2004

WORKING PAPER SERIES

/1/

CNB CZECH NATIONAL BANK

WORKING PAPER SERIES

Predicting Bank CAMELS and S&P Ratings: The Case of the Czech Republic

Alexis Derviz
Jiří Podpiera

1/2004

THE WORKING PAPER SERIES OF THE CZECH NATIONAL BANK

The Working Paper series of the Czech National Bank (CNB) is intended to disseminate the results of the CNB-coordinated research projects, as well as other research activities of both the staff of the CNB and colaborating outside contributors. This series supersedes previously issued research series (Institute of Economics of the CNB; Monetary Department of the CNB). All Working Papers are refereed internationally and the views expressed therein are those of the authors and do not necessarily reflect the official views of the CNB.

Printed and distributed by the Czech National Bank. The Working Papers are also available at http://www.cnb.cz.

Reviewed by:	Jarmila Musilová	(Czech National Bank)
	Josef Jílek	(Czech National Bank)
	Jan Hanousek	(CERGE-EI, Prague)
	Walter Schwaiger	(Vienna University of Technology)
Project Coordinator:	Tibor Hlédik	

Predicting Bank CAMELS and S&P Ratings: The Case of the Czech Republic

Alexis Derviz, Jiří Podpiera*

Abstract

In this paper we investigate the determinants of the movements in the long-term Standard & Poors and CAMELS bank ratings in the Czech Republic during the period when the three biggest banks, representing approximately 60% of the Czech banking sector's total assets, were privatized (i.e., the time span 1998–2001). The same list of explanatory variables corresponding to the CAMELS rating inputs employed by the Czech National Bank's banking sector regulators was examined for both ratings in order to select significant predictors among them. We employed an ordered response logit model to analyze the monthly long-run S&P rating and a panel data framework for the analysis of the quarterly CAMELS rating. The predictors for which we found significant explanatory power are: Capital Adequacy, Credit Spread, the ratio of Total Loans to Total Assets, and the Total Asset Value at Risk. Models based on these predictors exhibited a predictive accuracy of 70%. Additionally, we found that the verified variables satisfactorily predict the S&P rating one month ahead.

JEL Codes: C530, E580, G210, G330.
Keywords: Bank rating, CAMELS, ordered logit model, panel data analysis.

* Czech National Bank, Na Příkopě 28, 115 03, Prague Czech Republic. E-mail: alexis.derviz@cnb.cz; jiri.podpiera@cnb.cz. This paper was written within the framework of the Czech National Bank Research Project No. 17/2001. The authors would like to thank the referees J. Musilová, J. Hanousek and W. Schwaiger for carefully reviewing the paper and the Banking Regulation Department of the CNB for providing a unique data set.

Nontechnical Summary

The assessment of commercial banking performance based on bank ratings is studied with respect to detecting situations with the potential for adverse development towards failure, and owing to the costly nature of frequent supervisory examinations. A set of a limited number of rating-downgrade predictors which exhibit a high degree of predictive accuracy is of utmost importance. In this paper we study models of rating downgrades and consider a specific set of indicators that are suitable as determinants of a bank's rating. The conclusions about the predictors obtained from the analysis of downgrades are applicable in relatively stable banking sector situations.

Banks experiencing minor liquidity trouble might raise their interest rates on deposits, but a regulator would have a hard time distinguishing which bank has increased its deposit rate because of liquidity problems and which has done so owing to an increase in its cost of funds caused by some other factor. Therefore, in our approach the cost of funds – one of the plausible downgrade indicators – is used in the form of the bank's "credit spread".

In addition to credit spread, we tested the inclusion of the Value at Risk (VaR) indicator in the form of Total Asset VaR, as we believe that this type of indicator might play an important role in determining the level of the rating due to its easy computability and data availability to the public.

We focused on the Capital-Assets-Management-Earnings-Liquidity-Market Risk based composite (CAMELS) rating and the Standard and Poors (S&P) ratings. The choice of our sample is determined by the fact that cross-section data is probably less appropriate given the specific character of the relatively small banking market in the Czech Republic. The three chosen banks, i.e., Česká Spořitelna (CS), Komerční Banka (KB) and Československá Obchodní Banka (CSOB), cover a dominant portion of the market, the rest being occupied by small narrowly specialized banks or foreign bank branches. Therefore, we used panel data with three banks and their financial indicators to analyze the change in the CAMELS and S&P ratings.

We found that the reliable predictors of a bank's S&P rating are Credit Spread, Capital Adequacy, and the Total Loans to Total Assets ratio. In the case of the CAMELS rating we verified the Total Asset VaR, the ratio of Total Loans to Total Assets, and Capital Adequacy as reliable predictors. In addition, we find that the CAMELS rating does not yield itself easily to predictions within any horizon with the studied technique. On the contrary, the S&P rating can be relatively precisely predicted one month in advance.

1. Introduction

The assessment of commercial banking performance is central to the regulatory function of central bankers. Banking supervisors are able to recognize a worsening of a supervised bank's performance with the potential for adverse development towards failure if they perform frequent supervisory examinations (for details see Gilbert, 1993, and Cole and Gunther, 1998). However, examinations and timely partial rating constructions are time-consuming and cost-intensive. Therefore, detecting a set of a limited number of predictors of a rating downgrade or bank failure which exhibit a high degree of predictive accuracy is of utmost importance. There are basically two complementary approaches to the analysis of such predictors. The first approach is based on analysis of bank failures, whereas the second approach focuses on analysis of bank rating downgrades. Models of downgrades exhibit a significant improvement of predictive ability over time as new observations become available, in contrast to the bank failure models, where the database is less extensive and enlargements (i.e., data on newly failed banks) are irregular and infrequent. Gilbert et al. (2000) argue that the downgrade model can be most beneficial in periods in which the majority of the banks are healthy, and should not be used as a replacement for the bank failure model in general, since the sets of variables predicting bank downgrade and bank failure might be different. This fully intuitive argument is based on the possibly different conditions under which we collect evidence of a rating downgrade and bank failure. Thus, conclusions about predictors obtained from the analysis of downgrades are applicable in relatively stable banking sector situations. Nevertheless, there arises an opportunity for comparison from the point of view of the overlapping predictors that have been identified within the framework of downgrade models on the one hand and bank failures on the other.

Data on bank failures contain valuable information about the most important indicators that can explain and detect possible bank failures in the future. The literature devoted to bank failures is rich in applied techniques. Among the most common are: the logit model family, the proportion hazard model (Henebry, 1997), Discriminant Analysis, and Genetic Algorithms. A coherent comparison of these techniques can be found in Back et al. (1996).

The approach investigating bank downgrades in contrast to bank failures focuses on comparing banks that have been downgraded with those that have not been downgraded, and thereby defining the probability of a downgrade. The seminal paper in this line of research is Gilbert et al. (2000).

Predictors of bank failure may be dependent on the particular technique employed and do not necessarily coincide with those identified in the bank downgrade literature. For instance, Gilbert et al., employing a CAMEL (Capital-Assets-Quality-Management-Earnings-Liquidity) downgrade probit model and the U.S. banking data, found that the set of verified explanatory variables such as net worth, return on assets, size and securities roughly corresponds to those verified in the case of bank failures. However, the evidence from the proportional hazard models, which are supposed to be superior[1] to a simple static logit model for predicting bank failure (for instance in Henebry, 1997), is rather contradictory in the valuation of the predictors found by Gilbert et al. (2000).

[1] See, for instance, the argumentation in Shumway (1999).

Henebry (1997) establishes that the Primary Capital to Total Assets ratio, Non-performing Loans to Total Loans ratio and Total Loans to Total Assets ratio are the only three time-stable predictors of bank failure. This is a sign of the relatively low importance of a particular variable relative to the more broadly defined group of variables such as liquidity, asset quality, etc. in the role of reliable predictors, meaning that within a category of indicators some degree of interchangeability is possible.

