Credit Ratings and Bank Monitoring Ability

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Abstract

In this paper we use detailed credit rating data from two Swedish banks to elicit evidence on these banks' loan monitoring ability relative to the Swedish credit bureau. We test the banks' abilility to forecast the credit bureau's ratings and show, using ordinary least squares and ordered probit regressions, that one of the banks is a better monitor than the credit bureau. This is evidence that bank credit ratings can be a reasonable basis for risk management and represents a new basket of straightforward techniques that can allow intermediaries and regulators to assess the performance of credit ratings systems.

1 Introduction

In this paper we develop and test a method for quantifying the ability of a bank to monitor its commercial loans, using the bank's credit rating to forecast the credit ratings of a public monitor, in this case a credit bureau. We assume that both the bank's credit rating and the public monitor's credit rating are that institution's estimate of the creditworthiness of the borrower.

Banks' internal credit ratings, taken as a group, summarize the risk characteristics of the bank loan portfolio. They are used by the bank to manage the bank's overall risk, and, under the Basel II accord, used as the fundamental building blocks of efforts by regulators to measure the bank's risk and therefore the capital required for safe operation of the bank. In addition, credit ratings are typically used to monitor the effectiveness of individual loan officers. These credit ratings can also be viewed as potential evidence of the private information possessed by banks, private information that reduces the liquidity of loans but also gives the bank a special value as a lender. Treacy and Carey (2000) and English and Nelson (1998) describe U.S. bank credit rating systems and Jacobsen et al (2003) Swedish bank credit rating systems; these two descriptions are enough alike so that we may perhaps speak of bank credit rating systems, at least of developed economies, in general.

Banks are not the only providers of credit ratings. Credit bureaus and bond rating agencies also provide credit ratings for businesses; these are public information, which ought to be impounded into the banks' credit ratings. If the bank has private information which it obtains in its role as a loan monitor, one would expect the bank's credit ratings to be superior to those of the credit bureau or bond rater in evaluating the performance of loans.

Is it possible to empirically demonstrate the informational superiority of bank credit ratings over public alternatives? Research has been extensive in this area, since Fama (1985) put forth the hypothesis that banks were special relative to alternative lenders, for example, Lummer and McConnell, 1989. Mester et al (2004) describe details of bank monitoring – based on bank access to borrowers' transaction accounts – that may make banks superior monitors of loans. Here we focus on the relative information of banks and credit bureaus. We discuss and implement a test that is applicable to the full range of credit ratings.

One test of the validity of credit ratings is if they contain information useful to forecast defaults. There is an extensive body of work on bond credit ratings, for example, that test the value of bond ratings relative to other financial data in forecasting defaults, interest rate spreads, and portfolio governance. For a summary of recent research on credit ratings, see Cantor,2004. We plan to pursue this route by testing the ability of the private bank ratings and the credit bureau to forecast defaults, but we have not yet done so. This test focuses of necessity on the riskier end of the credit risk spectrum. It is also a test that has relatively low power, as defaults occur relatively seldom, and tend to bunch temporally. Another possible objection to the use of defaults as a measure of bank information is that defaults may be endogenous; the bank's belief that the borrower's creditworthiness has fallen may cause it to reduce the borrower's access to credit and raise the likelihood of default.

This paper is focused on a new test, one that emphasizes the forecasting power of informationally superior estimates of creditworthiness. Our fundamental model is that each borrower has an underlying creditworthiness, which we model as a variate that follows a random walk with normal disturbances. We think of creditworthiness as being a monotonic transform of the probability of default, even though as Loffler(2004) and Altman and Rijken (2004) argue, credit ratings may have a more complex objective than summarizing credit risk.

There are two monitors: a private monitor, the bank, and a public monitor, the credit bureau. Our monitors receive noisy signals on the random walk. The public monitor receives a public signal. The bank receives the public signal but also a private signal.

Each monitor processes its signals to estimate a borrower's creditworthiness optimally, using a Kalman filter. The continuous processed signal is aggregated into a discrete categorical rating. A consequence of the aggregation (we do not have a good rationale for why this aggregation takes place) is that some of the information in the continuous credit rating is lost.

