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CREDIT RATINGS AND BANK MONITORING ABILITY

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Credit Ratings and Bank Monitoring Ability*†

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Abstract

In this paper we use credit rating data from two Swedish banks to elicit evidence on these banks' loan monitoring ability. We do so by comparing the ability of bank ratings to predict loan defaults relative to that of public ratings from the Swedish credit bureau. We test the banks' abilility to forecast the credit bureau's ratings and vice versa. We show that one of the banks has a superior predictive ability relative to the credit bureau. This is evidence that bank credit ratings do contain valuable private information and suggests they may be be a reasonable basis for risk management. However, public ratings are also found to have predictive ability for future bank ratings, indicating that risk analysis should be based on both public and bank ratings. The methods we use represent a new basket of straightforward techniques that enable both financial institutions and regulators to assess the performance of credit ratings systems.

Keywords: Monitoring, banks, credit bureau, private information, ratings, regulation, supervision.
JEL codes: D82, G18, G21, G24, G32, G33

1 Introduction

How can bank managers, investors, bank regulators and other stakeholders know whether a bank is a good monitor? This question has gained in importance since

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the onset of the recent financial crisis, during which a large number of banks around the world have shown to be insufficiently attentive to risks within their portfolios. In this paper we develop and test a method for quantifying the ability of a bank to monitor its commercial loans. We are able to do so by using both internal bank credit ratings and external credit bureau ratings of corporate borrowers and investigating if bank ratings are able to forecast the ratings of the public monitor. If banks collect private information about the borrowers they monitor, as economic theory tells us, in addition to the public information that a credit bureau possesses, and if credit ratings summarize the information included in them, then bank credit ratings should be able to forecast future changes in credit bureau ratings. On the other hand, credit bureau ratings should not be able to predict changes bank ratings.

Diamond (1984) and Fama (1985) first put forth the hypothesis that banks were special relative to alternative lenders: Investors delegate the monitoring of borrowers to financial intermediaries because the latter are more efficient. Then, provided banks are sufficiently large and diversified, lending through such intermediaries dominates direct lending by investors. Research in this area has been extensive. Lummer and McConnell (1989) and Mester, Nakamura and Renault (2007) describe in detail how banks' monitoring activities, by using transaction account information that provides ongoing data on borrowers' activities, makes these intermediaries superior monitors of loans. Another strand of literature has studied what conditions may weaken banks' or other investors' monitoring efforts. Recent work has also shown that screening and monitoring quality by financial intermediaries dropped substantially in the wake of the current financial crisis (Keys, Mukherjee, Seru and Vig,.2009). However, the general notion that financial intermediaries are superior monitors relative to, for example, public alternatives and other investors, remains empirically unchallenged. In particular, the informational superiority of bank credit ratings over public alternatives has not been demonstrated empirically.

The ability of a bank to collect private information and thereby produce a superior judgement of borrowers' expected performance is of relevance not only for regulators and banks, but potentially also for the industrial organization of borrowers and for business cycle theory. Dell'Ariccia and Marquez (2004), for example, have pointed out that informational asymmetries among lenders affect banks' ability to extract monopolistic rents by charging high interest rates. As a result, banks finance borrowers of relatively lower quality in markets characterized by greater information asymmetries. When forced to curtail lending, they reallocate their loan portfolio towards more creditworthy, more captured borrowers. Povel, Singh and Winton (2007) investigate the relation between the cost of monitoring,and reporting fraud incentives for companies across the business cycle. Their work has implications for how carefully financial institutions should scrutinize firms in which they invest and for the gains from increased informativeness of publicly available information.

The focus of this paper is on proposing a new basket of straightforward techniques that enable both financial institutions and regulators to assess the performance of credit ratings systems. We present a new test that emphasizes the forecasting power of informationally superior estimates of creditworthiness We do so by carrying out quantitative tests of the relative informativeness of banks and credit bureaus, as revealed by their credit ratings.[1] In our theoretical model, we have two monitors: a private monitor, i.e. the bank, and a public monitor, i.e. the credit bureau. Both monitors receive noisy signals of the borrower's creditworthiness. The public monitor receives a public signal, while the private monitor receives both a public and a private signal. We think of creditworthiness as being a monotonic transform of the probability of default.[2] and model it as a variate that follows a random walk with normal disturbances. Each monitor processes its noisy signals to make an optimal estimate of the borrower's creditworthiness using a Kalman filter. The output from this estimation, a continuous processed signal, is then reported in a coarsened form as a discrete categorical rating. A consequence of this coarsening is that some of the information in the continuous signal is lost.[3]

While we do not investigate at length if credit ratings are indeed able to forecast defaults, we do assess whether the bank credit ratings are sufficient statistics for forecasting default or whether there is information in the public credit ratings that has not been impounded in the bank ratings.[4] We perform tests of the ability of the two types of ratings to forecast default using semi-parametric Cox proportional hazard regressions; in particular, we can ask if the public credit ratings add information to the bank credit ratings in forecasting default.

A limitation of default forecasts is that they focus, of necessity, on the riskier end of the default risk spectrum. Tests based on such ratings tend to have relatively low power, as defaults occur relatively seldom and tend to bunch temporally (Das, Duffie, Kapadia and Saita, 2007). [5] One additional complication is that the credit bureau is mainly concerned with predicting legal events of

[1] Grunert, Norden and Weber (2005) present information on non-financial factors in internal credit ratings which suggest that judgmental factors are valuable in bank credit ratings, but acknowledge that such information may be obtained by public monitors such as bond rating agencies.

[2] Löffler (2004) and Altman and Rijken (2004) argue that credit ratings may have a more complex objective than summarizing default risk. In our case we know that the sole objective of the bank and credit bureau ratings is to predict counterparty default risk. We will later return to the exact definition of a default.

[3] There is not yet any formalized rationale for why this coarsening takes place.

[4] We do not investigate at length if credit ratings are indeed able to forecast defaults, since there is already an extensive body of work on bond - and other credit ratings that, for example, tests the value of bond ratings relative to other financial data in forecasting defaults, interest rate spreads, and portfolio governance. Cantor (2004) and Krahnen and Weber (2001) contain a summary of and references to recent research in this area. Default forecasts focus, of necessity, on the riskier end of the default risk spectrum. Tests based on such ratings tend to have relatively low power as defaults occur relatively seldom and tend to bunch temporally (Das et al., 2007).

[5] Other potential complications that may occur and need to be addressed when using defaults and default forecasts as a measure of bank information is that they may be endogenous; a bank's belief that a borrower's creditworthiness has fallen or will fall may cause the lender to reduce the borrower's access to credit, thereby raising the likelihood of default. See Carey and Hrycay (2001) for these and other difficulties with ratings.

default and bankruptcy, while banks are more concerned about regulatory definitions of default. For example, banks typically reserve against a credit when loan delinquency extends past 60 days. These two events are closely related, but they are not identical. Credit bureau defaults normally concern legal bankruptcies. In our tests, we use both a credit-bureau-based definition of default and a bank-based definition of default.

Banks' internal credit ratings, taken as a group, summarize the risk characteristics of the bank loan portfolio. Bank managers employ them to manage the bank's overall risk profile and regulators, under the Basel II accord, use them to measure the riskiness of banks and the capital they require for safe operation. Sometimes, credit ratings are used by bank managers to monitor the effectiveness of individual loan officers. Credit ratings can also be viewed as potential evidence of the private information banks possess, i.e., 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 while Jacobson, Lindé and Roszbach (2006) and Krahnen and Weber (2001) do the equivalent for European bank credit rating systems. These descriptions display so many similarities that it appears reasonable to think of a common set of principles underlying bank credit rating systems, at least for developed economies. Banks are not the only providers of credit ratings, however. Other common producers of credit ratings for businesses are credit bureaus and bond rating agencies. These ratings are typically public information, which can and ought to be impounded in the credit ratings produced by banks.

We want to show that the bank, in its role as a loan monitor, acquires information about the borrower that is not in the public signal. This private information should enable the bank to forecast movements in the public signal. In the context of credit ratings, one would expect bank credit ratings to be more precise than those of credit bureaus or bond raters in evaluating the creditworthiness of loans. A more formal way to think about this is that 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 who obtains a less precise signal. Under these conditions the bank has a more precise signal than the public signal because it combines the public signal with additional information. At the same time, the public monitor's signal should not be able to forecast the bank's signal, since all information in the public monitor's signal is embedded in the bank's signal. Thus if one has access to the underlying continuous optimally-processed signals, one would have clean tests at hand for the presence of private information in the bank: a bank's signal of creditworthiness should forecast (Granger cause) the public monitor's signal, but vice versa public signals should not forecast private signals. If the public monitor's credit rating were to forecast the bank's credit rating, then this would constitute prima facie evidence that the bank's credit rating is not a sufficient statistic for the borrower's creditworthiness. Hence regulators should look beyond the bank's credit rating to measure the riskiness of that bank's loan portfolio.

The technique we use here is related to the methodology in Berger, Davies and Flannery (2000), who use vector autoregressions and Granger-causality to compare market and supervisory assessments of bank performance. In particular, they examine bank supervisors' assessments of banks and bond rating agencies ratings, as a test of the relative information of supervisors and rating agencies. However, they do not imbed their tests within an explicit model of information updating as we do. As a consequence, we have tighter tests that are more explicit about the sources of apparent violations of optimal forecasting theory.

We show that both the banks that we study do not pass the stringent test described above mentioned, i.e., the public signal has predictive power for future changes in the private signal. This implies that the banks' credit ratings are not sufficient statistics for their borrowers' creditworthiness.

In our analysis of defaults, where we use a semiparametric Cox proportional hazard model, we find that using both the bank rating and the credit bureau's rating increases the accuracy of default predictions - except for the very largest borrowers. This holds irrespective of whether we define a default using the credit bureau or the bank definition. This reinforces our finding that the bank ratings contain some private information but are not sufficient statistics for their borrowers' creditworthiness.

