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EU Banks Rating Assignments: Is There Heterogeneity Between New And Old Member Countries?

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Abstract

We model EU countries' bank ratings using financial variables and allowing for intercept and slope heterogeneity. We find that country-specific factors (in the form of heterogeneous intercepts) are a crucial determinant of ratings. Whilst "new" EU countries typically have lower ratings than "old" EU countries, after controlling for financial variables, all countries are found to have significantly different intercepts, which confirms our hypothesis. This intercept heterogeneity may reflect differences in country risk and the legal and regulatory framework that banks face (such as foreclosure laws). In addition, ratings may respond differently to the liquidity and operating expenses to operating income variables across countries: typically ratings are more responsive to the former and less sensitive to the latter for "new" EU countries compared with "old" EU countries.

Keywords: EU countries, banks, ratings, ordered choice models, index of indicator variables

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.

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. The objective of our paper is to analyse the determinants of individual bank ratings conducted by Fitch Ratings (FR) and to investigate whether the country of origin matters for individual ratings. For this purpose, 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). Second, we examine whether bank ratings are systematically determined by the country origin of commercial banks. One hypothesis is that FR might assign higher ratings to commercial banks from "old" EU countries that have the same financial position as those from "new" EU countries. This could reflect differences in country risk (given that bank ratings cannot exceed sovereign ratings) or differences in legal and regulatory factors (including their enforcement), such as foreclosure laws. Another hypothesis is that FR might set ratings differently for "old" and "new" EU countries in terms of response to financial factors. That is, the coefficients on financial variables in a regression explaining ratings may be different for "old" and "new" EU countries.

In other words, we test if commercial banks from "new" EU countries are assigned ratings on the basis of their financial ratios in the same way as "old" EU countries or if other factors are considered. To this end, we incorporate "new" EU and country-specific indicator variables to capture heterogeneous variations in ratings under that rationale that a bank's rating is related to the country in which it is based. As country-specific indicators we construct index-of-indicator variables that are in the spirit of the method applied in Hendry (2001) and Hendry and Santos (2005), although we extend it to allow heterogeneous slopes. This methodological approach has recently been proposed by Caporale et al. (2009) and represents a novel contribution in the context of modelling bank ratings. We also assess the predictive power of our model to classify the individual ratings of the commercial banks in question.

The ability to predict the financial soundness of banks, corporations and sovereign countries has been of central importance for analysts, regulators and policy makers. A large number of studies have employed financial ratios to predict failures of individual firms (banks), for example, Altman et al. (1977) and Ohlson (1980). Models that predict bank failures using so-called Early Warning Systems (EWS) have appeared in a number of studies, including Mayer and Pifer (1970), and Kolari et al. (2002). Within this context, the financial variables of commercial banks have been utilised in several ways.

Yet the ability of ECAIs to assign ratings correctly has been extensively questioned (Altman and Saunders, 1998, Levich et al., 2002, Altman and Rijken, 2004, Amato and Furfine, 2004, Portes, 2008). One of the most frequent arguments about the prediction abilities of rating agencies (RAs) is that they could provide misleading information since the analysis is backward- rather than forward-looking. In addition, the low transparency of ratings assignments contributes to the concern over the accuracy of ratings. Further, ECAIs do not have, and cannot have, superior information to market participants about uncertainty and the degree of insolvency (illiquidity) of companies. By modelling ratings we seek to identify their determinants and, using measures of fit, gauge how transparent ratings assignments are.

There are numerous studies that predict bond ratings such as Kamstra et al. (2001), who utilise ordered-logit regression. Other evidence from recent studies (Kim, 2005; Huang et al., 2004 and Lee, 2007) show that artificial intelligence methods do not provide superior predictions of bond ratings compared with 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 allowing for heterogeneous country effects, which is the aim of this paper.

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

We model the individual ratings of EU banks as produced by Fitch Ratings (FR). These ratings are divided into six main categories (A, B, C, D, E, F) which, with intermediate subdivisions (A/B, B/C, C/D, D/E), give ten categories of bank performance. We use data on 1168 European banks' ratings, denoted Y_i, between 1996 and 2008. Y_i is ordinal and has ten categories that are assigned integer values, 0 to 9: lower values indicate a lower rating. The ten rating categories are: F (0), E (1), D/E (2), D (3), C/D (4), C (5), B/C (6), B (7), A/B (8), A (9).

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):

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

where X_{ki} is the kth explanatory variable for the ith bank, 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 ten categories) as follows:

$$\begin{aligned} &Y_i = 1 \quad \text{if } Y_i^* \le \lambda_1 \\ &Y_i = j \quad \text{if } \lambda_{\text{j-1}} < Y_i^* \le \lambda_j, \quad j = 2, 3, ..., 9 \\ &Y_i = 10 \quad \text{if } \lambda_9 < Y_i^* \end{aligned} \qquad \textbf{(2)}$$

where λ_1, λ_2,…, λ_9 are unknown parameters (limit points) to be estimated with the coefficients (the β_k s). We are primarily interested in 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 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_{ki}. 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, while the logit form assumes a logistic distribution. Greene (2008) suggests that probit and logit models yield results that are very similar in practice and so we focus on those from the probit form.

The first explanatory variable that we consider is for the year in which the rating was made [$Date_i$]. This is 3 in 1996, 4 in 1997, 5 in 1998 and so on.[4] The second set of covariates considered is the first *lagged* values of the following seven financial variables: the ratio of equity to total assets [denoted $Equity_i$], the ratio of liquid assets to total assets [$Liquidity_i$], the natural logarithm of total assets [$\ln(Assets)_i$], the net interest margin $[NIM_i]$, the ratio of operating expenses to total operating income [OE_OI_i], other operating income to total assets, $[OOIA_i]$ and the return on assets [ROA_i].[5] Current values of financial variables are not used as they may contain information not known when the rating was made.[6] The choice of variables is guided by the past literature.

A third set of variables employed are country indicator (or dummy) variables. Two broad types of indicators are considered. First, we construct a shift dummy variable, D_i^{New}, that is defined to take the value of unity for "new" EU countries and is zero for the 15 "old" EU countries.[7] This dummy variable, multiplied by a financial variable, Z_i, yields the shift in that variable's slope coefficient for a "new" EU country, $Z_{ki}^{New} = Z_{ki} \times D_i^{New}$. Second, we develop index-of-indicator variables that allow each country to have different intercept and slope coefficients. However, an ordered-choice model incorporating 27 dummy variables for each covariate cannot be estimated; hence, we employ a method that is in the spirit of Hendry (2001) and Hendry and Santos (2005) to construct indices-of-indicator variables for each covariate.

