks, both in terms of variable selection and model specification. The implicit assumption we make is that a single rating methodology is applied consistently across banks, as described in a number of public documents by Moody's (see, e.g., Moody's Investors Service 2002a, 2002b, 2006a, 2006b). The preferred model is estimated using a panel of annual data for 293 banks from thirty-three countries, covering the period 1999–2006. In employing bank-specific financial indicators to predict bank ratings, special attention is given to differences in accounting standards across jurisdictions and their possible impact on reported figures by banks. In particular, we control for country effects and we distinguish between banks that report their financial statements under International Financial Reporting Standards (IFRS) or national Generally Accepted Accounting Practices (GAAP).

However, accounting-based financial indicators are likely to be subject to cyclical variations. Albertazzi and Gambacorta (2006), for example, find evidence of procyclicality in measures of profitability and asset quality. Hence, the extent to which bank-specific financial indicators are informative about future ratings could depend on the phase of the business cycle. Higher profits, for example, and lower levels of write-offs during benign economic conditions are often supported by high business volumes, ample availability of credit, and strong asset valuations. But they could also mask vulnerabilities building up on banks' balance sheets, which could crystallize if economic conditions deteriorate. Therefore, increased profitability and perceived high asset quality during good times may not necessarily imply higher ratings if ratings take a long-term perspective, i.e., if they look through the cycle. In contrast, banks that are able to perform better relative to their peers regardless of the phase of the business cycle, should, in theory, be those that attract the higher ratings. In order to control for the phase of the business cycle, we consider the deviations (gaps) of domestic real GDP from a trend. We also consider the term spread (slope) of the yield curve as a forward-looking indicator of domestic economic activity, as suggested by Estrella and Hardouvelis (1991).

In addition, we consider country-level measures of financial imbalances that have been identified in the literature as forward-looking indicators of banking-sector vulnerabilities. Following Borio and Lowe (2002), variables that could help improve the explanatory power of the empirical model include measures of domestic credit expansion by the banking sector, asset market valuations, and foreign exchange mismatches. Deviations of those variables from a trend (gaps) are used to capture the potential buildup of financial imbalances. Borio and Lowe suggest that credit expansion above normal levels could *sow the seeds* of a subsequent deterioration in banks' risk profile (and possibly ratings) if economic conditions deteriorate. This view is supported by a number of studies (see, e.g., Dell' Ariccia, Igan, and Laeven 2008; Jiménez and Saurina 2006; Lown, Morgan, and Rohatgi 2000) showing that excessive credit expansions tend to be associated with relaxations in lending standards. Loose credit policies could lower banks' asset quality, which could then lead to credit risk crystallizing on banks' balance sheets as the economy enters a period of slowdown.

By considering cyclical variations in economic activity and financial conditions, we are able to examine whether senior unsecured ratings assigned to banks by Moody's look through the cycle. This adds to the empirical literature that investigates whether corporate ratings, more broadly, tend to be procyclical (see, e.g., Amato and Furfine 2004; Cantor and Mann 2003). We consider two possible channels through which procyclicality in bank ratings could manifest itself: (i) lending boom-bust episodes and (ii) cyclical fluctuations in bank-specific measures of profitability and asset quality.

In theory, bank ratings that look through those channels would also tend to look through the cycle. Otherwise, any inherent procyclicality in the financial system, as well as in measures of bank profitability and asset quality, could also translate into procyclical bank ratings.

Controlling for bank financial characteristics, we find empirical support for procyclicality in bank ratings stemming from lead-lag effects between the credit cycle and the business cycle. In particular, macroeconomic slowdowns (negative real output gaps, in one-year lag) that follow credit booms (positive credit gaps, in two-year lag) tend to imply lower ratings. Similarly, when credit expansion above a trend is followed by strong economic performance, bank ratings tend to be higher. We also find significant evidence that bank ratings internalize cyclical variations in asset quality by penalizing low asset quality more aggressively in good times than in periods of economic slowdown. However, no significant evidence is found for a similar *filter* applied to bank profitability, with ratings showing similar sensitivity to shocks in earnings both during economic booms and in periods of economic slowdown. Finally, bank ratings appear to correlate positively with the slope of the yield curve and tend to increase with sovereign ratings, market share of lending, and bank size. Overall, the estimated coefficients of bank-specific financial indicators are statistically significant and consistent with economic intuition and public statements by Moody's. The model performs well both in and out of sample and the results are robust to alternative model specifications.

The structure of the paper is as follows. Section 2 provides an outline of Moody's approach in assigning bank ratings. Section 3 describes the data and defines explanatory variables for the empirical model. Section 4 outlines the ordered probit methodology and discusses issues relating to model and sample selection. Section 5 presents the results and discusses robustness checks. Section 6 concludes.

## 2. Rating Methodology

Moody's aims for globally consistent rating scales, providing a rank ordering of risks associated with the ability and willingness of borrowers to meet debt obligations in full and on a timely basis. Moody's produces bank ratings on the basis of a general-to-specific approach (Moody's Investors Service 1999). Firstly, they examine the economic environment of the country of domicile and they consider strengths and weaknesses of the industry as a whole. Then, they consider debtor-specific characteristics in relation to peer groups. As part of their credit assessment process, Moody's has access to nonpublic information, either under the U.S. Regulation Fair Disclosure, which prohibits selective disclosure of nonpublic information but provides a conditional exception for rating agencies, or through private confidentiality agreements with issuers.[2]

Bank ratings by Moody's are based on five main areas of fundamental analysis: capital adequacy, asset quality, management, earnings and profitability, and funding and liquidity (CAMEL). Capital is aimed to absorb unexpected losses. After profitability, capital provides the second buffer to banks to withstand financial shocks, and the higher these buffers, the higher the resilience of banks to shocks. Asset quality is central to bank solvency and is therefore important for maintaining confidence among investors. Management quality, the most challenging category to capture quantitatively, spans a wide range of qualitative characteristics, such as cost efficiency, experience, and integrity—all of which affect the bank's riskiness and quality of earnings. Earnings capacity relates to the franchise value and profitability of the bank. It offers a first line of defense to debtholders in periods of stress and is considered by Moody's to be the *cornerstone of bank credit assessment* (see, e.g., Moody's Investors Service 2002a). Liquidity is relevant to bank credit assessment because banks are susceptible to customers' loss of confidence and sudden withdrawals of funds. Because of banks' maturity transformation role, high leverage, and intrinsic opaqueness, liquidity problems may become funding problems and even lead to insolvency.[3]

Moody's also aims to produce ratings that accommodate at the same time both rating stability and prudence, which are two widely

[2]Fight (2001) reports that more than 90 percent of rated firms reveal nonpublic information to the rating agencies.

[3]Flannery, Kwan, and Nimalendran (2004) and Morgan (2002) provide evidence on the opaqueness of banking institutions.

recognized criteria for rating.[4] In addition, senior unsecured ratings incorporate the probability and expected scale of official safety nets.[5] That could lead to more stable bank ratings over time—relative to what is predicted by an empirical model that is based on financial indicators and macroeconomic variables, as those ratings may react only partially, and sometimes not at all, to standard measures of bank financial health.

Based on these observations about the rating process, we now turn to discuss data and variable definitions for the empirical model.

## 3. Data and Variable Definitions

In order to estimate the empirical model presented in section 4, we employ a panel of annual data for 293 banks from thirty-three countries, covering the period 1999–2006. We consider senior unsecured ratings that are assigned to banks by Moody's as of the end of each calendar year. Data on bank ratings are obtained from Moody's Investors Service, spanning the rating spectrum of seventeen categories from Aaa through Caa3 in the familiar Moody's symbol system.[6] Because estimation of the empirical model requires a sufficient number of observations per rating class, we group banks into ten rating categories, where we focus our analysis. We assign the value 10 if a bank has a rating of Aaa–Aa1; 9 if Aa2; 8 if Aa3; 7 if A1; 6 if A2; 5 if A3; 4 if Baa1; 3 if Baa2–Baa3; 2 if Ba1–Ba3; and 1 if B1 or below.

Bank-specific financial ratios and country-level financial and macroeconomic indicators are used to define explanatory variables. We also consider sovereign ratings to control for sovereign credit

[4]Cantor and Mann (2007) argue that rating stability is desirable because rating changes can lead to actions by investors that are costly to reverse, primarily due to rating-based triggers in loan covenants and portfolio restrictions. Prudence is intrinsic to the interests of debtholders, which rating agencies aim to represent, implying that agencies prefer to err on the conservative side.

[5]By official safety nets we mean bank regulation and supervision, as well as emergency liquidity assistance by the official sector if a bank is in financial distress.

[6]Following Amato and Furfine (2004), we focus on rating actions that involve some degree of judgment by Moody's. Therefore, we eliminate observations of banks in the state of default, given that default is defined mechanically on the basis of well-known criteria. Nevertheless, bank defaults in the sample period that we examine are extremely rare events.

risk in a bank's country of domicile. Data on bank financial ratios are obtained from Bankscope.[7] Country-level data include finally revised figures from the IMF International Financial Statistics. Data on domestic interest rates are obtained from Global Financial Data. As with bank ratings, data on sovereign ratings are obtained from Moody's Investors Service. Next we discuss bank- and country-level explanatory variables.