In the Czech banking sector context, evidence of the application of quantitative dependent variable models to bank failures and rating downgrades is virtually non-existent. To the best of our knowledge there is no research investigating bank rating changes. Hanousek and Roland (2001) estimated a logit model of bank failures and argued that the banking supervisor – relying on Return on Assets or Capital Adequacy indicators – did not have a better ability to predict bank failures than the general public, who were assumed to use the interest rate on deposits (it is a well-accepted stylized fact that banks in liquidity trouble tend to raise their deposit interest rates). However, we believe that the interest rate on deposits is not generally applicable as a signal for a bank downgrade or upgrade, differently from bank failure predictions, where it is a widespread element of the prediction techniques per se. Banks experiencing minor liquidity trouble might raise their interest rates on deposits, but a regulator would have a hard time distinguishing which bank has increased its deposit rate for the reason of liquidity problems and which has done so owing to an increase in its cost of funds caused by some other factor. Therefore, in our approach the cost of funds – one of the plausible downgrade indicators – is used in the form of the bank's "credit spread". The credit spread is represented by the difference between the bank's nominal average deposit rate and the prevailing money market rate.

Credit spread as a measure of corporate borrower creditworthiness has been at the center of credit risk literature ever since the groundbreaking work of Merton (1974). The modern theoretical foundation for quantitative risky debt credit spread modeling has been laid down in Leland (1994), Jarrow and Turnbull (1995), Longstaff and Schwartz (1995), and Duffie and Singleton (1997). In principle, bank outstanding debt analysis is amenable to the same type of reasoning, although the great variability of existing bank liabilities falling into the discussed category (client and inter-bank deposits, CDs, standard and structured bonds and notes, etc.) complicates the construction of testable quantitative models in the mainstream non-arbitrage theoretical finance vein. There are many highly stylized models of bank lending behavior where the cost of funds relative to the standing riskless rate (i.e., the money market as the closest proxy) has an impact on the corporate lending rate and volume (see, for instance, Derviz and Kadlčáková (2002) and the references therein). Nevertheless, the banks themselves usually rely on the money market rate as the prime natural benchmark against which to measure their cost of funds.

In addition to credit spread, we tested the inclusion of the Value at Risk (VaR)[2] indicator in the form of Total Asset VaR, as we believe that this type of indicator might play an important role in determining the level of a rating due to its easy computability and data availability to the public.

[2] We would like to thank Walter Schwaiger for pointing out this type of indicator as a plausible rating predictor.

Moreover, the construction of VaR itself allows for cross-bank VaR comparison, as the heterogeneity of banks is removed by comparing the most severe expected loss on total assets.[3]

In this paper, we focus on the Capital-Assets-Management-Earnings-Liquidity-Market Risk based composite (CAMELS) rating and the Standard and Poors (S&P) ratings. The choice of our sample is determined by the fact that cross-section data are probably less appropriate given the specific character of the relatively small banking market in the Czech Republic. The three chosen banks cover a dominant portion of the market, the rest being occupied by small narrowly specialized banks or foreign bank branches. In addition, these three banks, together with at most one other, are roughly the only comparable banks in terms of services offered, regional availability, etc. So, the inclusion of other banks, which usually have a much narrower range of activities, would introduce heterogeneity problems. Therefore, we used panel data with three banks and their financial indicators to analyze the change in the CAMELS and S&P ratings.

As the CAMELS rating in the Czech Republic takes the form of a continuous variable,[4] whereas the standard S&P rating does not, we used different estimation techniques for each case. In the case of the S&P rating we employed the Ordered Logit Model (see the description in Subsection 3.1) to analyze the determinants of the S&P rating in the group of large banks. This group consists of Česká Spořitelna (CS), Komerční Banka (KB) and Československá Obchodní Banka (CSOB) and covers the whole group of large banks according to the Czech National Bank classification. This group represents roughly 60% of the market for client deposits and loans in the Czech Republic. Since we were limited by the data availability of the CAMELS rating for the group of large banks, and since the CAMELS rating takes the form of a continuous variable, we were unable to apply a panel data framework to banks outside the group of large banks (which form a reasonably representative group in the Czech banking sector). The time span covered by the sample is 1998–2001. The sample contains monthly (in the case of the S&P rating) and quarterly (in the case of the CAMELS rating) data. Our sample period is determined by the most frequent records of rating changes within the group of large banks. However, these unique data on rating changes were collected in the period of privatization of these banks and hence we might have determined predictors of bank ratings conditional on dramatic changes in the indicators. Consequently, the applicability of the predictors might be limited to the situation under privatization and not to the more stable period of operation by the new owners.

As the explanatory variables, we considered selected indicators covering the usual CAMELS structure, the VaR indicator evaluated for total assets, and the credit spread. The latter variable is defined as the difference between the money market interest rate and the deposit rate offered by the given bank. It is the spread on credit that the depositors grant to the bank in deposit form.

We found that the reliable predictors of a bank's S&P rating are Credit Spread, Capital Adequacy, and the ratio of Total Loans to Total Assets. In the case of the CAMELS rating we verified the

[3] We did not include financial market data in the form of stock prices of banks, which would be a plausible candidate for VaR, because they are not freely available in longer time series and for the full sample of banks that we considered.

[4] In the U.S., the CAMELS rating has the form of a discrete variable constructed from partial ratings. For details see Gilbert et al. (2000).

Total Asset VaR, the ratio of Total Loans to Total Assets, and Capital Adequacy as reliable predictors. All the models fit the out-of-sample predictions satisfactorily well; the models' average predictive accuracy is 70%.

The problem formulation in the panel data framework in both the S&P and CAMELS rating cases allows us not just to determine the predictors of the ratings, but also to identify the time horizon within which these variables predict the future ratings level. We find that the CAMELS rating does not yield itself easily to predictions within any horizon with the studied technique. On the contrary, the S&P rating can be relatively precisely predicted one month in advance.

The rest of the paper is organized as follows: Section 2 presents the data used. Section 3 focuses on the S&P rating predictions and Section 4 focuses on the CAMELS rating. Section 5 summarizes the main conclusions for both the S&P and CAMELS ratings.

2. Data and Background

One of the most popular external ratings is the Standard and Poors rating (S&P). The S&P rating is published in a letter and equivalent numerical scale that has the nature of a discrete variable. The scale of the numerical S&P long-term rating, chosen in this analysis as the representative "off-site" rating (from publicly available data), has its limits at 1 (meaning superior financial security and the highest degree of safety) and 23 (denoting regulatory action connected with placement under administration, rehabilitation or liquidation).

An alternative rating, developed and internationally used by bank supervisors, is CAMELS, which is based on the balance sheet figures reported to the supervisory bodies of the national banks. This rating is based on many subindicators that carry information about C-capital, A-asset quality, M-management, E-earnings, L-liquidity, and S-market risk. This rating is computed in a numerical scale and has its limits at 1 (the soundest banks) and 5 (unsafe and unsound banking practices).

The time span choice (1998–2001) for our data sample is motivated by an effort to record a sufficient number of rating changes resulting from the evolution of the Czech banking environment during the transition period and, consequently, the changing ownership structure caused by the privatization of the major banks: Česká Spořitelna (CS), Komerční Banka (KB) and Československá Obchodní Banka (CSOB). These are the three banks that are listed in the "large banks" category in the Czech National Bank's supervisory classification. The sample of these three banks was chosen so that the rating data would reflect the most typical transformation processes in the Czech banking sector as a whole. From the representativeness point of view, the large banks in our sample account for 61.7% of total banking sector assets, while their share in the market for client deposits is 72.2% and client loans 60.6% (average figures for the period 1999–2001). On the other hand, our choice does not limit the methodological side of the analysis, since the same procedure can be used for a future comparison of the estimated model with the S&P ratings of other Czech banks of smaller size, provided that the S&P or similar rating is available.