[4] Originally we had data from 1994 where 1994 took the value of 1. However, data prior to 1996 was lost due to missing observations on some variables.
[5] Some other variables were considered but were omitted from the analysis due to multicollinearity.
[6] 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.
[7] The twelve "new" EU countries in our sample are: Bulgaria, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia and Slovenia. The fifteen "old" EU countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the UK.

To construct a country index for the intercept we estimate two probit models, one for "new" EU countries and one for "old" EU countries. That is, one probit regression of ratings on the 12 "new" EU countries' (intercept) dummy variables, D_{mi}, $\mathrm{m} = 1,2,...,12$, is estimated, thus:

$$\hat{Y}_i^* = \sum_{m=1}^{12} \hat{\delta}_m D_{mi} \tag{3}$$

where, $\hat{\delta}_m$ denotes the respective estimated coefficients.

The initial index for "new" EU countries is constructed as the sum of the products of the coefficients for the significant variables and their corresponding dummy variables, thus:

$$I_i^N = \sum_{m=1}^{12} \hat{\delta}_1 D_{mi} \tag{4}$$

Similarly, the following ordered-choice model is fitted to the 15 "old" EU country dummy variables, D_{mi}, $\mathrm{m} = 13,14,...,27$:

$$\hat{Y}_i^* = \sum_{m=13}^{27} \hat{\delta}_m D_{mi} \tag{5}$$

The initial index for "old" EU countries is correspondingly constructed as:

$$I_i^O = \sum_{m=13}^{27} \hat{\delta}_1 D_{mi} \tag{6}$$

To obtain a preliminary index for all countries, ratings are then regressed on these two indices, thus:

$$\hat{Y}_i^* = \hat{\gamma}_N I_i^N + \hat{\gamma}_O I_i^O \tag{7}$$

The initial country index is constructed as:

$$I_i^C = \hat{\gamma}_N I_i^N + \hat{\gamma}_O I_i^O \quad \textbf{(8)}$$

This index was checked for appropriateness by running a single regression that included the initial country index plus one individual country's dummy, that is:

$$\hat{Y}_i^* = \hat{\lambda} I_i^C + \hat{\alpha}_m D_{mi} \quad \textbf{(9)}$$

If the latter individual dummy variable was significant the value of its coefficient, $\hat{\alpha}_m$, was incorporated into the country index. This was repeated for all 27 countries, that is, 27 regressions containing 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 27 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 result is the intercept country index – reported in Table 4.

A modified procedure was employed to construct indices for the non-intercept covariates. For each covariate (except for $Date_i$) a slope interaction variable, Z_{kmi}^C, was constructed as:

$$Z_{kmi}^C = Z_{ki} \times D_{mi} \quad \textbf{(10)}$$

For the k[th] covariate one regression is estimated for the "new" EU countries as ratings on the financial variables, date and the 12 "new" EU countries' slope interaction term for the k[th] variable, thus:

$$\hat{Y}_i^* = \sum_{k=1}^{K} \hat{\phi}_k Z_{ki} + \sum_{m=1}^{12} \hat{\theta}_m Z_{kmi}^C \quad \textbf{(11)}$$

A corresponding regression for the k[th] financial variable is estimated for the group of 15 "old" EU countries, as:

$$\hat{Y}_i^* = \sum_{k=1}^{K} \hat{\phi}_k Z_{ki} + \sum_{m=13}^{27} \hat{\theta}_m Z_{kmi}^{C} \quad \textbf{(12)}$$

Initial indices for the k^th covariate for "new" and "old" EU countries are constructed using only the statistically significant interaction terms, as:

$$I_{ki}^{N} = \sum_{m=1}^{12} \hat{\theta}_m Z_{kmi}^{C} \quad \textbf{(13)}$$

$$I_{ki}^{O} = \sum_{m=13}^{27} \hat{\theta}_m Z_{kmi}^{C} \quad \textbf{(14)}$$

To obtain a preliminary index of the k^th covariate for all countries we regress ratings on these two indices, thus:

$$\hat{Y}_i^* = \hat{\omega}_N I_{ik}^{N} + \hat{\omega}_O I_{ik}^{O} \quad \textbf{(15)}$$

The initial country slope index for the k^th financial variable is constructed as:

$$I_{ki}^{C} = \hat{\omega}_N I_{ik}^{N} + \hat{\omega}_O I_{ik}^{O} \quad \textbf{(16)}$$

This index was refined by the following iterative process. A single regression that included the date, the financial variables, the initial country index plus one individual country's interaction term was estimated as follows:

$$\hat{Y}_i^* = \sum_{k=1}^{K} \hat{\phi}_k Z_{ki} + \hat{\rho} I_{ik}^{C} + \hat{\mu}_m Z_{kmi}^{C} \quad \textbf{(17)}$$

If the latter individual interaction term was significant the value of its coefficient, $\hat{\mu}_m$, was incorporated into the country index. This was repeated for all 27 countries. After all the coefficients of the individual country interaction terms that were significant in these 27 regressions had been incorporated into the index this iteration was complete. Further iterations were repeated until there was convergence giving the final country slope index,

I_{ki}^{CF}. Complete convergence would be achieved when no Z_{kmi} term was significant at the 5% level for any country in (17) in a full iteration. Convergence may also be achieved even if interaction variables can be added with significance between iterations if the change in the index is small between iterations (to some tolerance level). We found that 999 iterations was sufficient for all but the liquidity index to achieve complete convergence or make the changes between the values in the indices sufficiently small to conclude that they had converged. For the liquidity index there is non-convergence such that the index is not the same between adjacent iterations but is exactly the same for every other iteration. In this case we tried both possible indices for liquidity in our regressions.[8] Plots of the 998th and 999th iterations of the index for each of the financial variables are given in Figure 1 to Figure 7.[9]

3. Empirical Results

The first set of ordered probit regression results for the determinants of bank ratings are presented in Table 1. We report a general model and one favoured parsimonious specification obtained using a cross-sectional variant of the general-to-specific methodology.[10] When there was ambiguity over which model to favour we selected the model with the lowest SBC. In all cases the favoured parsimonious models only include variables that are individually significant according to z-statistics and jointly significant according to a likelihood ratio test, denoted LR statistic. The restrictions placed on the general model to obtain the parsimonious model cannot be rejected according to a likelihood ratio test [LR(general→favoured)]. The favoured parsimonious models will yield more efficient inference relative to the general model and so they are used for inference.