These findings do not necessarily mean that the banks' underlying continuous signals are not optimal. Since the discretization and coarsening of the ratings can lead to a loss of information, it is possible that one of these transformations of the continuous signals is responsible for the test failure. In simulations we show that if the number of baskets into which the credit ratings are demarked is small, that is, less than 10, then enough information can be lost to cause a test failure. Under such conditions, one would thus expect that a public monitor's rating would, in fact, forecast future bank credit ratings. Hence, with discrete rather than continuous ratings, we cannot always expect to obtain clean Granger causality tests. Our results further suggest that increasing the number of rating grades – while in principle desirable – is not a panacea for these problems. One of the two banks in our sample increased the number of grades in its rating system without increasing the relative informativeness of its ratings.

Our findings demonstrate that the ratings of both banks do forecast movements in the credit bureau rating. We take this to be evidence that each bank has some private information. However, we also provide evidence that credit bureau ratings can forecast the bank ratings. This finding can interpreted in two ways: either the banks fail to incorporate publicly available information optimally or information is lost by the banks in the process of setting their ratings.

As a consequence, it is not optimal for either the banks' risk managers or for their regulator to accept the bank's own private credit ratings as the single measure by which to evaluate of portfolio credit risk. Instead, it would be beneficial to incorporate more information into a risk review. In particular, credit bureau ratings could be used to improve overall portfolio risk evaluation.

We have left it open to further research whether the bank credit rating optimally impounds the credit bureau rating but is too coarse and is updated too infrequently, or if the bank rating is in fact suboptimal. It seems to us possible that the difficulty of adding soft information to hard information in generating credit ratings is greater than has been generally recognized.

The remainder of this paper is organized as follows: In Section 2 we set forth the theory, develop simulations to more closely mimic the underlying rating process, and enunciate our hypotheses. In section 3 we describe the data we use to test the theory. In section 4 we set up a series of tests, including OLS, Ologit, and dummy variable tests, that seek to account for the possibility that the credit ratings may not be linear in risk. Section 5 concludes.

2 Theory

A well-known theory of banking is that banks possess private information about the creditworthiness of borrowers. One channel for obtaining this is information derived from the transaction accounts of borrowers (Mester et al, 2007), which provides a bank lender with uniquely fresh information about the activities of its borrowers. If this theory is true, it follows that banks are uniquely suited to measuring the risks of their borrowers. As a consequence, bank examiners have been encouraged to use banks' internal credit ratings as the best available measure of the risk of the bank loan portfolio. In the language of statistical theory, these credit ratings are taken to be sufficient statistics of the creditworthiness of loans.

In this section we will set forth a simple theory of signal extraction, that describes how producers of credit ratings optimally process different signals of a borrower's creditworthiness. The theory will produce a number of testable implications for the relation between ratings based on publicly available information and ratings based on both publicly and privately obtained information. In Section 2.1 we formulate a simple theoretical model. Section 2.2 contains a description of the testable hypotheses implied by the theoretical model . Later on, n Section 5, we present the results from a number of simulations of the model in Section 2.1. The purpose of these simulations is to create a setting where we can filter out differences in the relative informativeness of public credit bureau ratings and internal bank ratings that may be due to other causes than information collection by banks.

2.1 Model

In our signal extraction model we make three important assumptions. First, we postulate that bank credit ratings are measures of borrowers' creditworthiness, i.e., probability of default. Second, we assume that the creditworthiness of a borrower is unidimensional Our third assumption is that the bank and credit bureau ratings measure the same objective underlying risk of default.

By means of our first assumption we exclude cases where ratings are loan-specific. The second assumption is a common one in credit risk analysis and implies that credit ratings, for example, do not aim at predicting the bank's potential loss experience once a borrower defaults (LGD). In nearly all models of default behavior this has been a starting point, among others because there are, to our knowledge, no formalized theories of loss experience. By the same assumption, we also exclude cases where ratings reflect not only risk but also potential profitability. The last assumption is important because different definitions of a default exist, both within the banking industry and between banks and credit bureaus. A reasonable justification for this assumption is that banks use the ratings of credit bureaus as acceptable measures of borrowers' probability of default (PD), and that bank regulators accept them as such. Given these three assumptions and provided updating occurs at an appropriate frequency we can then think of a bank's credit ratings as intended to capture the riskiness of its loan portfolio at any moment in time.

In the theoretical model we set up below, banks will have private information about the creditworthiness of their borrowers. This information is modeled as a noisy signal that the bank receives. We then show that, if a bank's credit ratings capture risk optimally, given the information available to them, those ratings should forecast movements in the public ratings of a credit bureau. On the other hand, the credit bureau ratings should not forecast movements in the bank's ratings. When the unobserved state, i.e., actual creditworthiness, follows a random walk with noise, and the signal of creditworthiness, that a monitor receives, itself is noisy too, we arrive at this result by applying the Kalman filter to obtain Muth's formula on exponentially weighted lags of past signals. Stated differently, a monitor's expectation of creditworthiness turns out to be an exponentially weighted lag of its past signals, with a base coefficient, d_i, on the current period's signal. The size of this base coefficient is determined by the relative noisiness of the monitor's signal q_i.

We assume that each borrower j has some actual measure of creditworthiness, y_{jt}, that follows a random walk and is only observed with some noise u_{jt} that is normally distributed, $u_{jt} \sim N\left(0, \sigma^2\right)$. For notational simplicity we will however suppress the superscript j. Each period, the noise term u_t permanently shifts the underlying creditworthiness y_t:

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

There are two monitors indexed by i, $i \in \{b, c\}$.where b is a bank and c is a credit bureau. The signal of the underlying creditworthiness that each monitor i receives contains a temporary, normally distributed, noise term $\eta_{it} \sim N\left(0, \sigma^2_{i\eta}\right)$ .If we define the precision of monitor c's observation q_c relative to the disturbances of the actual creditworthiness, i.e., $q_c \equiv \sigma^2/\sigma^2_{i\eta}$, then it follows that $\sigma^2_{i\eta} = \sigma^2/q_c$.

For example, the credit bureau c observes a noisy, public signal, s_{ct} of a borrower's creditworthiness y_t:

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

Because y_t follows a random walk (1), this implies that:

$$s_{ct} = y_{t-1} + u_t + \eta_{ct} \tag{3}$$

The credit bureau's rating for any borrower is based on the bureau's estimate of creditworthiness, which based on the signal s_{ct} it receives. Each monitor's optimal expectation of the creditworthiness of a borrower j at time t, $y^j_{t|t}$, is characterized as a function of the noisy signal s^j_{it} the monitor observes.

We will use the following notation for a set of frequently used expectations:

$$\begin{array}{lll} y_{ct|t} & \equiv & E\left(y_t|s_{ct}\right) \\ y_{ct|t-1} & \equiv & E\left(y_t|s_{ct-1}\right) \\ s_{ct|t-1} & \equiv & E\left(s_{ct}|s_{ct-1}\right) \\ V_{ct|t} & \equiv & E\left(y_t - y_{ct|t}\right)^2 \end{array} \tag{4}$$

Here the first expectation, $y_{ct|t}$, is the filtered signal, which we will interpret as the updated credit rating, and $y_{ct|t-1}$ is the credit rating before receiving the current period's signal. The last term is the expected mean square error of the credit rating.

If the noise terms are normally distributed, then the process by which the bank updates its credit ratings must be linear in the past period's rating and the current signal and equals the following regression equation:

$$y_{ct|t} = (1-d_c)y_{ct-1|t-1} + d_c s_{ct} \tag{5}$$

where d_c is a regression coefficient that we can calculate as:

$$d_c \quad = \quad \left[E\left(y_t - y_{ct|t-1}\right)\left(s_{ct} - s_{ct|t-1}\right)\right] \cdot \left[E\left(s_{ct} - s_{ct|t-1}\right)^2\right]^{-1} \tag{6}$$

Since $s_{ct} = y_{t-1} + u_t + \eta_{ct}$, this estimate incorporates in each period a proportion d_c of the current shock u_t and a proportion $1-d_c$ of the past shocks incorporated in $y_{ct-1|t-1}$. In (5) we can use repeated substitution to obtain Muth's formula:

$$y_{ct|t} = d_c \sum_{i=o}^{\infty} (1-d_c)^i \, s_{ct-i} \tag{7}$$

It can be shown that the stationary solution is (Chow,1980):

$$d_c = \frac{q_c}{2}\left(\sqrt{1+4/q_c} - 1\right) \tag{8}$$

Moreover,

$$V_{ct|t} = \frac{\sigma^2}{2}\left(\sqrt{1+4/q_c} - 1\right) \tag{9}$$

The variance of the one-period change in forecasts is:

$$E\left(y_{ct|t} - y_{ct-1|t-1}\right)^2 = \sigma^2 \tag{10}$$

We can show that d_c rises with q_c. In what follows we omit the subscripts for notational simplicity:

$$\begin{aligned}
\frac{\partial d_c}{\partial q_c} &= \frac{\partial \frac{q}{2}\left(\sqrt{1+4/q}-1\right)}{\partial q} \\
&= \frac{1}{2}\left(\sqrt{1+4/q}-1\right) - \frac{1}{q\sqrt{1+4/q}} \\
&\propto \left(1+\frac{4}{q}-\sqrt{1+4/q}\right)-\frac{2}{q} \\
&= \left(1-\sqrt{1+4/q}\right)+\frac{2}{q} \\
&> \left(1-\sqrt{1+4/q+4/q^2}\right)+\frac{2}{q} \\
&= 0
\end{aligned} \tag{11}$$

so that $\frac{\partial d_c}{\partial q_c} > 0$. A monitor thus updates his expectation of creditworthiness more slowly as the noise of its signal increases. In Table 1 we display how the updating coefficient d_c varies with the precision of monitor's signal, q_c. The table shows that d_c falls faster in ranges where q_c is very small. For example, doubling the standard deviation of the noise cuts the updating speed in half. In what may be considered the relevant ranges of precision for a monitor, a doubling of the relative noise in a signal reduces d_i by approximately 10 percent.

