Bad times, good credit

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Abstract. Banks' limited knowledge about borrowers' credit worthiness constitutes an important friction in credit markets. Such information frictions may explain some of the cyclical swings of the credit supply. Alternatively, if tough times reveal information about firm quality, information problems may be reduced in recessions. We test these alternative hypotheses using loan data from a large bank. This banks' ability to sort borrowers by credit quality is best in recessions, and worst in good times. We estimate that adverse selection can explain at most 6 percent of this variation. Our results imply that information frictions are counter-cyclical in corporate credit markets.

Keywords: Credit markets, corporate loans, information frictions, business cycles.

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"Only when the tide goes out do you discover who is not wearing swim trunks"

Ascribed to Warren Buffett, CEO Berkshire Hathaway

Credit is the main form of financing for both firms and households, and credit funds new corporate and household investment, consumption, and transactions. Credit flows are cyclical, however. In recessions, the volume of new credit is low and loan spreads are high. There is a long-standing concern that lower credit flows reflect a low supply of credit due to some friction in credit markets, and that this may exacerbate business cycles (see e.g., Bagehot 1873).[1] In this paper, we examine one potential driver of cyclical swings in the credit supply: variation in the quality of lenders' information about individual borrowers.

Information frictions are understood as central to understanding many features of credit markets, including the formation of long-term relationships between borrowers and lenders (Petersen Rajan 1994), the existence of credit registries (Pagano Japelli 1993 and Hertzberg Liberti Paravisini 2011), and the use of covenants in debt contracts (Smith Warner 1979). Information frictions have been identified as important to both quantities (Garmaise Natividad 2013) and prices (Ivashina 2009) in credit markets.

Given the importance of information frictions, it may seem natural to ask how they contribute to credit market cycles. Which, if any, of the various information problems identified in the literature are likely to be cyclical? Information frictions can assume many shapes, including asymmetric information between borrower and lender about borrower quality (Stiglitz Weiss 1981); asymmetric information between banks; or ex-ante uncertainty about an individual project's future payoff (Townsend 1979, Gale Hellwig 1985). Whether these frictions are more

[1] Some of the cyclical pattern in credit flows reflects lower demand for external credit as firms and households have fewer investment opportunities in recessions. For corporate debt, the evidence for cyclical supply is diverse. Dell'Ariccia, Detragiache, Rajan (2008) use cross-sector variation to document the cyclical nature of credit supply. Chava and Purnanandam (2011), Jiménez, Ongena, Peydró and Saurina (2012) and Peek and Rosengren (1997) document large contractions in the corporate credit supply associated with the Asian crisis in 1997, the recent financial crisis, and Japan's stock market collapse in the early 1990s, respectively.

(or less) severe in cyclical downturns is not obvious.[2] Several theories suggest that information problems between lenders and borrowers are *less severe in downturns*. For example, banks may be better able to sort firms based on their credit risk in bad periods because they try harder, reflecting counter-cyclical incentives to screen (Ruckes 2004). Alternatively, loan officer skills may deteriorate in booms (because there is less feedback about prior credit decisions in times of low default rates), reducing the quality of bank credit decisions (Berger Udell 2004). Yet another mechanism involves the amount of effort exerted by banks: Dell'Ariccia and Marquez (2006) develop a model where booms are characterized by a reduced need to screen new borrowers, leaving the bank with less precise signals. Finally, credit officers may exert more effort in bad times because they become more risk averse (Cohn, Engelmann, Fehr, Maréchal 2015). In contrast, another set of models involves information frictions that are *more severe in bad times*. For example, Kurlat (2013) models an economy where lower investment opportunities increase AI problems, which generates a feedback to growth. Both Ordonez (2013) and Guerrieri and Shimer (2014) also model economies where worsening AI is the driver of cyclical downturns.

Thus, there are several arguments consistent with both pro- and counter-cyclical information frictions in credit markets. Prior evidence is mostly indirect. For example, Dilly and Mählmann (2015) document that initial credit ratings of corporate bonds issued in recessions are more accurate than those initial ratings issued in better times, consistent with *lower* information frictions in bad periods.[3] Can credit flow data help settle the question? Financing with bank loans is likely more reliant on overcoming asymmetric information than financing with bonds. Indeed, bank lending is more cyclical than arm's-length credit (Kashyap Stein Wilcox 1993; Becker Ivashina 2014, 2015). This pattern could reflect cyclical variation in information frictions, but is also consistent with other factors holding back bank lending (e.g. bank capital depletion as in Holmström Tirole 1997).

[2] We focus on corporate bank loans when discussing theory. The cyclical nature of supply is especially pronounced for bank credit (as opposed to the bond market), and our empirical results concern a bank. Many theories would apply equally to other borrowers (i.e., households) and instruments (i.e., bonds).

[3] Dilly and Mählmann interpret the pattern to reflect time-varying conflict of interest between rating agencies and investors.

In this paper, we attempt a more direct examination of the quality of bank information about borrowers. We use data from a large Swedish bank to test whether the bank's assessments of credit quality of its corporate clients is cyclical. The data provides detailed information on the bank's corporate loans and borrowers through two business cycles. Our main tests examine whether the banks' internal metrics of credit quality perform better or worse in bad times.

This bank employs an internal rating system to summarize information about the credit quality of its borrowers. We compare the precision in these internal ratings over time by regressing a measure of loan defaults (or borrower bankruptcy) on the bank's past internal ratings for borrowers. This method faces an econometric challenge in that borrowers with better ratings are more likely to be granted more credit (or be charged less interest or otherwise be offered better terms), and these credit decisions can affect future default risk, possibly in different ways over the cycle.[4] Therefore, we need to separate the predictive power of ratings (holding credit offered constant) from the effect of credit decisions (which rely on the ratings) on future credit quality. We try to address this challenge by controlling for the amount of credit a firm is granted. In other words, for two similar borrowers, with the same amount of credit outstanding, is the one with a better internal rating less likely to default? In our sample, the answer is yes. We find a strong negative correlation between the predictive power of ratings and macro-economic performance (GDP growth, stock market index, consumer confidence index). This applies both to the magnitudes of coefficient estimates and to measures of explanatory power such as R-squared. Thus, this bank is best able to predict default in business cycle downturns, a pattern consistent with information frictions being pro-cyclical, i.e. weaker in recessions.[5]

We address several alternative explanations of the results or potential problems with our interpretation of the results. Our first concern is that borrowers may differ over the business

[4] The impact of new credit on default risk may be complicated. In the short run, the likelihood of default risk is almost certainly lower after new credit, but in the long run, the firm has more leverage and may therefore be more likely to default. This "term structure" of default risk may vary across firms, industries and the business cycle. See for example Glennon and Nigro (2005).

[5] Default is defined as missed payments (interest or amortization) by at least 60 days. See empirical section.

cycle in some way that affects the precision of internal ratings. We consider whether the mix of borrowers is more challenging in good times, e.g., because there are more new entrants in the pool of rated borrowers (this prediction is made by Dell'Arriccia and Marquez 2006). Our results hold for new and old borrowers, and with comparable magnitudes. Thus, compositional shifts do not drive our results. Similarly, variation in industry composition does not appear to explain the time-series patterns we observe.

