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Guglielmo Maria Caporale • Roman Matousek •
Chris Stewart

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DIW Berlin
German Institute for Economic Research
Mohrenstr. 58
10117 Berlin
Tel. +49 (30) 897 89-0
Fax +49 (30) 897 89-200
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Rating Assignments: Lessons from International Banks

Guglielmo Maria Caporale[1]
Roman Matousek[2]
Chris Stewart[3]

March 2009

Abstract

This paper estimates ordered logit and probit regression models for bank ratings which also include a country index to capture country-specific variation. The empirical findings provide support to the hypothesis that the individual international bank ratings assigned by Fitch Ratings are underpinned by fundamental quantitative financial analyses. Also, there is strong evidence of a country effect. Our model is shown to provide accurate predictions of bank ratings for the period prior to the 2007 – 2008 banking crisis based upon publicly available information. However, our results also suggest that quantitative models are not likely to be able to predict ratings with complete accuracy. Furthermore, we find that both quantitative models and rating agencies are likely to produce highly inaccurate predictions of ratings during periods of financial instability.

Keywords: International banks, ratings, ordered choice models, country index,

JEL Classification: C25, C51, C52, G21.

[1] Research professor at DIW Macroanalysis and Forecasting Department. Centre for Empirical Finance, Brunel University, West London, UB8 3PH, UK. Email: Guglielmo-Maria.Caporale@brunel.ac.uk

[2] Centre for International Capital Markets, London Metropolitan Business School, London Metropolitan University, 84 Moorgate, London, EC2M 6SQ. Tel: 020-7320-1569. E-mail: r.matousek@londonmet.ac.uk.

[3] London Metropolitan Business School, London Metropolitan University, 84 Moorgate, London, EC2M 6SQ. Tel: 020-7320-1651. E-mail: c.stewart@londonmet.ac.uk.

1. Introduction

The current global financial crisis has severely damaged the reputation of ratings agencies (RAs) that mispriced credit risk through their ratings assignments. A number of banks, which were relatively financially sound according to ratings assignments, were forced to close or had to be bailed out by governments. This raises the question whether RAs systematically inflate ratings and misprice credit risk.

Ratings of banks and companies assigned by RAs provide investors with information about the financial position of the institution in question and on credit risk. Pinto (2006) argues that therefore they facilitate capital allocation. Indeed, the importance which is attached to them can be justified on the grounds that they reduce asymmetric information between investors and companies.

However, the ability of RAs to assign ratings correctly has extensively been questioned (Altman and Saunders, 1998, Levich *et al*., 2002, Altman and Rijken, 2004, Amato and Furfine, 2004, Portes, 2008). One of the most frequent criticisms of the prediction abilities of RAs is that they could provide misleading information since the analysis is backward- rather than forward-looking. Their low transparency raises further concerns about their accuracy. Further, RAs cannot have superior information compared with market participants about uncertainty and the degree of insolvency (illiquidity) of companies.

In this paper, we model the bank ratings assigned by Fitch Ratings (FR) with the aim of shedding light upon their determinants. Firstly, we consider whether (and which of) the key financial variables of banks affect individual ratings. Secondly, we examine whether bank ratings are systematically determined by the timing of the rating. Thirdly, we incorporate a country index to establish whether country-specific factors affect bank ratings. This methodological innovation, within the context of modelling bank ratings, is an additional contribution of our study – we demonstrate that it substantially enhances the predictive accuracy of our models. Fourthly, we assess our models and the ratings assigned by FR with specific reference to three of the first commercial banks (Glitnir, Kaupthing and Northern Rock) affected by the 2007–2008 crisis.