Table 1: Values of d_c as a function of q_c
All entries have been constructed using equation (5)

q_c	3.2	1	0.27	.05	.011	.0026	.00064
d_c	.800	.618	.402	.200	.100	.050	.025

The above equations summarize the rating formation process for a monitor that receives a single, public signal such as the credit bureau. The bank not only observes the same public signal as the credit bureau but, in addition, gets a noisy, private signal, s_{pbt}, of borrowers' actual creditworthiness:

$$s_{pbt} = y_t + \eta_{pbt} \tag{12}$$

where

$$\eta_{pbt} \sim N\left(0, \sigma^2/q_{pb}\right) \tag{13}$$

After receiving the signals, the bank aggregates them in proportion to their precision, q_i,to form a composite signal,

$$\begin{aligned}
s_{bt} &= \left(q_{pb}s_{pbt} + q_c s_{ct}\right)/\left(q_{pb}+q_c\right) \\
&= y_t + \eta_{bt}
\end{aligned} \tag{14}$$

where

$$\begin{aligned}
\eta_{bt} &= \left(q_{pb}\eta_{pbt} + q_c \eta_{ct}\right)/\left(q_{pb}+q_c\right) \\
&\sim N\left(0, \sigma^2/q_b\right)
\end{aligned} \tag{15}$$

and

$$q_b = q_{pb} + q_c \tag{16}$$

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

$$y_{bt|t} = d_b \sum_{i=o}^{\infty} (1 - d_b)^i \, s_{bt-i} \tag{17}$$

and

$$d_b = \frac{q_b}{2} \left(\sqrt{1 + 4/q_b} - 1 \right) \tag{18}$$

We shall call the filtered signals credit ratings. It is obvious that the public monitor's credit rating will not forecast the bank's credit rating. The bank's credit rating will forecast the public monitor's credit rating, on the other hand, for two reasons. One is that the bank has a better fix on the true creditworthiness, because it has private information that the credit bureau does not. The other reason is more subtle: the bank incorporates the credit bureau signal more rapidly into its rating than does the credit bureau itself ($\mathrm{d}_b > \mathrm{d}_c$). That is, the bank is not simply updating with the credit bureau rating, but is actually incorporating the information in the credit bureau signal faster than the credit bureau does itself. It can do so because overall its information is more precise.

If we would translate this updating behavior into a regression model that aims to explain how credit ratings are revised using both bank ratings and credit bureau ratings, then the resulting fundamental regression equations would be:

$$y_{bt|t} = a_{10} + \alpha_{11} y_{ct|t-1} + \alpha_{12} y_{bt|t-1} + e_{1t} \tag{19}$$

$$y_{ct|t} = a_{20} + \alpha_{21} y_{ct|t-1} + \alpha_{22} y_{bt|t-1} + e_{2t} \tag{20}$$

Considering equation (19), we expect that the credit bureau's rating will not be able to forecast the bank rating, since the information underlying it is already embedded in the bank rating, so that $\alpha_{11} = 0$. Because the underlying information follows a random walk, the coefficient on the lagged bank rating should be unity and the constant term should be zero: the forecasts are expected to be martingales. For equation (20), we again expect the constant term to be zero. However, because of the private information encompassed by bank ratings, the sum of the coefficients of $\alpha_{21} + \alpha_{22}$ should be unity and $\alpha_{22} \geqslant 0$.Using these restrictions, we can rewrite equations (19) and (20) in terms of stationary variables:

$$\Delta y_{bt|t} = \alpha_{11} \left(y_{ct|t-1} - y_{bt|t-1} \right) + e_{1t} \tag{21}$$

$$\Delta y_{ct|t} = \alpha_{21} \left(y_{ct|t-1} + y_{bt|t-1} \right) + e_{2t} \tag{22}$$

where we expect the coefficient α_{11} in the first equation to be zero and the coefficient α_{21} in the second equation to be positive.

In Section 4 we will test two necessary, but not sufficient, conditions for the optimality of credit ratings: that the bank's credit rating for borrowers forecasts the public monitor's credit rating but that the public monitor's credit rating does not forecast the bank's credit rating. These are the standard Granger causality conditions and we could test them using VARs with one lag on each equation, as in equation (19) and (20) . If the bank's credit ratings are forecastable by the public monitor, then this constitutes prima facie evidence that the bank credit ratings are not sufficient statistics for the creditworthiness of the bank portfolio. It also means that an optimal measure of the risk of the bank portfolio should include measures of borrower quality from outside the bank's credit rating system.

When we test the above conditions in Section 4, we will also want to some quantitative support for interpreting the goodness of fit of an estimated equation (21) and (22) We therefore derive a general result on the maximum attainable R^2 in regression equations (19) and (20). From equation (3) it follows that the change in the underlying estimate of creditworthiness is:

$$\begin{aligned} y_{ct|t} - y_{ct|t-1} &= d_c \left(s_{ct} - y_{ct|t-1} \right) \\ &= d_c \left(u_t + \eta_{ct} + y_{t-1} - y_{ct|t-1} \right) \end{aligned} \tag{23}$$

Then, because the components u_t, η_{ct}, and $y_{t-1} - y_{ct|t-1}$ are independent, we have that the variance (using equation (9)) is:

$$\begin{aligned} \sigma^2 &= E \left(y_{ct|t} - y_{ct|t-1} \right)^2 \\ &= E \left(d_c \left(u_t + \eta_{ct} + y_{t-1} - y_{ct|t-1} \right) \right)^2 \\ &= d_c^2 \left(\sigma^2 + \frac{\sigma^2}{q_c} + V_{t-1|t-1} \right) \end{aligned} \tag{24}$$

The change in the credit bureau's rating can be decomposed into contributions from the new shock to the underlying creditworthiness, u_t, the new shock to the signal, η_{ct}, and the error in the credit bureau's rating at time t-1, $V_{t-1|t-1}$ The first two parts are clearly unforecastable noise terms. So the only part of the change in the credit bureau's rating that is potentially forecastable is the part due to $V_{t-1|t-1}$,that is, $d_c^2 V_{t-1|t-1} = d_c^2 V_{t|t}$, because of stationarity. Using (7) and (8), we obtain:

$$d_c^2 V_{t|t} = \tfrac{1}{8} q^2 \sigma^2 \left(\sqrt{1 + 4/q} - 1 \right)^3 \tag{25}$$

Expression (25) implies that the proportion of the movement in the credit bureau's credit rating that can be forecasted based on knowledge of y_{t-1} is $d_c^2 V_{t|t} / \sigma^2$.Below, we show that for $q = .5$, $d_c^2 V_{t|t}$ reaches its maximum at $.25\sigma^2$. This means that the *maximum* R^2 one can expect based on knowledge at $t-1$, is .25. This implied maximum will be important later on, in Section 4, when we evaluate the empirical fit of our regressions.

$$\begin{aligned} d_c^2 V_{t|t} &= \frac{\partial q^2 \left(\sqrt{1+4/q} - 1 \right)^3}{\partial q} \\ &= 2 \frac{\left(\sqrt{\frac{1}{q}(q+4)} - 1 \right)^2}{\sqrt{\frac{1}{q}(q+4)}} \left(q - q\sqrt{\frac{1}{q}(q+4)} + 1 \right) \end{aligned} \tag{26}$$

When $q = .5$ the parenthetical expression on the right hand side equals zero. We can show that this derivative is positive for $q < .5$ and negative $q > .5$. This will imply that the above expression achieves a global maximum at q=.5.

The sign of expression (26) depends on the sign of the parenthetical expression on the right-hand side, since the remainder of the expression is always positive. The parenthetical expression on the right-hand side has a negative derivative since

$$\frac{\partial\left(q-q\sqrt{\frac{1}{q}(q+4)}+1\right)}{\partial q} \quad = \quad -\frac{\sqrt{\frac{1}{q}(q+4)}}{q+4}\left(q-q\sqrt{\frac{1}{q}\left(q+4\right)}+2\right) \tag{27}$$

This derivative is always negative, because the parenthetical expression on the right-hand side of (27) is always positive, since

$$q\sqrt{\frac{1}{q}\left(q+4\right)} \quad < \quad q\left(2/q\right)=2 \tag{28}$$

This in turn implies that the original expression reaches its maximum at $q = .5$.

2.2 Hypotheses

In this section we summarize the implications that the simple model we presented in Section 2.1, has for the relation between public (credit bureau) and private (bank) borrower ratings. In Section 4, we will test these hypotheses.

In the model, we treat borrower credit ratings as a forecast of the likelihood of default or of the loan's expected value. Based on the model, we expect that the credit bureau's rating will not be able to forecast the bank rating because the information contained in credit bureau ratings is already embedded in the bank rating. In terms of equations (19) and (20), $\alpha_{11} = 0$. Because the underlying information follows a random walk, the coefficient on the lagged bank rating should be unity and the constant term should be zero. Hence, under rational expectations, forecasts of bank credit ratings should be martingales. Of course, conditioned on information outside the information set from which the forecast has been made, changes in the rating may no longer be unforecastable. As a consequence, one test of whether one forecast is based on a larger information set than another (on a refinement of the information set) is that it will be able to forecast the movements in the other: A cross-sectional information advantage implies intertemporal advantage.

Hypothesis 1. *Changes in a bank's credit ratings should not be forecastable.*

If the credit bureau's rating does forecast the bank's future credit ratings, not only do we know that the bank's ratings are not sufficient statistics, but the proof is constructive: it tells us how to improve on the bank's ratings as a measure of risk.

Corollary 1. *If changes in a bank's credit ratings are forecastable, then (the variables in) the equation that predicts the change in the bank's credit ratings will improve estimates of the riskiness of bank borrowers.*

Corollary 1 also means that if bank credit ratings are forecastable then an optimal measure of the risk of the bank portfolio should include measures of borrower quality from outside the bank's credit rating system.

If a bank has private information, then its ratings should be capable of forecasting the credit bureau's future rating. If it did not do so, then we would have evidence against the joint hypothesis that the bank (i) has private information and (ii) rationally uses this information. Therefore the bank's credit rating should forecast the public monitor's credit rating, for two reasons. One is that the bank has a better fix on the true creditworthiness, because it has private information that the credit bureau does not take in. The other reason is more subtle: the bank incorporates the credit bureau signal more rapidly into its rating than does the credit bureau itself, i.e., $d_b > d_c$. That is, the bank is not simply updating with the credit bureau rating, but is actually incorporating the information in the credit bureau signal faster than the credit bureau does itself. It can do so because overall its information is more precise.