The model in the column headed "No shift" in Table 1 contains no coefficients that shift for "new" EU countries (all the coefficients are the same for all countries). In the favoured

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[8] This happened for the liquidity index where for one country, Luxembourg, the value in the index could take on one of two values: –1.046 or 2.589. We used the index that produced the best fit in our experiments, being the value (–1.046) corresponding to the 998th iteration. See Figure 2 for a plot of the 998th and 999th iteration of the index for this variable's index.

[9] The indices for assets, operating expenses to operating income and other operating income to assets converge completely by the 999th iteration. The indices for equity, net interest margin and return on assets almost completely converge by the 999th iteration.

[10] 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.

model all the significant coefficients have plausible signs. That is, liquidity has a positive effect on ratings: banks with greater liquidity have a higher rating; the natural log of assets has a positive effect on ratings: banks with a larger size of assets have a higher rating; the net interest margin (NIM) has a positive correlation with ratings: a bank with a higher margin has a higher rating.[11] Further, operating expenses to operating income (OE_OI) has a negative correlation with a bank's rating: a bank with a greater ratio of operating expenses to operating income has a lower rating. This benchmark model's percentage of correct predictions is 33.6% which exceeds the predictive accuracy of 10% (given 10 rating categories) expected if the ratings were assigned randomly. Hence, the model adds predictive performance that is 22.6 percentage points greater than that obtained by chance.

The favoured model in the column headed "Intercept shift" in Table 1 contains the intercept dummy variable that shifts for "new" EU countries, D_i^{New}, but no slope coefficient shift variables. The same financial variables as for the "No shift" model are significant and have the same plausible coefficient signs, while the shift in the intercept is significant and negatively signed. The latter implies that, given the financial variables, "new" EU countries receive a systematically lower rating than "old EU" countries. This may reflect, for example, higher country risk and/or regulatory and legal deficiencies in "new" EU countries and confirms our hypothesis that the country of origin is an important determinant of a bank's rating. This model's percentage of correct predictions of is 37.4%, thus allowing the intercept to shift notably increases the model's predictive performance.[12]

The favoured model in the column headed "All shift" contains variables that allow both the intercept and slope coefficients to shift depending upon whether the nation is an "old" EU or "new" EU country. Six "non-shift" variables are significant (equity, liquidity, ln(Assets), NIM, OE_OI and ROA) and their coefficients represent these variable's correlations with ratings for "old" EU countries. Seven of the "shift" variables are significant (intercept, equity, liquidity, ln(Assets), NIM, OOIA and ROA) which indicates that the influence of these variables on ratings is different for "new" EU countries and "old" EU countries.[13] The model's percentage of correct predictions is 39.6% and demonstrates that allowing slopes to

[11] A high NIM contributes to a bank's profitability and enables them to build up sufficient reserves/provisions for potential losses.

[12] The other reported measures of fit, pseudo R^2 and SBC, confirm this increase in fit and, being broader measures of fit, guard against the result arising because the former measure focuses only on whether a model predicts with complete accuracy or not.

[13] The likelihood ratio statistics indicate that these shift variables are jointly significant, confirming that the coefficients for "old" and "new" EU countries are different for all of these variables.

shift as well as the intercept further increases the model's predictive performance.[14] The negative coefficient on the intercept shift term suggests that, as for the previous model, "new" EU countries have systematically lower ratings than "old" EU countries after the effects of financial variables have been taken into account. Further, the significance of the slope shift variables' coefficients demonstrates that bank ratings responses to financial variables are different for "old" and "new" EU countries.

Table 2 reports the slope coefficients and t-ratios for "old" and "new" EU countries implied by the models reported in Table 1. From the results corresponding to the favoured specification 5 of the 6 significant coefficients have the expected signs for the "old" EU countries. An increase in liquidity, assets, net interest margin and return on assets will have a positive impact on ratings whereas an increase in operating expenses relative to operating income has a negative effect on ratings. All of these relations are plausibly signed. However, the negative correlation of equity and ratings is unexpected. One possible rationalisation is that banks use equity to create a buffer against possible loss or non-performing assets.[15] Thus, a higher equity to assets ratio may indicate potential problems with asset quality, which is reflected in a lower rating.[16]

For "new" EU countries 3 of the 4 significant coefficients of the favoured model reported in Table 2 have the expected signs. Increases in assets and operating income to assets have a positive impact on ratings whilst an increase in operating expenses relative to operating income has a negative effect on ratings. In contrast, the negative correlation of return on assets with a bank's rating is not expected.[17] However, the coefficient is only just significant and may be due to a Type-I error (of which there is a 5% chance given our chosen significance level). Indeed, this finding of a positive coefficient on return on assets is not repeated in any other regressions and may, therefore, be regarded as a fragile result.

The results of the favoured model reported in Table 2 provide clear evidence that ratings are determined differently for "old" and "new" EU countries. The coefficient for "new" EU countries is significantly larger than for "old" EU countries for equity, assets and operating income. Conversely, the coefficient for "new" EU countries is significantly smaller than for

[14] The other reported measures of fit, pseudo R^2 and SBC, confirm this increase in fit.
[15] Until recently (before the crisis) equity (or capitalisation) was not a problem in banking.
[16] In transition economies it has been essential that banks build up high equity because of higher risk, although we do not find a negative correlation between ratings and equity for "new" EU countries.
[17] Return on assets is an indicator of profitability. In this specific case high profitability can be considered as a weakness that is associated with imprudent lending policies. In other words, a high profit may result from reckless lending. This would be especially relevant for "new" EU countries.

"old" EU countries for liquidity, net interest margin and return on assets. Only for operating expenses to operating income are the coefficients the same for "old" and "new" EU countries.