Predictions on the financial soundness of banks, corporations and sovereign countries are of central importance for analysts, regulators and policy makers. In particular, research focusing on the prediction of bank failures by applying Early Warning Systems (EWS) has been extensive – see, for example, Mayer and Pifer (1970), Altman and Saunders (1998), Kolari *et al.* (1996) and Kolari *et al.* (2002). Another strand of empirical research focuses on ratings prediction models. There are numerous studies that predict bond ratings, such as Kamstra *et al.* (2001) who estimate ordered-logit regressions. Other recent studies (Kim, 2005, Huang *et al.*, 2004 and Lee, 2007) show that artificial intelligence methods do not provide superior predictions of bond ratings relative to standard ordered choice methods. Hence, using ordered logit/probit regressions is a valid way of addressing the main challenge in modelling ratings, which is to increase the probability of correct classifications. However, we are not aware of any previous studies that seek to model and predict individual *bank* ratings, which is the aim of this paper.

The organisation of the paper is as follows. Section 2 describes the data and the methods applied, while Section 3 discusses the main empirical findings. Section 4 considers our models' predicted ratings for the Glinir, Kaupthing and Northern Rock banks, and Section 5 offers some concluding remarks.

2. Data and Methodology

FR, as one of the largest rating companies for the banking industry in the world, releases four types of ratings: legal ratings, long- and short-term (security) ratings and individual ratings. As stated by FR, the rating is closely linked with financial performance (financial variables). FR divides banks into five categories according to their performance.[4] This study focuses on individual ratings, as our objective is to analyse their determinants. Within this context, financial variables of commercial banks have been utilised in several ways, for instance as an instrument for cross-section and trend analyses of banks. However, the question remains whether or not financial variables might be used as indicators of banks' future financial position and, therefore, their individual ratings.

We use data on 681 international banks' ratings , denoted Y_i ,[5] between 2000 and 2007 to estimate models of their determinants. This variable is ordinal and has up to nine 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),

[4] The standard classification of the individual rating is A, B, C, D and E. A further ranking among these five ratings is used, that is, A/B, B/C, C/D and D/E. 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 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.

[5] The BankScope database has been used to obtain a large sample of commercial banks rated by FR.

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 over time – we assess this possibility in our modelling.[6]

We apply ordered choice estimation techniques to model 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):[7]

$$Y_{it}^{*} = \sum_{k=1}^{K} \beta_{k1} X_{k,it-1} + \sum_{k=1}^{K} \beta_{k2} X_{k,it-2} + \sum_{k=1}^{K} \beta_{k3} X_{k,it-3} + \sum_{k=1}^{K} \beta_{k4} X_{k,it-4} + u_{it} \qquad \textbf{(1)}$$

where $X_{k,it-l}$, $l = 1, 2, 3, 4$ is the lth lag on the kth explanatory variables for the ith bank in period t, u_{it} is a stochastic error term, and Y_{it}^{*} is the unobserved dependent variable that is related to the observed dependent variable, Y_{it}, (assuming nine categories) as follows:

[6] 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 impression of a general decline in ratings. This would suggest that a time trend could enter the logit/probit ratings regressions with a negative coefficient.

[7] The model has both cross-sectional and time-series elements; however, the latter refers to the year a rating was made rather than the calendar year. Further, there is only one time-series observation for each bank's dependent variable, although lags are available on the explanatory factors. Therefore, the model is not a pooled data specification. Rather, it is a cross-sectional model with time-series dynamics in the explanatory variables.

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

where λ_1, $\lambda_2,\ldots,$ λ_8 are unknown parameters (limit points) to be estimated with the coefficients (the β_{kl} s). We are primarily interested in the general direction of correlation between the dependent and independent variables. Therefore, we use the sign of β_{kl} to provide guidance on whether the estimated signs of the coefficients are consistent 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) in response to a change in $X_{k,it-l}$. 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 [$time_{it}$].[8] We do not include lagged values of $time_{it}$; 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 $Equity_{it}$], the ratio of liquid assets to total assets [$Liquidity_{it}$] the natural logarithm of total assets [$\ln(Assets)_{it}$] and the net interest margin [*NI_Margin*], $NOA_{it} = OIA_{it} - OEA_{it}$ (where

[8] We do not add dummy variables for the month in which a rating was made to see whether this significantly affects the predictive accuracy of the model due to constraints on degrees of freedom. However, this would be desirable to consider in future work using a larger sample than considered here.