Another way to think about this is the following. If some agent A's forecast of some future event is superior to that of another agent B, this statistically speaking means that A will be accurate more often than B. Put another way, the future offers fewer surprises for A than for B. If the future event is more than one period away, and information is revealed in the meantime, it is more likely that the new information will confirm A's view of the future than it will B's. The forecast of B is then more likely to approach that of A, assuming it is rational, than that A's forecast will move toward B's. As a consequence, A's current forecast will tend to forecast B's future forecast, taking into consideration B's current forecast. Even stronger, if A's forecast is optimal and A knows B's forecast, then B's forecast cannot be better than A's, and will not forecast A's future forecast.

Hypothesis 2 *A bank's internal credit rating should be useful in forecasting changes in a public credit rating of the same borrower.*

If a bank's internal credit ratings *do* forecast changes in public credit ratings, *and* if the bank's future ratings are not forecastable by the public credit rating, it would appear likely that the bank has strictly superior information. We would then have no evidence against the hypothesis that the bank has private information it utilizes rationally. Moreover, we would have strong grounds for the belief that a bank supervisor should use the bank credit ratings in measuring the risk of the bank's loan portfolio.

3 Data

The primary sources of the data are the credit registries of two of the four major Swedish commercial banks, which we shall call Bank A and Bank B, and the registry of the leading credit bureau in Sweden, Upplyningscentralen AB (UC), which we shall call the credit bureau (CB). UC is an incorporated company that is jointly owned by in principle all Swedish banks. Ownership shares are strongly correlated with bank size. Non-financial enterprises and all financial institutions report data on loan applications and granted loans to UC. The data set covers the period starting 1997-Q3, ending 2000-Q1 for Bank A and ending 2000-Q2 for Bank B. Because of a change in the CB rating system, we have deleted the first two quarters of the bank data sets (the original data set began in 1997-Q1). This gives us between one and 11 quarterly observations for, on average, roughly 15,000 borrowers in Bank A and one to 12 quarterly observations on 8,000 borrowers in Bank B. Borrowers, incorporated businesses or aktiebolag, have at least the legally required minimum of SEK 100,000 (approximately $12,500 at that time) in equity. Many of them, particularly for Bank A, are very small. Roughly 37 percent of Bank A's borrowers are small borrowers, defined as having maximum borrowing of less than SEK 500,000 (about US$ 62,500 in the time period examined), adjusted for inflation. About four percent of Bank B's borrowers have borrowings this small. Although Bank B has roughly half as many total borrowers, its number of large borrowers is nearly as large as in Bank A, with large borrowers defined as having more than SEK 5 million in maximum borrowing (about US$ 625,000). As Table 2 shows, small and medium-sized borrowers represent between 60 and 80 percent of all borrowers but only a small proportion of the total loan portfolio of either lender. A more complete description of the bank data and credit bureau data can be found in Jacobson et al. (2006).

Both banks maintain an internal credit rating scheme: Bank A assigns each business customer to one of 15 credit rating grades, while Bank B uses seven classes. Higher numbers imply worse ratings and rating grade 15 and 7 in the respective systems represent defaulted customers. Both banks employ the same definition of a default, namely that (i) the principal or interest payments are 60 days overdue, and (ii) a bank official has to make a judgement and reach the conclusion that any such payment is unlikely to occur in the future. Both the credit bureau's and the banks' ratings are "borrower" ratings, not loan-specific ratings.

The definition of default the credit bureau has adopted is the following: a firm is given a default status once any of the following events occurs; the firm is declared legally bankrupt, has suspended payments, has negotiated a debt composition settlement, is undergoing a re-construction, or is distraint without assets. To keep track of these events, the credit bureau collects event data from Tingsrätten (District Court), Bolagsverket (the Swedish Companies Registration Office, SCRO), and Kronofogdemyndigheten (the Swedish Enforcement Authority). Once any of the above distress events occurs, the firm in question is at once registered as defaulted. This is observed by us on the last day of that particular quarter. In the following quarter, we then let the firm exit our data set. If more than one of these distress events is observed for a specific firm over our sample period, we assume the firm in question has defaulted in the quarter during which the first of these events took place. For about 45 percent of the defaulting firms one of the other default-triggering events occurs simultaneously, i.e. during the same quarter.[6]

In most of our analysis, we will exclude observations where a counterpart has defaulted because the default rating reflects actual behavior rather than a bank's estimate of creditworthiness. The only exception will be regressions where bank defaults are our dependent variable. In those regressions we will omit observations where borrowers had a default rating at the credit bureau (e.g., they either filed for bankruptcy or were declared bankrupt). Credit ratings need to be updated by loan officers at least once every 12 months. Tables $3A-C$ show that the credit ratings for both lenders are highly concentrated, just as 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. Table $3A$ demonstrates that Bank A's ratings are not single-peaked. Because of this, and to bring the system of Bank A more in line with that of Bank B, we have converted the 14 non-bankruptcy grades – somewhat arbitrarily – into a system of seven ratings that is single peaked. We grouped ratings 1 to 4, 5 to 7, 8 to 10, and left the remaining, high-risk, grades unaffected.

The credit bureau has five rating classes in addition to a default rating, and a numerically higher rating implies *higher* creditworthiness, the reverse of the bank ratings. The default rating is assigned if bankruptcy occurs or some other infrequent events that almost inevitably lead to actual bankruptcy. The exact definition of the default dummy is as follows: a firm obtains the credit bureau default status once any of the following events occurs: the firm has been declared legally bankrupt by District Court, has suspended payments, has negotiated a debt composition settlement, is undergoing a re-construction, or is distraint without assets. The distribution of credit bureau ratings is shown in Tables $4A$ and $4B$. 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. The two sets of ratings thus appear to be scaled quite differently.

The ratings of the credit bureau are costlessly available to the bank loan officers through an on-line computer system. That is, at the time that a loan officer establishes the credit rating, the latest available rating from the credit bureau and a set of background variables from the credit bureau are part of the loan officer's information set.

[6] About five percent of the firms that experience a credit bureau default re-emerge from their default status. We do not include these re-emerged companies in our data. Nearly all re-emerging companies default a second and final time, mostly in sample and some out of sample. The vast majority of all terminal credit bureau defaults concern legal bankruptcy declarations. For the firms that re-emerge after a default, the first default involves a legal bankruptcy in less than half a percent of all cases and "distraint, no assets" in 98 percent. At their second default, these percentages are reversed.

4 Empirical Results

In the theoretical model of Section 2.1, we implicitly made two important assumptions about the format and updating frequency of the credit ratings. To start with, we inherently treated the bank and the credit bureau as if they are updated simultaneously in each time period. Moreover, credit ratings were allowed to be continuous. The actual credit rating data depart from these model assumptions for two reasons.

First, we cannot control for the exact time at which updating of information sets occurs. Hence, credit ratings may be updated at different points in time by different monitors without the data explicitly accounting for differences in information sets. The data-providing banks update their credit ratings at least once a year, and in practice do so close to once per year on average. The credit bureau collects data from financial institutions, corporations and official resources at a higher frequency. For payments remarks, this occurs more or less daily. while for other variables this happens at a monthly, quarterly or yearly frequency. Thus in some instances, the credit bureau may have updated its credit rating more recently than the bank, thereby potentially allowing it to forecast the bank rating. At other times, banks may already have received (parts of) a company's annual statement, when it hasn't yet been filed, thereby generating an informational advantage that doesn't correspond to what is typically considered private information in banking theory.

A second deviation from the model's assumptions exists because credit ratings are categorical variables, not continuous variables. In moving from continuous variables to categorical variables, the bank signal may lose information, thereby making the credit bureau data more valuable. When bank credit ratings are categorical, some of the information in the public signal is not captured in the bank's credit rating. If credit bureau ratings are continuous, this means that the public monitor's rating provides information that has been lost in the aggregation. Then the public monitor's rating may well predict the bank's signal, even though the bank is fully aware of the public signal and "processes" it optimally. However, when both public and private monitors produce categorical ratings, we can no longer be sure what impact the loss of information due to converting continuous projections into categorical ratings will have on the mutual forecasting power of public and private ratings.

Because of the above deviations from our model's assumptions, testing whether the necessary conditions specified in Section 2.1 hold, will not provide us with an unambiguous test of bank ratings' optimality Instead, we will use two alternative, weaker, necessary conditions for optimality, namely that the informational content of the bank's credit rating should be greater than that of the public monitor. In doing so, we rely on the fact that the informational content can be normalized, because both ratings are efforts to estimate the same underlying variable - namely, the borrower's creditworthiness. The underlying filtered signals will therefore have the same variance if the signals are being optimally forecasted.

Tables 5 through 8 summarize the results from two sets of regressions. In

Section 4.1 we first run OLS regressions for the credit bureau ratings on its lagged values and then add a bank's lagged credit rating. We also check the linearity of the rating systems by using dummy variables for the ratings. Conversely, we also present the results of regressions for each bank's credit rating on its lagged values. We then also add the credit bureau's lagged credit rating. Tables 9 through 11 contain the results from running the same set of regressions as in Tables $5-7$, while using an ordered logit model instead of OLS. In Section 4.2 we display the results from several Cox regressions on the default hazard.

4.1 OLS and ordered logit results

If we define r_{bt} as the rating of the bank at t, and r_{ct} as the rating of the credit bureau at t then, under the assumptions in Section 2.1, equations (19) and (20) translate into the following regressions we can estimate:

$$r_{bt} = \alpha_{1b} r_{bt-1} + \beta_{1b} r_{ct-1} + \varepsilon_{1bt} \tag{29}$$

Because we explicitly wish to test for the marginal informational value of adding a lag of the credit bureau rating, we will also estimate the simple autoregressive form

$$r_{bt} = \alpha_{2b} r_{bt-1} + \varepsilon_{2bt} \tag{30}$$

In a similar fashion, we will estimate two regressions explaining the credit bureau rating updating process:

$$r_{ct} = \beta_{1c} r_{ct-1} + \alpha_{1c} r_{bt-1} + \varepsilon_{1ct} \tag{31}$$

$$r_{ct} = \beta_{2c} r_{ct-1} + \varepsilon_{2ct} \tag{32}$$

In its strictest version, Hypothesis 1 in Section 2.2 implies that $\alpha_{1b} = 1$ and $\beta_{1b} = 0$. However, because of the staggered updating of information and categorical nature of the ratings, we will test the weaker hypothesis that $\beta_{1b} = 0$. Under this hypothesis, the credit bureau rating does not forecast changes in the bank rating, or has an insignificant impact on the residual sum of squares (RSS) in the regression (29). This is what we would expect of an optimal bank forecast if it were continuous.