It is also important to understand whether selection problems may affect our results. The Swedish bank sector is very concentrated and borrower-lender relationships are stable. In a sample very similar to ours, Degryse et al (2016) report that less than 5% of corporate borrowers with a relationship get loans from other banks. In our sample, the fraction of new borrowers (with less than one year as customers) averages 10%, and the number of exits from our sample is only 3% (over the whole sample period). We estimate a simple structural model of adverse selection and conclude that the theoretical limit for how much can be explained by exits is 6% of the variation we observe in signal precision over the business cycle. Thus, adverse selection (as in Stiglitz and Weiss) is perhaps not that important to lending decisions in this market. Thus, we interpret changes in the predictive ability of the bank's signal as reflecting the information content of that signal.[6]

The banking industry in Sweden, as elsewhere, has been subject to regulatory reform during our sample period. May this in some way drive our finding that the precision of bank credit information varies with the business cycle? One general hypothesis about recent reforms is that they increased the cost of assigning low ratings, because this raises capital requirements under the internal ratings model. This generates an incentive to lower ratings (Behn Haselmann and Vig 2014), which might make them less precise (by adding noise). The Basel II system was introduced in Sweden in February 2007 and the largest banks have since then been allowed to

[6] Credit markets where relationships play a smaller role, and where borrowers have more choices, increase the scope for adverse selection. Such markets include the syndicated loan market (Berg, Saunders and Steffen 2015), mortgage lending to households (Agarwal, Chang and Yavas 2012) and the interbank market (Ennis and Weinberg 2013).

use the internal ratings model. However, transitional rules meant that Basel I requirements constituted a floor for capital requirements, initially until 2009 and later through an extension until the enactment of Basel III regulations. The new rules were expected to generally raise requirements on both large and SME (small and medium) corporates (Finansinspektionen 2006). To the extent that ratings became more noisy over the 2007-2009 period, we would predict deteriorating performance at the exact time when we find precision improves. Outside of this period, no reform of similar broad importance was introduced. We therefore conclude that regulation is unlikely to explain our results.

Overall, our results are consistent with the literature that sees information frictions in credit markets as key to credit markets. However, the information problem we study appears most severe in good times. Thus, broadly speaking, our findings do not fit the theories where information frictions in credit markets play a role in recessions, but is more consistent with models of poor lending decisions in booms.[7]

While our results point in the general direction of counter-cyclical information frictions, can they tell apart different mechanisms? Our data allows some examination of Ruckes' prediction that banks will work harder to discover the quality of borrowers in times when overall default risk is higher. We test this using an indicator for when the banks revises each borrower's ratings. We find that this monitoring activity is highly seasonal, but not cyclical. Thus, we see no sign that increased monitoring efforts in recessions are driving the greater precision the bank's risk assessments. Our results also do not appear to be explained by the mechanism proposed by Berger and Udell (deteriorating loan officer skill), because the variation in precision we observe is also observed for mechanical credit scores involving no judgment. A simple explanation that appears consistent with all our findings is that it is the environment itself, rather than the bank's actions, that lessen the extent of information frictions in recessions.

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[7] Our results do not speak to uncertainty about *aggregate* states (see e.g. Bloom 2007, Caballero Simsek 2013, Fajgelbaum, Schaal Taschereau-Dumouchel 2014, and Gilchrist, Sim Zakrajšek 2014). It may be the case that sorting corporate borrowers by credit quality is, in fact, easier in recessions, but that uncertainty about economic growth is simultaneously high.

Our paper is related to the broader literature on why credit markets are cyclical. If information frictions are counter-cyclical, other frictions must be even more cyclical, in order to explain observed patterns in the corporate credit supply. Such frictions may be located in the financial system: a low loan supply in recessions may reflect the impairment or weakness of the institutions that intermediate loans (Holmström and Tirole 1997) or incentive problems facing bank managers (Rajan 1992, Myerson 2012).[8] A second category of explanations involves agency problems between lenders and borrowers. Such agency problems can become more severe in recessions if corporate losses reduce equity value (Bernanke and Gertler 1989) or if asset values fall (Kiyotaki Moore 1997). Our results, by limiting the set of candidate explanations for credit cycles, provide indirect support for (at least some of) these mechanisms.

Our results are limited to the corporate credit market. Information frictions may have different cyclical properties in other financial markets. For example, the equity market may experience increased information asymmetries in crises. Given the key role of corporate credit markets for funding investment, the results presented here are nevertheless of great potential importance.

1. Data and variables

For our analysis, we use a comprehensive database of all corporate accounts of one of the major Swedish commercial banks (henceforth, "the bank"). The database contains all loan files the bank maintains for each borrower at a monthly frequency between 2004:01 and 2012:12. As our main unit of analysis, we use borrowers rather than individual loans, following the bank's own view that credit risk is mainly a firm-level issue. The bank therefore assesses borrower risk with its internal ratings system).

We supplement the bank's data with annual accounting information from Statistics Sweden and information from UC AB, the Swedish leading credit bureau, which is jointly owned by the largest Swedish banks. The credit bureau data includes the firms' payment histories and the

[8] Different kinds of evidence that financial institutions matter is provided by, e.g., Becker Ivashina (2014), Benmelech Meisenzahl and Ramcharan (2015), Chodorow Reich (2014), Ivashina and Scharfstein (2010), Jiménez, Ongena, Peydró and Saurina (2012), and Khwaja Mian (2008).

credit bureau's assessment of the firms' credit risk as captured by their credit score and an ordinal rating.[9]

Table 1 lists the variables used in this study and Table 2 presents some descriptive statistics for each variable for the entire sample: The mean, median, standard deviation, and number of observations. We analyze two sets of variables that pertain to the bank´s evaluation of their borrowers' riskiness and the bank's monitoring activity, respectively.

1.1 Borrower and loan data

In Table 3, we report data for firms with different internal ratings (IR). IR is the bank's own measure of the borrower's creditworthiness and uses seven main categories, with sub-grades of plus and minus. We code this variable from one to 21, where one is the worst rating (highest default risk) and 12 is the best (lowest default risk). The credit risk model used by the bank is based on multiple data sources including credit ratings from a credit bureau, borrower income statements, balance sheet information and other (soft) information (Nakamura and Roszbach 2010). Only borrowers to which the bank has a total exposure above a certain pre-determined threshold are assigned an internal rating. In our raw data, 70-80% of firms are assigned an IR each year, representing that vast majority of loans outstanding. IR values are stable over time: on average, 2% of firms change category from one quarter to next.

Our key outcome measure is the occurrence of a borrower default within a period of 12 or 24 months. The default variable is equal to one when any payment is over 90 days past due. Because defaults are sometimes resolved quickly and at a limited loss for the bank, we also use bankruptcy filings as an alternative dependent variable. Bankruptcy is somewhat rarer but typically more severe and more likely to be a terminal state than default is. In our data bankruptcies constitute a subset of default events (58% of default events are also bankruptcies in our sample).

[9] Jacobson, Lindé and Roszbach (2006) and Nakamura and Roszbach (2010) describe the credit bureau's modeling.

We report the average default and bankruptcy rate and loss given default by IR category in Table 3. The 12 and 24 month default and bankruptcy rate is by far the highest for rating category 1, and losses given default are on average highest for the worst IR as well. Despite this, more of the bank's credit losses are caused by firms with a better rating a year before their default. Thus, in an aggregate sense, the default risk of relatively safe firms is key to understanding the precision of the bank's information. Panel B of the table also provides data on the number of loans per firms, the share of loans that have some collateral, the average loan maturity and the average interest rate for each IR category.

Table 3 illustrates how default rates rise monotonically and in a convex fashion with falling rating categories. Using rating categories linearly in regressions may therefore be inefficient. On the other hand, allowing a completely flexible form (e.g., through separate dummy variables for each category) would complicated interpreting whether ratings are better or worse at predicting default. To both allow easy interpretation and a non-linear relationship between ratings and default rates, we estimate a 4th degree polynomial in IR (with only time FE), to generate a default prediction that fits (12 month) default rates. We call this variable "IR polynomial".[10]

As an alternative to IR, we explore a second measure of the borrowers' creditworthiness, "credit slack" in the online appendix (slack is defined as the amount of credit the loan officer is allowed to extend without further internal approval). All our results hold for this alternative measure.