OIA_{it} is the ratio of operating income to total assets and OEA_{it} is the ratio of operating expenses to assets), the ratio of operating expenses to total operating income [$OEOI_{it}$] and the return on equity [$ROAE_{it}$].[9]

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 always endeavour to incorporate the most recent information into their ratings, they may also form their views on the basis of the history of a bank's performance. This justifies considering 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 the lags that are found to be significant.

Finally, we incorporate a country index to capture country-specific variations in ratings. Because there are 90 countries an ordered choice model

[9] 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. Specifically, the simple correlation coefficients for the each pairing (calculated using a common sample) are the following: 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 well below 0.5 (most are substantially lower than this), which helps to ensure that the reported regressions do not suffer from severe multicollinearity.

incorporating 89 country dummy variables would need to be estimated; however, such a model could not be estimated. Therefore, we proceeded to construct a single country index reflecting cross-country differences, which is a cross-sectional variant of the method discussed in Hendry (2001). This index 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.[10] Since individual country dummy variables have clusters of zeros that can distort test statistics the combination of these dummies into a single country index should minimise these effects.[11] Including an index should also improve efficiency of estimation relative to using a number of dummy variables. Indeed, in the current application it was not possible to estimate a model with even half of the ninety countries' individual dummy variables and, therefore, constructing an index makes capturing all individual country effects possible. The introduction of this country index within the context of modelling bank ratings is a novel feature of this paper.

The country index was constructed as follows.[12]

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

[11] Hendry and Santos (2005) discuss the effects of using sets of impulse dummy variables within the context of a static OLS regression and find the following. The coefficients of the individual dummies can be consistently estimated; however, the t-ratio of such a dummy is inconsistent. When many impulse dummies are included this does not cause bias in the coefficients of the non-dummy variables in the model or adversely affect their significance. Hence, the use of many dummies in a general-to-specific framework is appropriate as the presence of impulse dummies need not affect model selection. However, tests of the normality of an OLS regression's residuals will have low power when the model incorporates many impulse dummies. Further, impulse dummies can cause substantial size distortion in White's test for heteroscedasticity in the residuals of an OLS regression because of many residuals being set equal to zero. Using an index of indicators is shown to make these problems less severe.

[12] There may be alternative methods for constructing this country index. For example using cluster analysis or factor analysis to group the countries or simply using the average bank rating for each country as a weight on a country dummy to form the index. Considering such alternatives may be worthwhile in future research. We consider just one method, based on the previous literature (if in a different context), to provide insight into the importance of accounting for such otherwise unmodelled country effects.

(1) Five regressions, each including 18 of the 90 country dummy variables, were used to initially determine the coefficient of each individual country's dummy variable and its significance.

(2) Country dummies with very similar coefficients (which we defined as the difference in the coefficients being less than half of the standard error of the dummy with the smallest 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 being entered as combined dummies.

(3) Using these combined dummies we were able to represent all of the countries in two separate regressions – countries that did not feature in any combined variable were entered as individual country dummies. Note that each country featured in only one of the two regressions. We then proceeded to further combine dummies (and composite dummies) whose coefficients differed by no more than one standard error and used LR tests to validate, or otherwise, such restrictions.

(4) Eventually, the process of combining the countries into groups of composite dummy variables reduced the number of these dummies sufficiently so that all countries could be represented in a single regression. From this regression a single index of country dummy variables was constructed using the coefficients on the composite dummy variables as weights on those dummy variables – once again any countries that could not be entered in a composite variable were entered separately. For example, assume that the following ordered choice model, $Y_{it}^{*} = \hat{\delta}_1 D_{1it} + \hat{\delta}_2 D_{2it} + \hat{\delta}_3 D_{3it} + \hat{\delta}_4 D_{4it} + v_{it}$, is fitted to four composite dummy variables, D_{1it}, D_{2it}, D_{3it} and D_{4it}, where $\hat{\delta}_1$, $\hat{\delta}_2$, $\hat{\delta}_3$ and $\hat{\delta}_4$ are the respective

estimated coefficients on these dummies and v_{it} is a stochastic error term. The index is therefore constructed as: $I_{it} = \hat{\delta}_1 D_{1it} + \hat{\delta}_2 D_{2it} + \hat{\delta}_3 D_{3it} + \hat{\delta}_4 D_{4it}$.