Table 3 reports results where a heterogeneous intercept and slopes (for the financial covariates) are allowed for all countries and not just for the "new" and "old" EU country groupings. The models reported in the column headed "Intercept heterogeneity" contain the intercept country index but no country indices for the covariates' slopes. From the favoured model we see that all significant coefficients have expected signs except equity. Date, liquidity, assets, net interest margin and operating income have plausible positive effects on ratings while operating expenses has a plausible negative correlation with a bank's rating. As before, equity has an unexpected negative impact on ratings suggesting that this may not be a fragile result.[18] It is particularly noteworthy that the intercept country index is highly significant and its inclusion in the model raises the model's percentage of correct predictions substantially compared with previous models to 48.0%.[19] This suggests that country-specific factors, beyond those captured by financial covariates, are very important determinants of ratings.

The models reported in the column headed "All heterogeneity" of Table 3 contain both heterogeneous intercept and slope indices. The same non-index covariates as reported in the favoured model under the "Intercept heterogeneity" column are significant, except for Date, and have the same coefficient signs. The index variables that are significant are for the intercept, liquidity and operating expenses: these are the only variables that exhibit coefficient heterogeneity. The percentage of correct predictions is 50.5%, which suggests that adding covariate indices (giving slope heterogeneity) raises the predictive performance by 2.5 percentage points relative to the model only allowing intercept heterogeneity.

The values of the intercept coefficients from the intercept country index are given in Table 4. All of the countries have different intercepts, indicating that all countries' ratings contain a country-specific element. All of the "old" EU countries have larger intercepts than the "new" EU countries, indicating that country-specific factors lower "new" EU countries' ratings relative to "old" EU nations, which confirms our initial hypothesis. However, it is worth emphasising that within "old" and "new" EU country groupings there is intercept heterogeneity. Hence, factors such as sovereign risk and country differences in the legal and

[18] A higher equity to assets ratio may be an indication of potential problems with asset quality which is reflected in a lower rating.

[19] This intercept index variable substantially improves predictive performance relative to a model with no heterogeneity or shifts by 14.4 percentage points. The model headed "Intercept heterogeneity" in Table 3's predictive performance is 48.0% compared with the model headed "No shift" in Table 1 of 33.6%.

regulatory frameworks in which banks specifically operate affect the ratings at the individual country level. Whilst we confirm that “new” EU countries have lower ratings than “old” EU countries (after controlling for financial variables) our results emphasise that ratings do not simply differ by “old” and “new” EU country cohorts.

The country-specific coefficients for the liquidity and operating expenses to operating income variables are reported in Table 5. All of the countries’ coefficients have the expected signs, except for Romania’s liquidity coefficient which is relatively small in magnitude, being virtually zero. With the exception of Romania (and Spain) “new” EU countries tend to have larger coefficients for both variables compared with “old” EU countries. Further, ratings tend to be more sensitive to liquidity for “new” EU countries relative to “old” EU countries, while ratings tend to be less responsive to operating expenses to operating income for “new” EU countries compared with “old” EU countries. Whilst there is some heterogeneity for both variables, many coefficients are the same. That is, for 16 out of 27 countries the coefficients are the same for liquidity and for 13 out of 27 countries they are the same for operating expenses. We note that only two financial variables show coefficient heterogeneity and within these variables many of the different countries are the same, which contrasts with the intercept index which indicates a different index for all countries. It therefore appears that the main country heterogeneity comes from the intercept variable and only a small part comes from the different country responses of ratings to financial variables.

Further, recall that the predictive performance of the benchmark model containing no heterogeneous (or shifting) coefficients is 33.6%. Thus, the incorporation of a heterogeneous intercept increases this performance by 14.4 percentage points to 48.0%. Adding indices for both heterogeneous slopes and a heterogeneous intercept raises the model’s predictive accuracy to 50.5%, which is a relatively modest increase of 2.5 percentage points (compared with the model containing a heterogeneous intercept). This suggests that most of the improvement in fit comes from adding a heterogeneous intercept and only a small percentage from the addition of heterogeneous slopes. Thus, the heterogeneous intercept appears to be a crucial determinant of ratings.

4. Conclusions

Our models of EU country ratings show that ratings are determined by financial variables and that these covariates have the expected coefficient signs except for equity. We suggest that the explanation for this latter result may be that a higher equity to assets ratio can be an indication of potential problems with asset quality which is reflected in a lower rating. Country-specific factors (in the form of heterogeneous intercepts) are a crucial determinant of ratings. Whilst “new” EU countries typically have lower ratings than “old” EU countries, after controlling for financial variables, it should be emphasised that all countries have significantly different intercepts – this confirms our initial hypothesis. This intercept heterogeneity may reflect differences in country risk and the legal and regulatory framework that banks face (such as foreclosure laws).

There may be some differences across countries in the assignment of ratings due to the liquidity and operating expenses to operating income variables. There is some evidence that ratings are typically more responsive to liquidity and less sensitive to operating expenses for “new” EU countries compared with “old” EU countries. However, it is clear that the primary country heterogeneity in ratings arises from the intercept rather than from the slopes. Construction of slope heterogeneity indices is a novel development in the methodology of constructing index-of-indicator variables.

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Table 1: Bank ratings probit regressions with new EU coefficient shift