In it strictest version, Hypothesis 2 implies that $\alpha_{1c} > 0$ and thus $\beta_{1c} < 1$.[7] However, for the same reasons we mentioned in the context of Hypothesis 1, we will test the weaker hypothesis that $\alpha_{1c} > 0$. Under this hypothesis, the bank rating does forecast changes in the credit bureau rating and has a significant impact on the RSS in regression equation (31).

In each of the Tables 5, 6, and 7 we show the results for six regressions, using data on borrowers in Bank A, and borrowers in bank B (employing both compressed and uncompressed bank B ratings) respectively. Of the six regressions in each table, four are exact estimates of equations (29)-(32). The remaining

[7] In the actual regressions, we expect that $\alpha_{1c} < 0$ because higher bank credit ratings imply higher risk levels, while credit bureau ratings indicate lower risk as the ratings grade increases.

two are variations where we have included dummy explanatory variables for the credit ratings instead of a simple one-period lag, in order to allow for nonlinearities in the impact on the dependent variable. To verify if our results are robust to variations in firm size, we also repeat the regressions for only small, medium-sized or large firms. These results are presented in Appendix Tables $1A-C$, $2A-C$, and $3A-C$. In Tables $9-11$, we verify the robustness of our findings in Tables $5-7$ with respect to estimation method by applying ordered logit instead of OLS. Thereby we allow the ordering of the relevant dependent rating variable to occur in a nonlinear fashion with respect to the information in the explanatory variables. By also including dummy variables in the ordered logit models, we attempt to control for the widest range of nonlinearities in the data. Hereafter we will focus on results from the "full" regressions and refer to the subsets only when differences occur. When contrasting the results in each of the Tables $5-7$, we will focus on the robust t-statistic on the lag of the credit bureau rating in the regression explaining the bank rating and compare differences in the RSS across regressions.

4.1.1 Hypothesis 1

When considering the results for equations (29)-(30), the overall results make clear that, with between 12,000 and 200,000 observations, even small coefficients are significant. For both banks we obtain highly statistically significant negative coefficients for the first lag of the credit bureau rating in regressions with a bank credit rating as the dependent variable (Tables 5 and 7, column 5).[8] this result is robust to transformations of the rating scale (Table 5 vs. Table 6), to variation in firm size and independent of the estimation method (Tables $5-7$ vs. Tables $9-11$).[9] We also ran regressions where we replace the lagged dependent variable by lagged dummy variables. However, doing so invariably worsened the fit of the regression (results are not displayed here, but are available upon request).

The smallest coefficients on the lag of the credit bureau ratings are in the order of .01-0.2 in the OLS regressions for bank B and in the range 0.05-0.10 for Bank A. Even taking into account the different scales that the two banks employ, this suggests that credit bureau ratings are more informative for predicting ratings in Bank A than in Bank B. In columns (4)-(6) of Table 6 we see that Bank A credit ratings remain relatively forecastable even when they are compressed, although not as much as the uncompressed ratings. Typically, adding lagged credit bureau ratings to the regression (column 5) reduces the RSS by more then when a lag of Bank A's rating is added to a regression on the credit bureau rating (column 2). The only exception is made up by the subset of large borrowers. For those borrowers Bank A's ratings are, on the margin, more informative in predicting credit bureau ratings than credit bureau ratings are reversely.

[8] Coefficients ar negative because credit bureau ratings follow an inverted scale relative to bank credit ratings.

[9] The firm size regressions are presented in the Appendix Tables $1-3$. The Appendix is available att www.riksbank.com/research/roszbach and www.phil.frb.org/research-and-data/economists/nakamura/.

The general observation that Bank A ratings are less informative is confirmed by the results in Table 8, columns (3)-(4). There, we summarize the additional explanatory power of lagged credit bureau ratings when these are added to a regression of bank credit ratings on their own one-quarter lag. For example, the number 2.67 in Table 8 equals the percentage decrease in RSS when moving from column 4 to column 4 in Table 6). Depending on the size of the borrowers, credit bureau ratings explain between 2.08 and 3.01 percent of the RSS for Bank A, compared to .58 - 0.90 percent for Bank B. For Bank A, credit bureau ratings are most informative in predicting small business ratings. An inspection of the corresponding results for Bank B reinforces this picture. Adding one lag of the Bank B rating lowers the RSS of the credit bureau regression substantially more than adding the same lag of the credit bureau rating lowers Bank B's rating RSS. This holds both for the complete sample of borrowers and in all three of the subsamples. Columns (1) and (2) also make it clear that Bank B ratings are more informative than Bank A ratings with respect to the credit bureau ratings, as adding the former reduces the RSS by more than adding the latter does. The ordered logit regressions in columns (4)-(6) of Tables $9-11$ broadly confirm the findings in the OLS regressions.

Overall, the above findings constitute distinct evidence against the hypothesis that bank ratings are not predicted by lagged credit bureau ratings. Moreover, the results clearly indicate that this holds all the more for bank A , and that Bank A ratings are relatively less informative.

4.1.2 Hypothesis 2

When examining the robust t-statistic on the lag of the bank rating in a regression of the contemporaneous credit bureau rating, we again find highly significant negative coefficients in all cases. As before, this finding is robust to variations in firm size, to transformations of the rating scale (Table 5 vs. Table 6), to varying the estimation method (Tables $5-7$ vs. Tables $9-11$) and stable across banks (cf. Tables $5-6$ vs. Table 7).[10]

In addition, we again verify if the results are robust to an exchange of the lagged bank rating by a set of lagged rating dummies. The results of this regression are shown in column (3) of Table 5 and the individual coefficients on the Bank A rating dummies are displayed in panel *B* of Table 5. Evidently, there is nonlinear information in the Bank A ratings. Unfortunately, the coefficients turn out to be non-monotonic in the rating. In other words. the improvement in the regression RSS is caused in part by the fact that the order of the ratings does not properly reflecting the risk ranking, as measured by the credit bureau ratings. The coefficients for Bank A rating grades 5 and 8 are, for example, significantly greater than for the two following ratings, i.e., grades 6-7 and 9-10 respectively. The additional explanatory power of the Bank A rating dummies is thus due to rating differences that do not correspond to their ordinal rank! This is strong prima facie evidence that Bank A's ratings are not adequately cap-

[10]Firm-size regressions are available in Appendix Tables $1-3$.

turing relative risk and that worse bank credit ratings sometimes correspond to improved credit bureau ratings. It can then hardly be expected that these bank credit ratings are strictly ordinally related to an underlying optimal measure of creditworthiness in any appropriate way.

Some interesting differences can be observed *between* the banks. For example, if we add the lagged bank A rating in an OLS regressions of the credit bureau rating on its own lag, then the RSS drops from 55575 (column 1, Table 5) to 55236 (column 2), a reduction of less than 0.6 percent. Interestingly, when adding the credit bureau rating to a regression of the bank A credit rating on its own lag the RSS falls to from 174853 to 163526, a decrease of over 6 percent. Thus, over the entire portfolio, the credit bureau appears to have better information than the bank since it has a proportionally bigger impact on the error! In this context it is worthwhile to recall that we concluded in Section 2.1 that the maximum attainable decline in the RSS is 25 percent. A decrease of over 6 percent is thus a very large proportion of the change in the signal.

Above, we already argued that the uncompressed Bank A ratings suffer from some suboptimality. The extremely large degree of forecastability of the Bank A credit ratings offered additional evidence in this direction. As we mentioned earlier, columns (5)-(6) in Table 6 show that Bank A credit ratings are relatively well forecastable by public credit bureau ratings. By contrast, appending the lag of the credit bureau rating to a regression on the Bank B rating in Table 7 only reduces the RSS by 0.8 percent. However, adding the lagged Bank B rating reduces the RSS of the credit bureau rating regression by 1.3 percent. Bank B thus has relatively better information than the credit bureau. Ordered Logit regressions presented in the Appendix show that these findings are not sensitive to the estimation method one uses. Even here, Bank B appears as a relatively better rater.[11]

On the whole, the above findings offer strong evidence in support of the hypothesis that bank ratings predict credit bureau ratings. We also corroborate our earlier conclusion that Bank A ratings appear less informative than Bank B ratings.

[11] The results in the Ordered Logit regressions resemble those in the OLS regressions. Consistent with our earlier findings, we see in Appendix Tables $4A-D$, $5A-D$ and $6A-D$ that Bank A is not as apt a rater as Bank B is. A regression of the credit bureau rating on its own lag gives a pseudo-R^2 of .5053, and adding the lag of the Bank A compressed rating raises the pseudo-R^2 by .0027 to .5080. By comparison, the regression of Bank A's compressed rating on its own lag gives a pseudo R^2 of approximately .6981. Adding the lagged information present in the bureau rating improves the fit, by .0053, to .7034. Although the contrast is not as clear as in the OLS regressions, the ordered logit regressions offer little evidence that Bank A's information collection and processing is superior to that by the credit bureau. As in the OLS regressions, the same image that Bank B is a relatively better rater emerges from Tables $6A-D$. Adding its lag increases the pseudo-R^2 of the regression forecasting the credit bureau rating by .0051, from .5113 to .5164. By contrast, adding the credit bureau lag to the regression forecasting the Bank B credit rating raises it only .0036.

4.2 Survival time regressions

In the previous section we found that bank ratings, which contain both public and private information, are only partially able to forecast credit bureau ratings, that are produced using publicly available information. Vice versa, we showed that, somewhat surprisingly, credit bureau ratings are able to partially forecast internal bank credit ratings. From a research perspective, an intuitively attractive conclusion to be drawn from these results would be that credit bureau ratings are of higher quality than one would expect from theory, whereas bank ratings are less so. If this were the case, then we should at least expect credit bureau ratings to also be better predictors of credit bureau defaults, i.e., bankruptcies, than bank ratings are. Since credit bureau ratings are constructed to predict bankruptcy whereas bank ratings are designed to predict defaults in loan portfolios, any other finding would cast doubt on our conclusions in Section 4.1

To verify if the above proposition holds, we therefore perform an additional test on the data and compare the explanatory power of bank credit ratings and credit bureau ratings in a duration model setting. We implement the test by estimating the following Cox proportional hazards model:

$$log\ h_i(t) = \alpha(t) + \beta x_{it} + \varepsilon_{it} \tag{33}$$

or equivalently

$$h_i(t) = h_0(t)\ exp(\alpha(t) + \beta x_{it} + \varepsilon_{it}) \tag{34}$$

for a number of competing specifications. Here, $h_i(t)$ is the hazard rate of firm i at time t, $\alpha(t) = log\ h_0(t)$, and $\mathbf{x}$ contains all time-varying covariates. The Cox model leaves the baseline hazard function unspecified, thereby making relative hazard ratios both proportional to each other and independent of time other than through values of the covariates.