(5) This index was checked for appropriateness by running a single regression that included the country index plus each individual country's dummy at a time. If the latter was significant the value of this dummy's coefficient was incorporated into the country index. This was repeated for all ninety countries, that is, ninety distinct regressions that contained only two variables (the country index and a particular country's dummy) were estimated. After all the coefficients of the individual country dummies that were significant in these ninety regressions had been incorporated into the index this step was repeated until no individual country dummies were significant at the 5% level (when included in a regression with the country index). The resulting country index (denoted $Country_{it}$) is specified by equation (3).[13]

Models were then constructed using this country index and the other explanatory factors (financial variables and time term). A cross-sectional variant of the general-to-specific method was employed to produce an initial favoured model.[14] 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 was considered for inclusion: it was included if the new model

[13] This country index does not include all countries' dummies because insignificant terms were excluded. 78 countries are represented in the country index 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.

[14] 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 delete all variables with z-statistics below 1.5 and then all explanatory factors with z-statistics below 1.96 (applying all 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.

exhibited a lower SBC. This should ensure that the specification of the model is relatively robust to the model selection procedure.

Four sets of models were 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 financial 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 between accuracy of estimation and the generality of lags considered in the model. This makes it difficult to determine which lag lenghtprovides superior inference. We therefore seek results that are consistent across lag specifications to draw inferences.

(3)

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

3. Empirical Results

The ordered logit and probit regression results for the determinants of bank ratings with four lags of the explanatory variables are presented in Table 1. The logit (probit) results for the three-lag, two-lag and one-lag specifications are all reported in Table 2 (Table 3).[15] For all four-lag specifications we report a general model (including all lags of the variables) and one parsimonious specification obtained using the general-to-specific methodology (followed by omitted variables testing). When more than one model could be chosen the favoured parsimonious model was selected as that which minimises Schwartz's Information Criterion (SIC).

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. 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 $Liquidity_{it-2}$ and $Liquidity_{it-3}$ into the difference variable, $\Delta Liquidity_{it-2} = Liquidity_{it-2} - Liquidity_{it-3}$, given that they have approximately equal and opposite signs in the specifications with three and four lags. Upon this basis the model favoured in the three- and four- lag specifications include $\Delta Liquidity_{it-2}$ for both probit and logit forms.[16] The favoured parsimonious models will yield more

[15] 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.

[16] Unreported potential alternative parsimonious models results are available from the authors upon request.

efficient inference relative to the general model and are, therefore, used for inference. The same models are favoured in the probit and logit forms for each lag specification.

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, the lower the rating, *ceteris paribus*; *Equity* (capital adequacy) has a positive effect on a bank's rating: a more capitalised bank has a higher rating.[17]; the natural log of assets also has a positive effect on bank ratings: banks with a larger size of assets have a higher rating;[18] *OEOI* has a negative correlation with a bank's rating;[19] the return on assets has a significant and positive impact upon ratings.[20] All of these effects are unambiguous and consistent with prior beliefs.

Country has a positive coefficient indicating that country-specific effects affect bank ratings: 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 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, and that there are country-specific effects that are not explained by the financial variables (rather like fixed-effects in a panel data model). Interestingly, Ireland (Andorra) is ranked in a relatively low (high) position in the country index.

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[17] 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.

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

[19] 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.

[20] The first lag of *ROAE* is significant regardless of the lag specification. 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.