What we want to show is that the banks learn information about the borrower that is not in the public signal. This private information implies more precise information which enables these monitors to learn more quickly about changes in the borrower's creditworthiness. Formally, the Kalman filter of a monitor who obtains a signal with greater precision places greater weight on recent signals than the filter of a monitor whose obtains a less precise signal.

This implies that the banks should be able to forecast movements in the public monitor's signal.

At the same time, the public monitor's signal should not be able to forecast the banks' signals, since all the information in the public monitor's signal is already embedded in the banks' signal. Thus if we possessed the underlying continuous optimally processed signals, then we would have clean tests for the private information of the banks: the banks credit signal should forecast (Granger cause) the public monitor's signal, but not vice versa.

Unfortunately, the same does not hold true, even approximately, for credit ratings if the number of baskets into which the credit ratings are demarked is small, that is, less than 10. We show this using simulations in which the underlying creditworthiness of borrowers follows a random walk. As a consequence, one would expect that the public monitor will in fact forecast the bank credit signal, and we cannot obtain clean Granger causality tests.

We thus propose an alternative test, which is whether the bank's forecasts are more informative than the public monitor's. This amounts to a test of whether bank's credit rating is more useful in forecasting the public monitor's credit rating than vice versa.

2 Model:

We use the Kalman filter to obtain Muth's formula on exponentially weighted lags of past signals. A borrower's creditworthiness, y_t, which is a continuous, normal function of its probability of default, is modeled as a random walk.

We characterize monitor i's optimal expectation of creditworthiness at time t ($y_{t|t}$) as a function of the noisy signal(s) observed by the monitor (s_{it}). (Underlying creditworthiness is shifted permanently each period by a shock, u, and the noisy signal observed has temporary noise η.) We show that this function is an exponentially weighted lag of past signals, with a base coefficient (d_i) that is in turn determined by the relative noise of the monitor's signal ($q_i \equiv \frac{\sigma_u^2}{\sigma_{i\eta}^2}$). In the relevant range, a doubling of the relative noise lowers d_i by 10 percent.

Assume:

y_t, the underlying, unobservable creditworthiness of the borrower at time t, follows a random walk

$$y_t = y_{t-1} + u \tag{1}$$

$u_t \sim N\left(0, \sigma^2\right)$

y_t is not observed directly. Monitor c, the credit bureau, observes a noisy, public signal, s_{ct}:

$$s_{ct} = y_t + \eta_{ct} \tag{2}$$

$\eta_{ct} \sim N\left(0, \sigma^2/q_c\right)$

q_c is the relative precision of the observation noise with respect to the disturbance terms on the random walk

The credit bureau's credit rating for the borrower is based on its estimate of creditworthiness, based on its signal:

Define these symbols:

$y_{ct|t} \equiv E\left(y_t|s_{ct}\right)$

$y_{ct|t-1} \equiv E\left(y_t|s_{ct-1}\right)$

$s_{ct|t-1} \equiv E\left(s_{ct}|s_{ct-1}\right)$

If the noise terms are normal then the following regression equation, which the bank uses to update its credit ratings, must be linear:

$$y_{ct|t} = (1-d_c)y_{ct-1|t-1} + ds_{ct} \tag{3}$$

where d is a regression coefficient which we can calculate as:

$d_c = \frac{E\left(y_t - y_{ct|t-1}\right)\left(s_{ct} - s_{ct|t-1}\right)}{E\left(s_{ct} - s_{ct|t-1}\right)^2}$

We can use repeated substitution to obtain Muth's formula:

$$y_{ct|t} = d_c \sum_{i=o}^{\infty} \left(1-d_c\right)^i s_{ct-i} \tag{4}$$

Each period this estimate incorporates a proportion d_c of the current shock u_t and a proportion 1-d of the past shocks u_{t-i}. At time t-1, then 1-d of the future movement of $y_{t|t}$ is forecastable if we know y_{t-1}exactly.