1.2 Monitoring

We construct different measures of the bank's monitoring activity. These measures are based on the frequency with which the bank reviews a borrower´s files and possibly revises either the client's credit rating or credit limit, reassesses collateral values, or makes other changes to the client's credit terms. By internal rules, loan officers are expected to review each client's file at least once every 12 months. The average time between two monitoring events is slightly above

[10] The definition is $0.41xIR - 0.083xIR + 0.0064xIR - 0.00022xIR - 0.0000029xIR$. A second, third or fifth order polynomial looks very similar over the relevant range: $IR \in \{1,2,..,21\}$.

10 months and it varies from 1 to 24 months. Long time gaps are rare: only 2.1% of firm-months are beyond the expected 12 month limit since their last reported monitoring.

1.3 Macro data

We use two variables to capture the evolution of the macro economy: the seasonally adjusted, real GDP growth (measured at quarterly frequency) and a stock market index return over the last 12 months (which we measure at the end of each month). We use the OMX30, a market value-weighted price index of the 30 most actively traded stocks on the Stockholm Stock Exchange. The two time series variables are correlated with each other (0.73) and also with consumer confidence measures of the business cycle (0.70 and 0.51 for GDP growth and stock market return, respectively). We define a recession dummy as equal to one when at least one of the trailing 12 month stock return and the real GDP growth is negative.

Figure 1 displays the two indicators and our recession dummy (shaded areas) over the sample period. During our sample period, Sweden experienced a steep but short recession in 2008 and 2009 (negative GDP growth in 2008Q1, 2008Q4 and 2009Q1) and a second, milder, slowdown from mid-2011 to mid-2013 (negative growth in 2011Q3, 2012Q3 and 2013Q2).

2. Empirical results

In this section, we test the competing hypotheses regarding the cyclical properties of banks' internal credit ratings, which summarize the information they have available on their borrowers.

2.1 The relationships between internal ratings and default

We start by documenting the basic relationship between the bank's measure of creditworthiness and borrowers' likelihood of default. To assess the precision of the bank's information, we use probit regressions. The advantage of probit models (or similar models, such as logit), over a linear probability model is that they can better fit very low probabilities (recall that defaults and bankruptcy is rare for firms in many ratings categories). We estimate probit regressions as follows:

$$\text{Default}_{t+s} = \text{IR}_t + \text{Controls}_t + \text{Time Fixed Effects} \quad (2)$$

We estimate (2) for defaults within twelve or twenty four months ($s = 12$ or $s = 24$).[11] Control variables capturing accounting based measures of firm performance as well as the firm's credit bureau score and borrowers credit contract characteristics. Results for both horizons, and with and without controls, are reported in Table 4, with two panels for two different credit variables. In all specifications, the bank's information variables are significant and have the expected, negative sign (i.e., better quality borrowers have lower default probability).

In Panel A, the credit variable is IR. In columns one and four, we leave out all controls except for time fixed effects. These regressions help us answer if IR, on its own, predicts default. We find that it indeed does. We include control variables in column two and five, to verify whether IR has predictive power for borrower default over and above the hard information captured in historic accounting data, payment remarks and the credit bureau's credit scores. This is close to asking whether IR reflects soft information that loan officers have (information not captured in the control variables). The credit variable (IR) again predicts default, and with a highly statistically significant coefficient. The estimated marginal effect of IR, evaluated at the mean of the dependent variable (i.e., around 1.5% default risk), implies that a three-unit increase in the rating (the standard deviation is 3.6) reduces the likelihood of default from 1.50% to 1.19%, or a 21% reduction.

In panel B, we repeat the tests using a fourth degree polynomial in IR (details are in the data section above). The magnitude of the estimated coefficient on IR polynomial is significantly different from zero with and without control variables. A one standard deviation increase in IR around the median IR (13) is associated with a 6% reduction of the default likelihood (from 1.50% to 1.42%). Because of the shape of the IR polynomial, the effect is much larger for higher risk firms. Dropping from the second worst to the worst IR group (from IR=5 to IR=2), while

[11] We have employed a range of alternative econometric models to assess the relationship between default, and internal ratings. These include survival models with various distributional assumptions, and replacing the default indicator with a bankruptcy indicator. These are not reported, but results are qualitatively very similar to table 4.

holding all control variables fixed, is associated with a 75% increase in default probability (from 12% to 21% risk of default), from the third worst to the second worst IR group (i.e., from IR=8 to IR=5) is associated with an increase of 47% (from 4.4% to 6.5%), and from the fourth worst to the third worst IR group (i.e., from IR=11 to IR=8) is associated with an increase of 22% (from 1.86% to 2.27%).[12]

The results in Table 4 show that IR is an economically and statistically significant predictor of default, with and without controlling for hard information such as accounting data. The connection between future defaults and the bank's assessments of its borrowers suggest (a) that the bank has some ability to predict defaults and (b) that IR captures meaningful parts of the bank's internal information. Additionally, since we control for a fairly large set of accounting-based variables and the credit bureaus score, the residual effect of IR can reasonably be considered "soft" information in the sense of Berger at al (2005).

2.2 Information over the business cycle

In this sub-section we turn to the cyclical patterns in informational asymmetries that are our primary object of interest. Our main tests investigate the time-series variation in the informativeness of IR. We first use several different non-parametric and graphical techniques to visually assess the informativeness of the bank IR, and then turn to regression-based estimation of the time-series properties of AI.

Predictive accuracy of the internal ratings

To measure the predictive performance of the IR variable, we first use Moody's (2003) concept of 'accuracy curves'. An accuracy curve is a plot of the proportion of defaults accounted for by firms below a certain rating (y-axis) against the proportion of the firm population that are below the same rating (x-axis). An accurate rating system is one where most defaults occur for firms with low ratings and few defaults for firms with high ratings. This means the accuracy curve is close to the upper left corner. Random assignment of ratings (i.e. uninformative ratings)

[12] These (conditional) marginal effects can be compared to the average IR group-to-IR group difference in (unconditional) default risk in in Table 3, which are larger.

produces an accuracy curve along the 45 degree line (as defaults are equally likely at all ratings levels). We construct accuracy curves for ratings at year end for all years, with a 12 month forward default horizon, and plot these annual curves in Figure 2. Clearly, ratings contain a lot of predictive power in. Additionally, the recession years 2008, 2009 and 2011 which contain negative growth quarters, have three of the four highest accuracy ratios. This could be interpreted as evidence that the banks' information is more precise in bad times. Considering our quarterly data at annual frequencies disregards a lot of the variation in accuracy rates. Our visual comparison does not work well when showing too many curves at once. Therefore we next consider a way of plotting precision over time.

Survival rates by rating over time

Our sample of firms is largely stable over time, although some firms do drop out of the panel. To deal with possible bias caused by selection on disappearance, we use Kaplan-Meier survival rates to examine the fine time-series variation in default rates across the various internal ratings. The Kaplan–Meier estimator is a nonparametric estimate of the survival function S(t) (and the corresponding hazard function), using the empirical estimator Ŝ(t):

$$\hat{S}(t_k) = \frac{n_k - h_k}{n_k} \tag{3}$$

where t_k is the kth lowest survival time, n_k is the number of "at risk" observations at time t_k (firms that have not defaulted by that time and have not left the sample for other reasons), and h_k is the number of defaults at that time.[13] Figure 3 shows 12 and 24 months survival rates for the four intermediate internal rating groups (i.e., we combine three adjacent IRs into one group), quarter by quarter until 2011q1. The weakest rating category is excluded to keep the scale small enough so that changes are visible, while the two strongest categories show little visible variation at the depicted scale. Borrowers with the best ratings have the lowest default frequencies in all periods. Survival rates display a clear business cycle pattern with survival

[13] Firms can exit the data without a default event when they repay their loans (for example because the firm changes bank).

rates falling for all categories during both recessions. The difference in survival rates between rating categories tends to increase in downturns. In other words, the difference in default risk between firms classified in different but adjacent ratings categories is largest in recessions. This suggests that the bank's ratings are most informative about risk in recessions.