Liquidity is only significant in models that allow at least three lags. Notably, both the second and third lag of this variable are significant and their coefficients are of 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 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 of ratings 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 in 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 most 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 4.[21] A prediction is correct when a particular observed rating is correctly assigned by the model.[22] From Table 4 (top section) we can 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.[23] The percentage of correct predictions for two versions of these models excluding the country variable are also reported in Table 4 for comparison purposes. The first version includes exactly the same variables as the favoured parsimonious models (reported in Tables 1 – 4) except the *Country* variable, which is removed (to save space we do not report these estimates; however, these results are available from the authors on request). The percentage of correct predictions for these models are given in the middle section of Table 4: they are in the range 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* which is included in the general model (again these results are available on request). The percentage of correct predictions associated with these regressions are reported in the bottom section of Table 4: these are between 30.84% and 36.57% for

[21] This prediction is calculated using the same sample employed to estimate the data. It is a fit measure rather than providing an assessment of out-of-sample performance. We did not drop any observations for the purpose of out-of-sample evaluation in order to maximise the period that could be used for estimation and, therefore, maximise its efficiency.

[22] The rating predicted for any particular bank from the ordered probit model can be determined either by comparing the estimated index, Y_{it}^{*}, with the estimated limit points, λ_j, and identifying the category according to equation **(2)** or by calculating the probability that any particular bank will have a particular rating and assigning the category with the highest probability. EViews automatically provides statistics on predictive accuracy using the latter method and these are what we report in the tables.

[23] 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.

the logit form and 29.41% and 34.07% for the probit specification. They are substantially greater (by approximately 20 percentage points) for the models that incorporate the *Country* variable compared with those that do not. The regressions including this country index also have much larger pseudo R^2 s and the country index is highly significant in all parsimonious models. This further demonstrates the importance of modelling country effects for predicting international bank ratings. It also indicates that ordered choice models of international bank ratings that exclude such effects will omit important information for predicting ratings.

From Table 4 we also note that our models have difficulty in correctly predicting the extreme A and E ratings. We believe that this is likely to be due to the relatively small numbers of banks that appear in these categories.

4. Predicted ratings for Glitnir, Kaupthing and Northern Rock

In this section we use our estimated models of international bank ratings to provide predictions for three high profile bank casualties of the international banking crisis of 2007–2008: Glitnir (Iceland), Kaupthing (Iceland) and Northern Rock (UK). We also consider some implications of the predicted ratings for these three banks.

Northern Rock and its rating

Given the difficulty that Northern Rock faced in autumn of 2007 we compare our favoured models' predictions of Northern Rock's rating with that made by FR.[24] Predictions for Northern Rock's rating are only available from the

[24] Llewellyn (2008) provides a detailed analysis of what went wrong with Northern Rock.

specifications with up to one and two lags because of data constraints. Our favoured model for the one (two) lag specification predicts a rating of B/C (B) which compares with FR's actual rating for Northern Rock of C/D. This was made on 17 September 2007 and represents a downgrading from the previous FR rating of A/B. Thus, whilst Northern Rock's financial variables (via our models) suggested a downgrading from A/B to either B or B/C in this period, it is clear that FR utilised information extraneous to our model (and beyond what financial variables would suggest) to downgrade the rating even further (to C/D). This may imply that FR did, to some extent, recognise the change in risk of Northern Rock and that it used information that is not fully captured by ordered choice models. Alternatively, FR may have overreacted when exposed to enormous pressure. The country index that we used shows that the UK's banking system was ranked 14th out of the 90 countries under consideration.[25] This reinforces the view that a UK bank, such as Northern Rock, would not have been expected to be most at risk or the first casualty of the international banking crisis. It also helps explain why our model predicts a higher rating than that given by FR since a country's standing in the index constructed above has not been altered (to reflect the impact of the crisis) in making the prediction.