	No shift		New EU intercept shift		New EU intercept and slope shift	
Variables (expected sign)	Gen	Fav	Gen	Fav	Gen	Fav
$Date$	–0.002 (–0.229)		0.014 (1.276)		0.018 (1.509)	
$Equity_{t-1}$ (+)	–0.572 (–0.631)		–1.237 (–1.023)		–4.216 (–2.277)	–4.047 (–2.252)
$Liquidity_{t-1}$ (+)	1.301 (8.049)	1.327 (8.354)	1.285 (7.358)	1.336 (7.714)	1.118 (5.735)	1.143 (5.946)
$\ln(Assets)_{t-1}$ (+)	0.243 (14.430)	0.249 (15.683)	0.177 (8.332)	0.183 (9.030)	0.181 (6.944)	0.181 (6.929)
NIM_{t-1} (–/+)	1.672 (1.560)	1.867 (2.115)	5.694 (4.493)	5.721 (4.780)	6.052 (4.032)	5.702 (3.953)
OE_OI_{t-1} (–)	–1.461 (–10.680)	–1.547 (–13.917)	–1.342 (–6.874)	–1.517 (–8.748)	–1.119 (–5.615)	–1.182 (–6.172)
$OOIA_{t-1}$ (+)	–13.388 (–1.693)		8.993 (1.271)		–5.319 (–0.476)	
ROA_{t-1} (+)	4.593 (1.110)		8.725 (1.355)		43.807 (4.000)	42.302 (3.976)
$Intercept\_New$			–1.548 (–14.163)	–1.485 (–14.455)	–0.983 (–1.609)	–1.356 (–2.674)
$Equity\_New_{t-1}$					7.039 (2.989)	6.681 (2.902)
$Liquidity\_New_{t-1}$					–1.350 (–2.870)	–1.478 (–3.273)
$\ln(Assets)\_New_{t-1}$					0.127 (2.801)	0.121 (2.790)
NIM_New_{t-1}					–6.814 (–2.778)	–7.571 (–3.231)
$OE\_OI\_New_{t-1}$					–0.637 (–1.126)	
$OOIA\_New_{t-1}$					33.272 (2.469)	24.723 (3.546)
ROA_New_{t-1}					–59.774 (–4.291)	–50.554 (–4.735)
Fit Measures						
% correct	33.390	33.647	37.158	37.414	39.555	39.555
Pseudo R^2	0.096	0.095	0.142	0.140	0.160	0.159
SBC	3.354	3.334	3.197	3.179	3.176	3.161
LR statistic	405.272 [0.000]	401.090 [0.000]	596.398 [0.000]	588.520 [0.000]	670.413 [0.000]	666.545 [0.000]
LR(general→favoured)		4.183 [0.382]		7.879 [0.096]		3.869 [0.276]
LR(slope shift)					74.015 [0.000]	73.218 [0.000]
LR(slope/intercept shift)					265.141 [0.000]	264.186 [0.000]
Observations	1168	1168	1168	1168	1168	1168

Table 1 notes. The dependent variable is a bank's rating which has ten categories that correspond to the integer values in the range of 1 to 10 and yields nine limit points, $\lambda_i,\ i = 1, 2, \ldots, 9$ (the intercept is not separately identified from the limit points). Z-statistics (in parentheses) are based upon Huber-White standard errors and the percentage of correct predictions (% correct) use the category with the highest probability to give the predicted rating. Also reported are the Pseudo R^2 and Schwartz's information criterion, SBC. Likelihood ratio tests for the model's explanatory power, LR Statistic, the deletion of variables from the general model to obtain the parsimonious model, LR(general→favoured) the deletion of slope shift variables, LR(slope shift), and the deletion of slope and intercept shift variables, LR(slope/intercept shift) from a model are additionally reported. Probability values are given in square parentheses. All regressions were estimated using E-Views 6.0.

Table 2: Implied slope coefficients and t-ratios of EU shift models

	General		Favoured	
Variables (expected sign)	Old EU	New EU	Old EU	New EU
Date	0.018 (1.509)			
$Equity_{t-1}$ (+)	–4.216 (–2.277)*	2.823 (1.917)	–4.047 (–2.252)*	2.634 (1.829)
$Liquidity_{t-1}$ (+)	1.118 (5.735)*	–0.232 (–0.542)	1.143 (5.946)*	–0.336 (–0.818)
$\ln(Assets)_{t-1}$ (+)	0.181 (6.944)*	0.309 (7.773)*	0.181 (6.929)*	0.302 (8.067)*
NIM_{t-1} (–/+)	6.052 (4.032)*	–0.762 (–0.378)	5.702 (3.953)*	–1.869 (–1.011)
OE_OI_{t-1} (–)	–1.119 (–5.615)*	–1.756 –(3.208)*	–1.182 (–6.172)*	–1.182 (–6.172)*
$OOIA_{t-1}$ (+)	–5.319 (–0.476)	27.953 (3.684)*		24.723 (3.546)*
ROA_{t-1} (+)	43.807 (4.000)*	–15.967 (–1.890)	42.302 (3.976)*	–8.251 (–1.991)*

Table 2 notes. The (implied) coefficients and t-ratios are reported for new EU and old EU countries based upon the general and favoured regressions reported in Table 1 under the column headed "New EU intercept and slope shift". The coefficients and t-ratios for the old EU countries are exactly the same as those reported in Table 1. The coefficients for new EU countries are the sum of the coefficients on the variable of interest and its corresponding shift term. The t-ratios for new EU countries are calculated based upon the variance of the sum of a particular variable's coefficient (a) and its corresponding shift variable's coefficient (b), that is, Var(a + b) = Var(a) + Var(b) + 2Cov(ab). An asterix indicates that a variable is significant at the 5% level (using a critical value of 1.96 in absolute value).

Table 3: Bank ratings probit regressions with country heterogeneity

	Intercept heterogeneity		Intercept and slope heterogeneity	
Variables (expected sign)	Gen	Fav	Gen	Fav
Date	0.026 (2.489)	0.026 (2.448)	0.022 (1.714)	
$Equity_{t-1}$ (+)	–3.447 (–3.704)	–3.142 (–3.537)	–3.518 (–2.770)	–3.272 (–2.723)
$Liquidity_{t-1}$ (+)	0.541 (3.212)	0.569 (3.424)	0.380 (1.903)	0.426 (2.370)
$\ln(Assets)_{t-1}$ (+)	0.233 (13.367)	0.234 (13.461)	0.297 (9.256)	0.290 (9.248)
NIM_{t-1} (–/+)	4.845 (4.402)	5.219 (4.987)	3.741 (2.968)	3.539 (3.176)
OE_OI_{t-1} (–)	–1.237 (–8.795)	–1.324 (–11.365)	–1.354 (–5.884)	–1.418 (–7.434)
$OOIA_{t-1}$ (+)	19.053 (2.329)	20.178 (2.486)	14.911 (2.022)	17.271 (2.551)
ROA_{t-1} (+)	4.621 (1.101)		0.946 (0.162)	
$Intercept\_Country$	1.065 (24.159)	1.065 (24.159)	1.065 (19.883)	1.056 (22.507)
$Equity\_Country_{t-1}$			0.00004 (1.570)	
$Liquidity\_Country_{t-1}$			0.135 (1.161)	0.299 (3.332)
$\ln(Assets)\_Country_{t-1}$			2.166 (1.294)	
$NIM\_Country_{t-1}$			–0.00003 (–1.088)	
$OE\_OI\_Country_{t-1}$			0.217 (1.964)	0.224 (2.475)
$OOIA\_Country_{t-1}$			–0.0001 (–0.201)	
$ROA\_Country_{t-1}$			–0.000001 (–0.768)	
Fit Measures				
% correct	48.116	48.031	50.086	50.514
Pseudo R^2	0.248	0.248	0.261	0.259
SBC	2.815	2.810	2.812	2.777
LR statistic	1042.631 [0.000]	1041.420 [0.000]	1095.051 [0.000]	1086.883 [0.000]
LR(general→favoured)		1.211 [0.271]		8.168 [0.318]
LR(slope heterogeneity)			52.420 [0.000]	51.460 [0.000]
LR(slope/intercept heterogeneity)			689.779 [0.000]	682.916 [0.000]
Observations	1168	1168	1168	1168