It can be shown that (Chow,1980):

$$d_c = \frac{q_c}{2}\left(\sqrt{1+4/q_c} - 1\right) \tag{5}$$

The variance of the one period change in forecasts:

$$E\left(y_{t|t} - y_{t-1|t-1}\right)^2 = \sigma^2 \tag{6}$$

Now we show that d rises with q, so that as the noise of the monitor's signal increases, it updates more slowly:

$\frac{\partial \frac{q}{2}\left(\sqrt{1+4/q}-1\right)}{\partial q} = \frac{1}{2}\left(\sqrt{1+4/q} - 1\right) - \frac{1}{q\sqrt{1+4/q}} \propto \left(1 + \frac{4}{q} - \sqrt{1+4/q}\right) - \frac{2}{q} = \left(1 - \sqrt{1+4/q}\right) + \frac{2}{q} > \left(1 - \sqrt{1+4/q+4/q^2}\right) + \frac{2}{q} = 0$

$$\frac{\partial d}{\partial q} > 0 \tag{7}$$

Table of values of d as a function of q, using (5):

q	3.2	1	0.27	.05	.011	.026	.00064
d	.8	.5	.4	.2	.1	.05	.025

As q becomes small, d falls in half when q falls by three-quarters – doubling the standard deviation of the signal noise cuts the rate of updating by one-half.

These equations summarize the results for a single, public signal such as that received by the credit bureau. The bank observes the same public signal as the credit bureau and in addition a noisy, private signal, s_{pbt}:

$$s_{pbt} = y_t + \eta_{pbt} \tag{8}$$

$\eta_{pbt} \sim N\left(0, \sigma^2/q_{pb}\right)$

The bank then aggregates the two signals it receives in proportion to their precisions, q_i,to form a composite signal,

$s_{bt} = \frac{q_{pb}s_{pbt}+q_c s_{ct}}{q_{pb}+q_c} = y_t + \eta_{bt}$

where $\eta_{bt} = \frac{q_{pb}\eta_{pbt}+q_c\eta_{ct}}{q_{pb}+q_c}$

$\eta_{bt} \sim N\left(0, \sigma^2/q_b\right)$

and

$q_b = q_{pb} + q_c$.

The composite signal will then be treated just like the public signal in Muth's formula, that is:

$$y_{bt|t} = d_b \sum_{i=o}^{\infty} (1-d_b)^i \, s_{bt-i} \tag{9}$$

and

$$d_b = \frac{q_b}{2}\left(\sqrt{1+4/q_b}-1\right) \tag{10}$$

In this case, it is obvious that the public monitor's filtered signal will not forecast the bank's signal, while the bank's filtered signal will not forecast the private monitor's signal. We could then test two necessary (but not sufficient) conditions for optimality: that the bank forecasts the public monitor but not vice versa. This is the standard Granger causality condition, and could be tested using VAR's with one lag on each equation.

Unfortunately, this proposition does not hold true for the credit ratings. Credit bureau forecasts bank credit ratings. Does this necessarily imply suboptimal behavior on the part of the banks? Possibly not. There are two dimensions on which our data depart from the model.

First, credit ratings are updated at different points in time by different monitors. Thus the credit bureau may have updated its credit rating more recently than the bank, allowing it to forecast the bank rating. Our banks tend to update their credit ratings on avaerage once a year.

Second, credit ratings are categorical variables, not continuous variables. In moving from continuous variables to categorical variables, may have lost a lot of information, making the credit bureau data more valuable.

Because the credit ratings are categorical, some of the information that was in the public signal is not in the bank's credit rating. This means that the public monitor's rating provides information that has been lost in the aggregation, and the public monitor's rating can predict the bank's signal, even though the bank is fully aware of the public signal and processes it optimally.

In this case, we shall have to use a weaker necessary condition for optimality, that the informational content of the bank's credit rating is greater than that of the public monitor. Relying on the fact that the informational content can be normalized because both are efforts to estimate the same underlying variable, namely, the borrower's creditworthiness, and if the signals are being optimally forecast then the underlying filtered signals will have the same variance.

We have been studying this loss of information using simulations. For the simulations we created a thousand random walks, each with 20 periods, which we think of as being quarters. Each period the random walks, which all start at zero, receive a standard normal shock. The monitors receive signals that include noise: the random walk plus a normal temporary noise. There are two sources of noise: the public signal's noise, and the bank monitor's noise. In the simulations we show here, for example, the public signal noise has a variance of 10, the bank has a private signal with a variance of 2.5. The credit bureau processes a single signal, while the bank combine the public signal with its private signal.