Glitnir and Kaupthing and their ratings

Because of a substantial deterioration in the bank's funding position the Icelandic government was forced to buy a 75% stake in the country's third largest bank, Glitnir, on 29 September 2008. This was followed on October 9 by the nationalisation of Iceland's largest bank, Kaupthing. FR downgraded both banks ratings from B/C

[25] The country index of indicators has been constructed to provide a broad measure of the general ranking of a country's overall banking system.

(made in 2005) to E (Glitnir) and C (Kaupthing) on 30 September 2008. Our models' in-sample predicted ratings for both of these banks (based only on the specification with one lag owing to data constraints) are identical to their pre-crisis rating of B/C. This suggests that FR did not employ any information extraneous to our model (and beyond what financial variables would suggest) in making the rating prior to the emergence of the crisis. The country index that we used in our models shows that the Icelandic banking system was ranked 10th out of the 90 countries that we consider. Hence, prior to the emergence of the crisis Icelandic banks were not considered to be particularly at risk, although Iceland's country rating was downgraded after the banking crisis emerged (at a similar time to the downgrading of its bank rating).

As for Northern Rock, FR *responded* to the problems with Glitnir bank by downgrading the Icelandic banks ratings: they did not *predict* the decline of the bank. Indeed, the liquidity position of these banks and their general performance had been regarded as good prior to the crisis.

5. Conclusions

Using data on 681 banks from around the world we examine whether international bank ratings are determined by financial variables, the timing of when the rating was conducted by Fitch Ratings and a bank's country of origin. We reach 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 a bank's ratio of operating expenses to total operating income ($OEOI$), the lower 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, overall ratings appear to reflect a bank's financial position (as measured by various financial variables).

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

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 predict accurately international bank ratings relative to models that exclude country effects. This suggests that international studies attempting to predict ratings, and not just identifying determinants, have to include country effects in their models. The inclusion of country-specific effects in our analysis represents a major contribution to the current research on predicting international ratings in general.

Since the predictions of UK and Icelandic bank ratings assigned by FR and our model are consistent, we conclude that our model made reasonable predictions of bank ratings for the pre-crisis period based upon publicly available information. However, our case studies of these banks raise doubts about the ability of both our model and RAs to predict ratings as the international banking crisis emerged.

The estimated results unambiguously support the hypothesis that individual ratings assigned by FR are underpinned by fundamental quantitative financial analyses. Of course, we recognise that the views of experts, and a certain degree of qualitative information, seem to be an integral part of the process followed to determine ratings. However, because this information is not publically available it cannot be formally included in our models. Hence, such models are not likely to be able to predict ratings with 100% accuracy and are likely to be highly inaccurate during periods of financial instability. Nevertheless, the assignments provided by RAs during stable periods do appear to be informative.