The bank privatization process took place gradually. The privatization of CSOB in June 1999 was followed by the emergency sale of the troubled Investiční a Poštovní Banka (IPB) to CSOB in June 2000. CS was sold to the Austrian Erste Bank in 2000 and subsequently merged with Erste

Bank's branch in the Czech Republic. KB was sold to Société Générale in 2001 and then merged with Société Générale's branch in the Czech Republic.

Since the new foreign owner or partner was expected to introduce standards of developed world banking, the Czech Government (through a clean-up by the Consolidation Agency of a large portion of the banks' bad loans) and sometimes the banks themselves made significant efforts to improve their outside image in various respects in the period preceding the actual merger or sale. The indicators worked on from both inside and outside the banks in an effort to see them privatized in a sound condition and at a better price were most probably reflected in changes in the S&P and CAMELS ratings. Therefore, by testing the predictive ability of the chosen numerical indicators we are also providing a quantitative measure of the banking sector transformation quality.

For the purpose of predictor quality verification we used a sample of two banks, i.e., CS and KB. The CSOB rating did not record any change during the studied period and hence cannot be used for identification of predictors in the econometric sense. Therefore, the data for CSOB were utilized in the out-of-sample prediction test of our models. The data cover the period 1998–2001 for KB and CS and from mid-2000 till the end of 2001 for CSOB (since we included only data that cover the period starting after another large bank in trouble, IPB, had been taken over by CSOB, i.e., June 2000).

The S&P long-term rating within the same category of large banks varies from 10 to 15 over the period of 1998–2001. We examined the monthly financial indicators that constitute the official data collected by the supervisory body of the Czech National Bank for the same time span. The CAMELS ratings in quarterly frequency for the three named banks were provided to us by the Banking Regulation Department of the Czech National Bank. The Value at Risk[5] variable was computed as the five percentile loss, i.e., the maximum fall in the total assets figure over a horizon of one year which could happen with probability of 0.05 or lower. Table 1 provides an overview of the indicators used.

Table 1: Indicators

C-Capital	
CA	Capital Adequacy
LEVERAGE	Tier 1 / Tangible Total Assets
GRR	Gross Revenue Ratio = Tier 1 / Total Revenues
E-Earnings	
ROA	Return on Assets
Credit Spread	= Pribor 3M minus nominal interest rate on deposits
L-Liquidity	
TLTA	Total Loans / Total Assets
S-Market Risk	
VaR	Total Asset Value at Risk

[5] For a survey of literature devoted to the utilization of Value at Risk indicators in bank credit risk from the regulator's perspective, see, for instance, Derviz and Kadlčáková (2001).

3. S&P Long-term Rating

In the case of the S&P long-term rating, we estimated the impact of the continuous explanatory variables on the discrete rating variable using an Ordered Logit Model. The latter captures the discrete and qualitatively ordered character of the rating for monthly data on two banks, Česká Spořitelna (CS) and Komerční Banka (KB), in 1998–2001.

3.1 Methodology

When investigating the levels of a discrete rating, one must take into account that the rating has a qualitative dimension to it: although the changes are quantitatively equal (unitary), the qualitative meaning is different at different initial rating levels. In order to account for this feature, we employ the Ordered Logit Model to the S&P rating in the framework of panel data. We carry out the Maximum Likelihood Estimation (MLE) using a log likelihood function defined as the sum of partial log likelihood functions[6] across panel member banks. This allows us to treat the observations within each bank as time dependent and only consider as independent the observation groups for different banks. The observations coming from one bank are, to a certain extent, serially correlated. Had we abstracted from this feature, the estimates' efficiency would have been lost, with a wrong conclusion about the possible predictors as a consequence.

Assuming that the Ordered Logit Model applies, let y be an ordered response taking values $\{0,1,2,...,J\}$. The Ordered Logit Model is derived from the model of a continuous latent variable y^*, which is assumed to exist[7] but remains unobserved. Variable y^* is assumed to exist and to be determined as follows:

$$y^* = X\beta + \varepsilon \qquad (1)$$

where ε stands for the logistically distributed random errors and β represents the vector of coefficients corresponding to the explanatory variables X. There exist unknown thresholds that define the tolerance within which the latent variable is allowed to fluctuate without a change in the rating being observed. At each of these thresholds, which we denote by $\alpha_1<,...,<\alpha_J$, the rating changes by a discrete unit jump. We can express the relation between the latent variable y^* and the observed discrete variable y as follows:

$$\begin{aligned} y &= 0 \quad \text{if} \quad y^* \leq \alpha_1 \\ y &= 1 \quad \text{if} \quad \alpha_1 \leq y^* \leq \alpha_2 \\ &\ \ldots \\ y &= J \quad \text{if} \quad y^* > \alpha_J \end{aligned} \qquad (2)$$

[6] For a reference on the utilization of partial likelihood functions for estimation in genuine panel data discrete dependent variable models, see, for instance, Wooldridge (2002).

[7] The concept of the latent variable was developed as a reaction to the variety of situations in reality where we collect observations of a certain variable in lower frequency due to the cost-intensive character of the data collection. The model discussed here belongs to the category in which continuous data collection would be possible but prohibitively costly, so the assumption about the continuous latent variable's existence is justified.

In general, the Ordered Logit Model log-likelihood function, consisting of the sum of partial likelihood functions for n banks and reflecting the feature that there is a certain degree of time dependence of observations within each bank but an independence across banks in the sample, can be written as follows:

$$\text{Log } L(\alpha,\beta) = \textstyle\sum_{i=1\ldots n} I(y_i=0)\log[\Lambda(\alpha_1 - X_i\,\beta)]+\ldots \qquad (3)$$
$$\ldots+I(y_i = 1)\log[\Lambda(\alpha_2 - X_i\,\beta)-\Lambda(\alpha_1 - X_i\,\beta)]+\ldots$$
$$\ldots+I(y_i = J)\log[1-\Lambda(\alpha_J - X_i\,\beta)],$$

where n=2 in our case, $I(y_i = 0)$ is the indicator function of the event $y_i = 0$ (i.e., it takes the value 1 if $y_i = 0$, and the value 0 otherwise). X_i is the matrix of explanatory variables for bank i in which the intercept column is not included, and β is the vector of coefficients common to all banks in the sample. The transformation in the form of the logistic density is applied to the argument of the estimated equation ($\alpha_i - X_i\,\beta$) in order to ensure that the model's predictions will mimic the latent continuous variable y^*. Λ denotes the logistic density function: $\Lambda(x)=((\exp(x))/(1+\exp(x)))$.

3.2 Estimation

The estimation for the group of large banks was carried out by maximizing the likelihood function (3) from Section 3.1 with respect to coefficients β and thresholds α. The key element in the application of the estimation procedure from Section 3.1 is the inclusion of the appropriate number of thresholds α that are to be estimated along with the linear regression coefficients β from (1). In our sample there are three thresholds: the first is between ratings 10 and 11, the second is between ratings 11 and 12, and the third is between ratings 12 and 15. We set the first threshold α1 equal to zero, as is the usual practice,8 and estimated the second and third ones, i.e., α2 and α3. The starting values for the parameters were estimated using a binary logit model on the whole sample.9 The estimation results are presented in Table 2.

The predictors presented in Table 2 were found using the following procedure: we included regressors10 ROA, LEVERAGE, CA, GRR, Credit Spread and TLTA, as described in Table 1, in the pooled regression for banks CS and KB, and selected the statistically significant predictors using the LR test.11 The predictors identified as making a significant contribution to predicting

[8] Setting one threshold to zero does not affect the estimation and interpretation of the estimated thresholds. The meaning of the threshold is in the size of the relative distance to another threshold which remains unaffected by this normalization. Nevertheless, the absolute value would be different if we did not normalize the first threshold at zero, and the estimates would be less efficient. Thus, this adjustment improves the efficiency and power of our significance tests.

[9] The binary logit model defines just one threshold, assumed to be the change from a rating lower than 11 to ratings higher than 11. The binary logit model is represented by a discrete variable that only takes the values one if the latent variable is bigger than the threshold and zero otherwise.

