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Ordered Choice Models of International Banks' Ratings with an Indicator Variable for Country Effects

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Ordered Choice Models of International Banks' Ratings with an Indicator Variable for Country Effects[1]

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Abstract

Using data on international banks' ratings we find that banks with a greater capitalisation, larger assets, and a higher return on assets have higher bank ratings. Further, the more a bank's liquidity increased in the past the greater is its rating, the larger is the ratio of its operating expenses to total operating income the lower is its rating and the more recent is the date that the rating is made the lower is the rating of the bank. There is also a strong country effect on bank ratings such that banks from certain countries have systematically higher ratings than others. The addition of this variable substantially raises the model's accuracy at predicting a bank's rating which is arguably the major challenge of modelling ratings. The inclusion and modelling of country-effects represents a notable innovation of this study.

Keywords: International bank ratings, ordered choice models, country indicator variable.

JEL Classification: C25, C51, C52, G21.

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1. Introduction

Ratings of banks and companies conducted by External Credit Assessment Institutions (ECAIs) may be seen as instruments that provide investors with *prima facie* information about the financial position of the subject in question and on the price of credit risk.

The role of ECAIs has increased since the introduction of the New Basel Capital Accord (NBCA). Banks have to fully rely on internal or external ratings. Banks applying a standardised approach are offered two options for calculating capital adequacy requirements. The first option requires that all banks will be assigned a risk weight one category less favourable than that assigned to claims on the sovereign of that country. This suggests a direct link between bank ratings and the country in which a bank is based. We investigate this link in our empirical modelling of bank ratings. The second option requires that banks use the external credit assessment of the bank itself.[4]

However, the role of ECAIs has been frequently questioned, see for example, Altman and Saunders (2001), Altman et al. (2002) and Bliss (2002). One of the frequent arguments employed against external ratings is the fact that there is no explicit guarantee that external rating agencies can assess credit risk better than banks themselves. For example, Altman and Saunders (2001) argue that agency ratings could provide misleading information since the analysis is backward looking rather than forward looking. In addition, low transparency of ratings assignments contributes to a critical view as well. In other words, ECAICs do not have and cannot have superior

[4] There is much disagreement about this concept. See, for example, Altman et al. (2002). A frequent argument against this approach is the fact that ECAIs are not regulated and this raises questions about their competence including a possible conflict of interests. Other problems can be seen as the failure of most ECAIs to predict financial crises in Asia in the late 1990s and even the recent subprime crises in USA and elsewhere.

information than market participants about uncertainty and about the degree of insolvency (illiquidity).

A prediction of financial soundness of banks, corporations and sovereign nations has been of central importance for analysts, regulators and policy makers. There are numerous empirical studies focusing on predicting either the failure of firms or ratings classifications. The first research studies trying to predict firms' failures were published by Beaver (1966), who used a univariate model. Altman's paper (1968) instigated research activities in this niche of corporate finance by applying discriminant analysis as a predictor of firms' bankruptcy. Altman (1977) using ZETA score models initiated a new generation of computer based models. These models have employed different estimation techniques and more advanced statistical and econometric software. Most of the current classification models use logit (probit) models or neural networks, see for example, Ohlson (1980) and Altman et al. (1998).

Research focusing on the prediction of bank failures by applying Early Warning Systems (EWS) has also been extensively published, see, for example, Mayer and Pifer (1970). The series of bank failures in the USA and elsewhere in the 1990s facilitated the estimation and exploration of these classification techniques. A large number of studies have been published and Altman and Saunders (1998) provide a survey of such research. Kolari *et al* (2002) summarise studies that have been focused on classification methods and have contributed to research in this field by introducing the trait recognition approach as an EWS method.

Another strand of empirical research is focused on ratings prediction models (Matousek, 1995). Ratings are ordinal measures that should not only reflect the current financial position of sovereign nations, firms, banks, etc. but also provide information about their future financial positions. Nevertheless, the main challenge in modelling ratings is to increase the probability of correct classifications. This strand of research motivates and guides our use of financial ratios as determinants of ratings in general and banks ratings in particular. In other words, we consider whether financial ratios are important in determining a given rating grade. In addition, we introduce a country indicator variable to capture country specific effects and, anticipating our results, demonstrate that it substantially enhances the predictive accuracy of our models.

The objective of our paper is to analyse the determinants of individual bank ratings conducted by Fitch Ratings (FR). That is, we first consider whether (and which of) the key financial ratios of banks reflect individual ratings (that is, according to FR, a key component for long and short term rating). Secondly, we examine whether bank ratings are systematically determined by the timing of the rating. Thirdly, we incorporate an indicator variable to capture country-specific variations in ratings under that rationale that a bank's rating is related to the country in which it is based. This methodological approach within the context of modelling bank ratings is an additional contribution to current research in this field. We also assess the predictive power of our model to classify the individual ratings of commercial banks in question.

The organization of the paper is as follows. Section 2 describes the data and the methods applied while Section 3 discusses the principal empirical findings. The last section concludes.

2. Data and Methodology

Fitch Ratings, as one of the largest rating companies for the banking industry around the world, releases three types of ratings; legal ratings, long term and short-term (security) ratings and individual ratings.

Legal ratings inform about the likelihood that the bank in question will be supported in the case of financial difficulties. A legal rating does not indicate how ‘good’ or ‘bad’ the bank is. The information that this type of rating contains is whether the bank will be supported if it gets into difficulty. This kind of rating has a great impact on a creditor’s decision but for the objective of our analysis cannot be employed. Long term and short term (security) rating answers the following question: if an investor lends money to a bank, how certain is it that it will be repaid on time? These ratings are determined by combining individual and legal ratings.

Individual ratings assess the financial position of a bank itself. As stated by FR the rating is closely linked with financial performance (financial ratios). The individual rating provided by FR is subdivided into five categories according to the performances of rated banks.[5] Individual rating is the most appropriate method of analysis for the objective of this study – which is to consider the determinants of these ratings.

[5] The standard classification of the individual rating is A, B, C, D and E. A further graduation among these five ratings is used, that is, A/B, B/C, C/D and D/E. The grade A says that the bank is in an impeccable financial position with a consistent record of above average performance. The B rating defines a bank as having a sound risk profile and without any significant problems. The bank’s performance generally has been in line with, or in a better position than, that of its peers. The C rating includes banks which have an adequate risk profile but possess one troublesome aspect, giving rise to the possibility of risk developing, or which have generally failed to perform in line with their peers. The D rating includes banks which are currently under-performing in some notable manner. Their financial conditions are likely to be below average and their profitability is poor. These banks have the capability of recovering using their own resources, but this is likely to take some time. Finally, the E rating includes banks with very serious problems which either require or are likely to require external support.

Within this context, the financial ratios of commercial banks have been utilised in several ways. They are used as an instrument for cross section analyses of banks and also one can apply them to trend analyses. However, the question remains whether or not financial ratios (and country) might be used as an indicator of banks' future financial position and, therefore, their individual rating.