We run three sets of regressions to verify the above assertion. In the first group of regressions, displayed in Table 12, the main variable of interest is a firms' hazard rate, or instantaneous risk of *bankruptcy* at time t conditional on survival to that time. First, we let $\mathbf{x}_{it} = r_{c,t-1}$ to compute the explanatory power of lagged credit bureau ratings for borrowers in both Bank A and Bank B (Table 12, columns 3, 7). Next, we take $\mathbf{x}_{it} = r_{b,t-1}$., where $b = 1, 2$. (columns 1, 5). In column 2 and 4 of these tables, we present results from regressions where we let

$$\mathbf{x}_{it} = \left[DUM\_r^1_{b,t-1}, DUM\_r^2_{b,t-1}...., DUM\_r^{G-1}_{b,t-1}\right] \tag{35}$$

and

$$\mathbf{x}_{it} = \left[DUM\_r^1_{c,t-1}, DUM\_r^2_{c,t-1}...., DUM\_r^{G-1}_{c,t-1}\right] \tag{36}$$

where G is the number of grades in a rating system, and $DUM\_r^g_{b,t-1} = 1$ if $r^g_{b,t-1} = g$ and zero otherwise.

The loglikelihood values in columns 1 and 3 of Table 12 show that the lagged credit bureau rating is better at explaining bankruptcy hazard rates than the lagged bank A rating is. This finding is robust to exchanging the lagged rating for a set of lagged rating dummies. The table also shows that the same results are obtained when using bank B ratings instead. The Appendix (Table $A7$) contains output from an additional robustness test, where we repeated the above regressions using a second lag instead of the first lag. This does not change the results qualitatively. As one would expect, the coefficients on the lagged rating dummies are monotonically increasing in risk for both the credit bureau and bank ratings. This reflects the fact that higher bank ratings and lower credit bureau ratings should be stronger indicators of future defaults. Hence, hazard rates should rise (fall) as bank (credit bureau) ratings become higher (lower).

Next, in Table 13, we present the results from a similar set of Cox regressions where the dependent variable is the instantaneous risk of a default *in a bank* at time t, conditional on survival to that time. A similar comparison between columns 1 and 3 makes it clear that for both Bank A and Bank B lagged credit bureau ratings are better at explaining bank default hazards than bank ratings are themselves. In the Appendix (Table $A8$) we again find these results are robust to exchanging the first lag by the second lags of the explanatory ratings. However, when we replace the lagged variables by a set of dummy variables, the credit bureau ratings lose their edge. This reversal may be indicative of the fact that the rating grades used by both banks are highly non-linear. Thus when using a parsimonious model that is linear in its explanatory variable, the *bank* ratings have less explanatory power.

In Table 14, we present the log likelihoods of the regressions that include the credit bureau rating alone, the bank ratings alone, and both credit bureau ratings and the bank ratings together. We have marked the significance of the likelihood ratio tests for the credit bureau rating for exclusion of the bank rating, and vice versa. For example, the log likelihood of the model with the credit bureau rating alone in the regression using credit bureau default, for all Bank A borrowers, is -1593.2. As the regression that uses both the credit bureau rating and the Bank A rating has a log likelihood ratio is -1555.2, twice the log likelihood ratio is 76.0, making the Bank A rating very significant in a chi-square test with one degree of freedom. As can be seen, neither the bank ratings nor the credit bureau ratings are on their own sufficient statistics of default. This is true for both Bank A and Bank B and for both definitions of default; it also holds when we lag both ratings an additional period. In particular, this provides striking evidence that the credit bureau rating adds information to the bank rating, even though the bank loan officers have ready access to the credit bureau ratings when they make their ratings.

In the Appendix Tables A-15 to A-17, we provide additional results on the log likelihoods and exclusion tests for subsets of small, medium, and large borrowers. An interesting conclusion from those tables is that the credit bureau ratings do notably better than bank ratings for small borrowers, while the reverse tends to be true for the large borrowers.

5 Simulations

For both the banks that we study, we have found that the credit bureau ratings forecast bank credit ratings. A direct implication of this is that a bank's ratings alone are not the best possible measure of the bank's portfolio's underlying overall creditworthiness. But there are two reasons, not mutually exclusive, why this could be happening. One possibility is that the bank's credit ratings do not impound the credit bureau's data optimally. The bank's loan officers may, for example, overvalue their private information vis-a-vis the credit bureau's rating. Another possibility is that the rating process itself, for example through the requirement that ratings be categorical, may reduce the information embedded in the ratings.

The first of these two causes is relatively hard to evaluate. However, as we argued in Section 4, the potentially staggered nature of rating updating and the categorical nature of the ratings in practice leads to deviations from our model assumptions. As a result we need to resort to a weaker optimality test than our model suggests. In this section, we therefore attempt to quantify how the above two characteristics affect our findings. Therefore, we simulate data for the model in Section 2.1 and estimating regressions that increasingly and step-by-step account for the possibility of staggered rating updating and categorization of discretization of initially continuous credit ratings.

For the simulations we generate 1,000 data series from a random walk process, each over 20 periods, which we think of as being quarters. In each period the random walk processes, which all start at time zero, receive a standard normal shock. The monitors receive signals that include noise: the random walk plus a normal temporary noise. As in the model, there are two sources of noise: the public signal's noise, and the bank monitor's noise. To capture the idea that banks collect private information in our simulations, the public signal noise will have a variance of 10, while the bank has a private signal with a variance of 2.5. The underlying creditworthiness of each borrower has a disturbance term that is a standard normal. The credit bureau processes a single signal, while the bank combine the public signal with its private signal. From these data, we can construct the credit bureau and bank signals, and the optimal Kalman filter that associated with them. In one of our experiments, we contrast these continuous signals with categorical credit ratings, which are created by aggregating the continuous signals ordinally.

The credit bureau's signal has a relative precision of .1. The bank's private signal has a precision of .4, but to this is added the credit bureau's signal Once combined with the credit bureau's signal, the bank's signal has a 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, namely period 20. In 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 standard deviation of creditworthiness is 20.5 = 4.472, while the actual standard deviation in the sample is 4.4702. The theoretical 4-quarter-ahead expected forecast variance is 4.

As preliminary evidence on the effect that coarsening of the data has, we measure the contemporaneous correlations between our simulated ratings. Note that the correlations between the credit ratings of the credit bureau and the credit ratings of banks are much lower than in the simulation. Tables $15A - B$ showed the quarterly correlations ranging from 0.29 to 0.57, which is substantially lower than the correlations in the simulated data (not reported). This variation over time may in fact explain some of the anomalies in the data and the concomitant results with respect to Bank A. Bank B's correlations with the credit bureau appear fairly consistent over time. Bank A's correlations, however, vary considerably and appear in general to drift downward except for an abrupt rise in 1999 Q2, followed by a resumption of the downward drift. It is also worth noting that the correlations are systematically lower for original Bank A ratings than when these are coarsened to 7 grades. The extra information in the ratings does not appear to be correlated with information in the credit bureau ratings. Additional analysis (not presented here) shows that the correlations are more or less unchanged when we use rank correlations instead.

In the Appendix, we present the results from an OLS regression on simulated data where credit ratings are continuous and rating updating takes place without staggering.[12] In a regression of the credit bureau rating on one lag of itself, the lag of the bank rating is highly significant when added. Moreover, when added to a regression of the simulated bank credit rating on a lag of itself, the lag credit bureau rating is not significant. The contemporaneous correlation between the bank and credit bureau two ratings in the simulated data is .9764.

In a second simulation, we stagger the data so that one-fourth of the credit ratings by each monitor are updated each quarter. This has a modest but significant impact on the regressions: the coefficient on the lagged credit bureau rating is now positive and significant, albeit small. Staggering of information updating thus has a significant but quantitatively modest impact on the apparent explanatory power of public ratings. However, it does make our test less clean because we cannot exclude the possibility that a rejection of hypothesis 1 is due to staggering of information updating. The contemporaneous correlation is now .9436.

This effect is reinforced when we discretize the continuous signals, even if we do not stagger the data. When we break up the continuous signals into six evenly spaced categories and re-run the above set of regressions , the coefficient on the lagged credit bureau rating becomes both significant and quantitatively more important. In addition, the residual sum of squares (RSS) of forecasts of the bank's credit ratings drops substantially when the lagged credit bureau rating is included. Interestingly, the contemporaneous correlation falls only slightly, to .9436. When we simulate data that is both staggered and aggregated into six intervals, the outcomes reveal that there is no monotonic relationship between the noisiness of the ratings and the size of coefficient for the lagged bank rating. The simulations do suggest that the RSS falls monotonically as ratings become more noisy. Similar results are obtained when ordered logit models are estimated

[12] The results in this Section are summarized in Appendix Tables $A9 - A14$.

instead of OLS.

Evidently, coarsening the data by placing it in as many as six categories reduces the ability of the ratings to forecast. Coarsening 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. Similarly, when information updating by monitors occurs in a staggered way, credit bureau ratings will have predictive power in explaining bank credit ratings. Most importantly, in relation to our analysis in Section 4, the above simulations indicate that our finding that bank credit ratings can be explained by credit bureau ratings and vice versa can be driven by a combination of factors: inefficient information collection by banks, loss of information when private information is converted into discrete ratings grades, and information lags due to infrequent and staggered updating of the information underlying bank ratings.