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

	Logit specifications				Probit specifications			
Variables	**General model**		**Parsimonious model**		**General model**		**Parsimonious model**	
Country	2.123	(12.580)	2.067	(14.269)	1.154	(12.65)	1.125	(13.52)
time	–0.298	(–2.112)	–0.246	(–2.129)	–0.182	(–2.50)	–0.155	(–2.42)
$Equity_{t-1}$	–0.002	(–0.044)			0.004	(0.17)		
$Liquidity_{t-1}$	0.272	(0.180)			0.328	(0.40)		
$\ln(Assets)_{t-1}$	0.815	(2.579)	0.529	(6.932)	0.499	(2.81)	0.293	(7.11)
$NI\_Margin_{\ t-1}$	–0.015	(–0.101)			–0.020	(–0.32)		
NOA_{t-1}	7.052	(0.725)			2.109	(0.41)		
$OEOI_{t-1}$	–0.515	(–2.028)	–0.504	(–3.437)	–0.288	(–1.93)	–0.300	(–3.73)
$ROAE_{t-1}$	0.021	(1.470)	0.033	(3.565)	0.015	(2.00)	0.019	(3.81)
$Equity_{t-2}$	0.034	(0.645)			0.013	(0.46)		
$Liquidity_{t-2}$	5.601	(2.903)			3.111	(2.90)		
$\ln(Assets)_{t-2}$	0.064	(0.090)			–0.133	(–0.34)		
$NI\_Margin_{\ t-2}$	0.103	(0.689)			0.061	(0.83)		
NOA_{t-2}	–30.396	(–1.677)	–11.333	(–2.570)	–15.979	(–1.61)	–6.303	(–2.22)
$OEOI_{t-2}$	–1.416	(–2.164)	–1.824	(–3.222)	–0.773	(–2.09)	–1.007	(–3.17)
$ROAE_{t-2}$	0.017	(1.635)			0.007	(1.25)		
$Equity_{t-3}$	0.071	(0.984)	0.086	(6.730)	0.049	(1.47)	0.051	(6.84)
$Liquidity_{t-3}$	–5.384	(–2.545)			–2.873	(–2.64)		
$\ln(Assets)_{t-3}$	–0.588	(–0.621)			–0.218	(–0.46)		
$NI\_Margin_{\ t-3}$	–0.078	(–1.007)			–0.041	(–0.97)		
NOA_{t-3}	5.409	(0.556)			3.486	(0.67)		
$OEOI_{t-3}$	–0.329	(–0.651)			–0.266	(–0.83)		
$ROAE_{t-3}$	0.000	(0.002)			–0.000	(–0.12)		
$Equity_{t-4}$	–0.005	(–0.114)			–0.007	(–0.33)		
$Liquidity_{t-4}$	–0.342	(–0.237)			–0.447	(–0.62)		
$\ln(Assets)_{t-4}$	0.288	(0.522)			0.169	(0.61)		
$NI\_Margin_{\ t-4}$	0.029	(0.923)			0.020	(1.09)		
NOA_{t-4}	–0.818	(–0.224)			–0.944	(–0.48)		
$OEOI_{t-4}$	–0.016	(–0.126)			–0.028	(–0.34)		
$ROAE_{t-4}$	0.003	(1.011)	0.004	(2.849)	0.002	(1.00)	0.002	(2.27)
$\Delta Liquidity_{t-2}$			5.751	(4.537)			3.227	(4.41)
Limit Points								
λ_1	–0.478	(–0.317)	–1.217	(–0.952)	–0.165	(–0.211)	–0.497	(–0.734)
λ_2	3.211	(2.113)	2.436	(1.863)	1.672	(2.107)	1.333	(1.962)
λ_3	5.738	(3.702)	4.928	(3.702)	3.043	(3.764)	2.686	(3.889)
λ_4	7.660	(4.836)	6.840	(5.004)	4.073	(4.937)	3.710	(5.256)
λ_5	9.954	(6.114)	9.118	(6.480)	5.341	(6.288)	4.967	(6.814)
λ_6	11.624	(7.063)	10.772	(7.584)	6.252	(7.249)	5.869	(7.926)
λ_7	14.161	(8.270)	13.259	(8.928)	7.637	(8.607)	7.227	(9.452)
Fit Measures								
Pseudo R^2	0.383		0.380		0.370		0.367	
SBC	3.001		2.686		2.935		2.621	
LR statistic	533.432	[0.000]	530.320	[0.000]	515.964	[0.000]	512.525	[0.000]
LR(general→*)	NA		5.986	[0.999]	NA		6.239	[0.999]
Observations	359		360		359		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, λ_i, $i = 1, 2, \ldots, 8$ (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)	2.117 (14.755)	2.127 (15.706)	2.140 (16.732)	2.158 (17.210)	2.124 (18.583)
$time$	–0.166 (–1.72)	–0.174 (–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)	0.470 (7.002)	0.445 (1.848)	0.450 (8.863)	0.460 (9.613)	0.450 (9.383)
NI_Margin_{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)	–0.364 (–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)	0.021 (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)		0.870 (0.839)			
$\ln(Assets)_{t-2}$	–0.188 (–0.36)		0.005 (0.022)			
NI_Margin_{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)	–0.869 (–3.966)	–1.293 (–2.355)	–0.960 (–4.328)		
$ROAE_{t-2}$	0.009 (1.34)		0.003 (0.326)			
$Equity_{t-3}$	0.044 (1.68)	0.057 (4.572)				
$Liquidity_{t-3}$	–3.997 (–2.89)					
$\ln(Assets)_{t-3}$	–0.045 (–0.11)					
NI_Margin_{t-3}	0.012 (0.25)					
NOA_{t-3}	–3.615 (–0.67)					
$OEOI_{t-3}$	–0.112 (–1.84)	–0.174 (–3.783)				
$ROAE_{t-3}$	0.007 (2.43)	0.003 (2.300)				
$\Delta Liquidity_{t-2}$		3.938 (2.975)				
Limit Points						
λ_1	–0.353	–1.207	–1.197	–0.823	–0.104	–0.193
λ_2	3.422	2.420	2.311	2.692	3.610	3.302
λ_3	6.023	4.977	4.871	5.244	6.057	5.747
λ_4	7.858	6.818	6.652	7.020	7.810	7.504
λ_5	10.098	9.040	8.685	9.042	9.917	9.613
λ_6	11.865	10.761	10.402	10.746	11.731	11.421
λ_7	14.299	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	0.381	0.370	0.369	0.361	0.361
SBC	2.821	2.659	2.779	2.691	2.705	2.676
LR statistic	641.176 [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	10.047 [0.690]	NA	3.095 [0.928]	NA	1.087 [0.780]
Observations	425	425	538	538	629	629