### *3.1 Bank-Level Variables*

Bank-specific variables are constructed using five key financial ratios (one for each CAMEL category): shareholders' equity/total assets; loan loss reserves/net interest income; operating costs/total assets; pre-tax, pre-provision profits/total assets; and deposits/customer loans. Using criteria that we discuss in section 4, we select these ratios from a set of financial indicators that we present in table 1. Table 1 also shows descriptive statistics on financial ratios to facilitate the discussion of results in section 5. In addition, we consider measures for market share and bank size, and we control for regional effects, such as country and sectoral concentrations. Regional effects are defined in terms of groups of countries that are shown in table 2, which also presents the regional distribution of observations and banks in the sample.

More specifically, the first bank-level indicator that we consider is capital. Managers target capital ratios that balance the requirements of many constituents, including shareholders, regulators, and rating agencies.[8] Therefore, instead of focusing on the rating impact of capital ratios per se, we consider percentage deviations of capital ratios from a *target*. The intuition is that capital adequacy is considered by Moody's in conjunction with the overall risk profile of a bank and the quality of its earnings (see, e.g., Moody's Investors Service 2002a, 2002b, 2006a). Hence, the impact of capital on ratings would depend on a bank's capital position relative to an appropriate target. Target ratios are estimated using a panel regression of capital

[7]Bankscope reports consolidated balance-sheet and income-statement information from banks' published accounts.

[8]The ability of banks to actively target a desired capital ratio has increased over recent years by the significant growth of structured credit products.

## Table 1. List of Bank Financial Indicators Considered

| **Variable** | **Mean** | **Mean Abs. Deviation** |
|---|---|---|
| **Capital (%)** | | |
| Tier 1 Capital/Risk-Weighted Assets | 12.48 | 6.60 |
| Tier 1 and Tier 2 Capital/Risk-Weighted Assets | 12.81 | 2.40 |
| Shareholders' Equity/Total Assets | 7.00 | 2.94 |
| Shareholders' Equity/Loans | 9.36 | 2.96 |
| Shareholders' Equity/Total Liabilities | 5.79 | 1.80 |
| **Asset Quality (%)** | | |
| Loan Loss Reserves/Loans + Loan Loss Reserves | 1.88 | 0.92 |
| Loan Loss Reserves/Net Interest Income | 20.55 | 18.18 |
| Loan Loss Reserves/Impaired Loans | 152.78 | 107.57 |
| Impaired Loans/(Loans + Loan Loss Reserves) | 2.99 | 2.49 |
| Loan Write-Offs/(Loans + Loan Loss Reserves) | 1.08 | 1.27 |
| **Management (%)** | | |
| Operating Costs and Provisions/Total Assets | 1.57 | 0.67 |
| Operating Costs/Income Before Provisions | 46.65 | 9.55 |
| Operating Costs/Total Assets | 2.19 | 1.07 |
| **Earnings (%)** | | |
| Net Interest Income/Total Earning Assets | 1.31 | 0.63 |
| Net Interest Income/Total Assets | 1.21 | 0.56 |
| Other Operating Income/Total Assets | 0.53 | 0.39 |
| Pre-Tax Profits/Total Assets | 1.07 | 0.80 |
| Pre-Tax, Pre-Provision Profits/Total Assets | 1.53 | 0.86 |
| Net Income/Total Assets | 0.07 | 0.62 |
| Net Income/Shareholders' Equity | 2.04 | 8.96 |
| Off-Balance-Sheet Exposures/Total Assets | 21.43 | 21.81 |
| **Liquidity (%)** | | |
| Money Lent to Banks/Money Borrowed from Banks | 87.44 | 46.94 |
| Customer Loans/Total Assets | 41.36 | 12.45 |
| Customer Loans/Short-Term Liabilities | 56.59 | 14.01 |
| Liquid Assets/Short-Term Liabilities | 9.00 | 4.79 |
| Liquid Assets/Total Debt Exc. Capital Instruments | 7.18 | 3.84 |

**Note:** The first column reports the list of bank-specific financial ratios that we consider as explanatory variables in the empirical model. The second and third columns report the sample mean and mean absolute deviation, respectively, for each financial ratio.

**Table 2. Number of Banks and Bank-Year Observations by Country Group**

| Country Group | Number of Observations | Number of Banks |
|---|---|---|
| United States, Canada | 301 | 57 |
| Denmark, Finland, Norway, Sweden | 82 | 17 |
| United Kingdom | 78 | 18 |
| Ireland, Portugal, Spain | 151 | 31 |
| Netherlands | 53 | 11 |
| Belgium, France, Luxembourg | 43 | 11 |
| Austria, Switzerland | 60 | 13 |
| Cyprus, Greece | 43 | 8 |
| Germany | 105 | 26 |
| Italy | 65 | 16 |
| Australia | 57 | 10 |
| Japan | 133 | 22 |
| Indonesia, Korea, Malaysia, Thailand | 64 | 19 |
| China, Hong Kong, India, Kazakhstan, Philippines, Russia, Singapore | 134 | 34 |
| **Total** | **1,369** | **293** |

ratios on a set of explanatory variables that control for differences in business mix, domestic economic conditions, and accounting policies. The estimation results for target ratios are presented in table 3.[9] We allow deviations of capital ratios from the estimated target to have an impact on ratings in a nonlinear fashion. Following Blume, Lim, and MacKinlay (1998), we model the relationship between ratings and the percentage deviation from the capital target as piecewise-linear. Let $C_{it}$ be the percentage deviation of capital ratio from the

[9]Estimation results in table 3 show that, ceteris paribus, banks with higher net interest income relative to other operating income tend to have higher capital ratios. This is not surprising given that net interest income relies on capital-intensive assets (e.g., loans), while other operating income, such as trading income and fees and commissions, typically depends on less capital-intensive business. The estimation results also show that banks tend to hold higher capital ratios in an economic slowdown (i.e., when the GDP gap is negative). This effect is associated with a deleveraging process by banks in a downturn that is documented in a number of studies (see, e.g., Shin and Adrian 2007).

**Table 3. Linear Regression Estimates for Target Capital Ratios, for the Period 1999–2006**

| **Dependent Variable:** *Shareholders' Equity/Total Assets* | **Coefficient** | **Robust Std. Error** | **z-stat.** |
|---|---|---|---|
| **Independent Variables:** | | | |
| Loan Loss Reserves/Total Assets | −2.044*** | 0.301 | −6.80 |
| Net Interest Income/Total Assets | 1.674*** | 0.511 | 3.27 |
| Other Operating Income/Total Assets | 0.472*** | 0.109 | 4.31 |
| Off-Balance-Sheet Exposures/Total Assets | 0.004 | 0.004 | 0.84 |
| IFRS Bank (Dummy): 1 if consolidated accounts in IFRS | −0.704* | 0.372 | −1.89 |
| Domestic Economic Slowdown (Dummy): 1 if real GDP gap < 0 | 0.428* | 0.251 | 1.71 |
| **Country Dummies** | | | |
| Belgium, France, Luxembourg | −1.811*** | 0.677 | −2.67 |
| Germany | −1.316 | 1.037 | −1.27 |
| United Kingdom | −1.158* | 0.660 | −1.75 |
| Australia | −1.085 | 0.664 | −1.63 |
| Austria, Switzerland | −0.944 | 0.846 | −1.12 |
| Italy | −0.793* | 0.473 | −1.68 |
| Netherlands | −0.496 | 0.736 | −0.67 |
| Ireland, Portugal, Spain | −0.046 | 0.506 | −0.09 |
| Japan | 0.064 | 0.814 | 0.08 |
| Indonesia, Korea, Malaysia, Thailand | 0.168 | 1.011 | 0.17 |
| Cyprus, Greece | 0.195 | 0.563 | 0.35 |
| Denmark, Finland, Norway, Sweden | 1.763 | 1.089 | 1.62 |
| China, Hong Kong, India, Kazakhstan, Philippines, Russia, Singapore | 2.484*** | 0.808 | 3.07 |
| **Constant** | 3.243** | 1.415 | 2.29 |

**Note:** The model is estimated using a data panel of 1,369 observations, for the period 1999–2006. The data panel includes published-accounts data of 293 banks from thirty-three countries (grouped in fourteen regions) and macroeconomic information.

*Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent. The first column reports the estimated coefficients of explanatory variables in the model. The second and third columns report robust standard errors and z-statistics.

estimated target for bank $i$ in year $t$. We consider three new capital variables $cj_{it}$ $(j = 1, 2, 3)$ such that

$$C_{it} = \sum_{j=1}^{3} cj_{it} \tag{1}$$

with $cj_{it}$ defined as follows:

| | $c1_{it}$ | $c2_{it}$ | $c3_{it}$ |
|---|---|---|---|
| $C_{it} \in [0, +\infty)$ | $C_{it}$ | 0 | 0 |
| $C_{it} \in [-15, 0)$ | 0 | $C_{it}$ | 0 |
| $C_{it} \in (-\infty, -15)$ | 0 | $-15$ | $C_{it} + 15$. |

By dividing $C_{it}$ into three ranges, $(-\infty, -15\%)$, $[-15\%, 0)$, and $[0, +\infty)$, we allow deviations from the target to have a different marginal impact on ratings.[10] Moreover, we are able to examine whether large negative deviations from the target convey any additional information about ratings or reflect factors unrelated to ratings, such as model error from the panel regression. In the latter case, the coefficient for $c3_{it}$ in the empirical model would not be statistically different than zero.

As a measure of asset quality, we consider the ratio of loan loss reserves to net interest income (*LLR/NII*). The intuition is that net interest margins must appropriately remunerate for the risks undertaken by the bank. An increase in this ratio would imply that interest margins do not sufficiently compensate for risks in the loan book. Hence, the higher that ratio, the lower is asset quality. However, when net interest income (*NII*) is negative, the ratio of loan loss provisions to net interest income becomes meaningless. Hence, we consider the sign of interest income to define our asset-quality variable as follows:

| *Asset-Quality Variable* | $(LLR/NII) \geq 0$ | $(LLR/NII) < 0$ |
|---|---|---|
| $NII \geq 0$ | $(LLR/NII)$ | $(LLR/NII)$ |
| $NII < 0$ | 0 | – |

If *NII* is positive, then provisions and *LLR/NII* have the same sign and we set the asset-quality variable equal to *LLR/NII.* If *NII* is negative and *LLR/NII* is positive, then provisions are negative and the asset-quality variable is set equal to zero. There is only one bank-year observation corresponding to such an event. Finally, if both *NII* and *LLR/NII* are negative, then provisions are positive

[10]For example, holding more capital may not necessarily lead to higher ratings. But a weakly capitalized bank relative to a target may be downgraded or be forced to increase its capital base to avoid a downgrade.

and there is no remuneration for risks that the bank undertakes. This event corresponds to five bank-year observations, which are omitted from the sample.

Management quality is an area particularly difficult to measure quantitatively. A possibility is to proxy management quality by using measures of cost efficiency. Cost ratios have attracted the attention of analysts as banks seek to cut costs and improve their operational efficiency. In order to limit the possibility of colinearity problems with other ratios, such as asset quality and profitability variables, we consider the ratio of operating costs to total assets.

As a profitability variable, we employ the ratio of pre-tax, pre-provision profits to total assets. Pre-tax, pre-provision profits are Moody's favorite indicators of earnings-generating power (Moody's Investors Service 2002a, 2006a). By adding back provisions into profits, the profitability variable controls for the profit margin that is available to debtholders to absorb adverse shocks. It also has the further advantage of avoiding obvious colinearity problems between the profitability and asset-quality ratio.

As a composite measure of a bank's liquidity and funding position, we consider its *funding gap*. This is defined as the difference of (customer loans)–(short-term liabilities), expressed as a percentage of customer loans. We consider as short-term liabilities all financial liabilities with remaining maturity of less than one year. Assuming that customer loans are typically long-term and illiquid assets, the higher the funding gap, the more illiquid the bank would be and possibly more vulnerable to a classic bank run à la Diamond and Dybvig (1983). Nevertheless, a too-low funding gap could be associated with excess liquidity and inefficient employment of financial resources. In the long run, that could weaken the underlying profitability of a bank and possibly have an adverse impact on its credit rating. Hence, the marginal effect of the funding gap on bank ratings may depend on the overall liquidity buffers that a bank tends to hold.

We also consider measures of bank size, which is often correlated with qualitative factors that are important to bank credit analysis, such as diversification of funding sources, geographic reach, and franchise value. Moody's, for example, argues the following:

> Larger banks may often have more granular loan portfolios and broader geographic reach, reducing concentration risk. Moreover, size often allows for economies of scale, which can result in increased operating efficiency [and] may also indicate resources necessary to invest in new products and services, or to enter new markets. . . . [It] may also be an indication of greater market share, which can contribute substantially to a bank's franchise value. [Moody's Investors Service 2002b, 5]

We define bank size according to the level of total assets, where year-by-year comparisons are made by deflating total assets to constant prices. We then split banks into sample quartiles by size and define dummies for medium-small, medium-large, and large banks, using small banks as a reference category.

However, a bank that is small by global comparison may be large from a domestic perspective. That would depend, for example, on its share of lending in the local economy. Market share could then be indicative of franchise value and pricing power, correlating positively with bank ratings. In addition, banks with a higher share of lending in the economy could possibly be perceived by the market as *too important to fail*, offering them a competitive advantage in relation to funding costs, interest margins, and possibly higher ratings.[11] Higher market share could also imply higher ratings given that senior unsecured ratings by Moody's incorporate perceptions about official safety nets. As a proxy for market share, we consider the ratio of total loans by a bank to total domestic lending by the banking sector.[12] However, the sample distribution of such a ratio has a large positive skewness (10.1), meaning that some transformation is required to capture potential nonlinearities. Hence, we consider the natural logarithm of the above ratio as our variable for market share, which has a sample skewness of −0.5.

[11] O'Hara and Shaw (1990) find evidence of a positive wealth effect to large U.S. banks, resulting from the introduction of the "too big to fail" doctrine by the Comptroller of the Currency in 1984, with a corresponding negative effect on smaller banks. According to Morgan and Stiroh (1999), preferential lending terms to large U.S. banks have persisted in the 1990s even after the introduction of the Federal Deposit Insurance Corporation Act of 1991.

[12] Such a ratio tends to overstate domestic market share by internationally active banks, because its numerator includes foreign loans.

In order to control for IFRS reporting by banks, we define a relevant dummy that takes the value 1 for IFRS banks and 0 otherwise. However, the impact of IFRS reporting on modeled ratings could be ambiguous. On the one hand, IFRS could enhance comparability of financial statements across banks and help market discipline. That could eventually lead to better management, more diversified sources of funding, and, possibly, higher ratings. On the other hand, IFRS numbers could be more volatile, as discussed in Annex 1.[13] As a result, estimated ratings of IFRS banks could be lower than those of non-IFRS banks, given that any rank ordering of banks' underlying riskiness would tend to penalize banks with more volatile reported figures.

Finally, we consider a dummy to control for the dichotomy between investment- and subinvestment-grade banks (defined by the Baa3 rating threshold). Considering interaction effects between such a dummy and bank-specific variables would allow ratings of investment-grade banks to respond to shocks differently than ratings of subinvestment-grade banks. For example, it is possible that low ratings may have already factored into the possibility of more volatile financial indicators. Therefore, ratings of subinvestment-grade banks may demonstrate low sensitivity to shocks, while for investment-grade banks similar shocks could lead to a significant risk reassessment.

### *3.2 Country-Level Variables*

Country-level variables for economic performance and banking-sector vulnerabilities could help to improve the explanatory power of the empirical model. We consider these variables both on a stand-alone basis and in the context of interaction effects (both among themselves and with bank-level variables).

As a measure of realized economic activity in a bank's country of domicile, we employ the real output gap, defined as the deviation of real GDP from a trend. As forward-looking indicators of banking-sector vulnerabilities, we consider measures of financial imbalances,

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[13]The mean absolute deviation of the profitability variable is 1.2 for IFRS banks in the sample, compared with 0.8 for non-IFRS banks, which could be indicative of higher volatility in IFRS figures. This is based on 312 observations under IFRS and 1,057 under GAAP.

as suggested by Borio and Lowe (2002). In particular, we consider deviations (gaps) from a trend for the ratio of domestic credit provided by the banking sector to GDP and the stock market capitalization.[14] In order to calculate deviations of variables from their trend, we use a Hodrick-Prescott filter and annual data from 1980 to 2006 (finally revised and rebased to 100 in the year 2000).

Credit expansion above normal levels (positive gap) could be associated with periods of loose credit standards and a significant increase in credit-risk exposures by banks. As economic conditions deteriorate, credit risk could crystallize, affecting bank ratings. Similarly, a significant correction (negative gap) in the stock market could signal a change in risk perceptions about asset valuations in general, and bank assets in particular, which could possibly have an impact on bank credit ratings.[15]

In order to allow for lending boom-bust episodes to have an impact on bank credit ratings, we consider interaction effects between the real output gap and the credit gap, using various lag structures. Moreover, we consider interaction effects between the real output gap and the profitability and asset-quality variables we discussed in section 3.1. These interaction effects aim to control for cyclical variations in measures of bank profitability and asset quality, allowing their impact on bank ratings to vary with the business cycle.

