Modelling bank credit ratings: A reasoned, structured approach to Moody's credit assessment.*

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Abstract

We conduct a panel ordered probit analysis of how bank ratings by Moody's relate to bank financial indicators and macro variables. We use a sample of 268 banks from 14 regions, covering the period from 1998 to 2005. The results confirm that Moody's consider the quality of earnings as the one of the key drivers of bank ratings, particularly for investment-grade banks. Earnings also appear to have an asymmetric effect, with negative shocks impacting more on ratings than positive shocks of equal magnitude. Asset quality, cost efficiency, liquidity, short-term interest rates and bank-size perform well in explaining ratings. Moody's also appear to consider the adequacy of (Basel I) Tier 1 capital ratio, but only in conjunction with a bank's risk profile and quality of its earnings. We also find evidence that IFRS figures for asset quality, cost efficiency, profitability and liquidity are more informative about ratings than GAAP numbers.

Key words: bank ratings, Moody's, IFRS, ordered probit

JEL Classification: G21; G24; C25

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1 Introduction

Bank credit ratings are summary statistics, encompassing a rating agency's view of the financial robustness of a banking institution. Credit ratings have become of fundamental importance for the functioning of the banking system. They have been incorporated in the regulatory apparatus and internal charters of institutional investors, affecting capital requirements, collateral calls and the ability of banks to function in the derivative and capital markets. Ratings also affect the price of wholesale funding,[1] whose importance as a source of financing, at least for UK banks, has increased due to a widening funding gap.[2] Hence understanding how bank ratings are determined is central to analysing risks associated with banks' funding costs, access to liquidity and, ultimately, solvency. This paper aims to determine how ratings assigned to banks by Moody's relate to bank characteristics, such as key financial ratios, and macroeconomic variables.

Our objective is twofold: to be able to explain bank ratings and, more specifically, predict rating downgrades. Predicting downgrades is of interest to both risk managers and policy makers. This is because downgrades can hamper the operations of banking institutions, especially if they lead to the breaching of rating thresholds that are perceived as crucial for getting access to, for example, the money and derivatives markets.

We use an ordered probit approach similar to the approaches of Afonso, Gomes and Rother (2007), Mora (2006), Hu, Kiesel and Perraudin (2002) and Blume, Lim and Mackinlay (1998). An ordered probit approach is particularly suitable to model ratings, which are relative (ordinal), rather than absolute (cardinal), measures of credit risk. This is because, ordered probit models recognise differences in the information content of rating changes at different points on the rating spectrum. For example, a downgrading of a highly rated bank by one rating grade (notch) may imply a different degree of deterioration in the bank's fundamentals than a one-notch downgrading of a low rated bank.

We estimate the model by using a data panel of 268 banks from 34 countries for a period of eight years from 1998 to 2005. We take an informed approach to Moody's credit assessment of banks, both in terms of variable selection and model specification. In addition, we work under the presumption that a rating methodology is applied consistently across banks worldwide, adjusting for country effects and differences in accounting standards to make reported figures comparable across countries. For example, among the issues we consider

[1] Empirical evidence suggests that higher rated institutions face lower and more stable wholesale funding costs than lower rated ones (Perraudin and Taylor (2004), Gropp and Richards (2001), Kliger and Sarig (2000), Hand et al. (1992), Kao and Wu (1990), Ingram et al. (1983)).

[2] By funding gap we mean the difference between customer lending and customer funding, where customer refers to all non-bank borrowers and depositors. According to the Bank of England's Financial Stability Report (April 2007), the funding gap of major UK banks stood at around 23% of customer lending at end-2006.

in constructing our dataset is the transition from national Generally Accepted Accounting Practices (GAAP) to the International Financial Reporting Standards (IFRS) in a number of jurisdictions, or the unilateral adoption of IFRS by banking institutions.[3] Under IFRS, some on and off-balance-sheet items, such as loan-loss provisions and securitised assets, are treated differently than under national GAAP. That could affect reported figures for total assets, earnings, capital, as well as measures of asset quality, liquidity and cost efficiency.

Regarding model specification, we consider both linear and asymmetric effects of variables on estimated ratings. Asymmetric effects imply that increases in variables may have a different absolute impact on ratings than falls of equal magnitude. That could arise if credit rating agencies (CRAs) prefer rather err on the conservative side (i.e. underrating than overrating banks). Asymmetric effects could also arise if a variable's impact depends on its initial level. Liquidity, for example, offers a buffer against unanticipated foreclosures of credit lines. But at a too high level, it may be associated with an inefficient use of financial resources. Thus the marginal effect of liquidity may be higher for relatively illiquid banks than for more liquid ones.

We find that the choice of model specification depends crucially on whether the key objective is to explain overall bank ratings or to predict rating downgrades. We show that including banks' previous year rating significantly improve the overall model's performance both in and out of sample. However, this comes at the cost of sharp deterioration in predicting rating downgrades. We show that a possible compromise is to distinguish whether the bank's previous period rating was above or below the subinvestment threshold (defined by the Baa3 Moody's rating). We also consider the impact of such a distinction on the estimated coefficients.

Distinguishing between investment and subinvestment grade banks allows for a rating process that may vary across rating classes. For example, there is empirical evidence by Johnson (2003) that CRAs tend to downgrade firms more aggressively when the starting rating of a firm is at the neighboring of subinvestment grades. Also CRAs may place different emphasis on certain variables, or interpret changes in those variables differently, depending on the starting rating of a bank. For example, low ratings may have already incorporated the possibility of more volatile financial ratios, given that ratings are ordinal measures of credit risk. Hence, they may respond less to negative shocks in variables compared to high ratings where negative shocks could lead to a significant risk reassessment.

Our results show that financial ratios for asset quality, earnings, cost efficiency and liquidity play a key role in explaining bank ratings. Overall, IFRS ratios tend to impact more on predicted ratings than GAAP numbers. That is consistent with the idea that

[3]Notwithstanding any explicit regulatory requirements, banks may opt to report their consolidated figures under IFRS, alongside national GAAP, in order to enable international comparability of their financial statements, improving their access to funding and expand their international shareholder base.

IFRS numbers are more comparable across countries and institutions and, possibly, more informative about bank creditworthiness.

Earnings appear to have an asymmetric effect on ratings, with negative shocks impacting more on ratings than positive shocks of equal magnitude. Such an asymmetric effect is more pronounced for investment than for subinvestment grade banks. This is consistent with the hypothesis that higher uncertainty about earnings may have already been discounted into lower ratings. Our results also confirm that Moody's consider the adequacy of Tier 1 capital ratio (calculated under the Basel I risk-weighting framework), but only in conjunction with the overall risk profile of a bank and quality of its earnings. The lower the quality of earnings the higher the Tier 1 capital ratio to support a bank's rating.[4]

Bank liquidity and ratings appear to be non-monotonically related. The more liquid a bank the less susceptible it is to a loss of confidence and sudden withdrawals of funds that could lead to solvency problems. Hence, *ceteris paribus*, bank ratings would tend to increase with liquidity. But subinvestment grade banks may also hoard a lot of liquidity to finance future investments if wholesale funding is too costly to rely on due to the low ratings. As bank ratings increase, banks may get easier access to wholesale funding, reducing the amount of (low-yielding) liquid assets that they need to hoard for future investment purposes.

We also consider the impact of short-term interest rates and annual GDP growth on banks ratings, as well as country and size effects. Short term interest rates are significant, with positive changes having a negative impact on bank ratings. This result is consistent with banks' asset-liability repricing mismatch implied by their maturity transformation function (Drehmann, Sorensen and Stringa (2006)). The coefficient for GDP is not significant, although with a positive sign, in line with Moody's through-the-cycle rating approach.

Bank size could be indicative of asset diversification, market share and the possibility of third party support in case of a crisis. As a result, larger banks appear to attract higher ratings. Also country dummies are mostly significant and in line with our prior about the perceived level of banking system development and the existence of state guarantees. German and Benelux banks appear to benefit the most from the country effect, followed by Scandinavian banks. Japan has one of the lowest coefficients, probably reflecting the problems experienced in the Japanese banking system over the past decade.

The structure of the paper is as follows. Section 2 offers an overview of the rating process, focusing on general rating criteria and the role of financial ratios as basic tools

[4]This is analogous to the way regulators set capital ratios above the *BIS* minimum to compensate for limitations in the Basel I risk-weighting framework. For example, a bank's risk profile and volatility of earnings are among the factors that the UK's FSA considers when setting a minimum (trigger) capital ratio under Basel I. Richardson and Stephenson (2000) offer a comprehensive discussion on capital requirements and the factors the FSA considers to set trigger ratios.

for quantitative credit assessment. It also discusses comparability issues of consolidated financial statements across jurisdictions and how the transition from national GAAP to IFRS may impact on financial indicators. Section 3 discusses the ordered probit methodology and section 4 presents the data. Section 5 discusses the estimation methodology and section 6 presents the results. Section 7 concludes.

2 The rating process

CRAs aim 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, in particular, produce their ratings on the basis of a general to specific approach (Moody's (1999)). They firstly examine the economic environment of the country of domicile, then they analyse strengths and weaknesses of the industry as a whole. Finally, Moody's examine debtor-specific characteristics in relation to peer groups. As part of their credit assessment process, CRAs have access to non-public information, either under the US Regulation Fair Disclosure, which prohibits selective disclosure of non-public information, but provides a conditional exception for CRAs, or through private confidentiality agreements with issuers.[5]

2.1 Rating criteria

Rating stability and prudence are widely recognised criteria for rating. Rating stability introduces persistency in ratings as agencies tend to move only one category (notch) at a time to avoid rating reversals. Prudence implies that agencies prefer to rather err on the conservative side. This may lead agencies to compete on the timing of downgrades.