[10] We could not test more variables in this regression as the low number of observations limited us in our data sample.

[11] The LR (likelihood ratio) test is used in discrete choice models for testing the joint insignificance of regressors and is based on the LR statistic, which is equal to $-2(\ln L_R - \ln L_U)$, where L_R and L_U represent the value of the likelihood function under the restricted and unrestricted model respectively.

the S&P rating are Credit Spread, were the ratio of Total Loans to Total Assets and Capital Adequacy. The remaining nonsignificant predictors were excluded from further consideration. The predictors identified on the pooled data set were used as starting values for the MLE using the sum of the partial likelihood functions (3).

Table 2: The S&P Rating Model Estimation

Variable	Time t ($X_{i,t,}$)	Time t-1 ($X_{i,t,-1}$)
Credit Spread	$-339.02^{***}_{(-3.11)}$	$-111.3^{***}_{(-2.77)}$
Capital Adequacy	$0.636^{***}_{(4.08)}$	$0.34^{***}_{(3.69)}$
Total Loans / Total Assets	$10.98^{***}_{(2.24)}$	$5.59^{*}_{(1.62)}$
Threshold	$0.55^{***}_{(2.01)}$	$0.63^{***}_{(2.05)}$
Threshold	$2.27^{***}_{(10.26)}$	$2.15^{***}_{(11.36)}$
Number of observations	76	74
LR – test (p-value)[a)]	$\chi^2_{(3)} = 5.55_{(0.135)}$	$\chi^2_{(3)} = 4.22_{(0.239)}$
Log Likelihood	-23.95	-29.59

Note: *** denotes the 1% significance level, ** the 5% significance level, and * the 10% significance level.
a) The null hypothesis: validity of exclusion of all variables other than the remaining ones.

The predictor selection is, however, to be taken with a certain level of caution, because the established significance of the predictors might be affected by the sample choice and small-sample properties of the estimator. The two large banks that comprise the panel may possess some specific features, since they went through consolidation and privatization during the period covered by the sample. For instance, the bad loan clean-up might have influenced the ratio of Total Loans to Total Assets. Accordingly, the rating improvement and the reduction in the volume of non-performing loans (and, consequently, in the loans in general), which were transferred to the bad loan workout Consolidation Agency, took place during the same period. As a consequence, a decrease in the ratio of Total Loans to Total Assets in our sample leads to an estimated decrease in the probability of downgrade from rating 15 and from ratings lower than 10 to rating 10.[12] That is, historically, a high percentage of bank assets in the form of loans had, prior to the final stage of Czech bank privatization, always meant increasing credit risk for the banks involved.

In the case of Credit Spread, calculated as the difference between the money market rate and interest rate expenses on client deposits, one would intuitively expect that an increase thereof should cause a decrease in the probability of downgrade from rating 15 and from ratings below 10 to rating 10. Similar logic, in terms of the downgrade probability changes, as in the Credit Spread case can be applied to Capital Adequacy.

Furthermore, as can be seen from Table 2, we investigated the time lag value for which the lagged explanatory variables can be considered reliable predictors of the rating at time t. We found that the predictors are statistically significant when one predicts the S&P rating one month in advance.

[12] In the rating intervals between 10 and 12 and 12 and 15, we cannot infer the direction of the influence from the sign of the estimated coefficients, since this will depend on the actual values of the density function.

3.3 Predictions

The predictions are obtained from the probabilities of the individual rating values conditioned on the observed variables X. These variables are the indicators listed in Table 1. Specifically, taking the current values X of the observed indicators as the most recent information at hand, we can write the probability that a bank will have rating a in the current period as $P(S\&P_t=a|X_t)$. If we can only condition on the observed variables in time t-1, then the probability, conditioned on the most recent available information, that a bank has rating a at time t is equal to $P(S\&P_t=a|X_{t-1})$. We constructed the model's predictions of the past rating values in order to evaluate the performance of its predictions. Using the selected predictors we derived the conditional probability of each rating level in each point in time for the sample of two banks. The probabilities of having the S&P rating equal to 10, 11, 12 and 15 (values of 13 and 14 do not appear in the sample) are:

$$
\begin{aligned}
P(S\&P &= 10|X_i)=P(y^*\leq 0|\, X_i)=\Lambda(-X_i\, b)\\
P(S\&P &= 11|\, X_i)=P(0\leq y^*\leq a_2|\, X_i)=\Lambda(a_2-\, X_i\, b)-\Lambda(-X_i\, b)\\
P(S\&P &= 12|\, X_i)=P(a_2\leq y^*\leq a_3|\, X_i)=\Lambda(a_3-\, X_i\, b)-\Lambda(a_2-\, X_i\, b)\\
P(S\&P &= 15|\, X_i)=P(y^*>a_3|\, X_i)=1-\Lambda(a_3-\, X_i\, b),
\end{aligned}
$$

where a, b denote the estimated coefficients, X_i is the matrix of explanatory variables for bank i=1,...,n and α_{j}, for j=1,...,N and β are estimated parameters. The predictions of the rating level for CS and KB are presented in Figures 1.1–1.4 (observations 1 to 76). The actual rating value is represented in the same figure by a probability equal to one if at that time the rating was equal to the value shown on the respective Figure, and zero otherwise.

In addition, Figures 2.1–2.4 (observations 1 to 76) show conditional probabilities of the rating level in the case of our predicting it one month in advance (i.e., using the values of the explanatory variables from the current month we could predict the rating in the future month).[13]

As can be seen from Figures 1 and 2 (observations 1 to 76), the highest performance of the model is manifested in its ability to discriminate between ratings 10, 11, and 12 and higher.[14] The rating level is predicted satisfactorily using the model with one month lagged explanatory variables in comparison with the current period explanatory variables (see Figures 1 and 2). In other words, it is not necessary to know the actual explanatory variables to make a reasonable prediction of how a bank is rated now. The rating prediction can be effectuated by selecting the value with the highest conditional probability. In this way, we are able to predict 69.7% of the S&P rating levels correctly. Alternatively, one could take the conditional mean and round off to the nearest integer rating value. The evaluation of the conditional mean forecast is given by:

$$CMF_t^i = \sum_{a=10,\ldots,15} AP(S\&P_t=A|X_t^i) \qquad (4)$$

[13] Where the X_{t-1}^i is the matrix of the explanatory variables for the bank i, and a, b (see Table 2) are estimated parameters corresponding to the specification with X_{t-1}^i.

[14] In order to obtain the prediction of a probability of rating 12 and more, we can sum up the probability predictions $P(S\&P=12|X_i)$ and $P(S\&P=15|X_i)$. (Recall that ratings 13 and 14 were not observed in the sample). The predictions obtained from X_{t-1}^i would be treated similarly.

where CMF_t^i denotes the conditional mean forecast of the rating level of bank i, A represents the rating value and $P(S\&P=A| X_t^i)$ denotes the conditional probability that the S&P rating of the bank i takes the value a, on the verified regressors X_t^i .[15]

The simulation of the conditional mean forecast can be found together with the actual rating values in Figures 3.1 and 3.2.

3.4 Out-of-Sample Prediction

As we could not use the data for Československá obchodní banka (CSOB) for improving our estimates (there was no change in the rating during the investigated period), we used the data for the out-of-sample predictions. This was done under the presumption that the latent variable thresholds found when the model was estimated are appropriate to use in the predictions for all three banks. This cannot be generally applied to any arbitrary bank rating prediction in the cardinal sense, because the latent variable thresholds are specific for every bank, reflecting the heterogeneity of banks. Therefore, the out-of-sample predictions should be helpful only in predicting relative changes (i.e., stability, downgrade or upgrade). Up to a certain scaling factor we can conclude that the predictions are reliable, as our model predicted the rating stability for CSOB for the whole prediction period (see Figures 1 and 2, observations 77 to 90). The situation becomes even more pronounced when one uses the conditional means as presented in Figure 3.1 (observations 77 to 90). Similarly, Figure 3.2 (observations 77 to 90) shows the conditional mean predictions one month ahead. Although, formally, the rating is predicted as a constant different from the actually observed one, our predictive ability criterion is based on the correct prediction of the change vs. no-change event (and, had the change occurred, of its direction and size), so that the specific predicted rating level is not essential.