We can then construct the credit bureau and bank signals, and the optimal Kalman filter that goes with them. These continuous signals are contrasted with categorical credit ratings, which are created by aggregating the continuous signals ordinally.The underlying creditworthiness of each borrower has a disturbance term that is a standard normal.

The credit bureau is compared to a bank. The credit bureau's signal has a relative precision of .1. The bank's private signal has a precision of .4, but this is added the credit bureau's signal, so the bank's signal once combined with the credit bureau has precision of .5 (an idiosyncratic variance of 2). To limit the problems associated with the long run increasing variance of the random walk, we focus on one time period, the 20th period. At the 20th period (5 years) the standard deviation of ratings is 4.4 for the bank and 4.2 for the credit bureau. The theoretical s.d. of creditworthiness is $20.5 = 4.472$; the actual s.d. in the sample is 4.4702. The theoretical 4-quarter-ahead expected forecast variance is 4. To permit staggering, we will observe our simulated data at annual (four quarter) frequencies.

In the simulation without staggering and without aggregating signals into rating categories, the lag of the bank rating is highly significant in a regression of the credit bureau rating that includes one lag of the credit bureau ratings. Moreover, the lag of credit bureau is not significant in a regression on the simulated bank credit ratings (Figure 1).

For the next simulation, we stagger the data so that one-fourth of the credit ratings by each monitor are updated each quarter. This has a modest impact on the regression; the coefficient on the lagged credit bureau rating is positive, but small. Thus staggering does not have a large impact, although it does have some impact in making our test less clean.

However, the same does not hold true if we aggregate the signals, even if the data is not staggered. If we break up the signal into 6 evenly spaced categories, and we run the same regression on the bank credit ratings the lagged credit bureau rating becomes both large and significant. The RMSE of forecasts of the bank's credit ratings drops substantially when the lagged credit bureau rating is included.

In the last simulation table, we carve up the simulated data to closely match the shape of the ratings of the credit bureau and of one of the banks described below as bank B, using the staggered data. The regression coefficient on the credit bureau rating is larger, and the RMSE drops even more.

Evidently, coarsening the data by placing it in as many as 6 categories reduces the ability of the ratings to forecast, and thus creates a greater role for the credit bureau variable, even though, as here, the credit bureau does not contain any truly independent information. Conversely, this warns us that the bank credit ratings may appear to contain information when they do not.

The upshot is that we cannot use the one way prediction test (Granger causality) to prove superior information. We have to use a more stringent criterion to demonstrate superior information. We have to rely on *relative* tests that show that the banks ratings have more information (percent reduction in RMSE) to predict the credit union ratings than the credit union ratings *appear to have.*

3 Data

The primary sources of the data are two of the four major Swedish commercial banks, which we shall call Bank A and Bank B, and the leading credit bureau in Sweden, Upplyningscentralen AB, which we shall call the credit bureau (CB). The data set covers the first calendar quarters of the years 1997 to 2000, giving us 1 to 4 observations on roughly 40 thousand borrowers for Bank A and 20 thousand borrowers for Bank B. Borrowers have at least $10 thousand in equity, but many of them, particularly for Bank B are very small. A more complete description of the banks and the credit bureau can be found in Jacobsen et al.

Both institutions maintain an internal credit rating scheme. Bank A assigns each business customer one of 15 credit ratings, while Bank B uses 7 classes (Figures 5 and 6). Class 15 for Bank A and class 7 for bank B are bankruptcy categories. Credit ratings are updated at least once every 12 months, which is our rationale for using data from the first calendar quarter of each year in our regressions. The credit ratings for both lenders are highly concentrated, as is true for U.S. large bank credit ratings. Bank A has some 60 percent of its ratings in its two largest rating categories, while Bank B has roughly the same amount in its largest rating category.