Table 3 notes. The dependent variable is a bank's rating which has ten categories that correspond to the integer values in the range of 1 to 10 and yields nine limit points, $\lambda_i,\ i = 1, 2, \ldots, 9$ (the intercept is not separately identified from the limit points). Z-statistics (in parentheses) are based upon Huber-White standard errors and the percentage of correct predictions (% correct) use the category with the highest probability to give the predicted rating. Also reported are the Pseudo R^2 and Schwartz's information criterion, SBC. Likelihood ratio tests for the model's explanatory power, LR Statistic, the deletion of variables from the general model to obtain the parsimonious model, LR(general→*) the deletion of slope shift country variables, LR(slope heterogeneity), and the deletion of slope and intercept country variables, LR(slope/intercept heterogeneity) from a model are additionally reported. Probability values are given in square parentheses. The variables corresponding to the country shift are all determined after 999 iterations except the one for liquidity, which alternated between two different forms, we used the form corresponding to the 998th iteration. All regressions were estimated using E-Views 6.0.

Table 4: Heterogeneous intercept (country weights)

Country	Weight	Country	Weight
Old EU		***New EU***	
Luxembourg	3.493	Estonia	0.653
Netherlands	2.527	Slovakia	0.590
UK	2.485	Malta	0.570
Denmark	2.450	Hungary	0.344
Spain	2.357	Cyprus	0.338
Sweden	2.137	Slovenia	0.284
Ireland	2.098	Czech R	-0.172
Portugal	1.851	Poland	-0.196
Finland	1.723	Bulgaria	-0.204
Belgium	1.559	Romania	-0.211
Austria	1.440	Lithuania	-0.227
Italy	1.263	Latvia	-0.601
France	1.182		
Germany	0.727		
Greece	0.670		

Table 4 notes. The coefficient of the individual countries embodied in the index of indicators variable, $Intercept\_Country$, are given. The coefficients are ranked from highest to lowest value.

Table 5: Heterogeneous slopes

<table>
<tr><th colspan="2">Liquidity</th><th></th><th colspan="2">Oe_oi</th></tr>
<tr><td>Malta</td><td>0.900</td><td></td><td>Sweden</td><td>-1.696</td></tr>
<tr><td>Lithuania</td><td>0.836</td><td></td><td>Denmark</td><td>-1.695</td></tr>
<tr><td>Latvia</td><td>0.802</td><td></td><td>Finland</td><td>-1.647</td></tr>
<tr><td>Bulgaria</td><td>0.676</td><td></td><td>Romania</td><td>-1.642</td></tr>
<tr><td>Slovenia</td><td>0.620</td><td></td><td>Germany</td><td>-1.601</td></tr>
<tr><td>Spain</td><td>0.533</td><td></td><td>Austria</td><td>-1.591</td></tr>
<tr><td>Austria</td><td rowspan="16">0.426</td><td></td><td>France</td><td>-1.587</td></tr>
<tr><td>Belgium</td><td></td><td>Italy</td><td>-1.577</td></tr>
<tr><td>Cyprus</td><td></td><td>Belgium</td><td rowspan="13">-1.418</td></tr>
<tr><td>Czech Republic</td><td></td><td>Cyprus</td></tr>
<tr><td>Estonia</td><td></td><td>Czech Republic</td></tr>
<tr><td>Finland</td><td></td><td>Estonia</td></tr>
<tr><td>France</td><td></td><td>Greece</td></tr>
<tr><td>Greece</td><td></td><td>Ireland</td></tr>
<tr><td>Hungary</td><td></td><td>Luxembourg</td></tr>
<tr><td>Ireland</td><td></td><td>Netherlands</td></tr>
<tr><td>Italy</td><td></td><td>Poland</td></tr>
<tr><td>Netherlands</td><td></td><td>Portugal</td></tr>
<tr><td>Poland</td><td></td><td>Slovakia</td></tr>
<tr><td>Portugal</td><td></td><td>Spain</td></tr>
<tr><td>Slovakia</td><td></td><td>UK</td></tr>
<tr><td>UK</td><td></td><td>Slovenia</td><td>-1.283</td></tr>
<tr><td>Sweden</td><td>0.276</td><td></td><td>Bulgaria</td><td>-1.215</td></tr>
<tr><td>Denmark</td><td>0.198</td><td></td><td>Lithuania</td><td>-1.194</td></tr>
<tr><td>Germany</td><td>0.132</td><td></td><td>Malta</td><td>-1.191</td></tr>
<tr><td>Luxembourg</td><td>0.114</td><td></td><td>Hungary</td><td>-1.184</td></tr>
<tr><td>Romania</td><td>-0.057</td><td></td><td>Latvia</td><td>-1.170</td></tr>
</table>

Table 5 notes. The coefficients for each individual country implied by the financial variables' parameters and the index of indicator variables, $Liquidity\_Country_{t-1}$ and $OE\_OI\_Country_{t-1}$, are given. These are constructed as the coefficient on the kth variable, $\hat{\beta}_k$, and the product of the kth variable's index, I_{ki}^{CF}, and its associated coefficient, $\hat{\beta}_k^{CF}$, that is, as, $\hat{\beta}_k + \hat{\beta}_k^{CF} I_{ki}^{CF}$. The coefficients are ranked from the highest to lowest value for liquidity and lowest to highest for operating expenses to operating income.