4. CAMELS Rating

In the case of the CAMELS rating we estimated the impact of the explanatory variables on the rating using panel estimation on quarterly data on two banks, Česká Spořitelna (CS) and Komerční Banka (KB), in 1998–2001. Although it would have been possible to use the observations to increase our sample and improve the estimates, we reserved the data on Československá Obchodní Banka (CSOB) for the out-of-sample predictions in order to have a parallel comparison with the S&P rating.

4.1 Estimation and Testing

When estimating the panel data structure we investigated which variables significantly contribute to explaining the CAMELS rating. We were also trying to find out whether there is a single common average rating for both banks in the panel over the studied period or whether there are two distinct average ratings. For the latter purpose, a fixed effect model (having an idiosyncratic constant term in the specification for each bank) versus plain ordinary least squares (having just one common constant term for all banks) was tested. We tested the fixed effect vs. random effect model specification using the Hausman test (Wooldridge 2002, p. 288). The unbiasedness and

[15] In the case of CMF_t^i derived from the one month lagged regressors, we use X_{t-1}^i instead of X_t^i in equation (4).

efficiency of our estimates was established by tests for serial correlation, cross-sectional correlation and cross-sectional heteroskedasticity. To decide on cross-sectional correlation, we used the Breusch–Pagan Lagrange multiplier test.[16] In the cross-section heteroskedasticity case we employed the White test.[17] Finally, in the fixed effects case, we used the standard F-test.[18] Additionally we applied a test for the cointegration relation on the regression residuals. We used two tests suggested by Kao in Baltagi (2001).[19]

4.2 Results

The predictors were derived by first including the following regressors: ROA, LEVERAGE, CA, GRR, Credit Spread and TLTA, as described in Table 1, in the regression and second, testing the joint insignificance of the least significant variables.[20]

As the F-test shows (see Table 3, row 12), the probability value of not rejecting the model restrictions justifies the use of the presented parsimonious model. In Table 3 the probability equals 0.47, hence we restrict the model, and the remaining significant predictors, featured in Table 3, are: Value at Risk, Capital Adequacy, and the Total Loans/Total Assets ratio. These variables proved to be significant predictors of the CAMELS rating.

In the case of Capital Adequacy, an increase of one unit creates a decrease in the CAMELS rating of 0.052 units. Similarly, in the VaR case, a unitary increase in the critical loss value causes an increase in the CAMELS rating of 2.28 units. Finally, an increase in the Total Loans/Total Assets ratio causes an increase in the CAMELS rating.[21]

As can be seen from Table 3, the fixed effect model proved to be superior to both the plain ordinary least squares (OLS) and the random effect model. Testing the fixed effects model against the OLS alternative shows that the probability of not rejecting the null hypothesis when it is not valid, i.e. erroneously concluding that the fixed effect model applies instead of plain OLS, is equal to 0.01. When we pit the fixed effect model against that random effect one, the probability of not rejecting the null hypothesis when we should have done so, i.e. falsely inferring that the fixed effect model is superior to the random effect model, is equal to 0.02.

---

[16] The Lagrange Multiplier test statistic is $\lambda_{LM} = T\sum_{i=2,\dots,N}\sum_{j=1,\dots,i-1} r_{ij}^2$, where r_{ij}^2 is the ij[th] residual correlation coefficient, calculated using OLS residuals. N=2 is the number of banks in the panel. The null hypothesis (H0, see Table 3 below) in this test is no cross-sectional correlation.

[17] The White test statistic: $LM=(T/2)\sum_i[((s_i^2)/(s^2))-1]^2$, where s^2 is the variance of the OLS residuals. The null hypothesis is no cross-sectional heteroskedasticity.

[18] $F_t=(((SSRR-SSRU)/R)/(SSRU/(n-k))) \sim F(R,n-k)$, where R is the number of restrictions and k is number of regressors in the unrestricted model (in the presented model, R=1 and n-k=19). SSR stands for the sum of squared residuals. The null hypothesis is no fixed effect.

[19] The first Dickey Fuller test statistic is defined as $DF1=(((\sqrt{N}T(\rho-1)+3\sqrt{N})/(\sqrt{(10.2)})))$, whereas the second one is defined as $DF2=\sqrt{(1.25)}t_\rho+\sqrt{(1.875N)}$, where N is the number of cross-section units (2 in this model), T is the time range for one cross section, ρ is the coefficient of the pooled residual autoregression and $t_\rho = (((\rho-1)\sqrt{(\sum_{i=1,\dots,N}\sum_{t=2,\dots T}e_{i,t-1}^2)})/((1/(NT))\sum_{i=1,\dots,N}\sum_{t=2,\dots,T}(e_{i,t}-\rho e_{i,t-1})^2))$; for details see Baltagi (2001).

[20] The test statistic is $F_t=(((SSRR-SSRU)/R)/(SSRU/(n-k))) \sim F(R,n-k)$, where R is the number of restrictions and k is number of regressors in the unrestricted model. In the presented model, R=3 and n-k=16. SSR stands for the sum of squared residuals.

[21] Note: an increase in the CAMELS value denotes a downgrade of the rating.

Table 3: The CAMELS Rating Model Estimation

Variable	Time t
VaR (Total Assets)	$-2.28^{*}_{(-1.83)}$ a)
Capital Adequacy	$-0.0524^{*}_{(-1.74)}$ a)
Total Loans / Total Assets	$1.344^{**}_{(2.1)}$ a)
Fixed effects CS, KB	2.84, 2.41
Fixed effects test	$F(1,19) = 8.01^{***}_{(0.01)}$ b)
Random vs. fixed effects	$\chi_{TS}{}^{2}{}_{(1)} = 5.6^{***}_{(0.02)}$ b)
Cross-sectional heteroskedasticity	$\chi_{TS}{}^{2}{}_{(2)} = 0.54_{(0.76)}$ b)
Cross-sectional correlation	$\chi_{TS}{}^{2}{}_{(1)} = 0.95_{(0.33)}$ b)
Serial autocorrelation (D.W.)	1.7
Number of observations	24
Dickey Fuller Cointegration Tests c)	$-3.57^{***}_{(-2.66)}$ / $-3.41^{***}_{(-2.66)}$
F-test (exclusion of 3 regressors)	$F(3,16) = 089_{(0.47)}$
R^2-adjusted	0.84

Note: *** denotes the 1% significance level, ** the 5% significance level, and * the 10% significance level. a) t-statistics are presented in parenthesis. b) p-values of not rejecting H0 are presented in parenthesis. In the Breusch–Pagan Lagrange multiplier test case, this is the probability of not rejecting the null hypothesis of no cross-sectional correlation. In the White heteroskedasticity test case this is the probability of not rejecting the H0 of no cross-sectional heteroskedasticity. And in the fixed effect test case this is the probability of not rejecting the H0 of no fixed effect. c) The cointegration tests are based on Kao's Dickey Fuller tests in Baltagi (2001), as described in Section 4.1, under the assumption of exogeneity of regressors and errors. In the parenthesis are the DF-critical values at the 1% significance level.

The tests for serial correlation, cross-sectional correlation and cross-sectional heteroskedasticity did not suggest data problems; the probabilities of not rejecting the null hypotheses that there is no heteroskedasticity and no autocorrelation are equal to 0.76 and 0.33 respectively. The cointegration tests proved the cointegration relation at the 1% significance level. The D.W. statistics in Table 3 suggests that there is no serial correlation of residuals. Thus we conclude that our estimators are unbiased and efficient.