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. In order to achieve rating stability, agencies aim to respond only to the perceived "long-term" component of credit quality changes. Thus, only significant changes in credit quality result in rating changes. But, in addition to rating stability, agencies also aim for rating timeliness, which is taken care of by the abovementioned prudent rating policy.

According to Carey and Hrycay (2001), accommodating rating stability and prudence at the same time is achieved via a "through-the-cycle" methodology, which is based on the assignment of ratings in the *bottom* of the credit cycle. That way, ratings become insensitive to fluctuations in the cycle and focus on the long term. But that could lead

[5] Fight (2001) reports that more than 90% of rated firms reveal non public information to the rating agencies.

to ratings exhibiting a negative bias that increases with uncertainty about fundamentals. Morgan (2002) finds evidence of a negative bias in Moody's ratings. Morgan also finds that, across various industries, such a bias is more pronounced for banks and insurance companies where uncertainties about fundamentals tend to be more acute.

Even within the same industry, rating prudence could lead to persistent underrating of low credit quality institutions (associated with more uncertainty about credit risk). Johnson (2003) documents aggressive downgrades at the neighboring of subinvestment grades. That could be due to increased uncertainties about fundamentals resulting from possible disruption in firms' operations and funding channels following a downgrading to subinvestment grade. Rating prudence could also induce asymmetric effects of variables on ratings, with a deterioration in an obligor's fundamentals having a larger absolute impact on its rating than an improvement of equal magnitude.

With regard to banks, the above features of the rating process will be tested using different model specifications. In terms of variable selection, we focus next on identifying broad classes of bank financial ratios from which to draw potential explanatory variables.

2.2 CAMEL approach to bank credit assessment

Bank ratings are based on five main areas of fundamental analysis, namely capital adequacy, asset quality, management, earnings and profitability, funding and liquidity (CAMEL).

After earnings, capital is a bank's second buffer against adverse shocks. Moody's consider capital adequacy in conjunction with the overall risk profile of a bank and the quality of its earnings. 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 qualitatively 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 franchising value and profitability of the bank. It offers a first line of defence to debtholders in periods of stress and is considered by Moody's as the cornerstone of bank credit assessment. Liquidity is relevant to bank credit assessment because banks are susceptible to loss of confidence and sudden withdrawals of funds. Due to the maturity transformation role that banks perform, the high leverage and intrinsic opaqueness, liquidity problems may become funding problems and even lead to insolvency.[6]

Reported figures from bank financial statements will be used as explanatory variables for all the abovementioned areas of CAMEL analysis. But published accounts numbers are susceptible to different interpretations of accounting policies, meaning that reported numbers need to be translated on a globally consistent basis. We proxy for Moody's

[6] Morgan (2002) and Flannery et al. (2004) provide evidence on the opaqueness of banking institutions.

cross-border comparison of financial figures by controlling for regional effects, as well as distinguishing between IFRS and national GAAP reporting.

2.2.1 Comparability of GAAP and IFRS figures

Different accounting systems may hamper direct cross-border comparison of financial statements. Hence banks' reported figures need to be adjusted to calculate performance ratios on a globally consistent basis.

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. Other countries, including Australia, Canada, China, Hong Kong, Indonesia, Malaysia, Russia, Taiwan, Thailand and Singapore, have adopted IFRS or plan to do so. Banks may also opt for IFRS reporting, alongside their national GAAP numbers, regardless of regulatory requirements to do so.

By controlling for IFRS reporting we test whether there is any content advantage in IFRS figures versus GAAP ones. IFRS, for example, are believed to offer a more realistic picture of profits and losses due to full disclosure of income and costs that arise from insurance business and the fair-value treatment of certain assets.[7] IFRS also introduced rules on how loan loss reserves are calculated, which could limit the scope for different interpretations of the rules by banks.

But controlling for IFRS is also important to avoid measurement biases due to different accounting rules. For example, IFRS generally increase the value of banking assets due to tighter netting rules, fair-value treatment of financial instruments and stricter criteria for moving securitised assets off balance sheet.[8]

Having covered general issues relating to the credit assessment of banks, we now discuss the ordered probit methodology to model ratings.

3 Ordered Probit Analysis

An ordered probit approach to ratings involves the simultaneous estimation of an underlying rating process and of rating cut-offs, which determine the transition from one rating category to another. To estimate such a model for bank ratings we use maximum likelihood estimation techniques and the information of a cross-section of banks over time.

[7] See, Bank of England, Financial Stability Review, December 2005, page 42.

[8] That may be especially an issue for countries such as the UK where, under GAAP reporting, financial instruments had traditionally been measured at cost and on a net basis. Barclays, for example, restated upwards its total assets by 33% under IFRS reporting in 2005.

More specifically, an ordered probit framework allows us to model bank ratings by offering a time-invariant partition of a continuous unobservable variable X_{it} that determines the credit standing of a given bank i at time t. Such a partition is characterised by a number of time-invariant cut-off points c_j, $j = 1, 2, ..K$, and the rating R_{it} of bank i at time t is defined as:

$$R_{it} = \begin{cases} K+1 & if \quad X_{it} \in [c_K, \infty) \\ K & if \quad X_{it} \in [c_{K-1}, c_K) \\ \vdots & \qquad \vdots \\ 1 & if \quad X_{it} \in (-\infty, c_1) \end{cases} \tag{1}$$

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

$$X_{it} = f\left(V_{it} | \boldsymbol{\theta}\right) + \varepsilon_{it} \tag{2}$$

$\boldsymbol{\theta}$ is a vector of unknown parameters and ε_{it} is a Gaussian disturbance term with a conditional expectation of zero. For a given vector of parameters $\boldsymbol{\theta}$ and cut-off points $\mathbf{c}$, the probabilities of rating categories are

$$\Pr\left(R_{it} = j | \boldsymbol{\theta}, \mathbf{c}\right) = \begin{cases} 1 - \Phi\left[c_K - f\left(V_{it} | \boldsymbol{\theta}\right)\right] & if \quad j = K+1 \\ \Phi\left[c_j - f\left(V_{it} | \boldsymbol{\theta}\right)\right] - \Phi\left[c_{j-1} - f\left(V_{it} | \boldsymbol{\theta}\right)\right] & if \quad j = K, K-1, \cdots, 2 \\ \Phi\left[c_1 - f\left(V_{it} | \boldsymbol{\theta}\right)\right] & if \quad j = 1 \end{cases} \tag{3}$$

In the analysis we focus on Moody's ratings which split credit quality in 21 categories through the familiar Aaa-C symbol system. However, in order to be able to estimate an ordered probit model of ratings, we need a minimum number of observations per rating category. Given the size of our dataset, we need at least 5% of observation per rating category in order for the estimation method to converge. Hence, we assign the value 9 to the bank ratings if bank i at date t has a rating by Moody's of Aaa-Aa1, 8 if Aa2, 7 if Aa3, 6 if A1, 5 if A2, 4 if A3, 3 if Baa1-Baa3, 2 if Ba1-Ba3 and 1 if B1 or below. Then, given our panel of bank-specific data and equation (3), the ordered probit model is estimated by using maximum likelihood estimation (for more details, see Greene, 1997, Section 19.8).

With the estimated vector of parameters $\widehat{\boldsymbol{\theta}}$ and cut-off points $\widehat{\mathbf{c}}$ in hand, we can predict the rating of each bank on the basis of the predicted probabilities in equation (3). Two alternative approaches to assign ratings to an institution have been used in the literature, namely *mean* and *mode* ratings. Under the mean ratings approach, which is used by Mora (2006), the predicted rating is equal to the expected rating that is evaluated under the predicted set of probabilities. But Moody's argue that they will normally assign a rating based on the most likely (mode) outcome, instead of a probability weighted (mean) rating, especially when the set of outcomes faced by the issuer are quite restricted and different from each other (Moody's (2002b, 2006a)).[9] A mode-rating approach to model ratings was used in Blume et al. (1998) and is also employed in this paper.

4 Data

We estimate the model using a data panel of bank specific information of 268 banks from 34 countries for the eight year period between 1998 and 2005. Bank specific information includes Moody's credit ratings and consolidated financial ratios. Data on financial ratios were obtained from Bankscope that reports consolidated balance sheet and income statement figures on an annual basis. Table A2 in the appendix offers a list of financial ratios that we consider, corresponding to the five CAMEL categories discussed in section 2.2.[10] The letter in each ratio's name refers to the category that the ratio belongs to, namely C for capital, A for asset quality, M for management, E for earning and L for liquidity. Based on a number of criteria that we discuss in section 6, certain ratios are then selected as potential explanatory variables.