The credit bureau has effectively 6 rating classes (Figure 7). It should be noted that Bank A and Bank B's borrowers are concentrated in the center of their distributions, while the credit bureau's ratings for these same borrowers are concentrated in the top rating. Thus the two sets of ratings appear to be scaled quite differently. Both Bank A and Bank B subscribe to the credit bureau and obtain its ratings for their borrowers. Thus the information in the credit bureau's ratings should be embedded in the ratings of the banks. This will not be completely true for two reasons. One we have discussed above, which is that the credit ratings are not continuous, but divided into buckets which dilute the information in the ratings. The other is that the bank may not have updated its rating after having received the rating from the credit bureau, so that its rating may be stale. We believe, however, based on simulations, that the latter impact is rather small relative to the information loss due to division into buckets.

Many of the loans are quite small, particularly for Bank A. Roughly 60 percent of Bank A's borrowers are small borrowers, defined as having credit lines less than 500 thousand Swedish kroner (SEK) (about US$60 thousand in the time period examined.) About 23 percent of Bank B's borrowers have credit lines this low. Although Bank B has roughly half as many borrowers, its number of large borrowers is nearly as large as Bank A's. As Figure 8 shows, small borrowers represent only a small proportion of the total loan portfolio of either lender.

4 Empirical Results

We have argued that the credit rating of a monitor with a less noisy signal about the underlying creditworthiness of a borrower should forecast the credit rating of a monitor with a noisier signal. This should certainly be true for a bank vis a vis a public monitor whose rating the bank has access to.

In figures 9 through 12 we show the results of regressing the credit ratings of the credit bureau on its lagged rating and then adding a bank's lagged credit rating. In each case, the bank's lagged credit rating is highly significant. We also show the results of regressing each bank's credit ratings on its lagged rating and adding the bureau's lagged credit rating, and vis a vis both banks, the credit bureau's lagged rating is highly significant.

We have argued that, in this situation, the bank's lagged rating should offer more information, that is lower the sum of squared residuals by more. Does this happen?

If we restrict to loans with a credit limit higher than 500 thousand SEK, then the banks do appear to have more information than the credit bureau, although the difference is substantial only for Bank B. But if we use all the data, then Bank A is not a good monitor while Bank B remains a good monitor. We show this using ordinary least square (OLS) and ordered probit regressions.

4.1 Ordinary least square regressions

If we regress (OLS) the credit union ratings on the lag of itself, the RMSE is .87173. If we add the lag of the bank A rating, the RMSE is .86196; that is, RMSE falls by 1.13 percent. On the other hand, the bank A credit rating regressed on the lag of itself has a RMSE of 1.759; adding the credit union rating the RMSE falls to 1.7218, a fall of 2.16 percent. Thus over the entire portfolio, the credit bureau appears to have better information than the bank.

By contrast, lag of the bank B rating reduces the RMSE of the credit bureau rating by 3.6 percent, while the lag of the credit union rating only reduces the RMSE of the bank B rating by 1.7 percent. Thus bank B has better information than the credit bureau.

On the other hand, if we restrict the data set to credits in which the line of credit is 500,000 SEK or greater, then we have somewhat different results. (Note that some restriction is reasonable to the extent that we might expect monitoring to improve risk by 1 or 2 percentage points – so monitoring a loan of 100,000 SEK may only be worth say 2000 SEK.)

The RMSE of the credit bureau rating falls 1.7 percent when we add the lag of bank A's rating, and the RMSE of bank A falls only 1.0 percent when we add the lag of the credit bureau rating. (A further difficulty is that bank A has more credit ratings than either bank B or the credit bureau. We need to see whether bank A's ratings advantage survives aggregation.)

The bank B results scarcely change when we restrict the credits: bank B's lagged credit rating reduces the RMSE of the credit union rating by 3.4 percent while the credit union's lagged credit rating reduces bank B's RMSE by 1.5 percent.

4.2 Ordered probits

Broadly, the results from the ordered probit regressions resemble those in the OLS regressions in the preceding subsection. In line with our earlier findings, we see in Figure 15 that bank A is not a very good rater. A regression of Bank A's rating on its own lag gives a pseudo R2 of approximately .1844. Adding the lagged information prsent in the bureau rating actually improves the fit, to .1881. The coefficient on both lags is significant, .47 on itself and .13 on the bureau rating

As before, B is a better rater. Regressing its internal ratings on its own lag gives a Pseudo R2 of 0.4459. Adding the bureau rating unlagged to the regression increases leads to a relatively small increase in the fit to .4571. The information in lagged values of its own ratings relatively to that in the public rating is more important than for bank A (a coefficient of 1.98 on itself and .20 on the public rating).