4.3 CAMELS Prediction

The estimated coefficients in Table 3 were used to evaluate the model's performance by comparing the model's rating outcome with the actual rating level. The model's fit of the actual data can be seen in Figure 4 (observations 1–23).[22]

The out-of-sample prediction was carried out using the quarterly data for CSOB for the time period 4Q 2000–2001. The results of the model's predictions and the actual rating levels can be seen in Figure 4 (observations 24–28).

[22] Note: the CAMELS rating presented was multiplied by a certain level of trend for the reason of confidentiality of this rating.

5. Conclusion

The conducted analysis had the objective of identifying the determinants of commercial bank ratings in the Czech Republic. We investigated changes in the external Standard and Poors (S&P) long-term rating and the CAMELS (Capital, Assets, Management, Earnings, Liquidity, and Market Risk) rating used by the banking supervisory body of the Czech National Bank. Our sample of banks covers the "large banks" group, specifically, the three biggest commercial banks in the country: Česká Spořitelna (CS), Komerční Banka (KB) and Československá Obchodní Banka (CSOB). The time range considered in the case of the S&P rating was 1998–2001 in monthly periodicity. In the case of the CAMELS rating the time range was the same but was spanned by quarterly data, since the considered CAMELS data have a quarterly reporting periodicity.

Our explanatory variables roughly corresponded to the indicator breakdown into the Capital, Assets, Management, Earnings, Liquidity, and Market Risk categories. Additionally, we used credit spread (represented by the difference between Pribor 3M and cost of funds) and Value at Risk (computed from total assets).

For the S&P ratings we constructed an ordered logit model that accounts for the fact that the observations are independent across the banks but not within each bank. The partial likelihood estimation technique was applied to that model. In the case of the CAMELS rating, we employed a panel data estimation for two banks observed over the whole considered time span and tested first a fixed effects vs. a plain Ordinary Least Squares-model, then a random effect vs. fixed effect model. We also investigated possible sources of inefficiency and biases in the estimates.

For the S&P case we verified, on a sample of two large banks, Credit Spread, Capital Adequacy and the ratio of Total Loans to Total Assets as the rating predictors. Moreover, we found that the period of one month is a time interval within which we can reliably predict the S&P rating using these variables in the group of large banks. In the case of the CAMELS rating we found that each bank has its specific average rating over the sample period and that the predictors are Capital Adequacy, VaR and the ratio of Total Loans to Total Assets. The CAMELS model explains 84% of the variability in the actual data, and similarly the models of the S&P rating demonstrate a predictive accuracy of 70%.

We think that the tested models provide material for addressing a number of policy-relevant questions.

First, do banking sector regulators have an informational advantage over the general public and the markets with regard to bank quality measurement, as summed up by the rating? Or can we, together with Hanousek and Roland (2001), claim that knowledge of the deposit interest rate offered by the bank is sufficient to assess its quality? Our results suggest that, at least in relation to the S&P rating, the exclusive information at the regulator's disposal provides a certain predictive advantage over outside observers (such as rating agencies). This is not so in the CAMELS rating case, since, evidently, an observer who is able to reproduce the construct of CAMELS for a given bank has very much the same information as the regulator.

Second, with regard to the rating's relationship to the bank's credit spread (its cost of funds), can an inverse inference be justified? That is, would one be able to infer a future change in the deposit rate by looking at a changed rating value? Here, the answer seems to be dependent on the systemic nature of the rating change event. An adjustment of deposit rate policy might be an idiosyncratic reaction of an isolated bank experiencing a revision of its specific properties by the markets. In that case, the rating revision may be an unambiguous quantitative expression of the said revision taking place. On the contrary, a rating change for systemic (business cycle, country credibility, etc.) reasons is unlikely to result in a deposit rate adjustment, since the competitive position of the individual bank is not directly at stake. The question cannot be resolved without a broader analysis of the macroeconomic context of the rating event.

Third, a question related to the previous one is whether the monetary authority would and should react with monetary policy measures to the observed rating changes of a major bank or banks under its jurisdiction. Again, the answer depends on the systemic nature (or lack thereof) of the rating event. In the past, the Czech National Bank's tight monetary policy (1997–1999) was often criticized by leading commercial bank representatives on the grounds of prohibitive costs for the sector. And, according to the conventional CAMELS approach, the corresponding rating levels would indeed have been affected by the cost factors hitting both the banks themselves and their borrowers (as can be deduced directly from the construction of the indicators and their significance for both ratings studied in the paper, see Tables 1–3). However, neither the banks' condition nor their ratings caused the high interest rate policy pursued by the central bank in the aftermath of the currency turbulence of mid-1997. The gradual cuts in key rates in subsequent years did take into account the already mentioned cost factors and, in this sense, were linked to the aggregate pattern of financial stability. The latter could be reflected in the outside rating of the leading banks. That is, mutual dependence of monetary policy and banking sector-wide rating levels certainly exists, but results from the dependence on common underlying factors, real and financial, and cannot be reduced to a simple causal relationship.

This specific conclusion about the predictors in the context of the Czech banking sector is, however, to be taken with caution due to the fact that the period covered by the data is one during which significant changes took place in the balance sheet structure, ownership and loan management practices of the banks involved. Hence, the conducted analysis primarily provides an illustration of how the determinants of rating changes can be identified in a particular period of denationalization of the large banks. Thus, the utilization of the model for predictions in the future is conditional on sequential testing of the ratings' predictors, which might be different from those verified in this analysis, as new observations about the rating changes become available.

References

BACK, B., T. LAITINEN, K. SERE, AND M. VAN WEZEL (1996): "Choosing Bankruptcy Predictors Using Discriminant Analysis, Logit Analysis, and Genetic Algorithms," Turku Centre for Computer Science, *Technical Report* No. 40.

BALTAGI, BADI H. (2001): *Econometric Analysis of Panel Data*, John Wiley & Sons Ltd., England.

COLE, R.A., AND J.W. GUNTHER (1998): "Predicting Bank Failures: A Comparison of On- and Off-Site Monitoring Systems," *Journal of Financial Services Research* 13 (No.2), pp.103–117.

COLE, R. A., B. G. CORNYN, AND J. W. GUNTHER (1995): "FIMS: A New Monitoring System for Banking Institutions," *Federal Reserve Bulletin*, Washington, Vol. 81, No. 1.

CZECH NATIONAL BANK (2001): *Banking Supervision Report*, CNB.

DERVIZ, A., AND N. KADLČÁKOVÁ (2001): "Methodological Problems of Quantitative Credit Risk Modeling in the Czech Economy," Prague: *Czech National Bank Working Paper Series*, No. 39.

DERVIZ, A., AND N. KADLČÁKOVÁ (2002): "Strategic Outcomes of Credit Negotiation and Prudential Capital Regulations," Prague: *CERGE-EI Discussion Paper* No. 2002-82 (March).

DUFFIE, D., AND K. SINGLETON (1997): "An Econometric Model of the Term Structure of Interest Rate Swap Yields," *Journal of Finance* 52, pp. 1287–1321.

GILBERT, R. A. (1993): "Implications of Annual Examinations for the Bank Insurance Fund," *Federal Reserve Bank of St. Louis Review* 75 (No. 1), pp. 35–52.

GILBERT, R. A., A. P. MEYER, AND M. D. VAUGHAN (2000): "The Role of a CAMEL Downgrade Model in Bank Surveillance," *Federal Reserve Bank of St. Louis Working Paper Series*, WP 2000-021A.

HANOUSEK, J., AND G. ROLAND (2001): "Banking Passivity and Regulatory Failure in Emerging Markets: Theory and Evidence from the Czech Republic," *CERGE Working Papers Series*, WP 192., Prague.

HENEBRY, K. L. (1997): "A Test of the Temporal Stability of Proportional Hazard Models for Predicting Bank Failure," *Journal of Financial and Strategic Decisions*, Vol. 10, No. 3.

JARROW, R., AND S. TURNBULL (1995): "Pricing Derivatives on Financial Securities subject to Credit Risk," *Journal of Finance* 50, No. 1, pp. 53–85.