6 Conclusion

This paper proposes a new basket of straightforward techniques that enable both financial institutions and regulators to assess the performance of banks' credit ratings systems. We develop and test a method for quantifying the ability of a bank to monitor its commercial loans. The method exploits the implied forecasting power of informationally superior monitors in estimates of borrowers creditworthiness. By using both internal bank credit ratings and external credit bureau ratings of corporate borrowers, we can investigate if bank credit ratings are able to forecast the ratings of a public monitor. The techniques can also be applied to bond ratings for larger commercial loans.

Our results contain evidence that some banks have superior information relative to a credit bureau whose ratings are produced using public information only. We also present evidence that other banks will not necessarily pass this test. When exploring to what extent these differences between the two lenders are reflected also in their ability to predict default, we show that both lenders fail to pass the stringent test we formulate. Our public monitor's ratings are found to have predictive power for future changes in the ratings of the banks. This implies that the banks' credit ratings are not sufficient statistics for their borrowers' creditworthiness.

Using simulations we explain that our findings do not necessarily mean that the banks' continuous estimates of borrower default risk are not optimal..The discretization and coarsening of ratings can lead to a loss of information, making it possible that discrete ratings based on optimal default risk estimates fail our test. Under certain conditions, a public monitor's rating will in fact forecast future bank credit ratings. Our simulations suggest that increasing the number of rating grades does not necessarily solve these problems.

Our findings can interpreted in two ways. One is that banks fail to incorporate publicly available information optimally. The other is that banks lose information in the process of generating credit ratings. Irrespective of the interpretation, this means that it is not optimal for either banks' risk managers or for their regulators to accept the bank's own private credit ratings as the single measure by which to evaluate of portfolio credit risk. Instead, it would be beneficial to incorporate more information into a risk review. In particular, credit bureau ratings could be used to improve overall portfolio risk evaluation.

Our analysis raises a number of deeper questions about the optimal way for banks to assess the creditworthiness of their customers. Why do banks use relative crude rating gradations instead of continuous assessments of default risk? Why does expanding the number of ratings in a way that increases their informativeness appear to be difficult? These questions are important issues for future research to address.

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Table 2: Descriptive statistics on loans outstanding

The table contains descriptive statistics on actually utilized credit in banks A and B. All numbers are averages over four years, i.e., over the period 1997Q1 to 2000Q1

	Bank A				Bank B			
	Total	Large	Medium	Small	Total	Large	Medium	Small
Total loan outstandings (Billion SEK)	91.7	85.3	5.73	0.664	110	103	7.07	0.845
Mean loan size (Million SEK)	4.397	20.8	0.639	0.085	10.4	25.9	1.141	0.204
Number of Loans, quarterly average	20851	4103	8954	7794	10586	3979	6192	415

Table 3A. Empirical distribution of bank ratings for Bank A borrowers
All numbers are over four years, i.e., over the period 1997Q1 to 2000Q1. Higher ratings imply worse creditworthiness. Observation are defined as quarter-borrower pairs.

Rating	Observations	Percent	Cumulative
1	157	0,08	0,08
2	505	0,24	0,32
3	887	0,43	0,74
4	1 833	0,88	1,62
5	17 817	8,54	10,17
6	26 532	12,72	22,89
7	6 477	3,11	26,00
8	26 843	12,87	38,87
9	61 346	29,42	68,29
10	21 466	10,29	78,59
11	30 003	14,39	92,98
12	9 363	4,49	97,47
13	3 589	1,72	99,19
14	1696	0,81	100,00
	208 514	100,00	
Mean rating	8.628		
Std. Deviation	2.174		

Table 3B. Distribution of compressed bank ratings for Bank A borrowers
Ratings have been compressed into seven instead of 14 grades. All numbers are over four years, i.e., over the period 1997Q1 to 2000Q1. Higher ratings imply worse creditworthiness. Observations are defined as quarterly-borrower observation.

Rating	Observations	Percent	Cumulative
1	3 382	1,62	1,62
2	50 826	24,38	26,00
3	109 655	52,59	78,59
4	30 003	14,39	92,98
5	9 363	4,49	97,47
6	3 589	1,72	99,19
7	1 696	0,81	100,00
	208 514	100,00	
Mean rating	3.042		
Std. Deviation	0.957		

Table 3C. Distribution of bank ratings for Bank B borrowers

All numbers are over four years, i.e., over the period 1997Q1 to 2000Q1. Higher ratings imply worse creditworthiness. Observations are defined as quarter-borrower pairs.

Rating	Observations	Percent	Cumulative
1	57	0,05	0,05
2	2 835	2,43	2,48
3	29 764	25,56	28,04
4	70 987	60,96	89,01
5	11 574	9,94	98,95
6	1 228	1,05	100,00
	116 445	100,00	
Mean rating	3.815		
Std. Deviation	0.682		

Table 4A. Empirical distribution of credit bureau ratings for Bank A borrowers
All numbers are over four years, i.e., over the period 1997Q1 to 2000Q1. Higher ratings imply improved creditworthiness. An observation is defined as a quarterly-borrower observation.

Rating	Observations	Percent	Cumulative
1	7 546	3.62	3.62
2	12 353	5.92	9.54
3	43 160	20.70	30.24
4	55 120	26.43	56.68
5	90 335	43.32	100.00
	208 514	100.00	
Mean rating	3.999		
Std. Deviation	1.097		

Table 4B. Empirical distribution of credit bureau ratings for Bank B borrowers
All numbers are over four years, i.e., over the period 1997Q1 to 2000Q1. Higher ratings imply improved creditworthiness. An observation is defined as a quarterly-borrower observation.

Rating	Observations	Percent	Cumulative
1	4 731	4.06	4.06
2	7 700	6.67	10.74
3	31 714	27.24	37.97
4	33 816	29.04	67.01
5	38 413	32.99	100.00
	116 445	100.00	
Mean rating	3.802		
Std. Deviation	1.094		

Table 5: OLS regressions with all borrowers, credit bureau and Bank A

Sample period is 1997Q3 to 2000Q1, standard errors are robust.

	Dependent variable					
Explanatory variables	Credit bureau rating			Bank A rating		
Constant	.480 (.00494)	.711 (.00861)	.711 (.0357)	0.859 (.0110)	1.472 (.0189)	1.470
Lag credit bureau rating	.885 (.00111)	.870 (.00123)	.856 (.00135)		-.110 (.00225)	
Lag Bank A rating		-.020 (.00057)		.908 (.00115)	.887 (.00133)	.887 (.00133)
Credit bureau rating dummies	No	No	No	No	No	Yes
Bank rating dummies	No	No	Yes	No	No	No
Residual Sum of Squares	55575	55236	54889	174853	163526	172059
Adj. R^2	.7784	.7798	.7811	.8226	.8252	.8255
Nobs	208514	208514	208514	208514	208514	208514

Table 5, panel B. Regressions with all borrowers, credit bureau and Bank A
The table contains details of the regression in Table 5, column 3, of the credit bureau rating on its lag and dummies of Bank A ratings, 1997Q3 to 2000Q1. Standard errors are robust. A * indicates that a coefficient is significantly different from that on the following two ratings at the 1 percent confidence level.

Variable	Coefficient	S.e.
constant	.711	.036
lagged credit bureau rating	.856	.001
dummy Bank A rating 2	-.056	.041
dummy Bank A rating 3	-.071	.038
dummy Bank A rating 4	-.062	.037
dummy Bank A rating 5*	-.083	.035
dummy Bank A rating 6	-.031	.035
dummy Bank A rating 7	-.028	.035
dummy Bank A rating 8*	-.144	.035
dummy Bank A rating 9	-.118	.035
dummy Bank A rating 10	-.060	.035
dummy Bank A rating 11	-.179	.035
dummy Bank A rating 12	-.254	.036
dummy Bank A rating 13	-.301	.037
dummy Bank A rating 14	-.391	.037

Table 6: OLS regressions with all borrowers, credit bureau and Bank A (compressed)
Bank A ratings have been compressed from 15 to 8 grades. Sample period is 1997Q3 to 2000Q1, standard errors are robust.

	Dependent variable					
Explanatory variables	Credit bureau rating			Bank A rating		
Constant	.480 (.00494)	.760 (.00868)	.632 (.0102)	0.217 (.00323)	.544 (.00816)	.579 (.0119)
Lag credit bureau rating	.885 (.00111)	.861 (.00131)	.860 (.00132)		-.0599 (.00122)	
Lag Bank A rating		-.0612 (.0041)		.938 (.00105)	.907 (.00130)	.907 (.00135)
Credit bureau rating dummies	No	No	No	No	No	Yes
Bank rating dummies	No	No	Yes	No	No	No
Residual Sum of Squares	55575	55021	55001	26540	25831	26540
Adj. R^2	.7784	.7806	.7807	.8610	.8647	.8652
Nobs	55575	55021	55001	26540	25831	26540

Table 7: OLS regressions with all borrowers, credit bureau and Bank B

Sample period is 1997Q3 to 2000Q1, standard errors are robust.

	Dependent variable					
Explanatory variables	Credit bureau rating			Bank B rating		
Constant	0.449 (.00593)	0.941 (.0144)	0.700 (.0476)	.162 (.00444)	.286 (.00703)	.279 (.00760)
Lag credit bureau rating	0.886 (.00142)	0.858 (.00169)	0.857 (.00170)		-.01907 (.0026)	
Lag Bank B rating		-0.102 (.00251)		.960 (.00116)	.947 (.00133)	.947 (.00134)
Credit bureau rating dummies	No	No	No	No	No	Yes
Bank rating dummies	No	No	Yes	No	No	No
Residual Sum of Squares	30607	30163	30147	4981	4940	4939
Adj. R^2	.7802	.7833	.7835	.9079	.9087	.9087
Nobs	116445	116445	116445	116445	116445	116445

Table 8: Explanatory power of lagged bank ratings or credit bureau ratings in OLS regressions

Entries in the table reflect the percentage by which the residual sum of squares is reduced when a one-period lag of bank ratings or credit bureau ratings is introduced as an explanatory variable in addition to the lagged dependent variable Tables 5, 6 and 7.

Dependent variable	Credit bureau rating		Bank A rating compressed	Bank B rating
Explanatory variable added	Bank A rating compressed	Bank B rating	Credit bureau rating	
All borrowers	1.00	1.45	2.67	0.82
Small borrowers	0.93	1.21	3.01	0.58
Medium-sized borrowers	1.04	1.40	2.63	0.90
Large borrowers	1.01	1.52	2.08	0.68

Table 9: Ordered logit regressions with all borrowers, credit bureau and Bank A
Sample period is 1997Q3 to 2000Q1, standard errors are robust.