Table 2 notes: see notes to Table 1.

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

Variables	General	Parsimonious	General	Parsimonious	General	Parsimonious
$Country$	1.156 (12.958)	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)	–0.103 (–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)	0.261 (7.232)	0.249 (1.742)	0.246 (8.834)	0.242 (8.744)	0.234 (8.420)
NI_Margin_{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)	–0.222 (–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)	0.013 (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)		0.565 (0.938)			
$\ln(Assets)_{t-2}$	–0.251 (–0.826)		–0.002 (–0.018)			
NI_Margin_{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)	–0.474 (–3.821)	–0.620 (–2.056)	–0.517 (–4.384)		
$ROAE_{t-2}$	0.004 (0.966)		0.001 (0.277)			
$Equity_{t-3}$	0.028 (1.989)	0.034 (4.970)				
$Liquidity_{t-3}$	–2.208 (–2.992)					
$\ln(Assets)_{t-3}$	0.051 (0.211)					
NI_Margin_{t-3}	0.011 (0.416)					
NOA_{t-3}	–1.266 (–0.428)					
$OEOI_{t-3}$	–0.054 (–1.647)	–0.085 (–3.097)				
$ROAE_{t-3}$	0.004 (2.293)	0.002 (2.113)				
$\Delta Liquidity_{t-2}$		2.188 (3.084)				
Limit Points						
λ_1	0.064	–0.343	–0.220	–0.082	0.356	0.174
λ_2	1.956	1.486	1.457	1.609	1.971	1.782
λ_3	3.322	2.834	2.788	2.932	3.223	3.035
λ_4	4.288	3.802	3.726	3.864	4.127	3.942
λ_5	5.500	5.007	4.810	4.944	5.246	5.061
λ_6	6.438	5.929	5.715	5.843	6.214	6.027
λ_7	7.771	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	0.363	0.349	0.347	0.338	0.337
SBC	2.893	2.729	2.861	2.775	2.800	2.771
LR statistic	610.337 [0.000]	601.618 [0.000]	744.871 [0.000]	741.219 [0.000]	841.519 [0.000]	840.352 [0.000]
LR(general→*)	NA	8.719 [0.794]	NA	3.652 [0.887]	NA	1.167 [0.761]
Observations	425	425	538	538	629	629

Table 3 notes: see notes to Table 1.

Table 4: Percentage of correct predictions of favoured logit and probit models

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

Figure 1: Percentage of ratings through time