Using data on 681 international banks' ratings between 2000 and 2007 we estimate models of the determinants of these ratings, denoted Y_i.[6] This variable is ordinal and has up to nine ranked categories that are assigned integer values from 1 to 9, such that lower values indicate a lower rating. The sample size falls as higher-order lagged explanatory factors are added to the model and this can cause all banks in a particular category to be excluded from the sample. In our application the number of categories is either 8 or 9 depending upon the lag specification. The nine rating categories (with assigned values in brackets) are: E (1), D/E (2), D (3), C/D (4), C (5), B/C (6), B (7), A/B (8), A (9). Figure 1 shows the percentage of banks that are awarded a particular rating each year. The five highest categories (A, A/B, B, B/C and C) have larger percentages in the first three years (2000, 2001 and 2002) compared to the latter years. In contrast, the four lowest categories (C/D, D, D/E and E) have broadly smaller percentages in the first three years compared to the latter years. This suggests that average bank ratings have declined through time – we assess this possibility in our modelling.[7]

[6] The BankScope database has been used to obtain a large sample of commercial banks rated by FR.
[7] Indeed, the average numerical ratings (where E = 1 and A = 9) are 5.00 in 2000, 5.41 in 2001, 5.83 in 2002, 5.10 in 2003, 5.11 in 2004, 4.31 in 2005, 4.70 in 2006 and 4.64 in 2007. Hence, ratings in the last three years are notably lower than in the first three years, confirming the suggestion of a general decline in ratings. This would suggest that a time trend could enter with a negative coefficient in the logit/probit ratings regressions.

We apply ordered choice estimation techniques to the models of this ordinal dependent variable because, as is well known, they are the appropriate method to use in this case. The ordered dependent variable model assumes the following latent variable form (see Greene 2008):

$$Y_i^* = \sum_{k=1}^{K} \beta_k X_{ik} + u_i \qquad \textbf{(1)}$$

where, X_{ik} are the explanatory variables, u_i is a stochastic error term and Y_i^* is the unobserved dependent variable that is related to the observed dependent variable, Y_i, (assuming nine categories) as follows:

$$\begin{aligned} &Y_i = 1 \quad \text{if } Y_i^* \leq \lambda_1 \\ &Y_i = j \quad \text{if } \lambda_{\text{j-1}} < Y_i^* \leq \lambda_j, \quad j = 2,3,\ldots,8 \\ &Y_i = 9 \quad \text{if } \lambda_8 < Y_i^* \end{aligned} \qquad \textbf{(2)}$$

where λ_1, λ_2,…, λ_8 are unknown parameters (limit points) to be estimated with the coefficients (the β_k s). Our interest is primarily confined to the general direction of correlation between the dependent and independent variables. Therefore, we use the sign of β_k to provide guidance on whether the estimated signs of coefficients concur with our *a priori* expectations. This is instead of looking at the marginal effects which indicate the direction of change of the dependent variable (for each value of the dependent variable) to a change in X_{ik}. For ordered choice models these marginal effects are difficult to interpret.

The probit form of this model assumes that the cumulative distribution function employed is based upon the standard normal random variable while the logit form assumes a logistic distribution. Greene (2008) suggests that probit and logit models yield results that are very similar in practice.

The first variable that we include in our model is for the year in which the rating was made [$time_t$]. We do not include lagged values of $time_t$, however, we do consider the lagged values of the following seven factors as further potential determinants of bank ratings. The ratio of equity to total assets [denoted $Equity_t$], the ratio of liquid assets to total assets [$Liquidity_t$] the natural logarithm of total assets [$\ln(Assets)_t$] and the net interest margin [*NI_Margin*]. Also considered as possible determinants are $NOA_t = OIA_t - OEA_t$ (where OIA_t is the ratio of operating income to total assets and OEA_t is the ratio of operating expenses to assets), the ratio of operating expenses to total operating income [$OEOI_t$] and the return on equity [$ROAE_t$].[8]

[8] The following three further variables were also considered for inclusion in the model: the ratio of operating expenses to assets [OEA], the ratio of operating income to assets [OIA] and the return on assets [$ROAA$]. These were excluded from the model because they would cause a high degree of multicollinearity and their effects could be captured in other ways. That is, the effects of OEA and OIA are captured by the variable $NOA = OIA - OEA$ while $ROAA$ is a close substitute of $ROAE$ (which it is highly correlated with). The highest pairwise simple correlations amongst the explanatory factors involve these variables (as follows). The simple correlation coefficients for the specified pairings (calculated using a common sample) are: OEA and OIA, 0.98; $ROAA$ and NOA, 0.89; OIA and NOA, 0.84; OEA and NOA, 0.72; OIA and $ROAA$, 0.71; $ROAA$ and $ROAE$, 0.62; $ROAA$ and OEA, 0.60. The simple correlation coefficients of pairs of variables retained in the model are all comfortably below 0.5 (most are substantially lower than this) which helps to ensure that the reported regressions do not suffer from severe multicollinearity.

We do not include current values of these seven variables because they may contain information that was unknown at the time the rating was made. For example, if a bank's rating was decided in January 2007 then the value of any explanatory factor measured over the whole of 2007 would be unknown when the rating was made. It is worth noting that as more lags are included in the model the sample size falls because there is information on all variables for fewer banks. Models could not be estimated when the lag length exceeded four. Therefore, models are estimated from one up to four lags of these variables.

Although rating agencies would always endeavour to incorporate the most recent information into their ratings they may also form their views based on the history of a bank's performance. This justifies the consideration of variables lagged more than one period in our model. Indeed, the relative importance of recent and older data in rating decisions will be indicated by the order of lags that are found to be significant.

Finally, we incorporate an indicator variable to capture country-specific variations in ratings. Because there are 90 countries an ordered choice model incorporating 89 country dummy variables could not be estimated. We therefore proceeded to construct a single indicator variable reflecting cross-country differences following a cross-sectional variant of the method discussed in Hendry (2001). This indicator variable will capture variations in bank ratings that are unaccounted for by the explanatory factors. As Hendry (2001) suggests, this should reduce chance correlations between ratings and explanatory variables and not remove the effects of explanatory variables that genuinely influence ratings.[9] Since individual country dummy variables embody clusters of zeros

[9] Hendry's analysis is within the context of modelling inflation using time-series data.

that can distort test statistics the combination of these dummies into a single indicator index should minimise these effects. The introduction of this country indicator variable within the context of modelling bank ratings is a novel feature of this paper.

The indicator variable was constructed as follows. Various regressions including subsets of the 90 country dummy variables were used to determine the coefficient and significance of each individual country's dummy variable. Dummies with very similar coefficients (where the difference is below half of the coefficient standard error of the dummy with the smallest coefficient standard error) were combined and the restriction involved tested using a likelihood ratio (LR) test. Only dummies with t-ratios exceeding 1.5 were considered for entering combined dummies. As the number of variables declined this process continued, combining dummies with no more than one coefficient standard error difference and using LR tests to validate restrictions. Next, a single country indicator variable was constructed using the coefficients on the composite dummy variables as weights. This was checked for appropriateness by running a regression including the country indicator variable and one particular country's dummy. If the latter was significant this value was incorporated in to the country dummy. After all country dummies that were significant had been incorporated this checking step was repeated until no individual country dummies were significant at the 5% level when included with the indicator variable. The resulting indicator variable (denoted $Country_t$) is specified by equation **(3)**.[10]

(3)

[10] This indicator variable does not include all countries' dummies because insignificant terms were excluded. 78 countries are represented in the indicator variable and 12 are excluded. The excluded countries are: Bermuda, Brazil, Cyprus, Egypt, Israel, Lithuania, Malaysia, Malta, Mexico, Poland, Slovakia and Thailand. These countries, with an implied zero coefficient, are ranked between the group San Marino and South Africa and the group Colombia, Costa Rica, Morocco and Peru.