LELAND, H. (1994): "Corporate Debt Value, Bond Covenants, and Optimal Capital Structure," *Journal of Finance* 49, No. 4, pp. 1213–1252.

LONGSTAFF, F., AND E. SCHWARTZ (1995): "A Simple Approach to Valuing Risky Fixed and Floating Rate Debt," *Journal of Finance* 50, pp. 789–819.

MERTON, R. (1974): "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance* 29, pp. 449–470.

SHUMWAY, T. (1999): "Forecasting Bankruptcy More Accurately: A Simple Hazard Model," http://www-personal.umich.edu/~shumway.

STANDARD AND POORS RATINGS: http://immediateannuities.com/ratings/sp.htm.

WOOLDRIDGE, J. M. (2002): *Econometrics Analysis of Cross Section and Panel Data*, MIT Press, Cambridge, London, 2002.

Appendix

Figure 1: S&P Rating: Current Period Regressors

Figure 1.1: Rating 10, Regressors time t

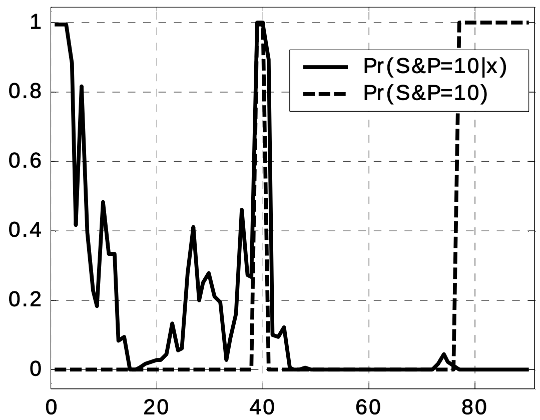


Figure 1.2: Rating 11, Regressors time t

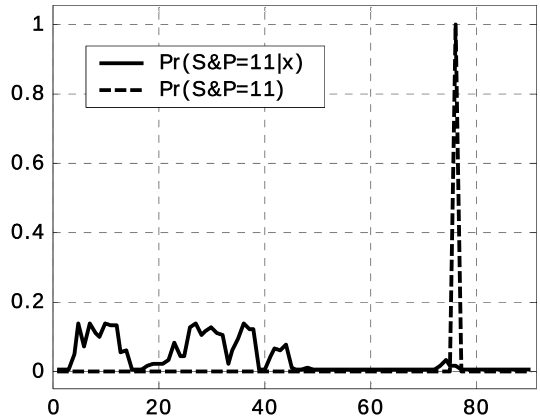


Figure 1.3: Rating 12, Regressors time t

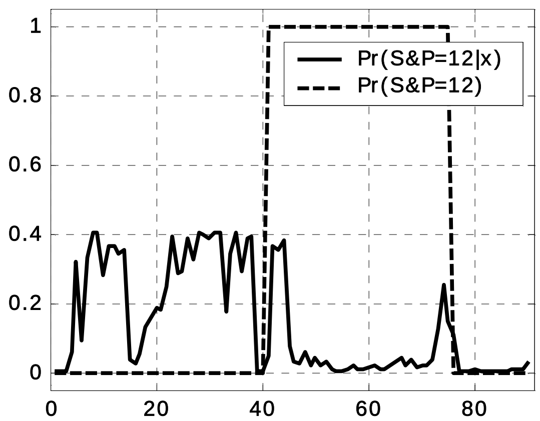


Figure 1.4: Rating 15, Regressors time t

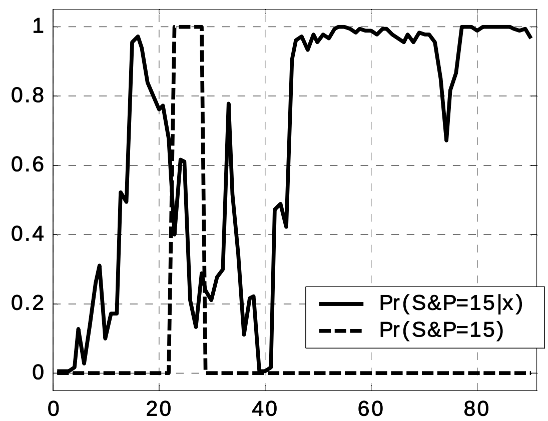


Figure 2: S&P Rating: One Period Lagged Regressors

Figure 2.1: Rating 10, Regressors time t-1

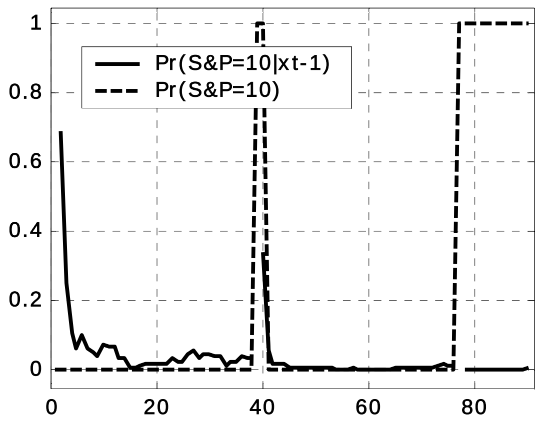


Figure 2.2: Rating 11, Regressors time t-1

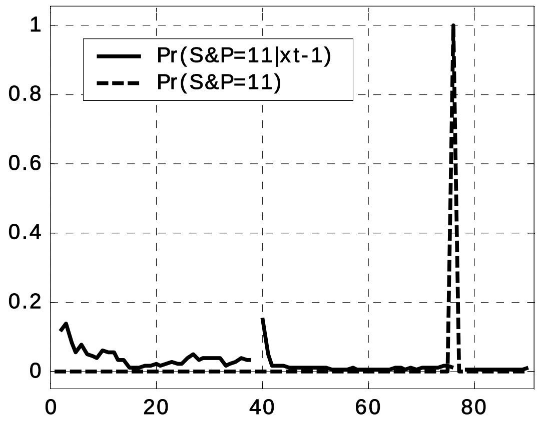


Figure 2.3: Rating 12, Regressors time t-1

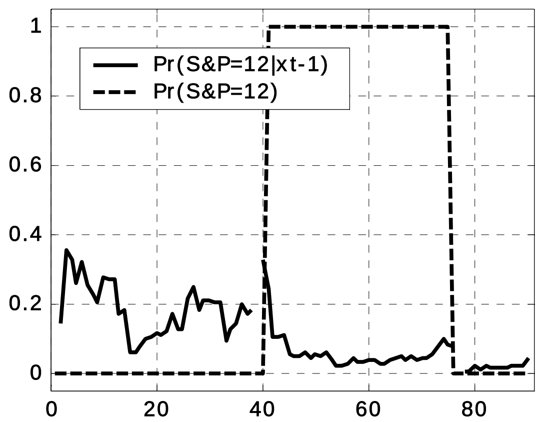


Figure 2.4: Rating 15, Regressors time t-1

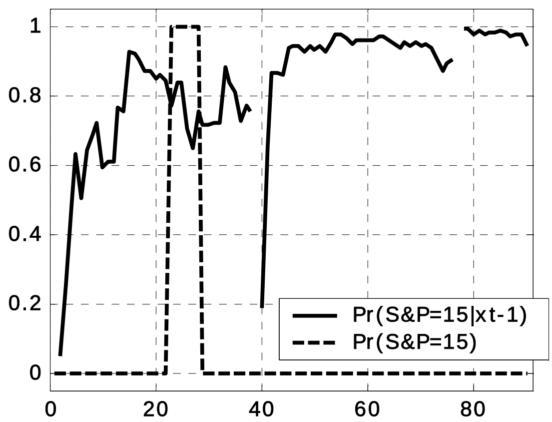


Figure 3: S&P Rating: Conditional Mean Forecast

Figure 3.1: Conditional Mean Forecast, Regressors time t

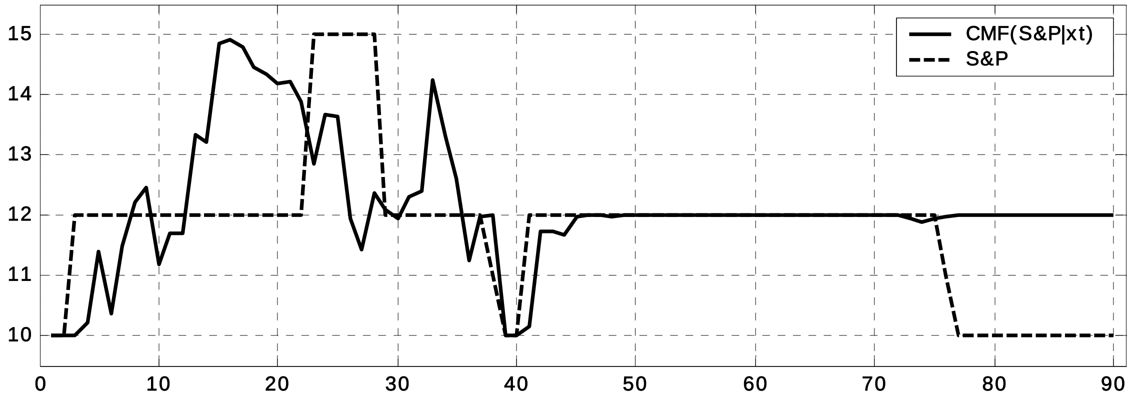


Figure 3.2: Conditional Mean Forecast, Regressors time t-1

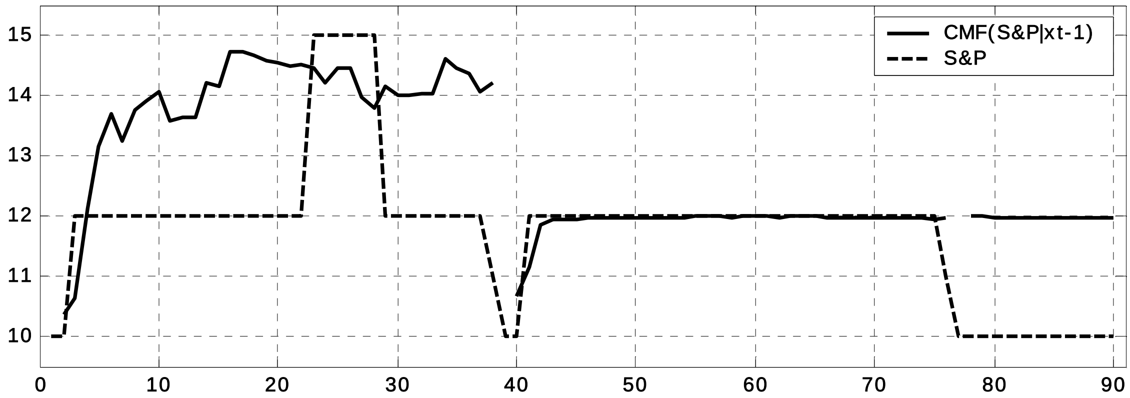
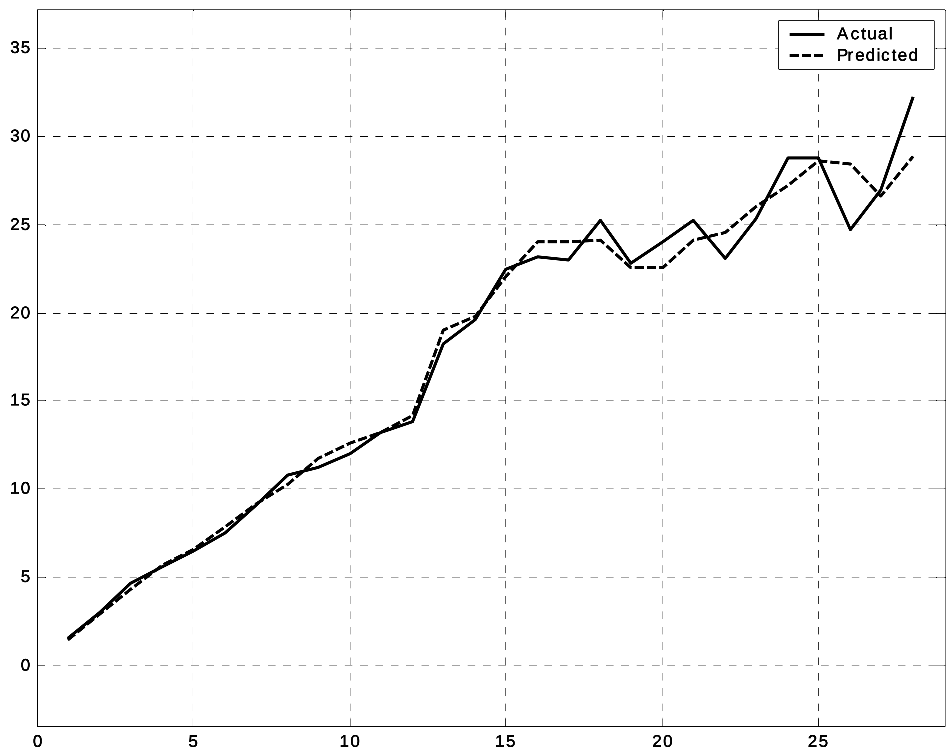


Figure 4: CAMELS Rating

Figure 4: CAMELS Rating (multiplied by a trend), time t



CNB Working Papers Series

1/2004	Alexis Derviz: Jiří Podpiera	*Predicting Bank CAMELS and S&P Ratings: The Case of the Czech Republic*