Comparing vertical distances between lines in Figure 3 corresponds to measuring differences in default risk. Once concern is that if default rates double, absolute differences may mechanically increase, even if the sorting of risks did not improve in a relative sense. To address this, it can be helpful to examine ratios instead of differences. Next, we operationalize the idea of comparing relative default rates across categories.

Relative default risk

We now turn to an explicit comparison of relative defaults rates of different ratings over time. To facilitate the comparison, we combine ratings into two categories, one group consisting of the three highest ratings and another containing the next three grades. We drop the lowest category where default is imminent for most firms; results are qualitatively unchanged with this category included. The two groups are of comparable size.[14] We define the default ratio as the default frequency for the weak group divided by the default frequency for the overall sample as follows:

$$Default\ ratio = \frac{\frac{D_{weak}}{N_{weak}}}{\frac{D_{weak}+D_{strong}}{N_{weak}+N_{strong}}} \qquad (4)$$

Here D measures the number of defaults and N_i the number of firms at risk in group i, and *strong* and *weak* are labels for the two groups. This default ratio has several attractive properties as a measure of the precision of the bank's sorting of its borrowers. First, if the ratings are uninformative, the default frequency will be the same for the two ratings categories, and the

[14] We have also varied the methodology by using finer categories based on qualifiers to internal ratings ("pluses" and "minuses") and letting the cutoff vary by quarter, in order to make sure that the two groups are of equal size. We have also used Kaplan-Meier adjusted default rates. Results are very similar.

default ratio becomes one. Thus, a lower bound for the ratio is one.[15] If all defaults occur in the weaker category ($D_{strong} = 0$), the best possible outcome, the ratio simplifies to $\frac{N_{weak}+N_{strong}}{N_{weak}}$, i.e. the ratio of sample size. Since we have constructed the two groups' size to be of very similar size, this ratio is close to two in our data. Taken together, this means that the ratio has a natural scale from one (no information) to two (very good information).

We plot the quarter by quarter default ratio in Figure 4, dropping IR category 7.[16] The average default ratio in expansions is 1.42 and in recessions 1.60. Based on the time series standard deviation of the ratio, the difference of 0.18 is significantly different from zero (t-stat of 7.30).[17] In other words, defaults are more concentrated among firms to which the bank assigned poor ratings during a recession than in good times. This result confirms that the bank's ability to assess credit risk appears strongly countercyclical.

The high precision of the bank's ratings might reflect hard and soft information, since the assignment of firms to ratings uses on both types of information. We therefore plot the Default ratio based only on sorting the credit score, which in principle is data available to any bank (and thus, a hard signal). The precision of this hard variable is *also* counter-cyclical. One interpretation of this is that the problem of predicting defaults is inherently easier in recessions, as even a mechanical procedure of sorting firms does better in bad times. Additionally, it appears that the performance of IR is better than performance using only credit scores. The overall average Default ratio is 1.47 for the IR-based sort and 1.22 for the sort based on credit scores only. The difference (0.247) is significantly different from zero (assuming time series independence, the t-stat is 12.9, and allowing for four auto correlation terms, the t-stat is 8.7).

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[15] In a perverse scenario where defaults are less frequent for *weak* than for *strong*, the ratio is smaller than one. However, it would then make sense to switch the labels of the categories, and the ratio would not be below one.

[16] Firms with IR = 7 are often already in default, and are perhaps not really a prediction challenge. Results are similar with these firms.

[17] The t-stat using Newey-West standard errors which allow for four auto-correlation terms is 5.0.

Can sample selection affect these results? To explain our patterns, selection would have to be more unfavorable in good times (i.e. well rated firms with relatively low default risk and poorly rated firms with relatively high default risk disappear from observed sample in bad times). A priori, this may not be realistic. Nevertheless, we develop a simple model of firms' credit choices over a one-year period to assess this. We consider a sample equally split between good and bad ratings, allow the default rate to vary between the groups. We assume that the sample exit rate is the same for both groups, but allow default rates in the exiting group of firms to differ. We will use the model to ask whether the time series changes in the default ratio can be driven by changes in selection over time. We calibrate the model to 2% exits per year (our sample contains 16,702 firms, of which 16,179 remain when we condition on no exits, implying 3% of firms disappear at some point), 1.5% annual default rates both in exit and non-exit samples, and a default ratio of 1.6. We start by assuming sample exits are no different from non-exits, and then ask what default rates among exits, if any, could drive the default ratio down to 1.42 (the observed boom period ratio). With these assumptions, default rates after sample selection must be 2.4% and 0.6% so that the default ratio is 2.4%/1.5%=1.6. Without any selection effect, these are also the default rates both in exit and non-exit samples. Can changes in the default rates of the exit firms reduce the default ratio in the remaining sample to 1.42? This is not possible while maintaining the 1.5% average default rate. If default rates in the good and bad exit samples are 0% and 3.0% (the widest spread consistent with 1.5% average), the remaining sample default ratio becomes 1.59. Thus, we conclude that while selection may contribute to the difference between good and bad times, in can only account for a small part of the differences we observe at a business cycle frequency (at most $\frac{1.60-1.59}{1.60-1.42} \approx 5.6\%$).[18]

There are two important caveats to using the relative default ratio. First, this methodology penalizes defaults among highly rated firms (as captured by $D_{strong} > 0$), but pays no attention to non-defaults among poorly rated firms. These errors can be loosely compared to type 1 and 2

[18] We do not deal formally with the scope for selection bias in later statistical estimates, given the small maximum impact it appears to have in this setting. Obviously, the simple structural model here would not apply directly to regression models using more of the ratings scale and with many control variables.

errors in statistics. The choice of ignoring missed non-defaults and focusing on missed defaults is sensible if missed defaults are much more costly. In credit decisions, this may be a fair assumption. Second, there are no control variables in this test. Next, we turn to regression specifications which deal with both these concerns (by allow control variables, and by implicitly looking at both types of mistakes).

Semi-parametric estimates of cyclicality

We now turn to regression-based estimates with many control variables. By filtering out information captured in these variables, we implicitly focus on the softer component of the bank's information (all the accounting based ratios are more or less hard information, and the credit score is hard, as well). To track time-series variation in the predictive precision of IR we adjust regression (2) by allowing the coefficients on bank's information (IR) to be different each quarter. This is a semi-parametric approach, in that we impose no structure on the time pattern of coefficients. We plot the quarterly coefficient estimates in Figure 5.

Several patterns are apparent in Figure 5. First, there is considerable time series variation in the predictive power of the measures we use to capture the bank's information. Second, this variation appears highly correlated with the business cycle: in the pre-crisis period (when credit markets were very strong and borrowers performed well). The statistical power, and the magnitude of coefficient estimates, rises in the 2008-2009 recession, then fades somewhat and finally seems to increase again during the second recession in 2011. These results suggest that the bank is better able to sort borrowers by credit quality at times when the economy is weak.