$$
\begin{aligned}
Country_t = {} & 2.4314\,(Canada + Norway + Sweden) \\
& + 2.2058\,(Andorra + Netherlands + Spain + Switzerland + USA) \\
& + 1.8885(Saudi\ Arabia) \\
& + 1.3660(Jordan) \\
& + 1.3707\,(Czech\ \mathrm{Re}public + Estonia + Iceland) \\
& + 1.1451\,(Austria + France + Hong\,Kong + Korea + Slovenia + UK) \\
& + 0.9697(Chile + Germany + Greece + Italy + Kuwait) \\
& + 0.5838(Bahrain + Qatar + UAE) \\
& + 0.4609(Australia + Macau + Oman + Panama + Trinidad\ and\ Tobago) \\
& + 0.3387(Japan) \\
& + 0.2256(San\ Marino + South\ Africa) \\
& - 0.3756(Colombia + Costa\ Rica + Morocco + Peru) \\
& - 0.5090(Indonesia + Taiwan + Turkey) \\
& - 0.6951(Ireland) \\
& - 0.8188(Bu\,\mathrm{lg}\,aria + El\ Salvador + Hungary + India + Latvia) \\
& - 1.2160\begin{pmatrix} Argentina + Benin + Iran + Jamaica + Kenya \\ + Lebanon + Mongolia + Nigeria + Tunisia \end{pmatrix} \\
& - 1.3660(Kazakhs\,\mathrm{tan} + Philippines + Romania + Russia + Venezuela + Vietnam) \\
& - 1.8885(China + Georgia + Pakis\,\mathrm{tan} + Ukraine) \\
& - 2.6810(Belarus + Do\,\mathrm{min}\,ican\ \mathrm{Re}\ public + Sri\ Lanka) \\
& - 2.3176\begin{pmatrix} Albania + Armenia + Azerbaijan + Bosnia\ and\ \mathrm{H}erzegovina \\ + Macedonia + Niger + Serbia \end{pmatrix} \\
& - 9.2844(Bangladesh)
\end{aligned}
$$

Models were then constructed using this country indicator variable and the other explanatory factors. A cross-sectional variant of the general-to-specific method was employed to produce an initial favoured model.[11] Omitted variable tests were then conducted by testing each excluded variable's individual significance (at the 5% level) using both z and LR statistics. Any significant variable would be considered for inclusion: it would be included if the new model exhibited a lower SBC. This should

[11] In this method we first delete all variables with z-statistics below one (or, exceptionally, 0.5 if the z-statistics are very small for a large number of variables) and apply a Likelihood Ratio, LR, test relative to the general model. If the restrictions cannot be rejected we then delete all variables with z-statistics below 1.5 and then all explanatory factors with z-statistics below 1.96 (applying LR tests relative to the general model). If any LR test for joint restrictions is rejected we experiment to find the variable(s) that cause this rejection and retain it (them) in the model.

ensure that the specification of the model is relatively robust to the model selection procedure.

Four sets of models are considered. The first allows a maximum of four lags, the second features a maximum of three lags, the third a maximum of two lags and the fourth has only one lag of the variables. The sample size ranges from 359 observations for the model incorporating four lags to 629 observations for the single lag model. There is a trade-off with precision of estimation and the generality of lags considered in the model. This makes it difficult to determine which order of lag specification provides superior inference. We therefore seek results that are consistent across lag specifications to draw inferences. We will also note ambiguities when inconsistencies across specifications arise in our empirical application.

4. Empirical Results

The ordered logit (probit) regression results for the determinants of bank ratings with four lags of the explanatory variables are given in Table 1 (Table 3). The logit (probit) results for three lags, two lags and one lag specifications are all reported in Table 2 (Table 4).[12] For all four lag specifications we report a general model (including all lags of the variables) and at least one parsimonious specification obtained using the general-to-specific methodology (followed by omitted variables testing).[13]

[12] For the four lag and three lag specifications the omission of data means that one category of the dependent variable (the category corresponding to an A rating, $Y_i = 9$) is omitted from the regressions. For the other lag specifications all categories of the dependent variable are included.

[13] The only model where an omitted variable was significant was for the logit model with 3 lags where $ROAE_{t-2}$ could be added. Hence, the favoured logit and probit models are potentially different for models with 3 lags due to $ROAE_{t-2}$s inclusion in the former and exclusion from the latter. However, although $ROAE_{t-2}$ is significant in the logit model including it, the model excluding $ROAE_{t-2}$ minimises the SBC. Hence, we argue below that the logit model with 3-lags excluding $ROAE_{t-2}$ should be favoured. Therefore, the favoured model for the 3 lag specification is the same for probit and logit forms.

In all cases the favoured parsimonious model only includes individually (according to z-statistics) and jointly (according to a likelihood ratio test, denoted LR statistic) significant variables.[14] In all cases the restrictions placed on the general model to obtain the parsimonious model cannot be rejected according to a likelihood ratio test [LR(general→)]. Whilst these generally are exclusion restrictions we also consider combining $Liquidity_{t-2}$ and $Liquidity_{t-3}$ into the difference variable, $\Delta Liquidity_{t-2} = Liquidity_{t-2} - Liquidity_{t-3}$, given that they have approximately equal and opposite signs in the specifications with 3 and 4 lags.

The favoured parsimonious model is that which minimises Schwartz's information criterion (SBC). Upon this basis the model favoured in the 4 lag specification includes $\Delta Liquidity_{t-2}$ for both probit and logit forms. In the 3 lag specification the favoured model includes $\Delta Liquidity_{t-2}$ and excludes $ROAE_{t-2}$ for both probit and logit forms (although $ROAE_{t-2}$ is individually significant when included in the logit model, the model excluding $ROAE_{t-2}$ has a lower SBC). There is no choice of parsimonious model for the 1 and 2 lag specifications and hence the model specified is favoured. The favoured parsimonious models will yield more efficient inference relative to the general model and are, therefore, used for inference. Models favoured for inference are indicated with bold emphasis. The same models are favoured for the probit and logit forms for each lag specification.

[14] A potential exception is the parsimonious probit specification with 3 lags because $ROAE_{t-2}$ is insignificant. However, this model, with $ROAE_{t-2}$ included, is not favoured for inference.

Considering the favoured parsimonious model for all four lag specifications we find that they include the following statistically significant effects with an unambiguous direction of correlation. The variable *time* has an unambiguous negative effect on bank ratings: the more recently the bank's rating was given the lower the rating will be, *ceteris paribus*. *Equity* (capital adequacy) has a positive effect on a bank's rating: a more capitalised bank has a higher rating.[15] The natural log of assets also has a positive effect on bank ratings: banks with a larger size of assets have a higher rating.[16] *OEOI* has a negative correlation with a bank's rating.[17] The return on assets has a significant and positive impact upon ratings.[18] All of these effects are unambiguous and consistent with prior beliefs.

Country has a positive coefficient indicating that country specific effects affect a bank's rating: a bank in a less stable/developed/rich economy appears to have a lower rating. For example, Canada, Norway and Sweden are in the group of countries with the highest country specific rating effects while Bangladesh has the lowest country specific rating. This finding confirms our hypothesis that a bank's country of origin plays an important role in assigning individual ratings. Interestingly Ireland (Andorra) is ranked in a relatively low (high) position in the country indicator variable.