As a forward-looking indicator of economic performance, we consider the slope of the yield curve. This is defined as the difference between the ten-year government bond and the three-month Treasury-bill rate. Both rates are calculated using annual averages of monthly data. According to Estrella and Hardouvelis (1991), a positive slope of the yield curve is associated with a subsequent increase in real economic activity, while a flattening of the yield

[14] Borio and Lowe also suggest that deviations of the real exchange rate from its trend may also help identify pressures building up in the capital account, as well as pressures on banks' balance sheets due to foreign exchange mismatches. However, such vulnerabilities may be more relevant to emerging-market economies with higher reliance on external capital flows and higher sensitivity to exchange rate fluctuations.

[15] For example, a fall in asset values could erode the equity buffers with which borrowers can withstand financial shocks, therefore increasing risk perceptions about secured lending. That could affect bank credit ratings if, as a result of lower collateral buffers, rating agencies thought that banks' loan portfolios had become riskier.

curve is indicative of lower future interest rates and a fall in real output. Moreover, the slope of the yield curve could correlate positively with bank profitability (especially net interest income) as a result of banks' maturity transformation role (see, e.g., Drehmann, Sorensen, and Stringa 2008).[16]

Sovereign ratings by Moody's are employed to control for sovereign credit risk in a bank's country of domicile. Sovereign ratings may act as a ceiling to senior unsecured ratings, consistent with the general-to-specific approach in producing bank ratings discussed in section 2. Moreover, senior unsecured ratings incorporate perceptions about the probability and expected scale of official safety nets. Hence, the higher the extent of official safety nets in a jurisdiction, the more we would expect bank ratings to be biased toward the sovereign ceiling. Therefore, we define dummies for sovereign ratings that correspond to the categories Aaa–Aa1, Aa2–Aa3, A1, A2, A3, Baa1–Baa3, Ba1–Ba2, and Ba3 or below, using the last category as a reference.

## 4. Econometric Approach

This section discusses model specification and sample selection issues. We start by describing the ordered probit approach to model bank ratings. Such an approach is particularly suitable for modeling ordinal variables, such as credit ratings, because it recognizes that the information content of one grade difference in ratings may vary along the rating scale. For example, a difference of one grade in ratings at the high end of the rating scale could imply a degree of (absolute) credit-risk differentiation that is not necessarily the same as a difference of one grade at the low end of the scale. We then discuss econometric issues relating to model and sample selection.

### *4.1 Ordered Probit Model*

An ordered probit model of bank ratings involves the simultaneous estimation of an index variable and cut-off points for the index that

[16]According to banks' regulatory returns—for example, U.S. SEC Form 20-F—balance-sheet management and money-market revenues typically fall as a result of rising short-term interest rates and a flattening of the yield curve.

determine the transition from one rating category to another. More specifically, a number of cut-off points $c_j$ $(j = 1, 2, \ldots, 9)$ define a time-invariant partition of index $X_{it}$ for bank $i$ at time $t$ in such a way that the bank's rating $R_{it+1}$ next period is given by

$$R_{it+1} = \begin{cases} 10 & \textit{if} \quad X_{it} \in [c_9, \infty) \\ 9 & \textit{if} \quad X_{it} \in [c_8, c_9) \\ \vdots & \qquad \vdots \\ 1 & \textit{if} \quad X_{it} \in (-\infty, c_1). \end{cases} \tag{2}$$

The unobservable index variable $X_{it}$ is assumed to be linked to a vector $V_{it}$ of explanatory variables through a deterministic index function $f(\cdot)$

$$X_{it} = f(V_{it}|\theta) + \varepsilon_{it}, \tag{3}$$

where $\theta$ is a vector of unknown parameters and $\varepsilon_{it}$ is a Gaussian disturbance term with a conditional expectation of zero. For a given vector of parameters $\theta$, cut-off points $c$, and explanatory variables $V_{it}$, the probability that bank $i$ attains a rating $R_{it+1}$ at time $t + 1$ is given by

$$\begin{aligned} &\Pr(R_{it+1} = j|\theta, c) \\ &= \begin{cases} 1 - \Phi[c_9 - f(V_{it}|\theta)] & \textit{if} \quad j = 10 \\ \Phi[c_j - f(V_{it}|\theta)] - \Phi[c_{j-1} - f(V_{it}|\theta)] & \textit{if} \quad j = 9, 8, \cdots, 2 \\ \Phi[c_1 - f(V_{it}|\theta)] & \textit{if} \quad j = 1. \end{cases} \end{aligned} \tag{4}$$

Equation (4) is estimated using maximum likelihood estimation techniques and the data panel we described in section 3 (for more details, see Greene 1997, sec. 19.8).

With the predicted probabilities from equation (4) in hand, there are various ways of predicting a bank's actual rating. Blume, Lim, and MacKinlay (1998) consider *mode* ratings (i.e., ratings with the highest probability to occur) as predictors of corporate ratings. However, if the predicted probability density is lopsided, then mode ratings may be subject to a *cliff effect*, where the most probable rating immediately follows, or precedes, a rating that has a low probability to occur. Mora (2006) considers probability-weighted (*mean*) ratings to predict sovereign ratings. Such an approach, however, could be problematic if the predicted probability density is bimodal. In that case, a mean rating would possibly be of scarce relevance because it would predict a rating that is unlikely to occur. As a modeling compromise, we use the *median* of the predicted probability density to forecast banks' actual ratings. The median rating is the one that splits the higher from the lower half of the predicted probability density of a bank's rating, rounded to the closest integer.[17]

### *4.2 Model Selection*

In order to select the best model, we start by using a general-to-specific approach on the basis of the likelihood ratio (LR) test and the Akaike information criterion (AIC). We also examine how the model performs in and out of sample, which is our key criterion for model selection. Special emphasis is placed on the ability of the model to predict rating downgrades.

In order to select the key financial ratios described in section 3, we start from a group of candidate ratios that is our *best guess* on the basis of Moody's documentation, basic economic intuition, and the objective to avoid introducing obvious colinearity problems. If for a given CAMEL category our best guess is not statistically significant, we try alternative variables from its category and also alternative model specifications.

We also consider trade-offs between the level of sophistication of financial ratios reported by Bankscope and data availability, as well as reporting issues that could have an impact on the information content of financial ratios. For example, the tier 1 capital ratio would naturally qualify as our best guess among capital ratios.[18] Instead, we employ the ratio of shareholders' equity to total assets in order to maintain a reasonably large sample size

[17]We examined how the three approaches (i.e., mode, mean, and median ratings) perform both in and out of sample and we found that, overall, median ratings perform better than mode and mean ratings.

[18]The tier 1 capital ratio is aimed to recognize different levels of riskiness across banks and fundamental differences in bank business models.

and permit model estimation.[19] Similarly with respect to liquidity, a variable that would naturally qualify as our best guess would be the *deposit run-off ratio*. This is often defined as the ratio of liquid assets to customer deposits and short-term funds. However, under IFRS, liquid assets such as Treasury bills and other eligible bills, as well as debt securities and equity shares, are not reported separately in banks' consolidated balance sheets. Instead, they are aggregated under *trading and financial assets designated at fair value*, or *available-for-sale investments*. As a result, figures for liquid assets that are collected by Bankscope may only include a fraction of banks' actual liquid asset holdings, which could potentially lead to misleadingly low deposit run-off ratios. Therefore, we focus on bank *illiquidity*, such as our measure of funding gap described in section 3.1.

In estimating bank credit ratings, we had to consider potential endogeneity issues. Financial indicators may reflect the accessibility and price of banks' credit, as well as banks' stock market performance, which may in turn be affected by the ratings themselves. The endogeneity issue is also likely to be quite pronounced because financial indicators are observed at a low (i.e., yearly) frequency, making it difficult to establish whether these variables could have been affected by developments triggered by rating actions. We address this endogeneity issue by including all bank financial indicator variables in the model with a lag. In particular, all bank-level variables have been lagged by one year to reflect at year $t-1$ market-available information upon which our model can predict ratings in the following year $t$. In choosing the lags of macroeconomic variables, we tried different lag structures and we used those that we found more significant. We then confirm the lack of endogeneity problems by carrying out the Davidson and MacKinnon (1993) test for endogeneity.

White robust standard errors are used to correct for heteroskedasticity in the residuals. To adjust also standard errors for the presence of within-cluster dependence, in both the cross-section across banks and across time, we use the generalized Huber-White

[19] Defining, for example, in section 3.1 deviations from the target capital ratio in terms of the tier 1 capital ratio would significantly reduce the sample size from 1,369 observations to 1,149.

approach of Froot (1989).[20] Time-series dependence may be driven by unobserved bank effects that lead to the residuals for a given bank being correlated across time. Unobserved bank effects may result from qualitative factors as well as from different interpretation of accounting policies, which may affect the information content of financial ratios across jurisdictions. Cross-sectional dependence implies that the residuals for a given year are correlated across banks. That could result from broad changes in accounting policies, such as the IFRS transition, and the implementation of new prudential standards. Industry-wide trends may also give rise to cross-sectional correlation as a result of developments in both the asset side (e.g., credit expansion) and the liability side (e.g., funding gap) of banks' balance sheets.