An additional measure of the ability of internal ratings to explain defaults is provided by R-squared. If the information contained in IR is more useful for predicting defaults in recessions, the R-squared should be higher. To examine this, we estimate monthly regressions in recession and non-recession periods. To simplify the setting, we focus on the contributions of the credit score and the internal rating (results are qualitatively similar with more controls). The credit score corresponds closest to the standard notion of hard information, since it is a numerical variable, publicly available (for a fee). On the other hand, the internal rating incorporates both hard information and the bank's own soft information. We report the average R-squared (for OLS regressions) and Pseudo R-squared (for probit regressions) in Table 5. Unlike the OLS statistic R-squared, the Pseudo R-squared cannot be interpreted as the share of variation explained by explanatory variables in the regression, but, on the other hand, we use Probit regressions for our tests. Thus we report both. The first row of Table 5 shows that the R-squared from internal ratings is several times higher in recessions than outside of recessions: 11% vs. 1.3%.[19] The model fit is also considerably better using the Pseudo R-squared: 23% in recessions vs 5% outside recessions. Credit scores also generate higher explanatory power in recessions, but the difference is small. Finally, we look at the marginal addition to explanatory power that internal ratings offer above credit scores, i.e. the difference in R-squared between a model with credit scores alone and one that also includes internal ratings. Here as well, the bank's information appears more important in recessions.

Parametric estimates of cyclicality

We next turn to a test of whether the cyclicality of bank information precision is related to business cycle variables in the sense of having a higher regression coefficient. To do this, we adjust the baseline regression by adding interactions of IR with a business cycle indicator:

$$\text{Default} = \{(\text{IR})\} \times \{\text{Recession dummy}\} + \text{IR} + \text{Controls} + \text{Time F.E.} \quad (5)$$

Results are reported in Table 6.[20] The table confirms that the differences in patterns between good times and bad times shown in Figure 4 are statistically significant. The magnitudes of the interaction estimates are economically meaningful. In column 1, the coefficient on IR is estimated to be -0.071 in normal times, but -0.096 in recessions. This implies, for example, that a drop of three IR steps (i.e., one IR group) corresponds to a 24% increase in default risk in good

[19] Throughout, when comparing the measures of statistical fit from Table 5, we focus on economic significance. Based on the standard deviation of R-squared statistics from the regressions, this difference is significant at the 1% level (also if we take into account that monthly regression statistics are correlated).
[20] We use 12-month default as dependent variable from this point on. Results are similar with 24 months.

times but a 32% increase in a recession (taking into account that the baseline risk is higher in recessions).

These results imply that the bank's is best at predicting defaults in recessions, as suggested by Figure 5. Next, we present robustness tests intended to distinguish between possible alternative explanations consistent with these cyclical patterns.

2.3 Robustness tests

In this section, we address a number of possible criticisms and questions about our main results. First, we rule out that our results reflect the mechanical impact of higher credit flows for better rated borrowers on short run default risk. Second, we try to compare two channels that may produce better information for the bank: either the difficulty of assessing borrowers rises in booms and falls in recessions, and or the bank is trying harder to figure out credit quality (for example by adjusting monitoring frequency). Finally, we consider whether variation in the borrower pool may make it easier to assess borrowers in bad times (fewer borrowers with short credit histories).

New credit

We first consider a possible mechanical problem with our results. Firms with better IR may less likely to default because they obtain more credit from the bank. In the short run, new credit almost surely reduces the default probability (the long run impact is ambiguous, since the additional credit will have to be repaid, increasing the amount of future commitments on which default is possible). This mechanism provide an alternative interpretation of our results, under which the precision of the bank's information might not vary over the cycle. By including controls for the level of credit from the bank, as well as the debt from all other sources, we have attempted to control for this in our baseline specifications. However, the default variable looks 12 months ahead. Current IR could predict new loans during this period. A simple way to test whether this is important is to drop any firm receiving new credit in the next 12 months from our bank (column 1 and 2) or any bank (2 and 3). Results for this subset are presented in Table

7.[21] The coefficients are statistically indistinguishable from those in the main specification (Table 6).

We conclude that the effects we capture do not appear to be mediated by new credit flows, and that variation in the predictive power of IR indeed are likely reflecting variation in the banks' ability to assess credit risk. We next turn to alternative mechanisms that may drive variation in the precision of bank credit assessments.

Screening frequency

Is it possible that the bank exerts more effort in bad times, and so produces a better signal, even if the information environment does not make it easier to distinguish between borrowers? Typical models of bank lending focus on the *precision* of banks' information, not how hard that information is to *come by*. Ruckes (2004) predicts that screening of borrowers is less important in good times, and we thus expect lower precision in those times. The only measure in our data that is related to screening intensity is the frequency with which the bank reevaluates the internal rating of each borrower.[22]

In Figure 6, where we plot the fraction of firms being subject to an evaluation by quarter. There is pronounced seasonality in this frequency, with a large peak in the fourth quarter of each year. This seasonality appears to increase over time, so that more and more of the banks evaluations are done at the end of the year. Importantly, for our purposes, there appears to be no time pattern in total rate of assessments by year. The increasing activity in the last quarter of each year is offset by reduced activity in the other three quarters. Thus, we cannot detect differences in monitoring frequency for different business cycle states. This is not strong evidence against cyclical variation in screening intensity, however. The bank may increase intensity of screening

[21] Since the borrowers' credit accounts were originally expressed in euros we allow for a 10 percent fluctuation in order to avoid picking up exchange rate fluctuation (a 5 percent cut-off delivered the same results).
[22] Note that this information on monitoring frequency cannot help detect if loan officer skills deteriorate in booms, as Berger Udell (2004) predict, or if credit officers work harder each time they evaluate a borrower -- for example, because they are more risk averse as in Cohn, Engelmann, Fehr, Maréchal (2015).

(and monitoring) while the number of evaluations is fixed, by, for example, hiring more officers, hiring better officers, or providing stronger incentives. However, the fixed frequency suggests that the bank's improved ability to detect risk in recessions is not mechanically driven by reassessing borrowers more often.[23]

New borrowers

The default risk of a new borrower may be more difficult for the bank to assess than the risk of existing borrowers, where there is a longer history of interaction and business. If banks get more new borrowers in good times, the average precision of credit quality signals will be worse as the composition of borrowers becomes less favorable (Dell'Arriccia and Marquez 2006). Potentially, this means that changes in the borrower pool could be a key mechanism behind our results.

We examine this hypothesis by separating borrowers into new and old. We define new borrowers as those that have appeared for the first time in the bank's database during the last 12 months. On average, around 10% of borrowers are new, through the sample period. The highest share of new borrowers is observed in the first half of 2006 (17.6%) and early 2007 (14.1%), while the lowest share of new borrowers occurs in the second half of 2011 (7.4%) and late 2012 (6.9%). The presence of some cyclicality is thus apparent, but perhaps not enough that it could plausibly explain our large differences in precision through the cycle.

Nevertheless, we re-estimate regressions for existing clients only. Results are reported in Table 8. The cyclicality patterns are similar to those for the full sample. The bank is better able predicting default among *existing* borrowers in recessions. Thus, we can conclude that the patterns we observe are not an artifact of time-variation in the mix of old and new bank clients.[24] We conclude that the Dell'Arriccia and Marquez (2006) mechanism does not appear

[23] As an additional robustness test (not reported), we have estimated our regressions using only fourth quarter observations or only observations with fresh reviews. Fourth quarter results are very similar to those for the full sample.

[24] We have also estimated results for new borrowers only. The sample is smaller, and significance slightly reduced. Coefficient estimates are similar.

quantitatively important in our sample. A related mechanism might involve other changes in the borrower pool making it harder to measure credit risk during recessions. We next turn to firm age and industry.

Borrower size and industry

So far, we have not considered the sample industry and size composition. In particular, small firms may be less well understood by the bank: they have less detailed accounting data and spending resources on assessing their performance and prospects is worth less to the bank.