Liquidity is only significant in models that allow at least three lags. Notably it is both the second and third lag of this variable that are significant and their coefficients are of

[15] For *Equity* only the first lag is significant in the one and two lag specifications, only the third lag is significant in the three and four lag specifications. The coefficient is always positive.

[16] Only the first lag of $\ln(Assets)$ is significant in the favoured parsimonious model for all four lag specifications.

[17] The only *OEOI* terms that are *insignificant* are the third and fourth lags of this variable in the four lag specification. All significant terms of this variable have a negative sign.

[18] The first lag of *ROAE* is significant in models with all lag specifications. The third lag of *ROAE* is also significant in the three lag specification while its fourth lag is significant in the four lag specification. The coefficient on this variable is always positive.

approximately equal and opposite sign – this is the case in both the three and four lag specifications. Hence, it is the second lag of the *change* in liquidity, $\Delta Liquidity_{t-2}$, rather than its level, that appears to be important and it has a plausible positive effect upon bank ratings. That is, a bank whose liquidity increased two periods ago has a higher rating. It seems that the time lag of this effect is important because liquidity was not significant in models allowing less than three lags. We note that this effect would not have been revealed had we not allowed for sufficient lags in the dynamic specification. We believe that allowing for such lags is a strength of our investigation relative to analyses that do not consider such dynamics. Indeed, we are not aware of any previous studies that have considered any dynamics in their models.

The variable *NI_Margin* is significant in only the two lag specification and, in this case, it is the second lag that is significant. If it is the timing of the lag that is important one would not expect *NI_Margin* to be significant in the one lag specification because it does not allow for a second lag. However, its second lag would be expected to be significant in the three and four lag specifications too, but it is not. This may be because it is dominated by the $\Delta Liquidity_{t-2}$ variable in these specifications. Thus, it appears that the effect of *NI_Margin* on bank ratings is fragile although, to the extent that there is an effect, it is a plausible positive relation.

Finally, NOA is significant in only the four lag specification with the second lag being the significant term. We are cautious of interpreting this as supportive of a significant effect upon rating because NOA_{t-2} is not significant in the two and three lag specifications. Further, in the model where it is significant it has a theoretically implausible negative sign. For these two reasons we are inclined to view this apparent correlation as likely being a Type I error (of which there is a 5% chance given our chosen significance level).

We also assess the percentage of correct predictions of the favoured parsimonious models for each lag specification in Table 5. A prediction is correct when a particular observed rating is correctly predicted by the model. From Table 5 (top section) we see that there are between 50.56% and 54.46% (50.83% and 53.42%) correct predictions for the favoured logit (probit) models including the country variable.[19] The percentage correct predictions for two versions of these models excluding the country variable are also reported in Table 5 for comparison purposes. The first version specifies exactly the same variables in the favoured parsimonious models (reported in Tables 1 – 4) except with *Country* removed. These estimated models are reported in Table 6 and their corresponding percentage correct predictions are given in the middle section of Table 5 (they are in the range of 28.46% – 32.94% for the logit specification and 27.51% – 33.41% for the probit form). The second version applies the general-to-specific method with all variables except for *Country* included in the general model. The estimated versions of these models are given in Table 7 and their associated percentage correct predictions are reported in the bottom section of Table 5 (these are between 30.84% and 36.57% for the logit form and 29.41% and 34.07% for the probit specification). The percentage correct predictions are substantially greater (by approximately 20 percentage points) for the models that incorporate the *Country* variable compared to those that do not – they also have much larger pseudo R^2s. In addition, the indicator variable is highly significant in all favoured parsimonious models, which further demonstrates the importance of country effects for predicting international bank ratings. It also indicates

[19] These percentage of correct predictions are extremely similar for probit and logit specifications with neither form of the model performing better across all lag specifications.

that ordered choice models of international bank ratings that exclude such effects will omit important information for predicting ratings.

From Table 5 we also note that our models have difficulty in correctly predicting the extreme A and E ratings. We believe that this is likely due to the relatively small numbers of banks that appear in these categories.

5. Conclusions

Using data on 681 banks from around the world we examine whether international bank ratings are determined by financial ratios, the timing of when the rating was conducted by Fitch Ratings and a bank's country of origin. We find the following clear conclusions. Banks with a greater capitalisation ($Equity$), larger assets [$\ln(Assets)$], and a higher return on assets ($ROAE$) have higher bank ratings. Further, the greater is a bank's ratio of operating expenses to total operating income ($OEOI$) the lower is a bank's rating. We also find a convincing positive effect for the second lag of the *change* in liquidity $(\Delta Liquidity)$: if liquidity increased two periods ago bank ratings will rise. This finding shows that FR's ratings reflect, at least to some extent, a bank's liquidity position. However, there is only weak and unconvincing evidence that the net interest margin (NI_Margin) and net operating income to total assets (NOA) are significant determinants of a bank's rating. Overall, we conclude that these are probably not important determinants of bank ratings.

Nevertheless, we can conclude that ratings reflect a bank's financial position (as measured by various financial ratios). The estimated results unambiguously support the hypothesis that individual ratings assigned by FR rely substantially on fundamental quantitative financial analyses. Of course, we recognise that the views of experts and a certain degree of qualitative information are likely employed by FR in establishing ratings. However, because this information is not publically available it cannot be formally included in our model. Hence, such models will unlikely be able to predict ratings with 100% accuracy.

There is strong evidence of country effects on bank ratings such that banks in some countries have systematically higher ratings than others. Inclusion of this country effect substantially raises the ability of an ordered choice model to accurately predict international bank ratings relative to those that exclude them. This suggests that international studies trying to find out not only ratings determinants but also to predict ratings grades have to include country effects in their models. The presented methodological concept of analysing the country effect represents a notable contribution of this study.

In addition, the date of the bank's rating ($time$) has a robust effect on ratings: the more recent is the date that the rating is made the lower is the rating of the bank. This result supports our working hypothesis that FR and other ECAIs have applied more prudent views and policies as a reaction to critiques of their role during the financial turbulence of the late 1990s.

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Table 1: Bank ratings ordered logit regressions (4 lags)