## 5. Empirical Results

The estimated coefficients of the ordered probit model are reported in table 4. Overall, bank-specific variables are statistically significant and consistent with economic intuition and public statements by Moody's. An important result is that we find significant evidence of procyclicality in bank ratings that manifests itself through lagged interaction effects between the real output and credit gap. But we also find evidence that bank ratings internalize cyclical variations in asset quality by penalizing low asset quality more aggressively in good times than in periods of economic slowdown. However, no significant evidence is found that bank ratings internalize cyclical variations in profitability, which could be a potential source of procyclicality in ratings. Bank ratings also appear to respond positively to a steepening of the yield curve and also tend to increase with sovereign ratings.

Next we discuss our empirical results in more detail. It should be emphasized that financial ratios, as well as gap and interest rate variables, are expressed in percentage terms, which may result in some coefficients appearing small in absolute terms, although economically significant. Therefore, the far-right column of table 4 reports the coefficient for each variable multiplied with the corresponding

[20]For a description of how standard errors are adjusted for within-cluster correlation in Stata, see Rogers (1993).

**Table 4. Ordered Probit Model for Bank Senior Unsecured Ratings by Moody's, for the Period 1999–2006**

| | | Investment-Grade Bank | | Interaction Effects if Subinv.-Grade Bank | | |
|---|---|---|---|---|---|---|
| DEPENDENT VARIABLE: *Bank Senior Unsecured Rating by Moody's* | Number of Lags (in Years) | Coefficient | Robust Std. Error | Coefficient | Robust Std. Error | Coefficient × (Mean Abs. Deviation) |
| INDEPENDENT VARIABLES: | | | | | | |
| **Bank-Level Financial Indicators** | | | | | | |
| *Capital*: Deviation of (Equity/Total Assets) Ratio from Target *c1* | 1 | 0.007*** | 0.002 | −0.004** | 0.002 | 0.109 |
| *c2* | 1 | 0.017* | 0.009 | 0.015 | 0.024 | 0.100 |
| *c3* | 1 | −0.002 | 0.003 | 0.002 | 0.003 | −0.001 |
| *Asset Quality:* Loan Loss Reserves/Net Interest Income | 1 | −0.005** | 0.002 | 0.000 | 0.003 | −0.084 |
| *Asset Quality*Real GDP Gap* | 1 | −0.056*** | 0.021 | — | — | −0.041 |
| *Cost Efficiency:* Operating Costs/Total Assets | 1 | −0.084*** | 0.032 | −0.163* | 0.091 | −0.205 |
| *Recurring Earning Power:* Pre-Tax, Pre-Prov. Profits/Total Assets | 1 | 0.194*** | 0.071 | −0.178** | 0.079 | 0.043 |
| *Recurring Earning Power*Domestic Business Cycle* | 1,1 | −0.027 | 0.189 | — | — | −0.002 |
| *Funding Gap:* (Loans – Deposits)/Loans | 1 | −0.002*** | 0.000 | 0.007*** | 0.002 | −0.142 |
| *Market Share:* Log (Loans/Domestic Credit Extension by Banks) | 1 | 0.213*** | 0.047 | — | — | 0.393 |
| **Bank-Level Dummies** | | | | | | |
| *Subinvestment-Grade Bank*: 1 if bank rating below Baa2–Baa3 | 1 | — | — | −2.236*** | 0.409 | — |
| *IFRS Bank:* 1 if consolidated accounts in IFRS | 1 | −0.631*** | 0.121 | — | — | — |
| *Bank Size:* | | | | | | |
| *Large Bank:* 1 if in 4th quartile by total assets ($US) | 1 | 1.815*** | 0.195 | | | — |
| *Medium-Large Bank:* 1 if in 3rd quartile by total assets ($US) | 1 | 1.074*** | 0.162 | | | — |
| *Medium-Small Bank:* 1 if in 2nd quartile by total assets ($US) | 1 | 0.637*** | 0.129 | | | — |

*(continued)*

## Table 4. (Continued)

| | | Investment-Grade Bank | | Interaction Effects if Subinv.-Grade Bank | | |
|---|---|---|---|---|---|---|
| INDEPENDENT VARIABLES: | Number of Lags (in Years) | Coefficient | Robust Std. Error | Coefficient | Robust Std. Error | Coefficient × (Mean Abs. Deviation) |
| **Macroeconomic Variables** | | | | | | |
| *Yield-Curve Slope:* (10-year gov. bond rate) – (3-month T-bill rate) | 1 | 0.051* | 0.028 | | | 0.043 |
| *Domestic Business Cycle:* Real GDP gap | 1 | 0.020* | 0.011 | | | 0.052 |
| *Domestic Bank Credit Cycle:* Bank credit gap | 2 | −0.001 | 0.002 | | | −0.013 |
| *Domestic Bank Credit Cycle*Domestic Business Cycle* | 2,1 | 0.169** | 0.087 | | | 0.037 |
| *Stock Market Performance:* Market capitalization gap | 1 | −0.001 | 0.001 | | | −0.018 |
| **Sovereign Rating Dummies** | | | | | | |
| Aaa–Aa1 | 1 | 4.560*** | 0.443 | | | |
| Aa2–Aa3 | 1 | 4.484*** | 0.457 | | | |
| A1 | 1 | 2.328*** | 0.462 | | | |
| A2 | 1 | 2.194*** | 0.464 | | | |
| A3 | 1 | 1.901*** | 0.412 | | | |
| Baa1–Baa3 | 1 | 1.823*** | 0.415 | | | |
| Ba1–Ba2 | 1 | 1.744*** | 0.375 | | | |
| **Region Dummies** | | | | | | |
| Denmark, Finland, Norway, Sweden | — | 0.587*** | 0.211 | | | |
| Germany | — | 0.429** | 0.187 | | | |
| United Kingdom | — | 0.394*** | 0.130 | | | |
| Australia | — | −0.391** | 0.189 | | | |
| Italy | — | −0.525*** | 0.190 | | | |
| Japan | — | −1.198*** | 0.161 | | | |

*(continued)*

## Table 4. (Continued)

| | | Investment-Grade Bank | | Interaction Effects if Subinv.-Grade Bank | | |
|---|---|---|---|---|---|---|
| INDEPENDENT VARIABLES: | Number of Lags (in Years) | Coefficient | Robust Std. Error | Coefficient | Robust Std. Error | Coefficient × (Mean Abs. Deviation) |
| **Lower Boundary for Rating Categories** | | | | | | |
| Aaa–Aa1 | — | 6.929 | 0.597 | | | |
| Aa2 | — | 6.402 | 0.586 | | | |
| Aa3 | — | 5.489 | 0.588 | | | |
| A1 | — | 4.725 | 0.585 | | | |
| A2 | — | 3.746 | 0.579 | | | |
| A3 | — | 2.752 | 0.583 | | | |
| Baa1 | — | 1.188 | 0.582 | | | |
| Baa2–Baa3 | — | −0.851 | 0.608 | | | |
| Ba1–Ba3 | — | −3.061 | 0.548 | | | |
| B1 and Below | — | $-\infty$ | — | | | |

**Note:** The model is estimated using a data panel of 1,369 observations, for the period 1999–2006. The data panel includes published accounts data of 293 banks from thirty-three countries (grouped in fourteen regions) and macroeconomic information. The original sample consisted of 2,022 observations. Of those, 251 observations were dropped due to lags in the explanatory variables; 350 observations were also omitted due to lack of contemporaneous observations for all explanatory variables; and 52 observations were omitted because of rating withdrawals.

*Significant at 10 percent; **significant at 5 percent; ***significant at 1 percent. The first column reports the lag structure of explanatory variables in the model. For interaction effects we report two lags, one for each interacting variable. The second column reports the estimated coefficients of explanatory variables in the model. The third column reports robust standard errors. The fourth column reports the estimated coefficients of interaction effects between explanatory variables and a dummy that takes the value 1 if the bank had a previous-year rating of subinvestment grade (below Baa2–Baa3) and 0 otherwise. Robust standard errors for these interaction effects are reported in the fifth column. The last column reports the product of the estimated coefficient with the corresponding mean absolute deviation of each explanatory variable (excluding dummies).

mean absolute deviation, which could help to assess the economic significance of estimated coefficients.

### *5.1 Bank-Level Variables*

Starting with bank-level variables, the coefficients of the first and second transformation of the capital variable (*c1* and *c2*) are statistically significant and with the expected sign. Negative deviations from the capital target (the second transformation) appear to have a larger absolute impact on ratings than positive deviations of equal magnitude (the first transformation). Also, the coefficient for positive deviations from the capital target appears more economically significant for investment-grade than for subinvestment-grade ratings. This is not surprising given that earnings of low-rated banks may be weaker to absorb adverse shocks, meaning that higher capital buffers would be needed to protect investors.[21] Hence, from a Moody's perspective, banks of lower credit quality and weaker profitability would possibly need to hold higher capital buffers to support their ratings, which could lessen any positive impact on ratings from holding capital above a theoretical target.