Bank ratings were obtained from Moody's Default Risk Service database, which records the exact date of all rating changes, so a consistent time series of up to daily frequency can be constructed. As a proxy for group ratings, we use Moody's estimated senior ratings of the leading entity in the effective domicile of the parent group. Senior ratings reflect Moody's valuation of the credit risk of fixed income obligations (with maturity greater than one year), incorporating the likelihood of default and the loss suffered in the event of default. Despite being ratings of debt obligations, senior ratings can still provide a good proxy for banks' overall financial strength. The only disadvantage is that senior ratings reflect the likelihood of non-repayment resulting from default, implicitly incorporating government support for a defaulting bank. Different governments may have different policies on repayment introducing some bias between the two ratings between countries. We control for these potential biases using regional and bank-size dummies.[11]

But combining blindly the Moody's and Bankscope dataset into a single panel could artificially decrease the explanatory power of financial ratios. Bankscope allocates balance

[9] For example, if the probability density of predicted ratings is bimodal then mean ratings tend to be of scarce relevance because they may predict a rating that is anyhow unlikely to occur.

[10] Table A2 also presents the sample mean and mean absolute deviation of financial ratios as a proxy for their relative size.

[11] Instead of using estimated senior ratings, we also considered bank financial strength ratings (BFRS). Those ratings refer to banks themselves, rather than to debt obligations, and represent banks' intrinsic safety and soundness without accounting for the likelihood of official support. Although BFRS could appear most appropriate to measure banks' perceived financial strength, closer inspection of the data revealed important inconsistencies, with banks often allocated contradicting financial strength ratings for the same date.

sheet data according to their year of publication. For example, if a bank released its published accounts in January 2004, Bankscope assigns the banks financial ratios to the year 2004. If the bank's ratings changed in December 2004, Moody's database allocates the new rating to 2004. It is likely that the bank's 2005 published accounts better explain the change in rating than the 2004 accounts given that Moody's had probably access to the more recent information. Both databases report not only the year, but also the month when new information is recorded. During the estimation we use Bankscope and Moody's month indicators to better link banks' financial ratios to their ratings.

Furthermore, there were cases where more than one rating changed occurred for the same bank within a year. For example, in Diagram 1 the dates in black represent the publication date of a bank's annual financial results, while the dates in red show the timing of changes in the bank's rating. In such cases it is necessary to select which of the ratings to link to the financial ratios. We arbitrarily take the latest change in ratings only if it has not passed the release date of the annual accounts by more than two months. In the example of Diagram 1 the chosen rating for 2005 would be Aa2. Finally, if no rating is issued in the following calendar year (2006 in the example), we make sure to recover the discarded rating (A1 in the example) and allocate it to the published accounts released in the following year (2006 in the example). Through this process we ensure that ratings are linked as close as possible to the actual information set that was used to determine them.

Figure 1: Rating timing

We also consider whether banks' ratings are directly affected by macro-factors. Data on countries' GDP growth rates and short-term interest rates were collected from Datastream and from central banks' web sites.

5 Estimation Methodology

Following the discussion of the rating process in section 2, this section describes model specification and the sample of potential explanatory variables.

5.1 Model specification

In order to select the best model, we start by using a general to specific approach on the basis of the Likelihood Ratio (LR) tests and the Akaike Information Criterion (AIC). We also check how the model performs in and out-of-sample, which will turn out to be a key criterion for the selection of the model specification. Given the objectives set out in the introduction, special emphasis will be placed on the ability of the model to predict rating downgrades.

Regarding bank specific variables, several combinations of the financial ratios described in Table A2 are taken into consideration. We start from a group of candidates (one for each CAMEL category) 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 macroeconomic variables and qualitative factors, such as an IFRS dummy to distinguish between IFRS and GAAP reported numbers, with interaction effects on financial ratios.

The unobservable linking variable X_{it} defined in section 3 may not be a linear function of the explanatory variables. Hence, we also consider a non-linear relationship between X_{it} and the explanatory variables. In particular, we test for quadratic effects for all variables in the model, aiming to capture possible asymmetric effects (e.g. an improvement in variables may have a different absolute impact on ratings than an equivalent deterioration as discussed in section 2.1) and the possibility of a decreasing marginal effect of variables on ratings.

Before discussing the selection of variables and estimation results, further considerations are required. For the econometric analysis of panel data, we control for heterogeneity by introducing region and size dummies, as discussed in section 5.2.2 below.[12] 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, both in the cross section across banks and across time, we use the generalised Huber-White sandwich approach of Froot (1989).[13] 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

[12] Countries are grouped in 14 regions according to Table A1 in the appendix, and region dummies are included using the U.S. and Canada as a benchmark region.

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

transition, and the implementation of new prudential standards. Industry-wide trends may also give rise to cross-sectional correlation as a result of developments both in the asset side (e.g. credit expansion) and liability side (e.g. funding gap) of banks' balance sheets.

5.2 Explanatory variables

5.2.1 CAMEL ratios

Capital is a carefully managed tool for banks. Managers target capital ratios that balance the requirements of many constituents including shareholders, regulators and CRAs. According to Moody's (1999, 2002a,c, 2006b), the level and sustainability of earnings is the main driver of bank ratings, while capital is a second line of defence behind earnings to support a bank's rating. The weaker the earnings the more capital a bank needs to hold to support its rating. In the absence of earnings, capital would be the only buffer against losses and, hence, a key driver of ratings. But supporting ratings solely on capital would not be sustainable in the long run given that earnings provide a source of capital and non-profitable bank may be unable to raise external capital indefinitely. We consider the Tier 1 capital ratio ($C1$) – i.e. shareholders funds plus perpetual non cumulative preference shares over risk-weighted assets – as our best candidate among ratios for capital adequacy. We also consider the four alternative candidates listed in Table A2 in the appendix. In the sample, $C1$ is calculated under the Basel I risk-weighting framework, which captures risks in a very coarse way (Basel (1988)). We would expect Moody's to compensate for limitations in the Basel I framework by requiring riskier banks to maintain a higher $C1$.[14]

In order to assess asset quality, a key ratio that is often used is loan loss provisions to net interest income ($A2$). The intuition is that net interest margins must appropriately remunerate for the risks undertaken by the bank. The lower that ratio the higher is asset quality. However, when the net interest income is negative, the ratio of loan loss provisions to net interest income becomes meaningless. Hence, we use the ratio of net interest income to total assets ($E2$) to adjust the loan loss provisions to net interest income ratio ($A2^a$), as follows:

$A2^a$	$A2 \geq 0$	$A2 < 0$
$E2 > 0$	$A2$	$A2$
$E2 \leq 0$	0	100%

If $E2$ is positive then the bank's provisions and $A2$ have the same sign and we set $A2^a$ equal to $A2$. If $A2$ is positive and $E2$ is negative, then provisions are negative and the asset quality variable is set equal to zero. There are 15 bank-year observations corresponding to

[14] That would be similar to how banking regulators respond to limitations in Basel I, by requiring riskier banks to hold higher capital ratios above the Basel minimum.

such an event. Finally, if both $A2$ and $E2$ are negative, then provisions are positive and there is no remuneration for risks that the bank undertakes. In that case, we set the asset quality variable equal to 100%, covering 14 bank-year observations. As a measure of asset quality we also consider the five alternative candidates listed in Table A2.

Management quality is an area of bank analysis where it is particularly difficult to derive a meaningful quantitative measure of performance. A ratio that is generally used to measure management efficiency is the ratio of overheads to income ($M2$). In order to limit the possibility of colinearity problems with other ratios such as asset quality and profitability variables, we consider as a potential explanatory variable the ratio of overheads to total assets ($M3$). We also consider an alternative for managerial efficiency, namely the ratio of overheads and provisions to total assets.

Pre-tax, pre-provision profits (PPP) are also one of Moody's favourite indicators of earnings generating power (Moody's (2002a, 2006b)). Therefore, we add the ratio of PPP to total assets ($E7$) among our explanatory variables. The further advantage of adding back provisions into a profitability variable is to avoid obvious colinearity problems between profitability and asset quality ratios. As a measure of profitability, we also consider the seven alternative candidates listed in Table A2.

Regarding bank liquidity, we could capture how vulnerable a bank is to a run *à la* Diamond and Dybvig by using the deposit run-off ratio. Two versions of such a ratio are the ratio of liquid assets to customer deposits and short-term funds ($L4$), or the ratio of liquid assets to debt ($L5$). However, liquid asset figures that are reported by banks under IFRS, capture only a fraction of the actual liquid asset holdings by banks.

That is because, under IFRS, liquid assets such as Treasury bills and other eligible bills, as well as debt securities and equity shares, are not reported separately on 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, the liquid asset figures reported to Bankscope may not include the abovementioned liquid assets, which potentially results in misleadingly low liquidity ratios. For that reason, we also consider the ratio of interbank lending to interbank borrowing ($L1$), the ratio of loans to total assets ($L2$) and the ratio of loans to customer deposits and short-term funds ($L3$).[15]

5.2.2 Macro variables and size effects

As already mentioned in section 2, Moody's follows a general to specific approach, starting from the domestic economic environment. Therefore, it is important to consider macroeconomic indicators as potential explanatory variables in the model. We include GDP growth

[15] To our knowledge, such measures of bank illiquidity are not subject to any obvious bias due to different accounting standards.

and the level of short term interest rates as explanatory variables in our model. Allowing for GDP growth is important because the quality of certain classes of assets, such as commercial loans, tends to be cyclical (Moody's (2002c)). Interest rates are also important to consider because they can affect the financial strength of banks (Drehmann, Sorensen and Stringa (2006)).[16] A bank's country of domicile may affect the bank's rating through considerations about the stability of the country's financial system and potential third party (official) support.