Variables	General model		Parsimonious models			
$Country$	2.123	(12.580)	2.080	(13.860)	**2.067**	**(14.269)**
$time$	–0.298	(–2.112)	–0.248	(–2.134)	**–0.246**	**(–2.129)**
$Equity_{t-1}$	–0.002	(–0.044)				
$Liquidity_{t-1}$	0.272	(0.180)				
$\ln(Assets)_{t-1}$	0.815	(2.579)	0.527	(6.886)	**0.529**	**(6.932)**
$NI\,M\arg in_{t-1}$	–0.015	(–0.101)				
NOA_{t-1}	7.052	(0.725)				
$OEOI_{t-1}$	–0.515	(–2.028)	–0.499	(–3.452)	**–0.504**	**(–3.437)**
$ROAE_{t-1}$	0.021	(1.470)	0.032	(3.593)	**0.033**	**(3.565)**
$Equity_{t-2}$	0.034	(0.645)				
$Liquidity_{t-2}$	5.601	(2.903)	5.996	(4.148)		
$\ln(Assets)_{t-2}$	0.064	(0.090)				
$NI\,M\arg in_{t-2}$	0.103	(0.689)				
NOA_{t-2}	–30.396	(–1.677)	–11.221	(–2.535)	**–11.333**	**(–2.570)**
$OEOI_{t-2}$	–1.416	(–2.164)	–1.794	(–3.073)	**–1.824**	**(–3.222)**
$ROAE_{t-2}$	0.017	(1.635)				
$Equity_{t-3}$	0.071	(0.984)	0.086	(6.605)	**0.086**	**(6.730)**
$Liquidity_{t-3}$	–5.384	(–2.545)	–5.767	(–4.527)		
$\ln(Assets)_{t-3}$	–0.588	(–0.621)				
$NI\,M\arg in_{t-3}$	–0.078	(–1.007)				
NOA_{t-3}	5.409	(0.556)				
$OEOI_{t-3}$	–0.329	(–0.651)				
$ROAE_{t-3}$	0.000	(0.002)				
$Equity_{t-4}$	–0.005	(–0.114)				
$Liquidity_{t-4}$	–0.342	(–0.237)				
$\ln(Assets)_{t-4}$	0.288	(0.522)				
$NI\,M\arg in_{t-4}$	0.029	(0.923)				
NOA_{t-4}	–0.818	(–0.224)				
$OEOI_{t-4}$	–0.016	(–0.126)				
$ROAE_{t-4}$	0.003	(1.011)	0.004	(2.859)	**0.004**	**(2.849)**
$\Delta Liquidity_{t-2}$					**5.751**	**(4.537)**
Limit Points						
λ_1	–0.478	(–0.317)	–1.182	(–0.931)	**–1.217**	**(–0.952)**
λ_2	3.211	(2.113)	2.489	(1.917)	**2.436**	**(1.863)**
λ_3	5.738	(3.702)	4.986	(3.775)	**4.928**	**(3.702)**
λ_4	7.660	(4.836)	6.896	(5.094)	**6.840**	**(5.004)**
λ_5	9.954	(6.114)	9.169	(6.567)	**9.118**	**(6.480)**
λ_6	11.624	(7.063)	10.821	(7.664)	**10.772**	**(7.584)**
λ_7	14.161	(8.270)	13.312	(9.028)	**13.259**	**(8.928)**
Fit Measures						
Pseudo R^2	0.383		0.380		**0.380**	
SBC	3.001		2.702		**2.686**	
LR statistic	533.432	[0.000]	530.465	[0.000]	**530.320**	**[0.000]**
LR(general→*)	NA		5.805	[0.998]	**5.986**	**[0.999]**
Observations	359		360		**360**	

Table 1 notes. The dependent variable is a bank's rating which takes a *maximum* of nine categories that correspond to the integer values in the range of 1 to 9 and yields *up to* eight limit points, $\lambda_i = 1, 2, ..., 8$ (the intercept is not separately identified from the limit points). Z-statistics (in parentheses) are based upon Huber-White standard errors. Also reported are the Pseudo R^2, Schwartz's information criterion, SBC, and likelihood ratio tests for the model's explanatory power, LR Statistic, and the deletion of variables from the general model to obtain the parsimonious model, LR(general→*). Probability values are given in square parentheses. All regressions were estimated using E-Views 6.0 and STATA 10.

Table 2: Bank ratings ordered logit regressions (1 – 3 lags)

Variables	General	Parsimonious				General	Parsimonious	General	Parsimonious
$Country$	2.194 (13.70)	2.171 (14.544)	2.142 (14.725)	2.147 (14.582)	**2.117 (14.755)**	2.127 (15.706)	**2.140 (16.732)**	2.158 (17.210)	**2.124 (18.583)**
$time$	–0.166 (–1.72)	–0.179 (–2.188)	–0.178 (–2.175)	–0.175 (–2.147)	**–0.174 (–2.133)**	–0.135 (–2.201)	**–0.128 (–2.233)**	–0.119 (–2.789)	**–0.125 (–2.991)**
$Equity_{t-1}$	0.053 (1.35)					0.031 (1.091)	**0.048 (4.327)**	0.052 (5.682)	**0.054 (6.795)**
$Liquidity_{t-1}$	–0.043 (–0.04)					–0.934 (–0.909)		0.111 (0.253)	
$\ln(Assets)_{t-1}$	0.744 (2.64)	0.482 (7.242)	0.482 (7.239)	0.470 (7.002)	**0.470 (7.002)**	0.445 (1.848)	**0.450 (8.863)**	0.460 (9.613)	**0.450 (9.383)**
$NIMargin_{t-1}$	0.023 (0.23)					–0.067 (–0.853)		0.031 (1.051)	
NOA_{t-1}	–0.498 (–0.09)					3.928 (0.832)		0.403 (0.170)	
$OEOI_{t-1}$	–0.334 (–2.84)	–0.314 (–2.928)	–0.327 (–3.004)	–0.351 (–3.266)	**–0.364 (–3.322)**	–0.241 (–2.187)	**–0.237 (–2.596)**	–0.355 (–3.006)	**–0.364 (–3.212)**
$ROAE_{t-1}$	0.017 (1.89)	0.015 (1.996)	0.016 (2.122)	0.020 (2.881)	**0.021 (3.001)**	0.013 (1.379)	**0.013 (2.061)**	0.022 (2.778)	**0.025 (4.123)**
$Equity_{t-2}$	–0.028 (–0.69)					0.018 (0.666)			
$Liquidity_{t-2}$	4.650 (2.80)	4.557 (3.077)		4.513 (3.092)		0.870 (0.839)			
$\ln(Assets)_{t-2}$	–0.188 (–0.36)					0.005 (0.022)			
$NIMargin_{t-2}$	–0.002 (–0.02)					0.116 (1.974)	**0.063 (2.935)**		
NOA_{t-2}	–6.033 (–0.78)					–7.142 (–0.973)			
$OEOI_{t-2}$	–1.082 (–1.85)	–0.557 (–2.816)	–0.563 (–2.861)	–0.862 (–3.956)	**–0.869 (–3.966)**	–1.293 (–2.355)	**–0.960 (–4.328)**		
$ROAE_{t-2}$	0.009 (1.34)	0.011 (2.132)	0.011 (2.128)			0.003 (0.326)			
$Equity_{t-3}$	0.044 (1.68)	0.058 (4.708)	0.059 (4.833)	0.056 (4.443)	**0.057 (4.572)**				
$Liquidity_{t-3}$	–3.997 (–2.89)	–4.003 (–2.967)		–3.946 (–2.954)					
$\ln(Assets)_{t-3}$	–0.045 (–0.11)								
$NIMargin_{t-3}$	0.012 (0.25)								
NOA_{t-3}	–3.615 (–0.67)								
$OEOI_{t-3}$	–0.112 (–1.84)	–0.126 (–2.733)	–0.130 (–2.832)	–0.170 (–3.581)	**–0.174 (–3.783)**				
$ROAE_{t-3}$	0.007 (2.43)	0.005 (2.823)	0.005 (2.801)	0.003 (2.360)	**0.003 (2.300)**				
$\Delta Liquidity_{t-2}$			3.991 (2.986)		**3.938 (2.975)**				
Limit Points									
λ_1	–0.353	–0.579	–0.678	–1.103	**–1.207**	–1.197	**–0.823**	–0.104	**–0.193**
λ_2	3.422	3.100	2.966	2.560	**2.420**	2.311	**2.692**	3.610	**3.302**
λ_3	6.023	5.699	5.546	5.137	**4.977**	4.871	**5.244**	6.057	**5.747**
λ_4	7.858	7.537	7.385	6.975	**6.818**	6.652	**7.020**	7.810	**7.504**
λ_5	10.098	9.751	9.609	9.188	**9.040**	8.685	**9.042**	9.917	**9.613**
λ_6	11.865	11.477	11.339	10.904	**10.761**	10.402	**10.746**	11.731	**11.421**
λ_7	14.299	13.887	13.740	13.299	**13.145**	12.870	**13.203**	14.128	**13.809**
λ_8						15.615	**15.953**	16.484	**16.159**
Fit Measures									
Pseudo R^2	0.387	0.383	0.382	0.381	**0.381**	0.370	**0.369**	0.361	**0.361**
SBC	2.821	2.679	2.667	2.671	**2.659**	2.779	**2.691**	2.705	**2.676**
LR statistic	641.176 [0.000]	635.086 [0.000]	634.014 [0.000]	632.253 [0.000]	**631.129 [0.000]**	789.309 [0.000]	**786.214 [0.000]**	901.181 [0.000]	**900.094 [0.000]**
LR(general→*)	NA	6.090 [0.867]	7.162 [0.847]	8.923 [0.710]	**10.047 [0.690]**	NA	**3.095 [0.928]**	NA	**1.087 [0.780]**
Observations	425	425	425	425	**425**	538	**538**	629	**629**