The coefficient for the ratio of loan loss reserves to net interest income is statistically significant and with a negative sign. The less net interest margins compensate for risks in loan portfolios, the lower is asset quality and the more negative the impact on ratings. But what is more interesting is that bank ratings tend to penalize low asset quality more aggressively when the economy is booming (positive real output gap) than when it is slowing down (negative real output gap). This is reflected in the statistically significant and negative coefficient for interaction effects between the real output gap and asset quality. Given that measures of asset quality tend to

[21] For subinvestment-grade banks, the sample distribution of the profitability variable has a mean absolute deviation of 1.6, compared with 0.7 for investment-grade banks. This is in line with intuition that earnings of low-rated banks are more volatile and, hence, less reliable to withstand adverse shocks in the long run. In addition, the sample distribution of the asset-quality variable has a mean absolute deviation of 34 for subinvestment-grade banks, compared with 14 for investment-grade banks, which implies that low-rated banks may be subject to larger shocks.

be procyclical (see, e.g., Albertazzi and Gambacorta 2006; Lown, Morgan, and Rohatgi 2000), the above result indicates that bank ratings tend to respond to asset-quality changes in a countercyclical fashion.

Less cost-efficient banks tend to attract lower ratings. This is reflected in the negative and statistically significant coefficient for the ratio of operating costs to total assets. Cost efficiency appears to be a particularly important driver of subinvestment-grade ratings. This is reflected in the statistically significant and negative coefficient for the interaction effect between the cost-efficiency ratio and the subinvestment-grade dummy. A similar result is obtained if, as a measure of cost efficiency, we use the ratio of operating costs to income.[22]

Profitability has a significant impact on bank ratings, as indicated by the statistically significant and positive coefficient for recurring earning power. Profitability also appears to be a more important driver of investment- than subinvestment-grade ratings, as reflected in the negative coefficient for interaction effects between recurring earning power and the subinvestment-grade dummy. This result supports the hypothesis that higher uncertainty about earnings may have already been incorporated into lower ratings which, as a result, may show lower sensitivity to shocks in earnings than investment-grade ratings. However, we find no evidence that ratings internalize cyclical variations in bank profitability. In particular, the coefficient for interaction effects between recurring earning power and real output gap is not statistically significant, although it appears with a negative sign. A negative coefficient would be indicative of a *discount* in the rating process for profits during good times, or a *premium* during periods of economic slowdown.

Regarding banks' liquidity position, investment-grade banks may get easy access to external sources of funding, which could reduce their marginal propensity to hoard (low-yielding) liquid assets. Then a higher funding gap would imply a higher ratio of (illiquid) customer

[22]In that case, the estimated coefficient for cost efficiency of investment-grade banks is not statistically different than 0, while for subinvestment-grade banks the coefficient (−0.011) is statistically significant at 5 percent. This further supports the hypothesis that cost efficiency is an important determinant of subinvestment-grade ratings.

loans to short-term liabilities and, hence, a lower buffer of liquid assets against unanticipated foreclosures of credit lines. That could lead to lower ratings, as indicated by the negative and statistically significant coefficient for funding gap in table 4. But subinvestment-grade banks may already hoard too much liquidity to finance future investment if access to wholesale funding is relatively costly. High levels of liquidity hoarding could then imply inefficient employment of financial resources, lower future profitability, and possibly lower ratings, as indicated by the positive coefficient for funding gap.

Larger banks also tend to attract higher ratings, given that all coefficients for size dummies are statistically significant and monotonic. As discussed in section 3.1, this is in line with the intuition that bank size could correlate with cross-border diversification of assets and funding sources, internal economies of scale, and, possibly, management quality. Moreover, the coefficient for domestic market share of lending is significant and with a positive sign. This is in line with the intuition that market share could be indicative of domestic franchise value, pricing power, and, possibly, systemic importance—all of which could lead to higher ratings.

Finally, we find evidence of a negative bias in the ratings of IFRS reporting banks, given the statistically significant and negative coefficient for the IFRS dummy. As discussed in section 3.1, such a negative bias could be due to higher volatility in IFRS numbers. Also, the benefits of IFRS reporting (e.g., better-quality management due to market discipline) may take some time to reflect in actual ratings and may not be fully captured in the early years of IFRS implementation that we consider in the sample.

### *5.2 Country-Level Variables*

Turning to macroeconomic variables, the lagged interaction effect between the credit gap and the real output gap is statistically significant and with a positive sign, which is indicative of procyclicality in bank ratings. When a credit boom (positive credit gap, in two-year lag) is followed by a subsequent macroeconomic slowdown (negative real output gap, in one-year lag), current ratings tend to be lower. However, when credit expansion above normal levels is followed by a year of economic boom, bank credit ratings tend to increase. A similar result is obtained if, instead of the real output gap, we consider a dummy for economic slowdowns (taking the value 1, if real output gap is negative, and 0 otherwise) and its interaction with the credit gap.[23] In addition, the coefficient for real output gap is statistically significant and positive, adding further support to the hypothesis of procyclicality in bank ratings.

A steepening of the yield curve also appears to have a positive impact on bank ratings, as indicated by the positive and significant coefficient for the yield-curve slope. This result is consistent with empirical evidence that identifies the slope of the yield curve as a predictor of turns in the business cycle (Estrella and Hardouvelis 1991). It is also consistent with banks' asset-liability repricing mismatch (implied by their maturity transformation function), which makes banks susceptible to a flattening of the yield curve (Drehmann, Sorensen, and Stringa 2008).

Finally, all dummies for sovereign ratings are statistically significant and monotonic. Ceteris paribus, the higher the sovereign rating of a bank's country of domicile, the higher the bank's rating. Country effects have possibly been absorbed by macroeconomic variables, country ratings, and the constructed variable to capture possible deviations from the capital target, which also considers country effects. Hence, most of the regional dummies in the estimated model are not significant, with table 4 presenting the coefficients of the statistically significant ones. These are in line with our prior about the level of banking-system development, the existence of state-owned institutions in the sample, and government guarantees. Scandinavian banks appear to benefit the most from the country effect, followed by German and UK banks. Japan has the lowest coefficient, probably reflecting the problems experienced in the Japanese banking system over the past decade, which nevertheless have not impacted materially on Japan's sovereign rating.[24]

[23] In line with the previous specification, the interaction effect in that case has a negative and statistically significant coefficient. Estimation results relating to alternative specifications of the model are available from the authors upon request.

[24] There is no apparent connection between the ratings of Japanese banks and the sovereign rating of Japan. While the Japanese banking system was in crisis, Japan was rated Aaa by Moody's until November 16, 1998, when it was downgraded to Aa1. It was upgraded again to Aaa on October 20, 2002.

### *5.3 Goodness-of-Fit and Robustness Checks*

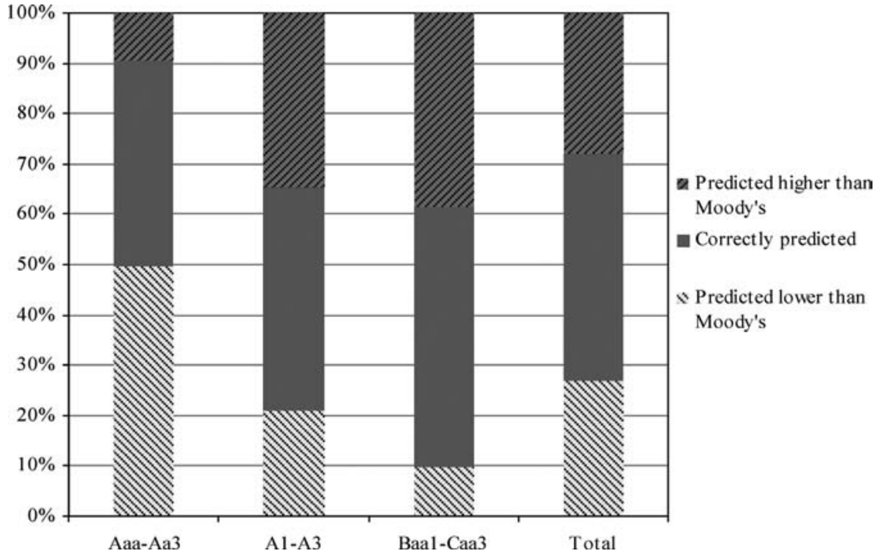
In order to assess the performance of the estimated model that is presented in table 4, we compare model predictions with actual ratings by Moody's. To illustrate such a comparison, we use bar charts showing the proportion of actual ratings that are correctly predicted by the model, as opposed to ratings that are either over- or underpredicted. For expositional convenience, comparisons between actual and predicted ratings are presented in terms of high (Aaa–Aa3), medium (A1–A3), and low (Baa1–Caa3) rating categories. We also show the total results across rating categories.