Small firms make up a large share of our sample, and if their share is time varying, it is possible that they affect the bank's precision in booms and recessions. We test this issue by estimating our regressions separately for small and large firms. In particular, we would like to test whether our results exist for larger firms, which are individually more important. In Table 9, we report regression results (similar to Table 6) for firms with 10 employees and up. These firms represent most of the credit volume in our sample but make up less than half of all firms. The results show that coefficients are similar in magnitude, but are less precisely estimated compared to those for the full sample.

We have also estimated regressions (not reported) separately for seven broad industry groups (retail, hotel/restaurant, transportation/communication, financial services, health services, social and personal services). Except for financial services, where there are very few borrowers, the cyclicality results are present in each industry.

We conclude that compositional effects probably are not the important mechanism(s) behind our cyclicality results.

3. Conclusions

The supply of corporate bank loans is highly pro-cyclical. Could this be because information frictions between lenders and borrowers are worse in recessions? Indeed, assessing borrowers' creditworthiness is a key challenge facing all lenders. Could the scope of this challenge be cyclical, contributing to low credit volumes in recessions? Our empirical results suggest that this information explanation of cyclicality appears not to be supported by the data. We study the loan portfolio of a large Swedish bank and find the opposite: corporate borrower defaults are in fact easiest to predict in recessions.

Our results suggest that this cyclical pattern does not reflect the composition of borrowers, e.g., the arrival of new, unknown firms. We also rule out that our results are contaminated by the extension of new loans. Instead, we show that that the cyclical patterns reflect the information environment.

To what extent can our results, from a sample based on a single Swedish bank during a specific period be extrapolated? One limitation is that this is a large bank, and small banks may use different lending technologies with different cyclical properties, or focus on different borrower sizes. However, the cyclical patterns we document do not appear sensitive to firm size or industry, suggesting that they may apply broadly. A working hypothesis is that the pattern we find is general to corporate lending.

A key implication of our findings relate to the literature on links between macro-economic fluctuations and financial frictions. Our findings suggest that the large swings in corporate credit availability probably do not reflect meager information about borrowers in bad times.

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Figure 1. The Swedish business cycle, 2004-2013

This figure displays two time-series measures of Sweden's business cycle. The last 12 months stock return refers to the OMX30 index of the largest thirty stocks by market capitalization, and quarterly GDP growth rate is seasonally adjusted real GDP growth.

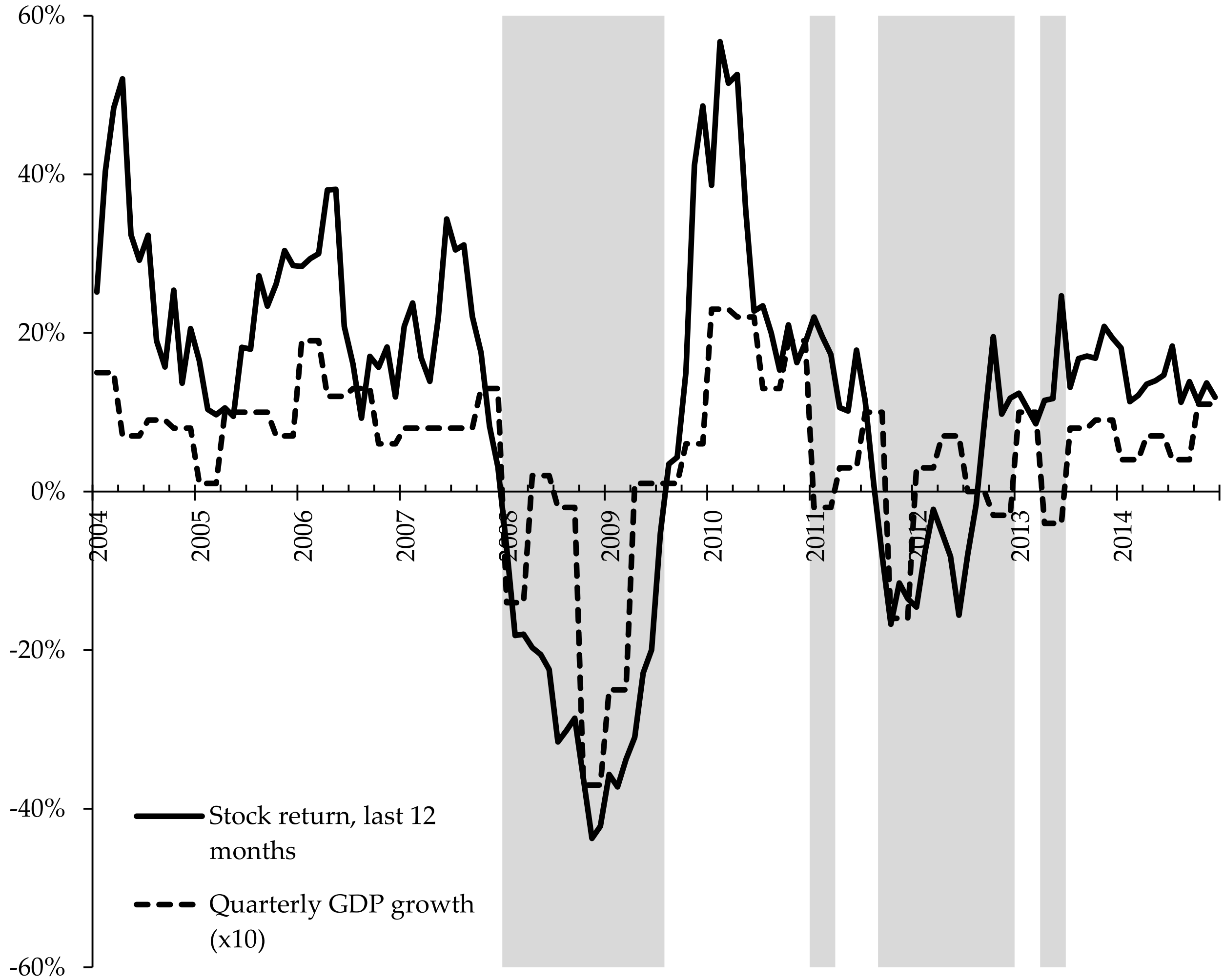


Figure 2. Accuracy of internal ratings by year, 2004-2011

This figure shows Moody's one-year cumulative accuracy profiles for the banks Internal Ratings for each year from 2004-2011. The accuracy curve maps the proportion of defaults within 12 months that are accounted for by firms with the same or a lower rating (y-axis) with the proportion of all firms with the same or a lower rating (x-axis).