Table 2 notes: see notes to Table 1.

Table 3: Bank ratings ordered probit regressions (4 lags)

Variables	General model		Parsimonious models			
Country	1.154	(12.65)	1.132	(13.37)	**1.125**	**(13.52)**
time	–0.182	(–2.50)	–0.156	(–2.43)	**–0.155**	**(–2.42)**
$Equity_{t-1}$	0.004	(0.17)				
$Liquidity_{t-1}$	0.328	(0.40)				
$\ln(Assets)_{t-1}$	0.499	(2.81)	0.292	(7.09)	**0.293**	**(7.11)**
$NI\,M\arg in_{t-1}$	–0.020	(–0.32)				
NOA_{t-1}	2.109	(0.41)				
$OEOI_{t-1}$	–0.288	(–1.93)	–0.296	(–3.69)	**–0.300**	**(–3.73)**
$ROAE_{t-1}$	0.015	(2.00)	0.018	(3.78)	**0.019**	**(3.81)**
$Equity_{t-2}$	0.013	(0.46)				
$Liquidity_{t-2}$	3.111	(2.90)	3.367	(4.18)		
$\ln(Assets)_{t-2}$	–0.133	(–0.34)				
$NI\,M\arg in_{t-2}$	0.061	(0.83)				
NOA_{t-2}	–15.979	(–1.61)	–6.253	(–2.20)	**–6.303**	**(–2.22)**
$OEOI_{t-2}$	–0.773	(–2.09)	–0.992	(–3.05)	**–1.007**	**(–3.17)**
$ROAE_{t-2}$	0.007	(1.25)				
$Equity_{t-3}$	0.049	(1.47)	0.050	(6.72)	**0.051**	**(6.84)**
$Liquidity_{t-3}$	–2.873	(–2.64)	–3.229	(–4.41)		
$\ln(Assets)_{t-3}$	–0.218	(–0.46)				
$NI\,M\arg in_{t-3}$	–0.041	(–0.97)				
NOA_{t-3}	3.486	(0.67)				
$OEOI_{t-3}$	–0.266	(–0.83)				
$ROAE_{t-3}$	–0.000	(–0.12)				
$Equity_{t-4}$	–0.007	(–0.33)				
$Liquidity_{t-4}$	–0.447	(–0.62)				
$\ln(Assets)_{t-4}$	0.169	(0.61)				
$NI\,M\arg in_{t-4}$	0.020	(1.09)				
NOA_{t-4}	–0.944	(–0.48)				
$OEOI_{t-4}$	–0.028	(–0.34)				
$ROAE_{t-4}$	0.002	(1.00)	0.002	(2.31)	**0.002**	**(2.27)**
$\Delta Liquidity_{t-2}$					**3.227**	**(4.41)**
Limit Points						
λ_1	–0.165	(–0.211)	–0.467	(–0.695)	**–0.497**	**(–0.734)**
λ_2	1.672	(2.107)	1.371	(2.032)	**1.333**	**(1.962)**
λ_3	3.043	(3.764)	2.727	(3.979)	**2.686**	**(3.889)**
λ_4	4.073	(4.937)	3.751	(5.373)	**3.710**	**(5.256)**
λ_5	5.341	(6.288)	5.005	(6.936)	**4.967**	**(6.814)**
λ_6	6.252	(7.249)	5.905	(8.045)	**5.869**	**(7.926)**
λ_7	7.637	(8.607)	7.263	(9.588)	**7.227**	**(9.452)**
Fit Measures						
Pseudo R^2	0.370		0.367		**0.367**	
SBC	2.935		2.637		**2.621**	
LR statistic	515.964	[0.000]	512.681	[0.000]	**512.525**	**[0.000]**
LR(general→*)	NA		6.053	[0.998]	**6.239**	**[0.999]**
Observations	359		360		**360**	

Table 3 notes: see notes to Table 1.

Table 4: Bank ratings ordered probit regressions (1 – 3 lags)