When regressing the bureau rating on its own lags, adding a lag of B's internal credit ratings to the regression increases the regression fit more than adding A. Also, the coefficient on bank B's rating is large relative to that on the public rating: .47 versus .67.

Some differences do occur however. Regressing UC on its own lag gives a Pseudo R2 of 0.1709. Adding lagged values of bank A's ratings increases the regression fit to 0.1820. The estimated coefficients are both significant and the bureau rating is explained to a larger extent by its own lagged values (.69) than bank A (.47).

If we study the smaller loans, in Figure 16, the regression fit is significantly worse for A but better for B. Adding the public rating to a regression on a bank rating still improves the fit, by about .013. The coefficient on a bank's own lagged rating becomes smaller for A, but bigger for B, indicating that especially for smaller firms/loans, bank B does a better rating job than bank A. Bank A contributes less to predicting UC rating than for the bigger loans, while bank B adds informational value in about the same way for smaller and bigger loans. The broad conclusions of the OLS regressions appear to hold for ordered probit regressions.

5 Conclusion

We can argue that we have preliminary evidence that some banks have superior information relative to credit bureaus whose ratings are produced using public information. We also have preliminary evidence that other banks will not necessarily pass this test. We have a technique (forecasting credit bureau ratings) that can be used by banks and regulators to test the validity of bank credit ratings.

This test could also be used with bond ratings for larger commercial credits. The tests discussed so far are preliminary. We shall explore whether these differences between the two lenders are reflected also in their ability to predict default.

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Continuous data simulation of ratings: Better bank					
	Credit Bureau loan ratings			Bank loan ratings	
Constant	.005 (.064)	-.022 (.056)	Constant	-.070 (.064)	-.070 (.064)
Lag 4 Credit Bureau rating	1.009 (.017)	.260 (.045)	Lag 4 Bank rating	1.009 (.017)	1.000 (.049)
Lag 4 Bank rating		.756 (.043)	Lag 4 Credit Bureau rating		.010 (.052)
RSS	4075	3113	RSS	4040	4040
Degrees of Freedom	998	997	Degrees of Freedom	998	997
Adjusted Rsq	.7691	.8235	Adjusted Rsq	.7886	.7884

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Staggered data simulation of ratings					
	Credit Bureau loan ratings			Bank loan ratings	
Constant	.061 (.065)	.047 (.055)	Constant	-.038 (.061)	-.068 (.060)
Lag 4 Credit Bureau rating	1.005 (.018)	.325 (.037)	Lag 4 Bank rating	.995 (.015)	.852 (.038)
Lag 4 Bank rating		.695 (.035)	Lag 4 Credit Bureau rating		.166 (.041)
RSS	4260	3039	RSS	3731	3669
Degrees of Freedom	998	997	Degrees of Freedom	998	997
Adjusted Rsq	.7659	.8328	Adjusted Rsq	.8068	.8097

Categorical data simulation of ratings					
	Credit Bureau loan ratings			Bank loan ratings	
Constant	.136 (.083)	.113 (.078)	Constant	.213 (.083)	.135 (.0)
Lag 4 Credit Bureau rating	0.926 (.020)	.414 (.049)	Lag 4 Bank rating	.898 (.019)	.603 (.049)
Lag 4 Bank rating		.533 (.047)	Lag 4 Credit Bureau rating		.334 (.051)
RSS	5601	4954	RSS	5644	5409
Degrees of Freedom	998	997	Degrees of Freedom	998	997
Adjusted Rsq	.6791	.7159	Adjusted Rsq	.6819	.6948