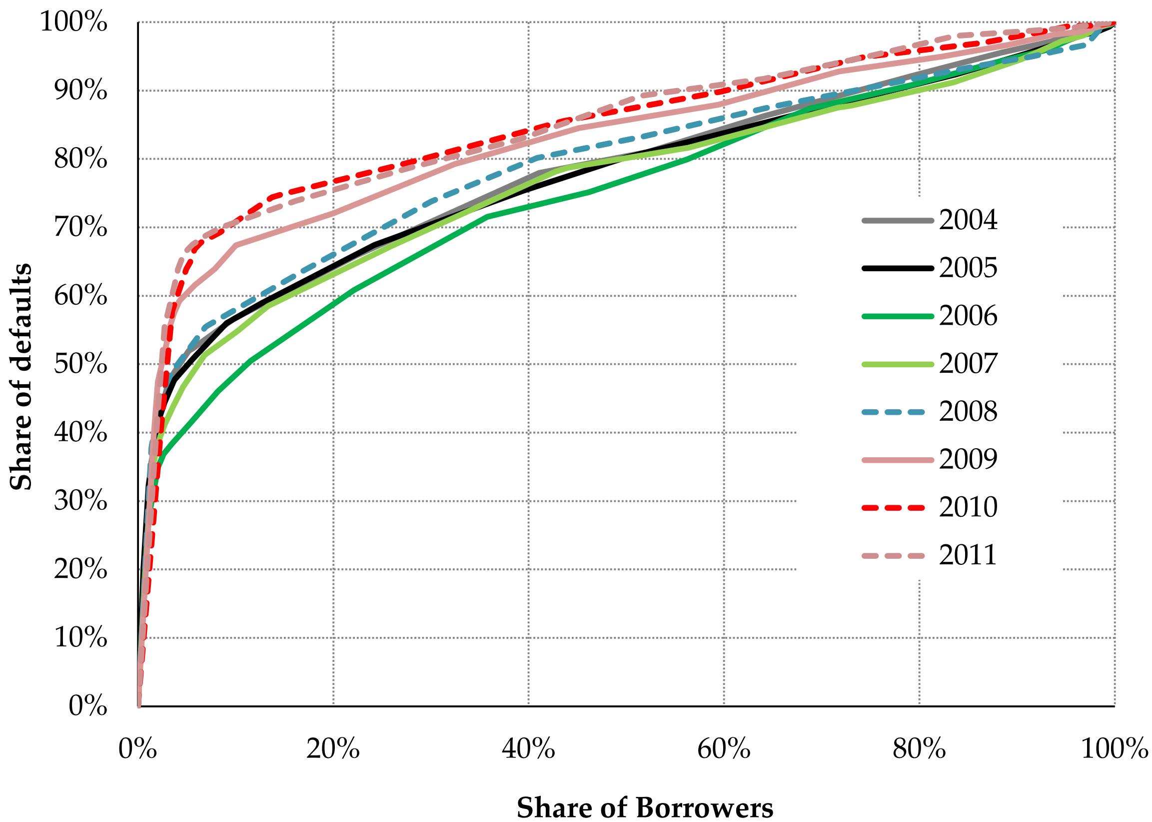
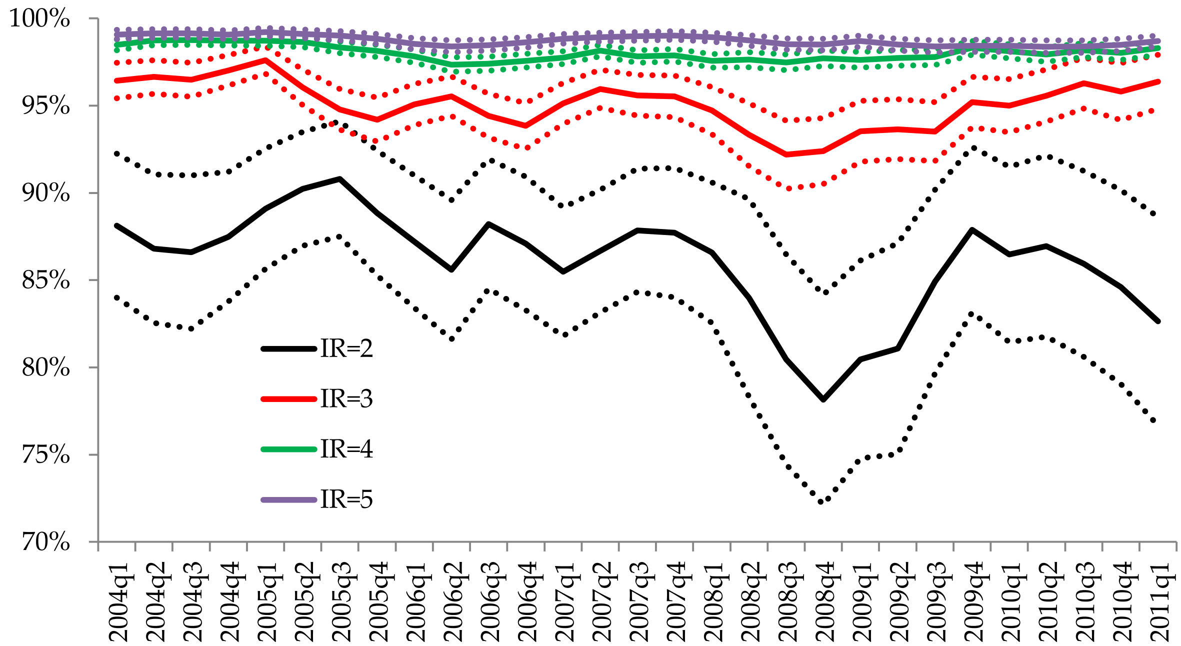


Figure 3. Kaplan Meier survival rates by internal rating

The Figure displays the survival rate, with 95 percent confidence intervals, for 4 internal rating categories. Panel A uses a 12 month default window and Panel B a 24 month window. The Kaplan–Meier estimator is the maximum likelihood estimate of S(t) where $\hat{S} = \prod_{t_i \leq t} \frac{n_i - losses_i}{n_i}$,and n_i is the number of survivors less the number of losses (censored cases). Only surviving cases (have not yet been censored) are "at risk" of an (observed) default.

A. Default within 12 months



B. Default within 24 months

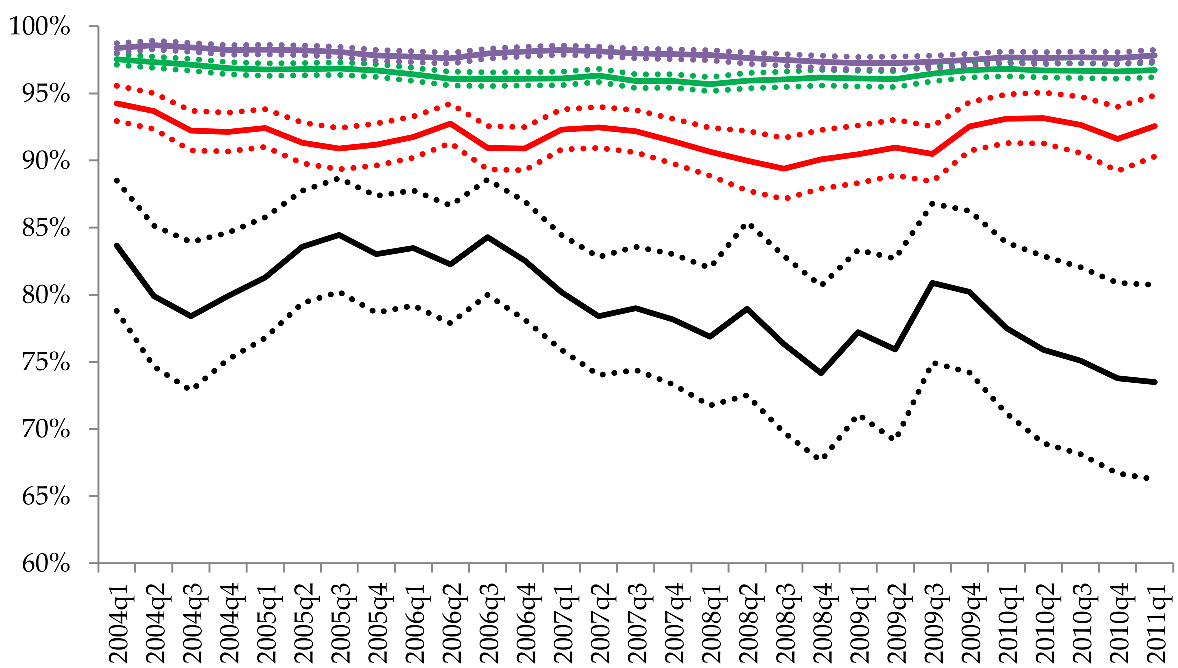


Figure 4. Default rates across ratings categories

The figure shows the relative default rates for firms of high and low credit quality. The black line represents the 12 month default rate for the top half of firms, based on the bank's internal rating categories, relative to the overall default rate (the lowest ratings category is excluded). The dashed, red line shows similar results using only credit bureau scores to sort firms. Shaded areas indicate recession periods (either trailing 12 month stock return is negative or nominal GDP growth is negative, or both). The dotted lines represent averages for recessions and expansions, respectively.