Bank size is included in our model because, according to Moody's, it is often correlated with qualitative factors such as asset diversification and management quality, which are important to bank credit analysis. Moody's, for example, claimed that:

> *...larger banks may often have more granular loan portfolio 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 bank's franchise value.* [Moody's (2002c), p.5]

Bank size may also relate to how essential an institution is to the banking system. For example, large institutions are likely to act as settlement banks in payment systems, or as counterparties of the central bank in open market operations. Large banks perceived by market participants as too big to fail may have a competitive advantage over smaller institutions in relation to funding costs.[17] That said, we determine bank size according to the level of total assets, where year by year size comparisons can be made by deflating total asset levels to constant prices. We then split banks into four quartiles in terms of total assets and we assign them in four categories (with category four being the one for large banks) using small banks as a reference category.[18]

[16] Ideally, we would use the unexpected change in short-term rates given that banks can hedge. However, building such a variable for 34 countries was beyond the scope of this paper.

[17] O'Hara and Shaw (1990) found 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.

[18] As mentioned in the data section 4, we use senior ratings which implicitly include government potential support for a defaulting bank. Those banks' whose countries are perceived to adopt a strong policy of support upon default will be rated higher than their balance sheet might suggest.

6 Results

The estimation methodology described in the previous section led to the results summarized next.

6.1 Basic model

In this section we consider a basic model with financial ratios, macro variable, country and size fixed effects, without trying to explicitly modelling rating persistency discussed in section 2.1. The impact of IFRS reporting on ratings is captured through a dummy (I_{IFRS}), with interaction effects on financial ratios. Results relating to IFRS reporting are analysed separately in section 6.1.1.

Following the estimation methodology in section 5, we identified the following financial ratios from Table A2 to be included in the model: $C1$ for capital adequacy, $A2^a$ for asset quality, $M3$ for cost efficiency, $E7$ for profitability and $L3$ for liquidity. The estimated coefficients and rating cut-off points are presented in Table A3 in the appendix.

Among these key financial ratios, the coefficients for $A2^a$, $M3$, $E7$ and $L3$ are statistically significant and with the expected sign. The coefficient for $C1$ is negative (although not statistically significant), in line with the intuition that Moody's may compensate for limitations in the Basel I framework by requiring riskier banks to maintain a higher $C1$, as discussed in section 5.2.1.

As far as asset quality is concerned, an increase in the ratio of provisions to net interest income ($A2^a$) implies that interest margins are not increasing sufficiently enough to cover for increasing risks in the lending book. Thus we would expect the rating of a bank to decrease as $A2^a$ increases. This intuition is confirmed by the negative and significant coefficient (-0.0022).

Cost ratios have increasingly attracted the attention of analysts as banks seek to cut on costs and improve their operational efficiency. We expect banks with lower ratios of overheads to total assets ($M3$) to have higher ratings, which is consistent with the significant and negative coefficient (-0.0678).

The fourth ratio in Table A3, $E7$, measures the margin of profit protection that is available to debtholders. As mentioned in section 5.2.1, pre-tax, pre-provision profits (PPP) is one of Moody's favourite indicators of earnings generating power. It is therefore not surprising that the coefficient of $E7$ is significant and positive (0.2022). The model also captures a strong asymmetric effect of profitability on predicted ratings, given the negative coefficient (-5.0893) for the square of the profitability ratio ($E7(squared)$). As a result, a decrease in bank profitability has a higher absolute impact on estimated ratings than an increase of equal magnitude. For example, we can easily verify that for a bank at the

Aa3/A1 rating cut-off (1.4406), an operating loss of 2% of total assets would result, ceteris paribus, in two-notches downgrading to A3/Baa1. But, from that level, an operating gain of 2% of total assets would only lead to a one-notch upgrading to A1/A2, instead of Aa3/A1.

The last financial ratio ($L3$) measures bank illiquidity, showing illiquid loans as a proportion of customer deposits and short term funding. Intuitively, more vulnerable banks should have higher ratios. Indeed, the coefficient is negative and significant (-0.0033). Also, the coefficient of square liquidity ($L3(squared)$) is significant and with a positive sign (0.0007).[19] That could indicate a decreasing marginal impact of illiquidity on credit quality if, for example, yields on illiquid assets are relatively high. The relationship between bank liquidity and ratings is revisited in section 6.3, where we discuss how liquidity effects may vary across the rating spectrum.

The coefficient for GDP growth is not statistically significant. That could be because Moody's assign ratings through the cycle.[20] But the coefficient of the short-term interest rate is significant and with a negative sign (-0.1425). That is not surprising given the maturity transformation role of banks (transforming short-term liabilities into long term assets) which makes them susceptible to increases in short term interest rates.[21] However, the interaction between interest rates and banks' balance sheets is complex and depends not only on the level, but also on the shape and changes in the yield curve, as well as on banks' hedging strategies.

We also examine fixed effects through a combination of country and bank size dummies. Table A3 shows the list of estimated coefficients for regional and size dummies. German and Benelux banks – i.e. regions 2 and 4 respectively – appear to benefit the most from the country effect, followed by Scandinavian banks (region 3). Japan (region 11) has one of the lowest coefficients, probably reflecting the problems experienced in the Japanese banking system over the past decade and the opacity of Japanese accounts.[22]

Finally, we find that larger banks tend to attract higher ratings. As discussed in section 5.2.2, bank size could be indicative of asset diversification, internal economies of scale and greater market share. Also larger banks may be more systemically important, hence ratings

[19] In absolute terms, the liquidity coefficient is small relative to coefficients for other ratios in the model. That is not surprising given that, on average, $L3$ is a larger ratio than, for example, the profitability variable $E7$ (i.e. 56.59% vs. 0.62%) as shown in Table A2 in the appendix.

[20] Amato and Furfine (2004) also find evidence that ratings do not generally exhibit sensitivity to the business cycle.

[21] 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 curves.

[22] According to the December 2002 GAAP Convergence Survey by the International Forum on Accountancy Development Japan, along with Iceland and Saudi Arabia are the only countries that have reportedly refused to converge with IFRS.

may encompass that government support is more likely for larger banks in case of crisis.

6.1.1 IFRS effects

The adoption of IFRS by banks could lead to enhanced comparability of financial statements across countries and help market discipline. That could lead to better management, enhance the diversification of sources of financing and, ultimately, lower funding costs. That intuition appears to be confirmed by the significant and positive coefficient (0.5743) of the IFRS dummy (I_{IFRS}).

Moreover, IFRS could provide a more realistic picture of income and costs than GAAP, and a more consistent treatment of loan loss provisions across countries and institutions, as discussed in section 2.2.1. Hence, IFRS ratios could be more informative about creditworthiness than GAAP figures, which could impact on estimated coefficients in the model. In particular, the coefficients for IFRS ratios could be higher (in absolute terms) than for GAAP ratios.[23]

This intuition is confirmed by the statistically significant interaction effects for asset quality ($A2^a * I_{IFRS}$), cost efficiency ($M3 * I_{IFRS}$), profitability ($E7 * I_{IFRS}$) and liquidity ($L3 * I_{IFRS}$), as shown in Table A3 in the appendix. In addition, the cumulative coefficient of $A2^a$ reported under IFRS (-0.0290) is more than 13 times larger than under GAAP (-0.0022). Similarly, the coefficient for $M3$ reported under IFRS (-0.6064) is almost 9 times larger than under GAAP reporting (-0.0678). The coefficient for $E7$ under IFRS (0.8864) is more than 4 times larger than under GAAP (0.2022). Finally, the coefficient for $L3$ under IFRS (-0.0074) is twice as large as under GAAP (-0.0033).

6.1.2 In and out-of-sample predictions

In order to assess the model performance we compare in and out-of-sample 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 (in dark blue), as opposed to ratings that are either over (in red) or under-predicted (light blue). For expositional convenience, comparisons between actual and predicted ratings are presented in terms of high (Aaa-Aa2), medium (Aa3-A3) and low (Baa1-C) rating category. We also show the average results across rating categories (the *Total* bar)

Regarding in-sample predictions, Charts A1 in the appendix shows that 36% of Moody's

[23] Higher coefficients for IFRS ratios could also result from a downward bias due to IFRS reporting. We mentioned in section 2.2.1 that banking assets tend to increase under IFRS. Thus, there could be a negative bias in IFRS ratios calculated as proportions over total assets. However, in the sample, only IFRS figures for $M3$ and $A2^a$ are, on average, lower than GAAP (14% and 6%, respectively), while IFRS figures for $E7$ and $L3$ are 12% and 6% higher than GAAP, respectively.

ratings are correctly predicted by the model, which does better in predicting low ratings (59%), compared to high (22%) and medium ratings (31%).[24] A similar pictures across categories arises with respect to out-of-sample predictions shown in Charts A3 and A4. And overall, 34% and 40% of ratings for 2004 and 2005, respectively, are correctly predicted by the model.[25]

Maybe more interestingly, the model suggests that Moody's underrates banks of low credit quality relative to higher credits. For example, Chart A1 shows that for ratings below Baa1, the incidence of overprediction by the model is 37%, compared to 4% underprediction. Yet for ratings above Aa2, overpredictions account for 8% of all cases, compared to 70% underpredictions. As discussed in section 2.1, such a negative bias for low credit quality banks could be attributed to a prudence criterion.[26] Consequently, the rating process may change as we move from high to low ratings. If such a change actually occurs, then it may not be fully captured by the rating cut-off points discussed in section 3 and shown in Table A3. In that case, we need to introduce more structure in the model. Hence, we discuss two alternative specifications of the model in sections 6.2 and 6.3.