Figure 1: Equity Index Iterations

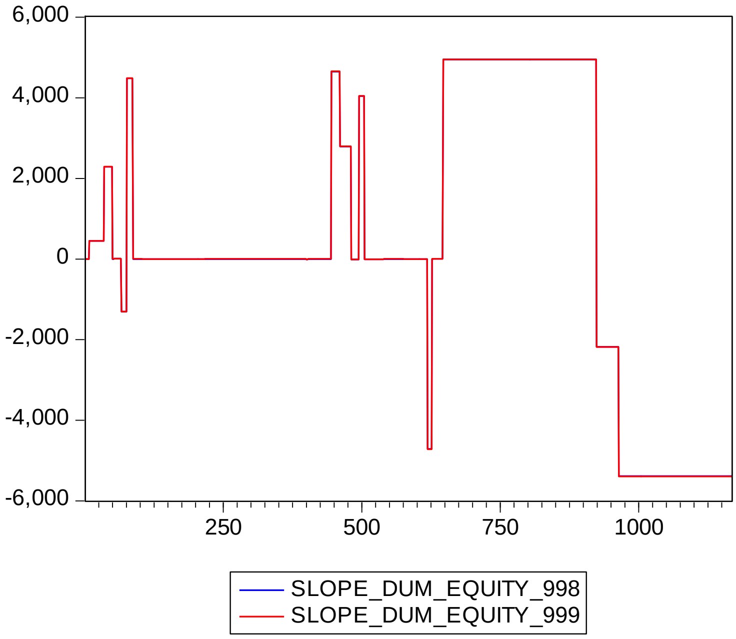

Figure 1 notes: slope_dum_equity_998 and slope_dum_equity_999 are the 998th and 999th iterations of the equity index.

Figure 2: Equity Index Iterations

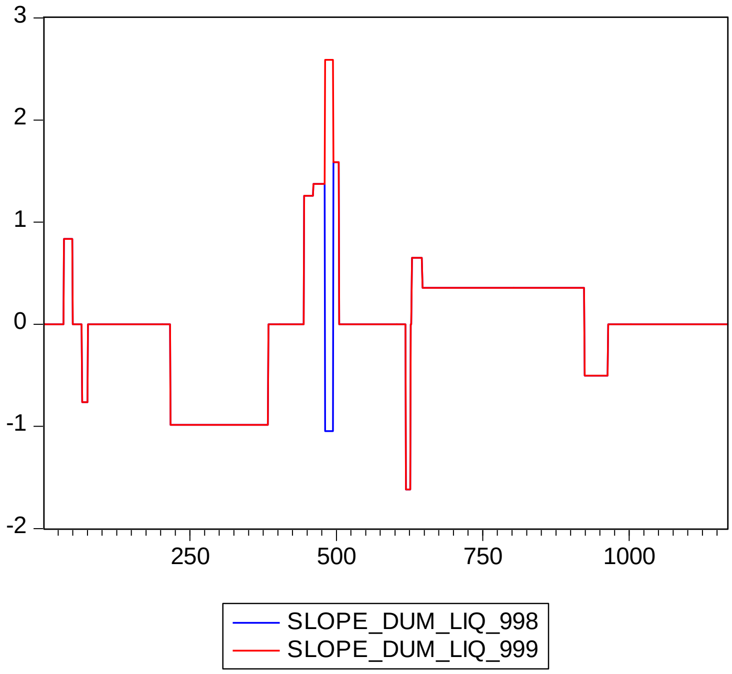

Figure 2 notes: slope_dum_liq_998 and slope_dum_liq_999 are the 998th and 999th iterations of the liquidity index.

Figure 3: Assets Index Iterations

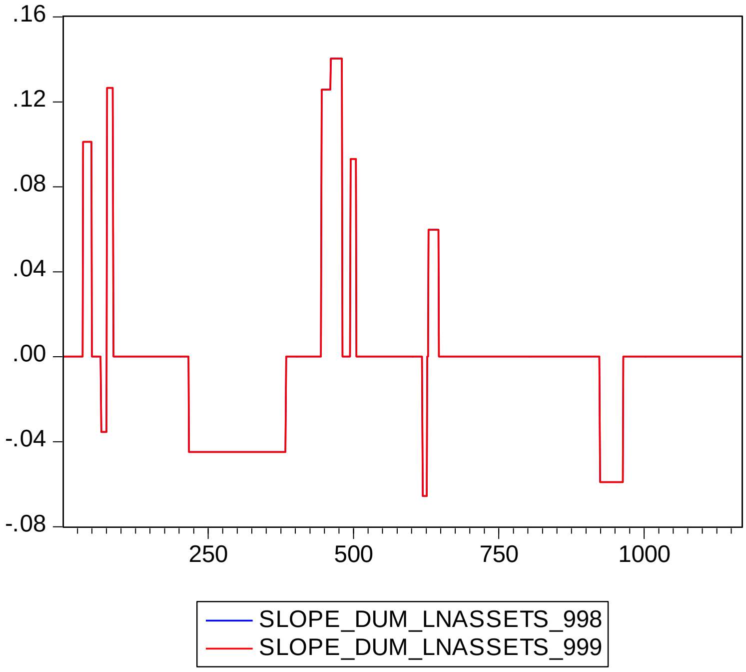

Figure 3 notes: slope_dum_lnassets_998 and slope_dum_lnassets_999 are the 998th and 999th iterations of the assets index.

Figure 4: NIM Index Iterations

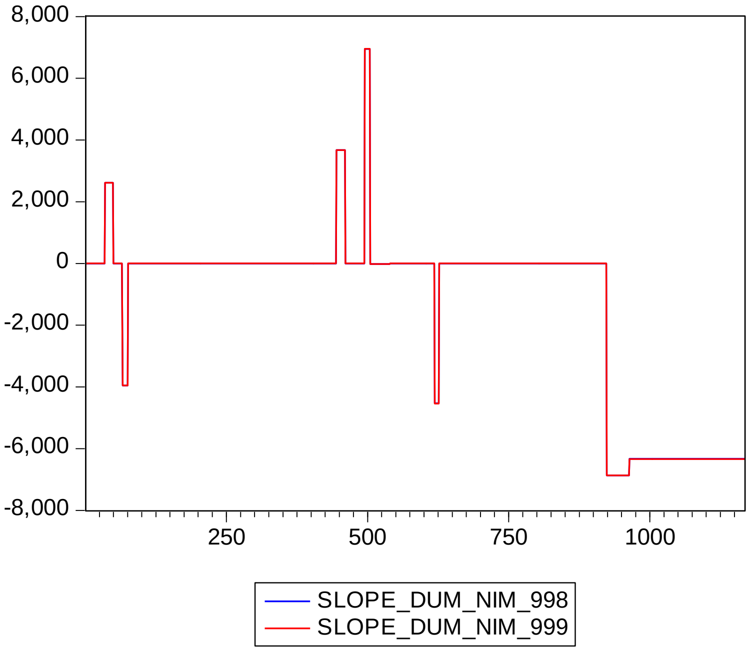

Figure 4 notes: slope_dum_nim_998 and slope_dum_nim_999 are the 998th and 999th iterations of the NIM index.