Staggering plus categorical data simulation of ratings					
	Credit Bureau loan ratings			Bank loan ratings	
Constant	.274 (.047)	-1.36 (.132)	Constant	.402 (.091)	.943 (.103)
Lag 4 Credit Bureau rating	0.907 (.021)	.610 (.030)	Lag 4 Bank rating	.893 (.019)	.637 (.034)
Lag 4 Bank rating		.571 (.044)	Lag 4 Credit Bureau rating		.226 (.023)
RSS	457.5	390.5	RSS	263.0	240.1
Degrees of Freedom	998	997	Degrees of Freedom	998	997
Adjusted Rsq	.6612	.7106	Adjusted Rsq	.6021	.6363

Bank A loans with credit bureau ratings			
Rating	Number of Loan/years	Frequency	Cumulative
1	55	0.06	0.06
2	222	0.24	0.30
3	361	0.39	0.69
4	762	0.83	1.52
5	8,655	9.39	10.91
6	9,556	10.37	21.27
7	6,306	6.84	28.11
8	10,926	11.85	39.96
9	27,348	29.66	69.63
10	7,442	8.07	77.70
11	12,216	13.25	90.95
12	4,282	4.64	95.60
13	1,906	2.07	97.66
14	849	0.92	98.59
15	1,304	1.41	100.00
Total	92,190		

Bank B Credit Ratings with Credit Bureau rating			
Rating	Number of Loan/years	Frequency	Cumulative
1	38	0.08	0.08
2	1,268	2.63	2.71
3	12,232	25.41	28.12
4	28,267	58.71	86.84
5	5,029	10.45	97.28
6	655	1.36	98.64
7	654	1.36	100.00
Total	48,143		

Credit Bureau Ratings of Bank A Loans			
Rating	Number of Loan/years	Frequency	Cumulative
1	43,033	46.68	46.68
2	22,373	24.27	70.95
3	15,477	16.79	87.74
4	5,879	6.38	94.11
5	3,383	3.67	97.78
6	2,045	2.22	100.00
Total	92,190		

Credit Bureau Ratings of Bank B Loans			
Rating	Number of Loan/years	Frequency	Cumulative
1	18,621	38.68	38.68
2	12,893	26.78	65.46
3	10,458	21.72	87.18
4	3,487	7.24	94.42
5	1,976	4.10	98.53
6	708	1.47	100.00
Total	48,143		

Small Loans represent a very small part of total loan portfolio, but for Bank A the preponderance of borrowers Loans Outstanding, utilized credits, average over 4 years					
	Total Loans			Total Borrowers	
	All Borrowers	Large Borrowers (credit limit greater than 500K SEK—about $60,000)	Small Borrowers (credit limit less than 500K SEK)	No of large borrowers	No of small borrowers
Bank A	116 B SEK	115 B SEK	1.4 B SEK	10141	15142
Bank B	135 B SEK	134 B SEK	0.9 B SEK	10320	2848

Regressions with all borrowers, Credit Bureau (CB) and Bank A				
	Credit Bureau Rating		**Bank A Rating**	
constant	.621 (.0070)	.193 (.014)	2.971 (.0279)	2.906
Lag of CB rating	.746 (.0031)	.698 (.0033)		
Lag of Bank A rating		.061 (.0017)	.682 (.0032)	.613 (.0066)
Residual Sum of Squares	42662	41710	170809	163526
Degrees of Freedom	56141	56140	56141	56140
Adjusted Rsq	.5101	.5211	.4503	.4737

Regressions with all borrowers, Credit Bureau and Bank B				
	Credit Bureau Rating		**Bank B Rating**	
constant	.831 (.0107)	-.273 (.0264)	.548 (.0144)	.592 (.0142)
Lag of CB rating	.682 (.0045)	.584 (.0049)		.083 (.0026)
Lag of Bank B rating		.342 (.0107)	.872 (.0037)	.816 (.0040)
Residual Sum of Squares	22200	20704	6178	5969
Degrees of Freedom	28472	28471	28472	28471
Adjusted Rsq	.4421	.4797	.6616	.6730