As we discussed in the introduction, one of our aims is to predict downgrades. So, we also examine how well the model performs in predicting downgrades. Chart A2 shows that the model correctly predicts 40 out of 70 downgrades (57%). While in 13 cases it predicts an upgrade, and in 16 cases it predicts no change in ratings. The model correctly predicts the highest proportion of downgrades for the Aa3-A3 category (63%).[27]

6.2 Allowing for rating persistence

In section 2.1 we discussed that stability, as a criterion for rating, could imply persistent (sticky) ratings. To capture such a persistence, we introduce dummies to the basic model, which account for the previous year rating of each bank, i.e. lagged ratings. Each of these dummies corresponds to a rating category (see section 3), using category B1 or lower

[24] From the 1,452 data-points considered, 210 correspond to banks rated Aaa-Aa2, 906 to banks rated Aa3-A3 and 336 to banks rated Baa1-C.

[25] For 2004, we considered 200 observations: 30 correspond to banks rated Aaa-Aa2, 127 to banks rated Aa3-A3 and 43 to banks rated Baa1-C. For 2005, we considered 210 observations: 30 correspond to banks rated Aaa-Aa2, 134 to banks rated Aa3-A3 and 46 to banks rated Baa1-C.

[26] The bias may also arise from the fact that approximately one third of highly rated banks in the sample are German banks. As already discussed in section 6.1, German banks appear to benefit the most from the country effect, which could be partly explained by the presence of state guarantees to landesbanks until July 2005.

[27] For the Aaa-Aa2 rating category the model predicts 8 out of 16 downgrades (50%), for Aa3-A3 it predicts 29 out of 46 downgrades (63%) and for Baa1-C the model predicts 3 downgrades out of 8 (38%).

ratings as the reference category (category 1).[28] The estimated coefficients and rating cut-off points of the model are reported in Table A4 in the appendix.

When controlling for lagged ratings, the coefficient of Tier 1 capital ratio ($C1$) becomes statistically significant, but with a negative sign (-0.0191). Following the discussion in section 5.2.1, the interpretation that underlies this result is subtle: Under Basel I, the risk weights are not time-varying. Hence, risk-weighted assets (the denominator in $C1$) do not react to changes in the riskiness of a bank's assets as quickly as earnings do. But a deterioration in a bank's underlying riskiness may quickly affect its earnings and, consequently, its credit rating. The bank may then aim to increase its capital buffer (the numerator in $C1$) either by freeing up some capital (e.g. contracting credit extension, securitisations etc.), or by raising new capital from investors.[29] Either way, $C1$ would increase and that could be reflected in the data as a negative relationship between (Basel I) $C1$ and ratings.

Similar to the basic model discussed in section 6.1, the coefficient for asset quality ($A2^a$) is statistically significant and with the expected sign (-0.0020), implying that changes in the ratio of provisions to net interest income can explain rating changes. Also, the coefficient of profitability ($E7$) is statistically significant (0.3873), as well as the coefficient for its square term (-4.6716), confirming the asymmetric profitability effect reported in section 6.1. Moreover, the coefficient for liquidity ($L3$) is statistically significant (-0.0026), as well as the coefficient for the square liquidity term (0.0004).

But when controlling for lagged ratings, management efficiency ($M3$) becomes statistically insignificant. Variables for management efficiency are relatively sticky and may not change much over time, meaning that most of their impact could be captured by lagged ratings. Also the coefficient of the IFRS dummy, as well as its interactions with financial ratios, become statistically insignificant after controlling for lagged ratings. That is not surprising given that CRAs have access to non-public information and the impact of IFRS could well be anticipated by Moody's and incorporated in previous ratings.

Moreover, controlling for lagged ratings results in the coefficient for GDP growth becoming statistically significant, with a positive sign and a moderate asymmetric effect on ratings (the coefficient for squared GDP growth is negative and less than unity). Hence, although GDP growth does appear to explain rating variations in the cross-section across countries, by taking lagged ratings into account, GDP growth appears to explain rating changes. Finally, the coefficient for short-term interest rates remains significant and with the expected sign (-0.1462).

What it is more important is that controlling for lagged ratings improves dramatically

[28] Interactions of those dummies with financial ratios are not considered given the large number of variables involved.

[29] That could be a response to regulatory demands for a higher minimum (trigger) ratio, or in order for the bank to target a credit rating consistent with its business model.

the in-sample performance of the model. 87% of Moody's ratings are now correctly predicted by the model (Chart A5), compared to 36% under the basic model (Chart A1). In addition, the prediction bias discussed in section 6.1 – i.e. overprediction of low relative to high ratings – disappears. Including lagged ratings also improves the out-of-sample performance of the model. Charts A7 and A8 show out-of-sample predictions for the years 2004 and 2005, respectively, where 88% and 92% of Moody's ratings are correctly predicted by the model.

There is, however, a cost in introducing lagged ratings. Compared to the basic model in section 6.1, the model with lagged ratings does poorly in predicting downgrades. Only 9 out of 70 downgrades (13%) are predicted by the lagged model (see Chart A6), while the basic model predicts 57% of the downgrades.

Summarising, allowing for rating persistence leads to more accurate predictions of Moody's overall ratings than the basic model, but it does worse in predicting downgradings. Because of rating persistence in the sample,[30] the model appears to attach too much weight to lagged ratings relative to other variables, which makes it less responsive to changes in ratios. In the following section we look for a modeling compromise by distinguishing between investment and subinvestment grade banks.

6.3 Investment-subinvestment grade effects

Let us now augment the basic model of section 6.1 by including a dummy ($I_{subinvest.}$) which distinguishes between investment and subinvestment grade banks, rather than including dummies for each rating category. We also include interaction effects between this dummy and financial ratios. The dichotomy between investment and subinvestment grade banks is defined in terms of previous year rating, with Baa1-Baa3 ratings (i.e. category 3) corresponding to the highest subinvestment grade. The estimated coefficients of the model and rating cut-off points are reported in Table A5 in the appendix.

As with the basic model, the coefficients for asset quality ($A2^a$), management efficiency ($M3$), profitability ($E7$) and liquidity ($L3$) are statistically significant and with the expected sign. Interaction effects between financial ratios and the IFRS dummy (I_{IFRS}) remain statistically significant and also in line with the discussion in section 6.1. For investment grade banks, the coefficient for Tier 1 capital ratio ($C1$) is also statistically significant and in line with the intuition discussed in sections 6.1 and 6.2. Moreover, there are statistically significant interaction effects between the subinvestment grade dummy ($I_{subinvest.}$) and Tier 1 capital ($C1 * I_{subinvest.}$), asset quality ($A2^a * I_{subinvest.}$) and liquidity ratio ($L3 * I_{subinvest.}$). Statistically significant interaction effects are also identified between $I_{subinvest.}$ and square profitability ($E7(squared) * I_{subinvest.}$), as well as between $I_{subinvest.}$

[30] From the 1,326 annual observations considered in the estimation only 178 involve a rating change.

and square liquidity ($L3(squared) * I_{subinvest.}$).

As discussed in section 5.2.1, a deterioration in the quality of earnings increases the importance of capital as a buffer against losses. Especially for subinvestment grade banks, where uncertainties about earnings may be particularly acute, holding more capital may allow a bank to attain a better rating. This intuition is confirmed by the positive cumulative coefficient (0.0207) for $C1$ when a bank is of subinvestment grade.

The above asymmetric impact of capital may suggest that changes in profitability could have a smaller impact on subinvestment than investment grade ratings. This intuition is confirmed by the larger coefficient (-6.5439) for square profitability for investment grade banks, relative to banks of subinvestment grade (-2.2947). In other words, it appears that changes in profitability have a different impact depending on whether the bank already attracts a high or low rating.

The model also predicts that bank liquidity and ratings are non monotonically related. Compared to medium-rated banks, both high- and low-rated banks tend to be more liquid (i.e. having lower illiquidity ratios ($L3$)). As discussed in section 5.2.1, liquid assets provide a buffer against foreclosures of credit lines, enhancing creditworthiness. Also, liquid assets are used as collateral in derivative and money market transactions (e.g. central bank's open market operations) where highly rated banks are major players. It is therefore not surprising that, for investment grade banks, the coefficient for $L3$ is negative (-0.0049). However, banks with very low ratings may hoard liquidity to finance future investment if they can access wholesale funding only at relatively high costs. As ratings increase, banks may then get easier access to external sources of funding, reducing their marginal propensity to hoard (low yielding) liquid assets. That could explain the positive coefficient for $L3$ (0.0131) for subinvestment grade banks.

Overall, controlling for investment and subinvestment grade banks improves the in-sample performance of the model relative to the basic model presented in section 6.1. 46% of Moody's ratings are now correctly predicted by the model (Chart A9), compared to 36% under the basic model (Chart A1). In addition, the overprediction bias of low relative to high ratings is mitigated, especially for ratings below Baa1. Similarly, the out-of-sample performance of the model is improved. For the years 2004 and 2005, Charts A11 and A12 show that 46% of the out-of-sample predictions are correct.