Variables	General	Parsimonious				General	Parsimonious	General	Parsimonious
Country	1.156 (12.958)	1.147 (12.325)	1.134 (12.617)	1.140 (12.472)	**1.124** **(12.786)**	1.122 (14.192)	**1.128** **(14.781)**	1.131 (15.355)	**1.115** **(16.169)**
time	–0.106 (–1.958)	–0.104 (–2.096)	–0.105 (–2.102)	–0.103 (–2.071)	**–0.103** **(–2.077)**	–0.083 (–2.400)	**–0.078** **(–2.315)**	–0.062 (–2.151)	**–0.064** **(–2.275)**
$Equity_{t-1}$	0.026 (1.194)					0.015 (1.043)	**0.027** **(4.463)**	0.030 (5.609)	**0.031** **(6.569)**
$Liquidity_{t-1}$	–0.206 (–0.269)					–0.600 (–0.955)		0.035 (0.136)	
$\ln(Assets)_{t-1}$	0.487 (2.955)	0.269 (7.475)	0.268 (7.436)	0.262 (7.283)	**0.261** **(7.232)**	0.249 (1.742)	**0.246** **(8.834)**	0.242 (8.744)	**0.234** **(8.420)**
$NIMargin_{t-1}$	–0.006 (–0.120)					–0.040 (–1.051)		0.018 (1.007)	
NOA_{t-1}	–0.104 (–0.322)					1.345 (0.530)		0.318 (0.211)	
$OEOI_{t-1}$	–0.205 (–2.925)	–0.200 (–3.064)	–0.208 (–3.135)	–0.214 (–3.206)	**–0.222** **(–3.268)**	–0.138 (–2.106)	**–0.137** **(–2.342)**	–0.217 (–3.104)	**–0.219** **(–3.284)**
$ROAE_{t-1}$	0.012 (2.388)	0.010 (2.480)	0.011 (2.637)	0.013 (3.244)	**0.013** **(3.417)**	0.008 (1.561)	**0.008** **(2.090)**	0.012 (2.802)	**0.014** **(4.232)**
$Equity_{t-2}$	–0.012 (–0.525)					0.014 (0.989)			
$Liquidity_{t-2}$	2.674 (2.966)	2.441 (3.093)		2.444 (3.109)		0.565 (0.938)			
$\ln(Assets)_{t-2}$	–0.251 (–0.826)					–0.002 (–0.018)			
$NIMargin_{t-2}$	0.010 (0.190)					0.072 (2.388)	**0.042** **(3.181)**		
NOA_{t-2}	–3.484 (–0.788)					–2.490 (–0.613)			
$OEOI_{t-2}$	–0.645 (–1.936)	–0.309 (–2.917)	–0.308 (–2.881)	–0.472 (–3.885)	**–0.474** **(–3.821)**	–0.620 (–2.056)	**–0.517** **(–4.384)**		
$ROAE_{t-2}$	0.004 (0.966)	0.005 (1.860)	0.005 (1.878)			0.001 (0.277)			
$Equity_{t-3}$	0.028 (1.989)	0.034 (5.147)	0.035 (5.247)	0.033 (4.875)	**0.034** **(4.970)**				
$Liquidity_{t-3}$	–2.208 (–2.992)	–2.186 (–3.058)		–2.175 (–3.052)					
$\ln(Assets)_{t-3}$	0.051 (0.211)								
$NIMargin_{t-3}$	0.011 (0.416)								
NOA_{t-3}	–1.266 (–0.428)								
$OEOI_{t-3}$	–0.054 (–1.647)	–0.065 (–2.632)	–0.066 (–2.678)	–0.083 (–3.006)	**–0.085** **(–3.097)**				
$ROAE_{t-3}$	0.004 (2.293)	0.003 (2.709)	0.003 (2.680)	0.002 (2.179)	**0.002** **(2.113)**				
$\Delta Liquidity_{t-2}$			2.199 (3.088)		**2.188** **(3.084)**				
Limit Points									
λ_1	0.064	0.002	–0.053	–0.279	**–0.343**	–0.220	**–0.082**	0.356	**0.174**
λ_2	1.956	1.858	1.787	1.566	**1.486**	1.457	**1.609**	1.971	**1.782**
λ_3	3.322	3.217	3.140	2.921	**2.834**	2.788	**2.932**	3.223	**3.035**
λ_4	4.288	4.185	4.108	3.889	**3.802**	3.726	**3.864**	4.127	**3.942**
λ_5	5.500	5.386	5.314	5.088	**5.007**	4.810	**4.944**	5.246	**5.061**
λ_6	6.438	6.307	6.239	6.007	**5.929**	5.715	**5.843**	6.214	**6.027**
λ_7	7.771	7.629	7.558	7.322	**7.241**	7.090	**7.211**	7.541	**7.349**
λ_8						8.493	**8.612**	8.728	**8.530**
Fit Measures									
Pseudo R^2	0.368	0.364	0.364	0.363	**0.363**	0.349	**0.347**	0.338	**0.337**
SBC	2.893	2.751	2.738	2.741	**2.729**	2.861	**2.775**	2.800	**2.771**
LR statistic	610.337 [0.000]	604.469 [0.000]	603.806 [0.000]	602.360 [0.000]	**601.618** **[0.000]**	744.871 [0.000]	**741.219** **[0.000]**	841.519 [0.000]	**840.352** **[0.000]**
LR(general$\rightarrow$*)	NA	5.868 [0.882]	6.531 [0.887]	7.977 [0.787]	**8.719** **[0.794]**	NA	**3.652** **[0.887]**	NA	**1.167** **[0.761]**
Observations	425	425	425	425	**425**	538	**538**	629	**629**

Table 4 notes: see notes to Table 1.

Table 5: Percentage of correct predictions of favoured logit and probit models

	Percentage correct predictions							
	Favoured Logit				**Favoured Probit**			
Rating	**4 lags**	**3 lags**	**2 lags**	**1 lag**	**4 lags**	**3 lags**	**2 lags**	**1 lag**
E	33.33	27.27	25.00	23.08	44.44	27.27	25.00	38.46
D/E	60.00	57.14	57.14	56.52	60.00	60.71	60.32	55.07
D	60.87	64.29	69.70	61.91	60.87	61.91	65.66	62.86
C/D	36.07	31.34	36.25	30.68	34.43	26.87	23.75	22.73
C	68.92	74.39	67.37	71.43	74.32	78.05	73.68	77.31
B/C	28.89	33.33	33.78	41.00	17.78	25.93	24.32	40.00
B	46.34	47.06	71.43	67.68	48.78	54.90	79.76	72.73
A/B	31.25	25.00	25.00	19.36	37.50	25.00	7.14	9.68
A	NA	NA	0.00	0.00	NA	NA	0.00	0.00
Total	***50.56***	***51.29***	***54.46***	***52.94***	***50.83***	***51.29***	***52.42***	***53.42***
	Logit excluding country 1				**Probit excluding country 1**			
Rating	**4 lags**	**3 lags**	**2 lags**	**1 lag**	**4 lags**	**3 lags**	**2 lags**	**1 lag**
E	11.11	9.09	8.33	7.69	11.11	9.09	8.33	7.69
D/E	35.56	39.29	38.10	30.44	35.56	37.50	30.16	28.99
D	44.93	52.38	58.59	51.43	47.83	54.76	59.60	51.43
C/D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C	72.97	65.85	44.21	54.62	74.32	65.85	35.79	52.94
B/C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B	36.59	35.29	39.29	37.37	19.51	35.29	39.29	38.38
A/B	6.25	5.00	7.14	3.23	25.00	10.00	7.14	3.23
A	NA	NA	0.00	0.00	NA	NA	0.00	0.00
Total	***32.78***	***32.94***	***29.74***	***28.46***	***32.50***	***33.41***	***27.51***	***28.14***
	Logit excluding country 2				**Probit excluding country 2**			
Rating	**4 lags**	**3 lags**	**2 lags**	**1 lag**	**4 lags**	**3 lags**	**2 lags**	**1 lag**
E	11.11	9.09	8.33	7.69	11.11	9.09	8.33	7.69
D/E	22.22	35.09	30.16	27.54	24.44	33.33	30.16	23.19
D	52.17	53.57	55.56	49.52	53.62	52.38	54.55	47.62
C/D	20.97	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C	70.27	70.73	57.90	58.82	75.68	71.95	54.74	60.50
B/C	0.00	0.00	0.00	6.00	0.00	0.00	0.00	0.00
B	41.46	37.26	53.57	45.46	36.59	31.37	55.95	45.46
A/B	18.75	5.00	3.57	3.23	18.75	15.00	3.57	3.23
A	NA	NA	0.00	0.00	NA	NA	0.00	0.00
Total	**36.57**	**33.80**	**32.71**	**30.84**	**34.07**	**33.33**	**32.34**	**29.41**

The favoured logit (probit) models are those reported in Tables 1 and 2 (Tables 3 and 4) whereas these models with the country variable removed (called logit/probit excluding country 1) are reported in Table 6. Models developed using the general-to-specific method where the country variable is excluded from the general model (called logit/probit excluding country 2) are given in Table 7 The percentage of correct predictions are the percentage of times that a particular observed rating (say A) is correctly predicted by the model.