In-sample prediction results are presented in figure 1. Overall, the model predicts correctly 45 percent of actual ratings in the sample. In terms of model performance across rating categories, the model predicts correctly 41 percent of high ratings, 44 percent of medium ratings, and 52 percent of low ratings.[25] The number of over- and underpredictions by the model are almost equally balanced at 28 percent and 27 percent, respectively. Table 5 offers a more detailed analysis of the goodness of fit of the estimated model. For example, the table shows that from 212 actual Aa3 ratings, the model predicts correctly 122, while it overpredicts 33 (by assigning a rating Aaa–Aa1 to 6 and Aa2 to 27) and underpredicts 57 (by assigning a rating A1 to 41, A2 to 13, and A3 to 3).

We observe that the estimated model tends to underpredict high ratings and overpredict low ratings. Figure 1 shows that for ratings above Aa3, the incidence of underprediction is 50 percent, compared with 9 percent of overprediction. Yet, for ratings between Baa1 and Caa3, the incidence of underprediction falls to 10 percent, while overprediction errors increase to 38 percent. For medium ratings, model errors are more balanced, representing 21 percent underprediction and 35 percent overprediction. To some extent, such a bias toward underrating high ratings and overrating low ratings is imposed by the model structure. In other words, the only way to err in predicting a rating at the top end of the rating spectrum is to underpredict it, and vice versa for the bottom end.

[25] From the 1,369 data points considered, 411 correspond to banks rated Aaa–Aa3, 622 to banks rated A1–A3, and 336 to banks rated Baa1–Caa3.

## Figure 1. In-Sample Estimates (Median Ratings)




## Table 5. Ordered Probit Model Predictions of Actual Ratings, for the Period 1999–2006

| | Predicted Ratings | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Actual Ratings** | Aaa–Aa1 | Aa2 | Aa3 | A1 | A2 | A3 | Baa1 | Baa2–Baa3 | Ba1–Ba3 | B1 or Below | Total |
| Aaa–Aa1 | 11 | 16 | 49 | 24 | 2 | 2 | 0 | 0 | 0 | 0 | 104 |
| Aa2 | 6 | 35 | 34 | 15 | 4 | 1 | 0 | 0 | 0 | 0 | 95 |
| Aa3 | 6 | 27 | 122 | 41 | 13 | 3 | 0 | 0 | 0 | 0 | 212 |
| A1 | 0 | 5 | 36 | 89 | 55 | 14 | 2 | 0 | 0 | 0 | 201 |
| A2 | 0 | 4 | 23 | 62 | 108 | 41 | 5 | 0 | 0 | 0 | 243 |
| A3 | 0 | 0 | 4 | 8 | 74 | 79 | 10 | 3 | 0 | 0 | 178 |
| Baa1 | 0 | 0 | 0 | 4 | 14 | 77 | 10 | 10 | 1 | 0 | 116 |
| Baa2–Baa3 | 0 | 0 | 0 | 0 | 1 | 1 | 4 | 76 | 17 | 0 | 99 |
| Ba1–Ba3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 22 | 58 | 5 | 85 |
| B1 or Below | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 5 | 30 | 36 |
| Total | 23 | 87 | 268 | 243 | 271 | 218 | 31 | 112 | 81 | 35 | 1, 369 |

**Note:** The matrix shows the number of actual versus predicted ratings using the estimated ordered probit model presented in table 4. Diagonal elements represent the number of correct model predictions per actual rating category on the far-left column. Elements above the diagonal represent number of underpredictions per actual rating category, while elements below the diagonal represent number of overpredictions.

The goodness of fit of the model at the top end of the rating spectrum may also be affected by omitted variables. We recognize that with the exception of bank size, market share, and country effects, the model does not consider variables for geographic and sectoral diversification, risk-management expertise, quality of staff, and integrity. In addition, it does not explicitly control for banks in the sample that are state sponsored (i.e., state-owned banks, or banks that are covered by government guarantees). Such banks would possibly receive the sovereign (ceiling) rating, regardless of their underlying financial indicators. Yet some of the impact of state sponsorship on bank ratings may be already captured by explanatory variables, such as country effects, market share, and dummies for sovereign ratings, as discussed in section 3.1.[26]

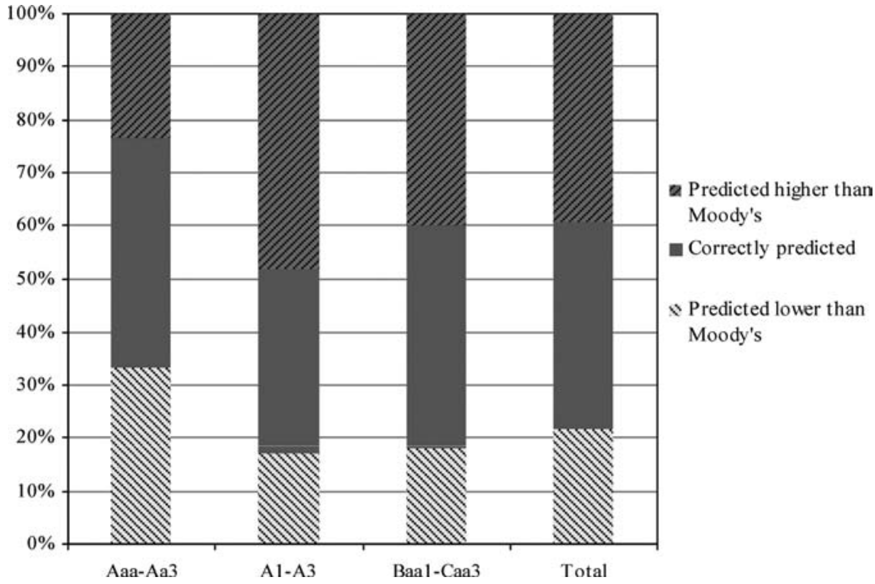
Another factor that could lead to underprediction errors for high ratings is the way that predicted ratings are defined. As discussed in section 4.1, we consider the median of the estimated probability distribution of ratings as the predicted rating. But for the median to correctly predict the rating category Aaa–Aa1 would require the estimated probability for that category to be at least 50 percent. By considering the most probable (mode) rating, we are able to improve the model performance in predicting Aaa–Aa1 ratings. In particular, compared with eleven correct predictions of Aaa–Aa1 ratings under a median-rating approach (see table 5), mode ratings predict correctly twenty-five ratings. However, that comes at a cost of higher prediction errors at lower rating categories, compared with median ratings.

The definition of the rating categories (see section 3) may also affect the goodness of fit of the model. We tried alternative designs of the rating categories (maintaining ten rating buckets), and the goodness of fit of the model remains broadly unchanged. But compared with other studies of credit ratings, the number of rating categories (ten) that we consider is relatively large.[27] As a result, the predicted

[26]For example, approximately one-third of the banks rated Aaa–Aa1 in the sample are German banks, especially Landesbanks, whose debt issuance until July 2005 was covered by explicit state guarantees. As already discussed in section 5, ratings of German banks are among those that benefit most from the country effect.

[27]Amato and Furfine (2004) consider eight rating categories and Blume, Lim, and MacKinlay (1998) only four, with success rates in predicting ratings 53 percent and 57 percent, respectively.

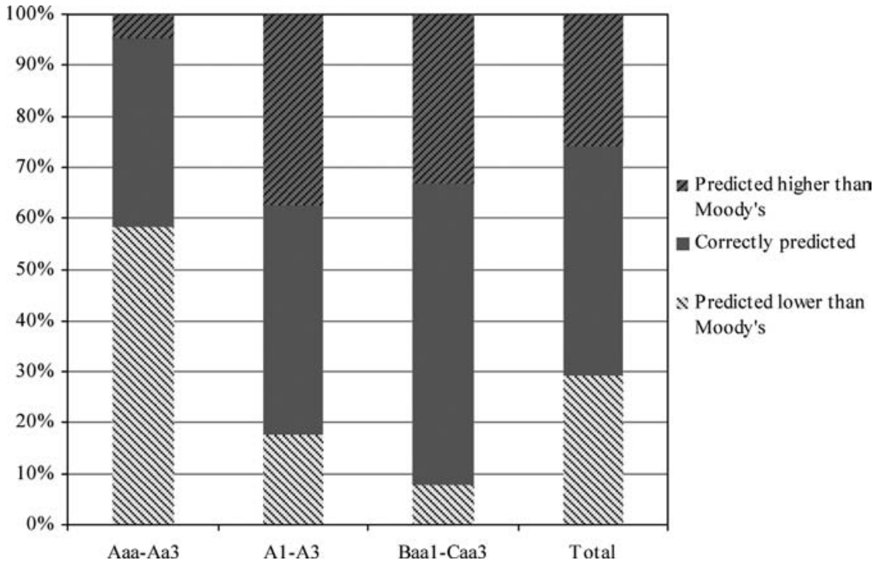
**Figure 2. Out-of-Sample Estimates for 2005 (Median Ratings)**




probabilities are spread across a relatively wide range of ratings categories, which makes it harder for median ratings to predict actual ratings. Therefore, we also considered coarser rating buckets, and the goodness of fit of the predicted model substantially improved. However, attaining a better fit of the model using coarser rating buckets would come at a cost of worse predictions relative to the true Moody's scale. That would clearly limit the practical use of the empirical model and, hence, we prefer more finely defined rating buckets. In any case, by grouping in table 5 the predicted and actual ratings into four rating categories (Aaa–Aa3, A1–A3, Baa1–Baa3, and B1 or below) similar to Blume, Lim, and MacKinlay (1998), 1,064 out of the 1,369 data points are "correctly predicted," which implies a quasi-success rate of approximately 78 percent.