Chart A10 shows that the model predicts 34 out of 70 downgrades (49%), it fails in 12 cases where it predicts an upgrade, while in 24 cases it predicts no change in ratings. The model predicts a higher proportion of downgrades than the basic model for the Aaa-Aaa2 and Baa1-C category, and a lower proportion for Aa3-A3.[31]

[31] For the Aaa-Aa2 rating category the model predicts 9 out of 16 downgrades (56%), for Aa3-A3 it predicts 20 out of 46 downgrades (43%) and for Baa1-C the model predicts 5 downgrades out of 8 (63%).

7 Conclusions

In this article we conduct a panel order probit analysis of how bank ratings by Moody's relate to bank financial indicators and macro variables. We select our best model focusing both on the model's in- and out-of-sample performace. We also place special emphasis on the ability of the model to predict downgrades. Our findings are fairly robust and quite unequivocal. Variables for provisions, profitability, cost efficiency, liquidity, short-term interest rates and bank-size perform well in explaining ratings. Our results also suggest that IFRS figures for provisions, cost efficiency, profitability and liquidity may be more informative about ratings than GAAP numbers. Moody's also appear to consider the adequacy of Tier 1 capital ratio, calculated under Basel I rules, but only in conjunction with a bank's overall risk profile and, in particular, profitability.

We find a strong asymmetric effect of profitability on estimated ratings, with negative shocks impacting more on ratings than positive shocks of equal magnitude. Such an asymmetric effect is more pronounced for investment than for subinvestment grade banks. Bank liquidity and ratings are shown to be non monotonically related. That could be due to endogenous effects, where low rated banks may hoard a lot of liquidity to finance future investments if wholesale funding is costly due to low ratings.

Short term interest rates are significant, with positive changes having a negative impact on bank ratings. But the coefficient for GDP is not significant, although with a positive sign, indicating that Moody's assign bank ratings through the cycle. Also larger banks appear to attract higher ratings, in line with the intuition that bank size could be indicative of asset diversification, market share and the possibility of third party support in case of crisis. Finally , country dummies are mostly significant and in line with our prior about the perceived level of banking system development and the existence of implicit state guarantees.

Further research could expand the dataset to investigate, for example, how the introduction of new capital adequacy rules under Basel II will impact on the relationship between capital ratios and bank ratings. Also, with a sufficient number of rating actions in hand, we could estimate the model using only the sample of changes in ratings (re-ratings). Given rating agencies' preference for rating stability, the same rating bucket may often contain banks with different underlying riskiness (point-in-time ratings). Consequently, starting with the premise that re-ratings are better indicators than point-in-time ratings, estimating the model using only re-ratings could lead to narrower rating densities per bank and, possibly, more accurate rating predictions by the model.

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8 Appendix

8.1 Tables

Table A1: Geographic regions

Region	Country
1	United States, Canada
2	Germany
3	Sweden, Norway, Finland, Denmark
4	Belgium, Luxembourg, Netherlands
5	Austria, Switzerland, France, Liechtenstein
6	United Kingdom
7	Spain, Portugal, Ireland, Greece
8	Australia
9	Italy
10	Hong Kong, Korea, Singapore, Taiwan
11	Japan
12	India, Indonesia, Malaysia, Philippines, Thailand
13	Russia, Kazakhstan
14	China

Table A2: List of financial ratios

Variable (%)	Description	Mean	Mean Abs. Deviation
Capital			
C1	Tier 1 capital / risk weighted assets	12.48	6.60
C2	Tier 1 and Tier 2 capital / risk weighted assets	12.81	2.40
C3	Shareholders equity / total assets	5.29	1.65
C4	Shareholders equity / net loans	9.36	2.96
C5	Shareholders equity / total liabilities	5.79	1.80
Asset quality			
A1	Loan loss reserves / gross loans	1.88	0.92
A2	Loan loss reserves / net interest income	5.33	10.15
A2[a]	*A2* if *E2* is positive, 100% if both *A2* and *E2* are negative and 0% otherwise	6.66	8.52
A3	Loan loss reserves / impaired loans	152.78	107.57
A4	Impaired loans / gross loans	2.99	2.49
A5	Loan write-offs less recoveries / gross loans	1.08	1.27
A6	Impaired loans / gross loans	0.04	0.01
Management			
M1	Overheads and provisions / total assets	1.57	0.67
M2	Overheads / income before provisions	46.65	9.55
M3	Overheads / total assets	1.19	0.51
Earnings			
E1	Net interest income / earning assets	1.31	0.63
E2	Net interest income / total assets	1.21	0.56
E3	Fees and other income / total assets	0.53	0.39
E4	Earnings before tax and unusual items / total assets	0.20	0.79
E5	Net income / total assets	0.07	0.62
E6	Net income / shareholders equity	2.04	8.96
E7	Pre-tax, pre-provision profits / total assets	0.62	0.56
E8	Dividend paid / net income	24.57	15.16
Liquidity			
L1	Lending to other banks / borrowing from other banks	87.44	46.94
L2	Net loans / total assets	41.36	12.45
L3	Net loans / customer deposits and short-term funds	56.59	14.01
L4	Liquid assets / customer deposits and short-term funds	9.00	4.79
L5	Liquid assets / total borrowing excl. capital instruments	7.18	3.84

Table A3: Panel ordered probit with IFRS interactions

Number of observation =1443 ; Pseudo R^2 =21.49 %

	Coefficient	Robust std. error	p-value
C1	-0.0116	0.0097	0.2320
$A2^a$	-0.0022	0.0009	0.0150
$A2^a * I_{IFRS}$	-0.0268	0.0096	0.0050
M3	-0.0678	0.0398	0.0880
$M3 * I_{IFRS}$	-0.5386	0.1174	0.0000
E7	0.2022	0.0929	0.0300
$E7 * I_{IFRS}$	0.6842	0.1543	0.0000
E7(squared)	-5.0893	1.5149	0.0010
L3	-0.0033	0.0013	0.0090
$L3 * I_{IFRS}$	-0.0041	0.0012	0.0010
L3(squared)	0.0007	0.0002	0.0000
GDP	0.0052	0.0272	0.8490
Interest rate	-0.1425	0.0362	0.0000
I_{IFRS}	0.5743	0.3267	0.0790
$I_{region\ 2}$ [1]	1.2434	0.2673	0.0000
$I_{region\ 3}$	0.7302	0.2259	0.0010
$I_{region\ 4}$	0.9338	0.2422	0.0000
$I_{region\ 5}$	0.6735	0.2095	0.0010
$I_{region\ 6}$	0.6220	0.2688	0.0210
$I_{region\ 7}$	0.6366	0.2210	0.0040
$I_{region\ 8}$	0.4142	0.2236	0.0640
$I_{region\ 9}$	0.1139	0.1868	0.5420
$I_{region\ 10}$	-1.2537	0.3927	0.0010
$I_{region\ 11}$	-1.7214	0.2251	0.0000
$I_{region\ 12}$	-1.3808	0.3707	0.0000
$I_{region\ 13}$	-0.6570	0.6118	0.2830
$I_{region\ 14}$	-2.2141	0.4651	0.0000
$I_{Q4\text{-}large\ banks}$ [2]	2.0750	0.3192	0.0000
$I_{Q3\text{-}medium\text{-}large}$	1.7006	0.1678	0.0000
$I_{Q2\text{-}medium\text{-}small}$	0.6503	0.1035	0.0000
	Rating cut-offs	**Robust std. error**	
Aaa/Aa2	2.8712	0.4212	
Aa2/Aa3	2.2934	0.4055	
Aa3/A1	1.4406	0.3836	
A1/A2	0.8262	0.3540	
A2/A3	0.1221	0.3190	
A3/Baa1	-0.6188	0.3216	
Baa3/Ba1	-2.0757	0.2721	
Ba3/B1	-3.1564	0.3266	

[1] For the region indicator variable the reference category is the region including United States and Canada.

[2] Q2-medium-small is a bank with total assets belonging to the second quartile, the reference category is banks belonging to the first quartile. Q3 and Q4 are the two highest quartiles.

Table A4: Panel ordered probit with lagged ratings and IFRS interactions

Number of observation =1317; Pseudo R^2 =75.57 %

	Coefficient	Robust std. error	p-value
C1	-0.0191	0.0058	0.0010
$A2^a$	-0.0020	0.0008	0.0130
$A2^a{*}I_{IFRS}$	-0.0099	0.0124	0.4250
M3	0.0160	0.0381	0.6750
$M3{*}I_{IFRS}$	0.0128	0.1192	0.9140
E7	0.3873	0.0860	0.0000
$E7{*}I_{IFRS}$	0.2492	0.2354	0.2900
E7(squared)	-4.6716	2.0944	0.0260
L3	-0.0026	0.0016	0.0970
$L3{*}I_{IFRS}$	-0.0007	0.0017	0.6900
L3(squared)	0.0004	0.0002	0.0880
GDP	0.1865	0.0325	0.0000
GDP(squared)	-0.8689	0.4620	0.0600
Interest rate	-0.1462	0.0543	0.0070
I_{IFRS}	-0.4499	0.2783	0.1060
$I_{region\ 2}$	0.2748	0.2574	0.2860
$I_{region\ 3}$	1.1491	0.2315	0.0000
$I_{region\ 4}$	0.9171	0.2020	0.0000
$I_{region\ 5}$	0.5189	0.2237	0.0200
$I_{region\ 6}$	0.9723	0.1877	0.0000
$I_{region\ 7}$	0.4095	0.1404	0.0040
$I_{region\ 8}$	0.5912	0.2226	0.0080
$I_{region\ 9}$	0.4792	0.1340	0.0000
$I_{region\ 10}$	-0.1405	0.3050	0.6450
$I_{region\ 11}$	-0.1826	0.3639	0.6160
$I_{region\ 12}$	-0.9760	0.3584	0.0060
$I_{region\ 13}$	0.6971	0.7704	0.3660
$I_{region\ 14}$	-0.0390	0.5698	0.9450
$I_{Aaa\text{-}Aa1}$	0.5424	0.2184	0.0130
I_{Aa2}	0.3612	0.1668	0.0300
I_{Aa3}	0.2261	0.1288	0.0790
I_{A1}	21.9377	1.2665	0.0000
I_{A2}	19.0119	1.1683	0.0000
I_{A3}	15.9753	1.0944	0.0000
$I_{Baa1\text{-}Baa3}$	13.1712	1.0303	0.0000
$I_{Ba1\text{-}Ba3}$	10.1229	0.8804	0.0000
$I_{Q4\text{-}large\ banks}$	7.7219	0.7310	0.0000
$I_{Q3\text{-}medium\text{-}large}$	5.0801	0.6170	0.0000
$I_{Q2\text{-}medium\text{-}small}$	2.2943	0.6155	0.0000