12/2003	Tibor Hlédik:	*Modelling the second-round effects of supply-side shocks on inflation*
11/2003	Luboš Komárek: Zdeněk Čech Roman Horváth	*ERM II membership – the view of the accession countries*
10/2003	Luboš Komárek: Zdeněk Čech Roman Horváth	*Optimum currency area indices – how close is the Czech Republic to the eurozone?*
9/2003	Alexis Derviz: Narcisa Kadlčáková Lucie Kobzová	*Credit risk, systemic uncertainties and economic capital requirements for an artificial bank loan portfolio*
8/2003	Tomáš Holub: Martin Čihák	*Price convergence: What can the Balassa–Samuelson model tell us?*
7/2003	Vladimír Bezděk: Kamil Dybczak Aleš Krejdl	*Czech fiscal policy: Introductory analysis*
6/2003	Alexis Derviz:	*FOREX microstructure, invisible price determinants, and the central bank's understanding of exchange rate formation*
5/2003	Aleš Bulíř:	*Some exchange rates are more stable than others: short-run evidence from transition countries*
4/2003	Alexis Derviz:	*Components of the Czech koruna risk premium in a multiple-dealer FX market*
3/2003	Vladimír Benáček: Ladislav Prokop Jan Á. Víšek	*Determining factors of the Czech foreign trade balance: Structural Issues in Trade Creation*
2/2003	Martin Čihák: Tomáš Holub	*Price convergence to the EU: What do the 1999 ICP data tell us?*
1/2003	Kamil Galuščák: Daniel Münich	*Microfoundations of the wage inflation in the Czech Republic*
4/2002	Vladislav Flek: Lenka Marková Jiří Podpiera	*Sectoral productivity and real exchange rate appreciation: Much ado about nothing?*
3/2002	Kateřina Šmídková: Ray Barrell Dawn Holland	*Estimates of fundamental real exchange rates for the five EU pre-accession countries*
2/2002	Martin Hlušek:	*Estimating market probabilities of future interest rate changes*
1/2002	Viktor Kotlán:	*Monetary policy and the term spread in a macro model of a small open economy*

Czech National Bank
Economic Research Department
Na Příkopě 28, 115 03 Praha 1
Czech Republic
phone: +420 2 244 12 321
fax: +420 2 244 14 278
e-mail: eva.grenarova@cnb.cz