Regressions with borrower’s loan limit greater than 500 thousand SEK, Credit Bureau and Bank A				
	Credit Bureau Rating		**Bank A Rating**	
constant	.772 (.0113)	.218 (.0225)	2.50 (.0393)	2.43 (.0390)
Lag of CB rating	.684 (.0051)	.628 (.0054)		.209 (.0094)
Lag of Bank A rating		.075 (.0026)	.742 (.0043)	.705 (.0046)
Residual Sum of Squares	18457	17851	54729	53607
Degrees of Freedom	23721	23720	23721	23720
Adjusted Rsq	.4278	.4466	.5557	.5648

Regressions with borrower's loan limit greater than 500 thousand SEK, Credit Bureau and Bank B				
	Credit Bureau Rating		**Bank B Rating**	
constant	.871 (.0119)	-.203 (.0293)	.6144 (.0162)	.6440 (.0160)
Lag of CB rating	.658 (.0051)	.568 (.0055)		.0779 (.0030)
Lag of Bank B rating		.332 (.0083)	.854 (.0042)	.805 (.0045)
Residual Sum of Squares	17217	16102	4913	4770
Degrees of Freedom	22888	22887	22888	22887
Adjusted Rsq	.4178	.4555	.6455	.6558

Forecasting Small borrowers' Credit Bureau ratings **Regressions with borrower's loan limit less than 500 thousand SEK**				
	Credit Bureau Rating with Bank A Loans		**Credit Bureau Rating with Bank B Loans**	
constant	.526 (.0088)	.201 (.0176)	.708 (.0247)	-.479 (.0612)
Lag of CB rating	.782 (.0038)	.742 (.0042)	.753 (.0097)	.635 (.0110)
Lag of Bank rating		.049 (.0023)		.371 (.0176)
Residual Sum of Squares	23982	23649	4915	4554
Degrees of Freedom	32418	32417	5582	5581
Adjusted Rsq	.5624	.5685	.5153	.5508

Forecasting Bank Ratings **Regressions with Small Borrowers**				
	Bank A Loan Ratings with Credit Bureau Rating		**Bank B Loan Ratings with Credit Bureau Rating**	
constant	3.327 (.0388)	3.335 (.0375)	.320 (.0315)	.419 (.0313)
Lag of Bank rating	.634 (.0046)	.532 (.0049)	.933 (.0079)	.855 (.0090)
Lag of CB rating		**.428** **(.0090)**		**.095** **(.0056)**
Residual Sum of Squares	**115097**	**107653**	**1248**	**1186**
Degrees of Freedom	32418	32417	5582	5581
Adjusted Rsq	.3734	.4139	.7132	.7273

Table 3. Ordered probit regressions (Loans > SEK 50K)
Pseudo R2 values on the first line are from regression on a variable's own lag only. The value on the line below is from a regression on both variables' lag.

Dependent var.	Explanatory var.	Coef.	Std. Err	Nobs	Pseudo R2
IR_a					
	IRaLag4Q	.4741642	.0040036	22423	0.1844
	IRucLag4Q	.1279965	.0068221		0.1881
IR_b					
	IRbLag4Q	1.981793	.0164653	22428	0.4459
	IRucLag4Q	.2041091	.0087438		0.4571
IR_uc					
	IRucLag4Q	.7045167	.0079334	22423	0.1709
	IRaLag4Q	.0936847	.0035919		0.1820
IR_uc					
	IRucLag4Q	.6730694	.0079892	22428	0.1700
	IRbLag4Q	.4616102	.0115305		0.1968

Table 4. Ordered probit regressions (Loans < SEK 50K)
Pseudo R2 values on the first line are from regression on a variable's own lag only. The value on the line below is from a regression on both variables' lag.

Dependent var.	Explanatory var.	Coef.	Std. Err	Nobs	Pseudo R2
IR_a					
	IRaLag4Q	.2969408	.0029684	33720	0.1083
	IRucLag4Q	.2246348	.0051578		0.1220
IR_b					
	IRbLag4Q	2.039016	.0321812	6046	0.4931
	IRucLag4Q	.2142893	.0162632		0.5062
IR_uc					
	IRucLag4Q	.7993203	.0065298	33720	0.2267
	IRaLag4Q	.0617027	.0030378		0.2320
IR_uc					
	IRucLag4Q	.6739592	.0144093	6046	0.1986
	IRbLag4Q	.4667039	.0220174		0.2238