Table 6: Bank ratings favoured models with country effects excluded

	Logit models				Probit models			
Variables	**4 lags**	**3 lags**	**2 lags**	**1 lag**	**4 lags**	**3 lags**	**2 lags**	**1 lag**
Country								
time	–0.253 (–2.484)	–0.325 (–4.162)	–0.347 (–5.845)	–0.266 (–6.285)	–0.148 (–2.493)	–0.179 (–4.033)	–0.198 (–6.208)	–0.152 (–5.962)
$Equity_{t-1}$			0.073 (4.743)	0.060 (3.210)			0.038 (5.039)	0.032 (4.531)
$Liquidity_{t-1}$								
$\ln(Assets)_{t-1}$	0.636 (8.167)	0.613 (9.129)	0.487 (8.004)	0.521 (9.372)	0.318 (7.479)	0.311 (8.302)	0.250 (8.074)	0.264 (9.387)
$NI\,M\arg in_{t-1}$								
NOA_{t-1}								
$OEOI_{t-1}$	–0.778 (–2.578)	–0.708 (–2.029)	–0.637 (–2.409)	–0.828 (–1.115)	–0.436 (–3.241)	–0.373 (–3.180)	–0.321 (–2.755)	–0.354 (–2.780)
$ROAE_{t-1}$	0.025 (2.901)	0.016 (1.982)	0.017 (1.972)	0.009 (0.657)	0.015 (3.275)	0.010 (2.327)	0.010 (2.191)	0.008 (2.265)
$Equity_{t-2}$								
$Liquidity_{t-2}$								
$\ln(Assets)_{t-2}$								
$NI\,M\arg in_{t-2}$			–0.101 (–3.014)				–0.054 (–3.374)	
NOA_{t-2}	–25.071 (–2.962)				–12.910 (–3.422)			
$OEOI_{t-2}$	–2.454 (–3.665)	–0.823 (–2.739)	–0.866 (–1.887)		–1.275 (–3.829)	–0.482 (–3.222)	–0.523 (–2.602)	
$ROAE_{t-2}$								
$Equity_{t-3}$	0.102 (4.767)	0.076 (4.194)			0.054 (6.160)	0.039 (4.812)		
$Liquidity_{t-3}$								
$\ln(Assets)_{t-3}$								
$NI\,M\arg in_{t-3}$								
NOA_{t-3}								
$OEOI_{t-3}$		–0.214 (–4.309)				–0.121 (–4.102)		
$ROAE_{t-3}$		–0.001 (–0.648)				–0.0002 (–0.239)		
$ROAE_{t-4}$	0.003 (2.005)				0.002 (2.163)			
$\Delta Liquidity_{t-2}$	4.710 (4.250)	4.170 (3.445)			2.832 (4.343)	2.339 (3.115)		
Fit Measures								
Pseudo R^2	0.115	0.107	0.097	0.073	0.103	0.096	0.089	0.066
SBC	3.696	3.711	3.757	3.809	3.742	3.755	3.787	3.835
LR statistic	160.747 [0.000]	178.233 [0.000]	206.611 [0.000]	181.157 [0.000]	144.224 [0.000]	159.302 [0.000]	190.033 [0.000]	164.703 [0.000]
Observations	360	425	538	629	360	425	538	629

Table 6 notes: see notes to Table 1. These are the favoured (highlighted in bold) parsimonious regressions reported in Tables 1 – 4 with the Country variable excluded.

Table 7: Bank ratings best fitting models with country effects excluded

	Logit models				Probit models			
Variables	**4 lags**	**3 lags**	**2 lags**	**1 lag**	**4 lags**	**3 lags**	**2 lags**	**1 lag**
Country								
time		–0.282 (–3.558)	–0.334 (–5.955)	–0.288 (–6.871)		–0.149 (–3.235)	–0.191 (–6.235)	–0.160 (–6.145)
$Equity_{t-1}$	0.131 (8.274)	0.060 (2.390)		0.083 (6.794)	0.067 (6.227)	0.032 (2.499)		0.044 (7.177)
$Liquidity_{t-1}$			–3.922 (–7.556)	–3.672 (–7.497)			–2.067 (–6.962)	–1.860 (–6.429)
$\ln(Assets)_{t-1}$	0.592 (7.070)	0.562 (7.190)	0.476 (7.808)	0.444 (7.750)	0.286 (6.241)	0.278 (6.701)	0.244 (7.369)	0.223 (7.480)
$NIMargin_{t-1}$		–0.122 (–3.837)	–0.132 (–4.243)	–0.178 (–6.763)		–0.076 (–4.598)	–0.075 (–4.598)	–0.103 (–7.423)
NOA_{t-1}		12.652 (1.938)	20.285 (3.153)			6.967 (2.396)	10.677 (3.847)	
$OEOI_{t-1}$	–0.824 (–5.069)	–0.775 (–2.676)	–0.635 (–2.310)	–0.892 (–4.657)	–0.444 (–4.725)	–0.429 (–3.519)	–0.338 (–2.907)	–0.452 (–4.392)
$ROAE_{t-1}$	0.025 (2.612)	0.033 (3.146)	0.025 (2.494)	0.032 (4.740)	0.014 (2.885)	0.019 (3.692)	0.014 (2.830)	0.017 (4.608)
$Equity_{t-2}$			0.070 (4.752)				0.039 (5.581)	
$Liquidity_{t-2}$								
$\ln(Assets)_{t-2}$								
$NIMargin_{t-2}$								
NOA_{t-2}		–25.577 (–2.634)	–30.415 (–2.965)			–14.101 (–3.157)	–16.097 (–3.475)	
$OEOI_{t-2}$	–1.471 (–4.094)	–2.232 (–3.187)	–2.476 (–3.498)		–0.805 (–3.869)	–1.229 (–3.914)	–1.351 (–4.288)	
$ROAE_{t-2}$								
$Equity_{t-3}$		0.045 (1.836)				0.024 (2.120)		
$Liquidity_{t-3}$	–3.619 (–6.256)	–2.990 (–5.990)			–1.920 (–6.019)	–1.671 (–5.967)		
$\ln(Assets)_{t-3}$								
$NIMargin_{t-3}$	–0.140 (–5.394)				–0.083 (–6.125)			
NOA_{t-3}								
$OEOI_{t-3}$	–1.463 (–5.885)	–0.176 (–3.178)			–0.779 (–5.434)	–0.099 (–3.131)		
$ROAE_{t-3}$	–0.006 (–4.188)				–0.003 (–3.616)			
NOA_{t-4}	6.590 (2.103)				3.684 (2.082)			
$ROAE_{t-4}$								
Fit Measures								
Pseudo R^2	0.156	0.151	0.141	0.121	0.140	0.137	0.129	0.109
SBC	3.553	3.585	3.617	3.634	3.613	3.637	3.665	3.685
LR statistic	218.064 [0.000]	250.440 [0.000]	300.759 [0.000]	303.978 [0.000]	196.581 [0.000]	228.325 [0.000]	274.866 [0.000]	272.179 [0.000]
Observations	361	426	538	629	361	426	538	629

Table 7 notes: see notes to Table 1. These models were developed without the country variable included in the general model, following the general-to-specific method, so as to best fit the data.

Figure 1: Percentage of ratings through time