Figure 5: OE_OI Index Iterations

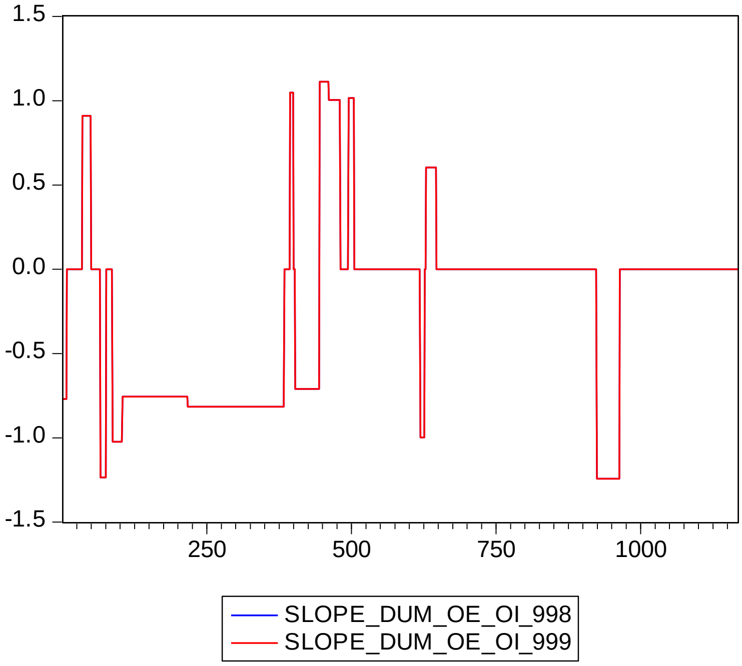

Figure 5 notes: slope_dum_oe_oi_998 and slope_dum_oe_oi_999 are the 998th and 999th iterations of the operating expenses to operating income index.

Figure 6: OOIA Index Iterations

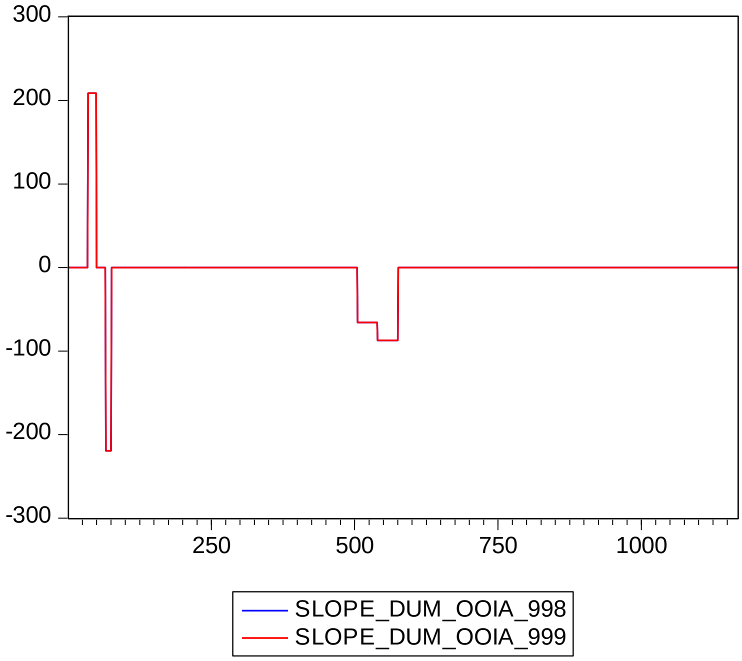

Figure 6 notes: slope_dum_ooia_998 and slope_dum_ooia_999 are the 998th and 999th iterations of the other operating income to assets index.

Figure 7: ROA Index Iterations

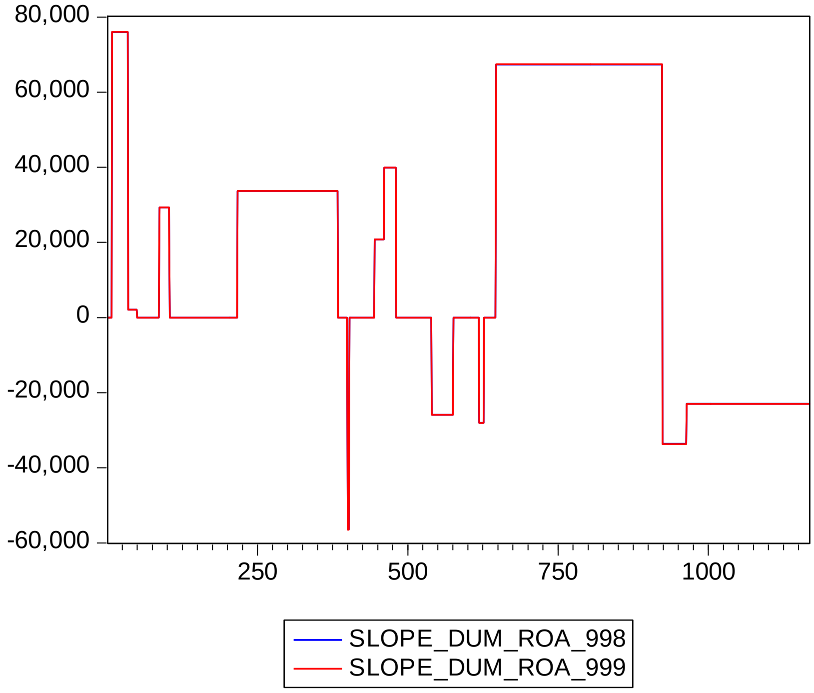

Figure 7 notes: slope_dum_roa_998 and slope_dum_roa_999 are the 998th and 999th iterations of the return on assets index.