	Dependent variable					
Explanatory variables	Credit bureau rating			Bank A rating		
Constant	4.682 (0.026)	3.705 (0.039)	3.820 (0.210)	3.372 (0.072)	2.955 (0.075)	2.585 (0.076)
Lag credit bureau rating	3.307 (0.011)	3.260 (0.011)	3.219 (0.011)		-0.087 (0.003)	
Lag Bank A rating		-0.086 (0.003)		2.805 (0.015)	2.793 (0.015)	2.789 (0.015)
Credit bureau rating dummies	No	No	No	No	No	Yes
Bank rating dummies	No	No	Yes	No	No	No
Pseudo-R^2	.5053	.5072	.5097	.5176	.5181	.5189
McKelvey & Zavoina's R^2	.799	.801	.803	.919	.919	.919
BIC	273945	272907	271684	411620	412294	412652
Nobs	208514	208514	208514	208514	208514	208514

Table 10: Ordered logit regressions with all borrowers, credit bureau and Bank A (compressed)
Bank A ratings have been compressed from 15 to 8 grades. Sample period is 1997Q3 to 2000Q1, standard errors are robust.

	Dependent variable					
Explanatory variables	Credit bureau rating			Bank A rating		
Constant	4.682 (0.026)	3.607 (0.037)	4.105 (0.053)	6.653 (0.038)	4.708 (0.048)	5.205 (0.055)
Lag credit bureau rating	3.307 (0.011)	3.240 (0.011)	3.236 (0.011)		-0.398 (0.006)	
Lag Bank A rating		-0.235 (0.006)		5.428 (0.022)	5.347 (0.022)	5.347 (0.022)
Credit bureau rating dummies	No	No	No	No	No	Yes
Bank rating dummies	No	No	Yes	No	No	No
Pseudo-R^2	.5053	.5080	.5085	.6981	.7034	.7035
McKelvey & Zavoina's R^2	.799	.802	.802	.889	.894	.894
BIC	273945	272477	272292	160754	157963	157949
Nobs	208514	208514	208514	208514	208514	208514

Table 11: Ordered logit regressions with all borrowers, credit bureau and Bank B
Sample period is 1997Q3 to 2000Q1, standard errors are robust.

	Dependent variable					
Explanatory variables	Credit bureau rating			Bank B rating		
Constant	4.827 (0.034)	2.618 (0.061)	3.809 (0.278)	9.856 (0.177)	7.492 (0.187)	7.859 (0.190)
Lag credit bureau rating	3.419 (0.014)	3.333 (0.014)	3.330 (0.014)		-0.444 (0.015)	
Lag Bank B rating		-0.473 (0.011)		7.205 (0.034)	7.063 (0.034)	7.069 (0.034)
Credit bureau rating dummies	No	No	No	No	No	Yes
Bank rating dummies	No	No	Yes	No	No	No
Pseudo-R^2	.5113	.5164	.5165	.8125	.8161	.8162
McKelvey & Zavoina's R^2	.809	.813	.813	.878	.884	.884
BIC	158263	156624	156614	44694	43849	43861
Nobs	116445	116445	116445	116445	116445	116445

Table 12: Cox regressions on Credit Bureau defaults

The Breslow method has been used for tied observations.

A * indicates that the variable had to be dropped because no defaults occur for the dependent variable at the relevant lag.

The "-" sign indicates that the particular RHS variable is not available for this regression.

	Dependent variable: Credit bureau default							
Explanatory variables	RHS: Lag 1, Bank A or CB				RHS: Lag 1, Bank B or CB			
Lag credit bureau rating			0.30 (0.019)				0.33 (0.025)	
Lag bank rating	2.39 (0.098)				3.45 (0.26)			
Lag, Dummy bank rating = 2		0.068 (0.029)				*		
Lag, Dummy bank rating = 3		0.12 (0.041)				*		
Lag, Dummy bank rating = 4		0.39 (0.13)				4.50 (1.93)		
Lag, Dummy bank rating = 5		1.20 (0.41)				32.59 (13.92)		
Lag, Dummy bank rating = 6		2.84 (0.98)				55.62 (28.24)		
Lag, Dummy bank rating = 7		4.27 (1.55)				-		
Lag, Dummy CB rating = 1				73.07 (22.60)				77.74 (36.49)
Lag, Dummy CB rating = 2				23.54 (7.73)				33.30 (15.93)
Lag, Dummy CB rating = 3				5.15 (1.74)				7.22 (3.48)
Lag, Dummy CB rating = 4				1.64 (0.67)				3.23 (1.69)
Residual Sum of Squares								
Number of subjects	31991	31991	31991	31991	17831	17831	17831	17831
Number of failures	180	180	180	180	136	136	136	136
Nobs	216968	216968	216968	216968	122927	122927	122927	122927
Loglikelihood	-1634.7	-1654.9	-1593.2	-1590.5	-1180.1	-1181.9	-1151.0	-1149.5

Table 13: Cox regressions on Bank defaults

The Breslow method has been used for tied observations.

A * indicates that the variable had to be dropped because no defaults occur for the dependent variable at the relevant lag.

The "-" sign indicates that the particular RHS variable is not available for this regression.

	Dependent variable: Bank A default				Dependent variable: Bank B default			
Explanatory variables	RHS: Lag 1, Bank A or CB				RHS: Lag 1, Bank B or CB			
Lag credit bureau rating			.27 (.013)				0.31 (0.020)	
Lag bank rating	3.04 (0.11)				5.74 (0.54)			
Lag, Dummy bank rating = 2		*				*		
Lag, Dummy bank rating = 3		2.16 (0.70)				*		
Lag, Dummy bank rating = 4		10.37 (3.29)				10.09 (5.96)		
Lag, Dummy bank rating = 5		40.39 (12.58)				73.18 (43.13)		
Lag, Dummy bank rating = 6		81.98 (26.17)				275.73 (167.53)		
Lag, Dummy bank rating = 7		216.54 (67.64)				-		
Lag, Dummy CB rating = 1				32.44 (5.76)				9.92 (2.24)
Lag, Dummy CB rating = 2				10.23 (2.02)				3.37 (0.88)
Lag, Dummy CB rating = 3				2.55 (0.51)				1.35 (0.31)
Lag, Dummy CB rating = 4				0.97 (0.24)				0.67 (0.18)
Residual Sum of Squares								
Number of subjects	31965	31965	31965	31965	17777	17777	17777	17777
Number of failures	315	315	315	315	166	166	166	166
Nobs	216427	216427	216427	216427	122421	122421	122421	122421
Loglikelihood	-2730.8	-2722.3	-2722.4	-2869.7	-1405.7	-1403.4	-1380.6	-1490.7

Table 14: Log Likelihoods in Cox proportional hazards model: All borrowers
Loglikelihood values for models with only one RHS variable are taken from Tables 13-14 (lag 1) and Appendix Tables A.7-A.8 (lag 2). Loglikelihood values for models with both CB and bank rating on the RHS are not reported elsewhere and provided for LR exclusion tests in the lower panel of the Table. Significance of an additional RHS variable is shown at the 10 (*), 5 (**), 1 (***), and 0.1 (****) levels.
In the likelihood ratio tests (lower panel), the value displayed is 2*log(likelihood ratio).

	Dependent variable			
	Credit bureau default		Bank default	
Explanatory variables	Bank A	Bank B	Bank A	Bank B
Lag of CB rating	-1593.2	-1151.0	-2722.4	-1380.6
Lag of Bank Rating	-1634.7	-1180.1	-2730.8	-1405.7
Lag of CB and Bank Rating	-1555.2	-1123.1	-2597.4	-1335.1
Lag 2 of CB rating	-1442.6	-940.2	-3192.9	-1558.3
Lag 2 of Bank Rating	-1476.3	-966.9	-3283.5	-1596.8
Lag 2 of CB and Bank Rating	-1423.0	-925.3	-3128.3	-1520.5
Likelihood ratio tests for exclusion of particular lags				
First Lag Only				
Exclusion of Lag of Bank Rating	76.0 ****	55.9 ****	249.9 ****	91.1 ****
Exclusion of Lag of CB Rating	159.0 ****	114.1 ****	266.7 ****	141.3 ****
Second Lag Only				
Exclusion of Lag 2 of Bank Rating	39.2 ****	29.7 ****	129.2 ****	75.6 ****
Exclusion of Lag 2 of CB Rating	106.6 ****	83.1 ****	310.2 ****	152.5 ****

Table 15A. Correlations by between credit bureau and bank ratings
Correlations are per quarter, scale is inverted for bank ratings.

Quarter	Bank A	Bank A Compressed scale	Bank B
1997 Q3	.4532	.4934	.4589
1997 Q4	.4381	.4847	.4771
1998 Q1	.4059	.4569	.4658
1998 Q2	.3625	.4414	.4614
1998 Q3	.3401	.4145	.4489
1998 Q4	.3087	.3892	.4453
1999 Q1	.2850	.3601	.4389
1999 Q2	.4776	.5728	.4285
1999 Q3	.4293	.5254	.4330
1999 Q4	.3794	.4781	.4245
2000 Q1	.3367	.4342	.4175
2000 Q2			.4214
All quarters	.3765	.4559	.4427

Table 15B. Correlations by between credit bureau and bank ratings
Correlations are per quarter, scale is inverted for bank ratings. Only observations drawn on in the regressions are used in the calculations.

Quarter	Bank A	Bank A Compressed scale	Bank B
1997 Q3			
1997 Q4	.4457	.4931	.4843
1998 Q1	.4130	.4664	.4685
1998 Q2	.3849	.4753	.4643
1998 Q3	.3449	.4240	.4528
1998 Q4	.3168	.4015	.4474
1999 Q1	.2927	.3719	.4482
1999 Q2	.4908	.5900	.4325
1999 Q3	.4414	.5425	.4383
1999 Q4	.3922	.4954	.4323
2000 Q1	.3474	.4501	.4266
2000 Q2			.4284
All quarters	.3834	.4709	.4472