We also consider how the model performs out of sample for the years 2005 and 2006. Out-of-sample predictions for 2005 are based on six years of data from 1999 through 2004 and are presented in figure 2. Predictions for 2006 are based on seven years of data from

**Figure 3. Out-of-Sample Estimates for 2006 (Median Ratings)**

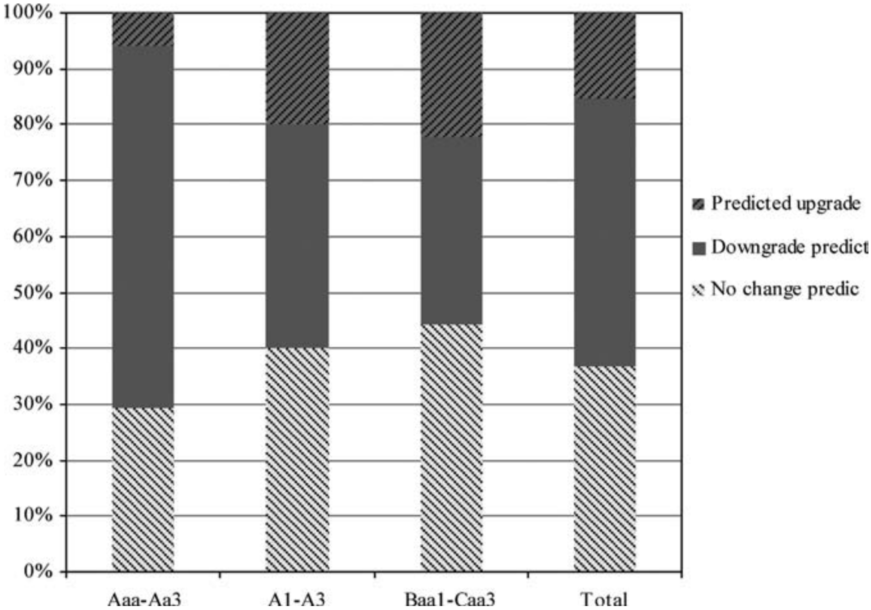



1999 through 2005 and are shown in figure 3. The estimated model predicts correctly 39 percent of ratings in 2005 and 45 percent of ratings in 2006.[28] Finally, we examine how well the model performs in predicting ratings downgrades. As figure 4 shows, the model predicts correctly twenty-two out of forty-six downgrades (48 percent), while in seven cases it predicts an upgrade, and in seventeen cases it predicts no change in ratings. The highest proportion of correctly predicted downgrades is achieved for the Aaa–Aa1 rating category (65 percent).[29]

[28] For the year 2005, we consider 188 observations, with 51 for high ratings (Aaa–Aa3), 87 for medium ratings (A1–A3), and 50 for low ratings (Baa1–Caa3). For 2006 we consider 195 observations, with 65 for high ratings, 91 for medium ratings, and 39 for low ratings.

[29] For the Aaa–Aa1 rating category, the model predicts eleven out of seventeen downgrades (65 percent); for A1–A3 it predicts eight out of twenty downgrades (40 percent); and for Baa1–Caa3 the model predicts three downgrades out of nine (33 percent).

**Figure 4. Predicting Downgrades (Median Ratings)**




## 6. Conclusions

A number of studies suggest that the financial system is intrinsically procyclical (e.g., Bernanke, Gertler, and Gilchrist 1999). Hence, credit risk that is built up on banks' balance sheets during good times may crystallize as credit and economic conditions deteriorate. Downgrades in bank ratings could then feed into negative market sentiment about the banking sector, precipitating a deleveraging process by banks attempting to improve their financial indicators. That could feed into a cycle of further tightening of credit conditions, financial distress by borrowers, and deterioration in banks' financial indicators and ratings. Therefore, a closer examination of the behavior of bank ratings and, in particular, of possible channels through which procyclicality in ratings could manifest itself, would be of interest both to market participants and to policymakers. To our knowledge, this is the first paper that discusses procyclicality of bank credit ratings focusing on (lagged) interaction effects between the credit and business cycle. It also examines the extent to which bank ratings internalize cyclical variations in measures of asset quality and profitability.

Controlling for bank financial characteristics, we find evidence that bank senior unsecured ratings correlate positively with the slope of the yield curve, sovereign ratings, market share of lending, and bank size. Moreover, we find significant evidence of procyclicality in bank ratings owing to lead-lag interaction effects between the real output gap and the credit gap. This is consistent with evidence from Moody's that changes in corporate bond *ratings are strongly correlated with cyclical indicators such as economic activity, default rates, and credit spreads* and that *average rating levels generally move in tandem with the cycle* (see Cantor, Mahoney, and Mann 2003). Bank ratings also appear to internalize cyclical variations in asset quality by penalizing low asset quality more aggressively in good times than in periods of economic slowdown. However, no significant evidence is found that bank ratings distinguish between profitability at different stages of the business cycle.

Bank ratings could correlate with the credit and economic cycle as a result of difficulties faced by market participants (including rating agencies) in assessing how systemwide risks evolve over time, or distinguishing between cyclical variations and structural changes. Such signal extraction problems could be exacerbated by complex feedback effects between the financial and the real sector, product innovation, and evolution of business models by banks. Although an analysis of these issues is beyond the scope of this paper, our results indicate that procyclicality in bank ratings could possibly be mitigated by adjusting the degree of pass-through of earnings performance into ratings, conditional on the stage of the economic and credit cycle.

## Appendix

### *IFRS Reporting and Modeling Implications*

IFRS are aimed to offer a more realistic picture of profits and losses due to full disclosure of income and costs that arise, for example, from insurance business and the fair-value treatment of certain assets (see Bank of England 2005, 42). IFRS could also facilitate cross-border comparisons of financial statements and, through stricter disclosure standards, could increase market discipline.[30] That could increase management efficiency and enhance the diversification of funding sources, which could potentially lead to higher bank ratings.

However, IFRS could also lead to higher volatility of reported figures, both across time and in the cross-section across banks. Reported figures, for example, could appear more volatile under IFRS as a result of the fair-value option in accounting for financial instruments and off-balance-sheet items (IAS 39). Under IFRS, such a fair-value option is combined with *neutrality*, which could lead to less smoothing of financial results over time. This represents a departure from many local GAAP standards, where income and expense are calculated on an accrual basis, financial instruments are accounted at historical cost (unless qualified for inclusion in the trading book), and there is a conservative bias toward *prudence* embedded in the accounts. Similarly, IFRS banks are prevented from provisioning against bad loans on a forward-looking basis, which could induce further procyclicality in their financial results (IAS 37). Last but not least, IFRS is a *principles-based* framework that, according to market commentators, could offer more leeway for interpretation, compared with well-developed rules-based systems, such as the US GAAP.[31] That could lead to a wider set of results under IFRS reporting, higher implementation uncertainties, and, possibly, higher litigation risk due to lawsuits by investors.[32]

More than 100 countries—including all EU countries, Australia, Canada, China, Japan, and Russia—are now using or adopting IFRS. Under EU regulation, all listed companies, including banks, are required to produce their consolidated financial statements according to IFRS, beginning January 2005. The majority of EU banks restated their 2004 financial results under IFRS to permit consistent computation and comparison of growth rates. Banks may

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[30] IFRS 7, for example, requires companies to make adequate disclosure about judgments and uncertainties in valuing financial instruments.

[31] As an indication of the potential scope for interpretation under IFRS, the IFRS principles-based framework is covered in some 2,500 pages, while the U.S. GAAP rules-based system is described in more than 25,000 pages.

[32] See, e.g., "A Single Standard for the World?" *Financial Times,* March 25, 2008.

also opt for IFRS reporting, alongside their national GAAP numbers, regardless of regulatory requirements to do so. Despite the fact that IFRS and U.S. GAAP have moved closer together since 2002,[33] it is only since 2006 that FASB and the IASB have agreed to a formal plan of convergence between the two sets of standards.[34] Given that the sample covers the period 1999–2006 (i.e., before the formal inauguration of convergence between IFRS and U.S. GAAP), the two sets of rules are considered distinct for the purposes of our analysis.

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[33]For example, the Norwalk agreement in October 2002 between the U.S. Financial Standards Board (FASB) and the International Financial Standards Board (IASB) resulted in the first common standard (IFRS 5), and in March 2003 FASB recognized the need for a *principles-based* approach to standard setting, similar to IFRS.

[34]In February 2006, the two Boards signed a memorandum of understanding that laid down a roadmap of convergence between U.S. GAAP and IFRS in the period from 2006 through 2008.

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