	Rating cut-offs	Robust std. error
Aaa/Aa2	21.3317	1.2016
Aa2/Aa3	18.5031	1.1544
Aa3/A1	15.1557	1.0987
A1/A2	12.1841	1.0559
A2/A3	9.3326	0.8274
A3/Baa1	6.7325	0.7107
Baa3/Ba1	3.1588	0.6974
Ba3/B1	0.0742	0.6062

Table A5: Panel ordered probit with IFRS and subinvestment-grade interactions

Number of observation =1443 ; Pseudo R^2 =30.87 %

	Coefficient	Robust std. error	p-value
$C1$	-0.0181	0.0080	0.0240
$C1_* I_{subinvest}$	0.0388	0.0178	0.0300
$A2^a$	-0.0026	0.0009	0.0020
$A2^a{}_* I_{IFRS}$	-0.0309	0.0110	0.0050
$M3$	-0.1295	0.0356	0.0000
$M3_* I_{IFRS}$	-0.5415	0.1293	0.0000
$E7$	0.2395	0.0837	0.0040
$E7_* I_{IFRS}$	0.6752	0.1661	0.0000
$E7(\ squared)$	-6.5439	2.2518	0.0040
$E7(\ squared)_* I_{subinvest.}$	4.2492	2.2654	0.0610
$L3$	-0.0049	0.0014	0.0010
$L3_* I_{IFRS}$	-0.0035	0.0015	0.0160
$L3_* I_{subinvest.}$	0.0180	0.0042	0.0000
$L3(\ squared)$	0.0008	0.0002	0.0000
$L3(\ squared)_* I_{subinvest}$	-0.0030	0.0007	0.0000
GDP	0.0338	0.0247	0.1710
Interest rate	-0.1694	0.0356	0.0000
I_{IFRS}	0.5164	0.3874	0.1830
$I_{subinvest.}$	-4.2810	0.4274	0.0000
$I_{region\ 2}$	0.9464	0.2599	0.0000
$I_{region\ 3}$	0.3979	0.2274	0.0800
$I_{region\ 4}$	0.6406	0.2676	0.0170
$I_{region\ 5}$	0.3690	0.1978	0.0620
$I_{region\ 6}$	0.2978	0.2405	0.2160
$I_{region\ 7}$	0.2732	0.2130	0.1990
$I_{region\ 8}$	0.3630	0.2455	0.1390
$I_{region\ 9}$	-0.1955	0.1898	0.3030
$I_{region\ 10}$	-0.8394	0.3610	0.0200
$I_{region\ 11}$	-1.6029	0.2153	0.0000
$I_{region\ 12}$	-1.9520	0.3589	0.0000
$I_{region\ 13}$	-1.2400	0.6822	0.0690
$I_{region\ 14}$	-1.1990	0.4898	0.0140
$I_{Q4\text{-}large\ banks}$	1.9003	0.3158	0.0000
$I_{Q3\text{-}medium\text{-}large}$	1.5104	0.1796	0.0000
$I_{Q2\text{-}medium\text{-}small}$	0.6261	0.1227	0.0000
	Rating cut-offs	**Robust std. error**	
Aaa/Aa2	2.1721	0.4061	
Aa2/Aa3	1.5836	0.3905	
Aa3/A1	0.7029	0.3695	
A1/A2	0.0434	0.3430	
A2/A3	-0.7819	0.3095	
A3/Baa1	-1.9536	0.3057	
Baa3/Ba1	-4.2816	0.3053	
Ba3/B1	-5.5114	0.3849	

8.2 Charts

Chart A1: In-sample estimates (basic model)

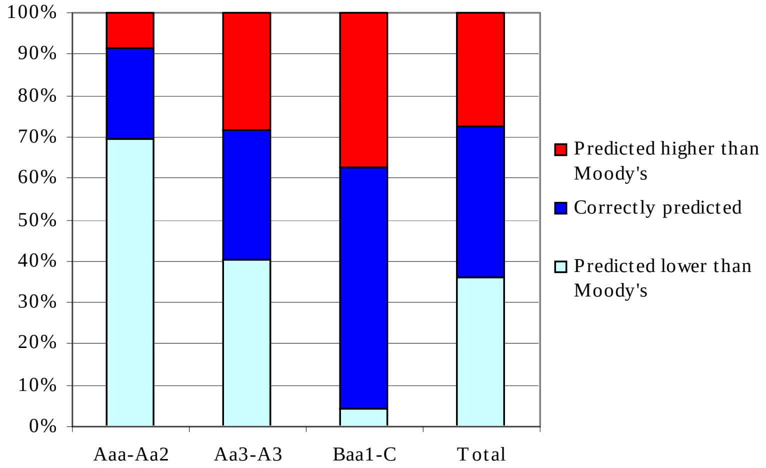

Chart A2: Predicting downgrades (basic model)

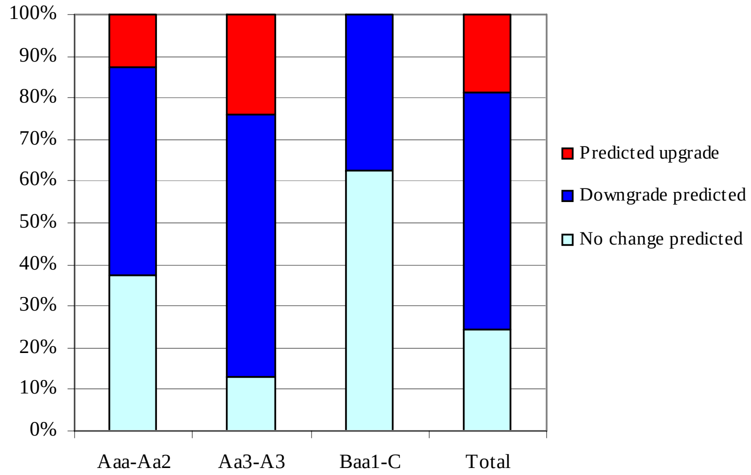

Chart A3: Out-of-sample for 2004 (basic model)

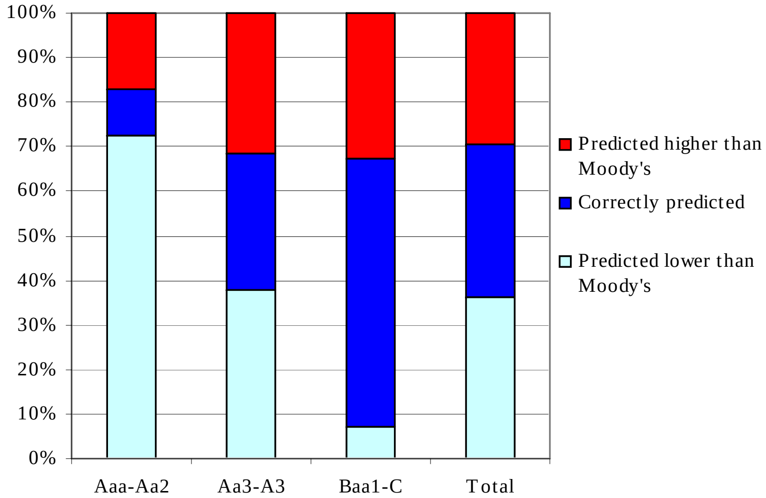

Chart A4: Out-of-sample for 2005 (basic model)

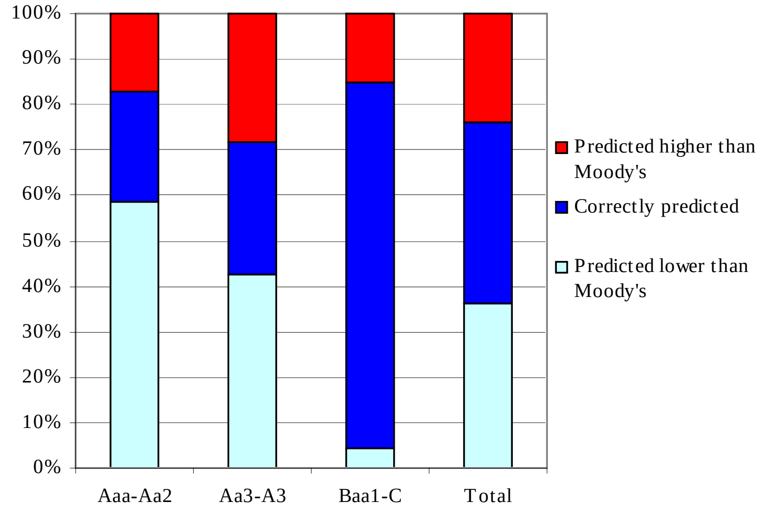

Chart A5: In-sample estimates (model with lagged ratings)

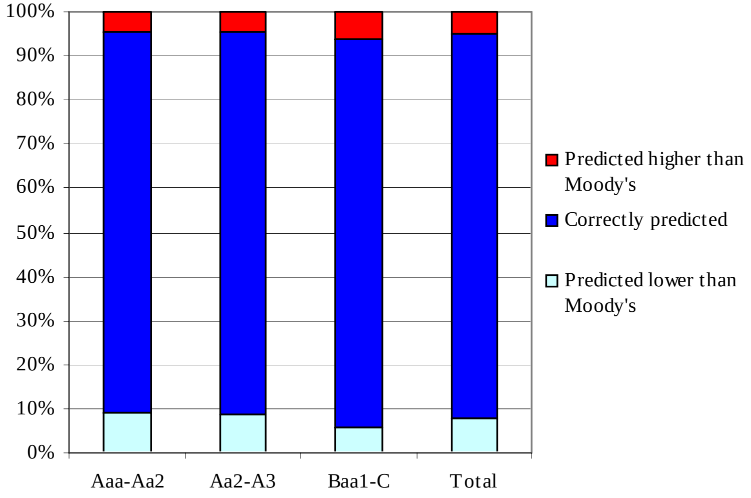

Chart A6: Predicting downgrades (model with lagged ratings)

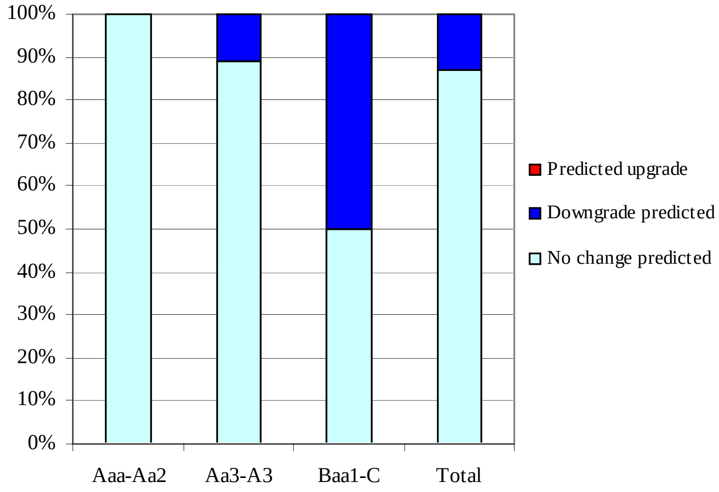

Chart A7: Out-of-sample for 2004 (model with lagged ratings)

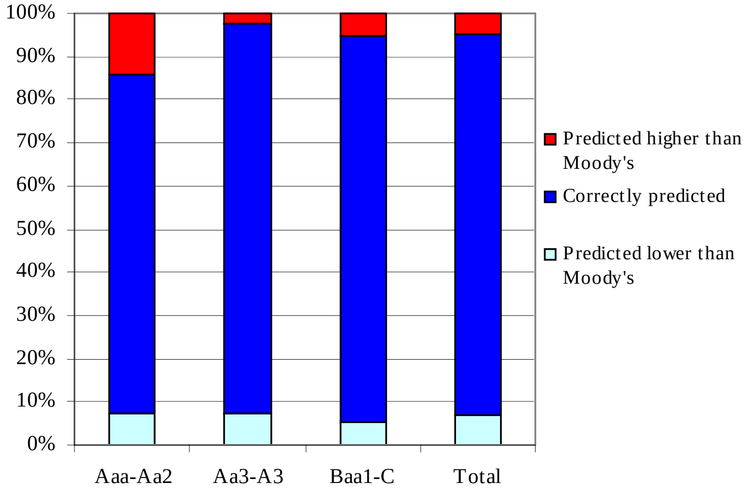

Chart A8: Out-of-sample for 2005 (model with lagged ratings)

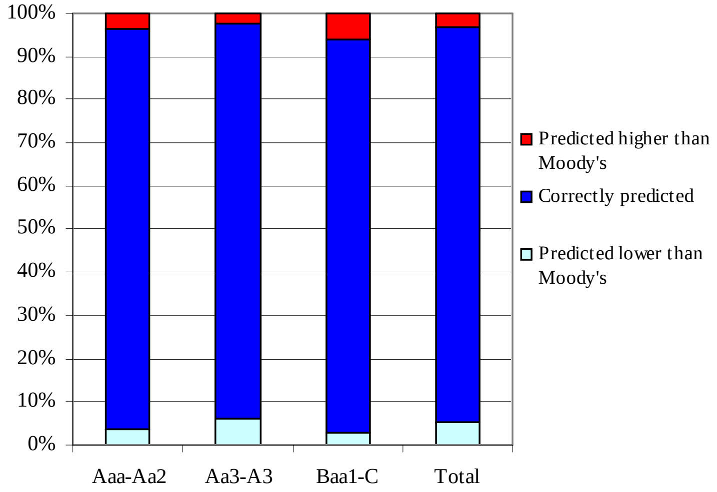

Chart A9: In-sample estimates (model with subinvestment interactions)

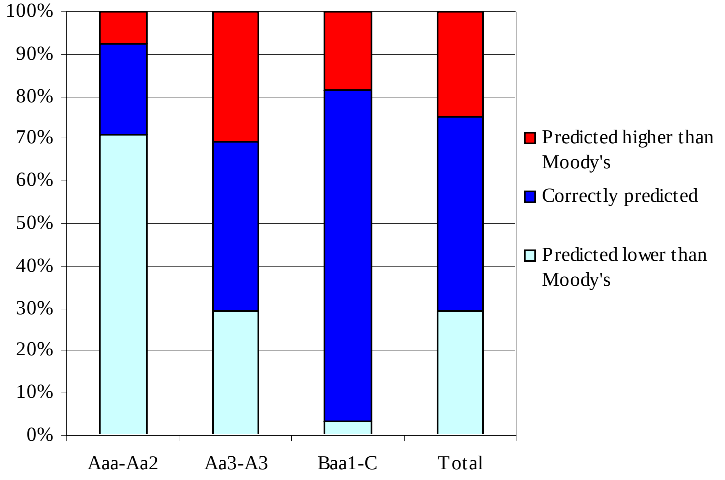

Chart A10: Predicting downgrades (model with subinvestment interactions)

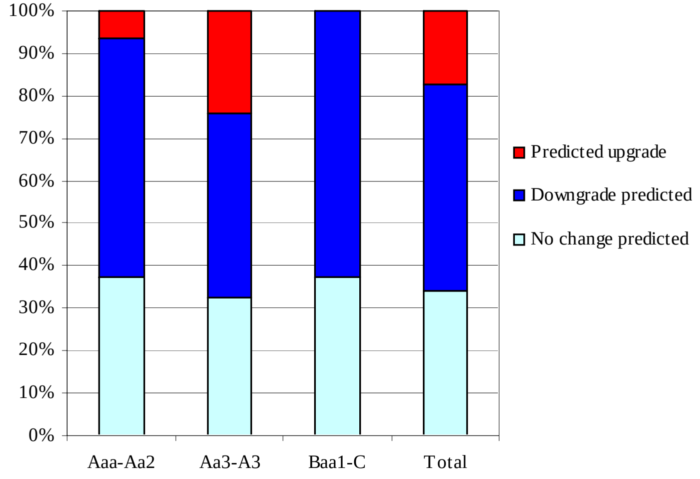

Chart A11: Out-of-sample for 2004 (investment/subinvestment effects)

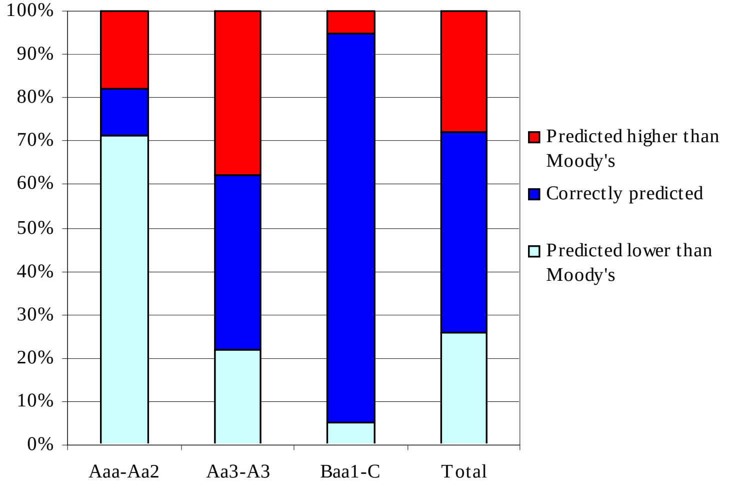

Chart A12: Out-of-sample for 2005 (model with subinvestment interactions)