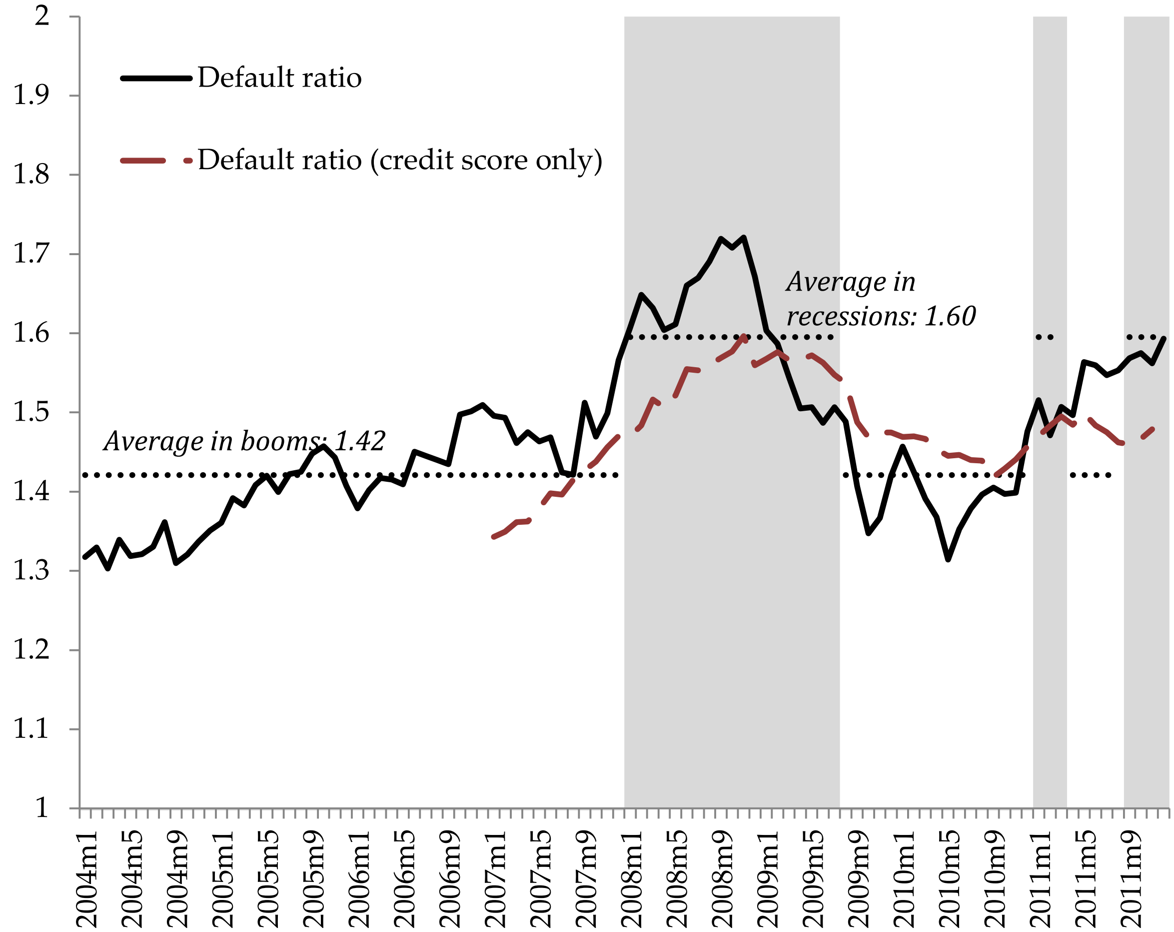


Figure 5. Predicting default over the business cycle

This figure displays the $\beta_1$coefficients from probit regressions of default on internal ratings. Coefficients are from the following regression: $Default_{within\ 12m} = \beta_{1t}IR * timeF.E. + \beta_2 X + i.t + \varepsilon$. Controls (X) include credit bureau risk score, collateral and other credit contract characteristics, accounting variables. Errors are clustered at the borrower level. The line displays real GDP growth (renormalized). White bars represent coefficients that are insignificantly different from zero, while light gray, medium gray and dark gray are significant at the 10%, 5% and 1% level, respectively. Shaded areas indicate recession periods.

Internal Rating, 12 months

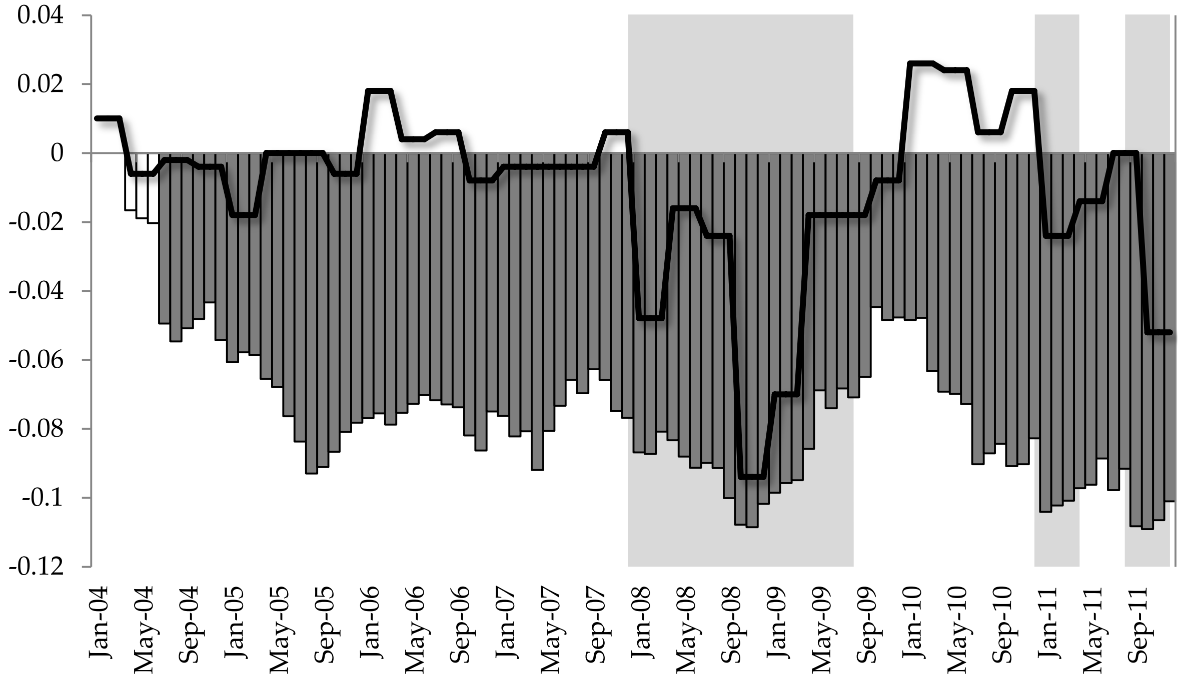


Figure 6. Proportion of borrowers being assessed by quarter

This figure shows the share of borrowers that are being reviewed by a loan officer in each quarter. The dotted line shows the average share of borrowers (four quarters rolling).

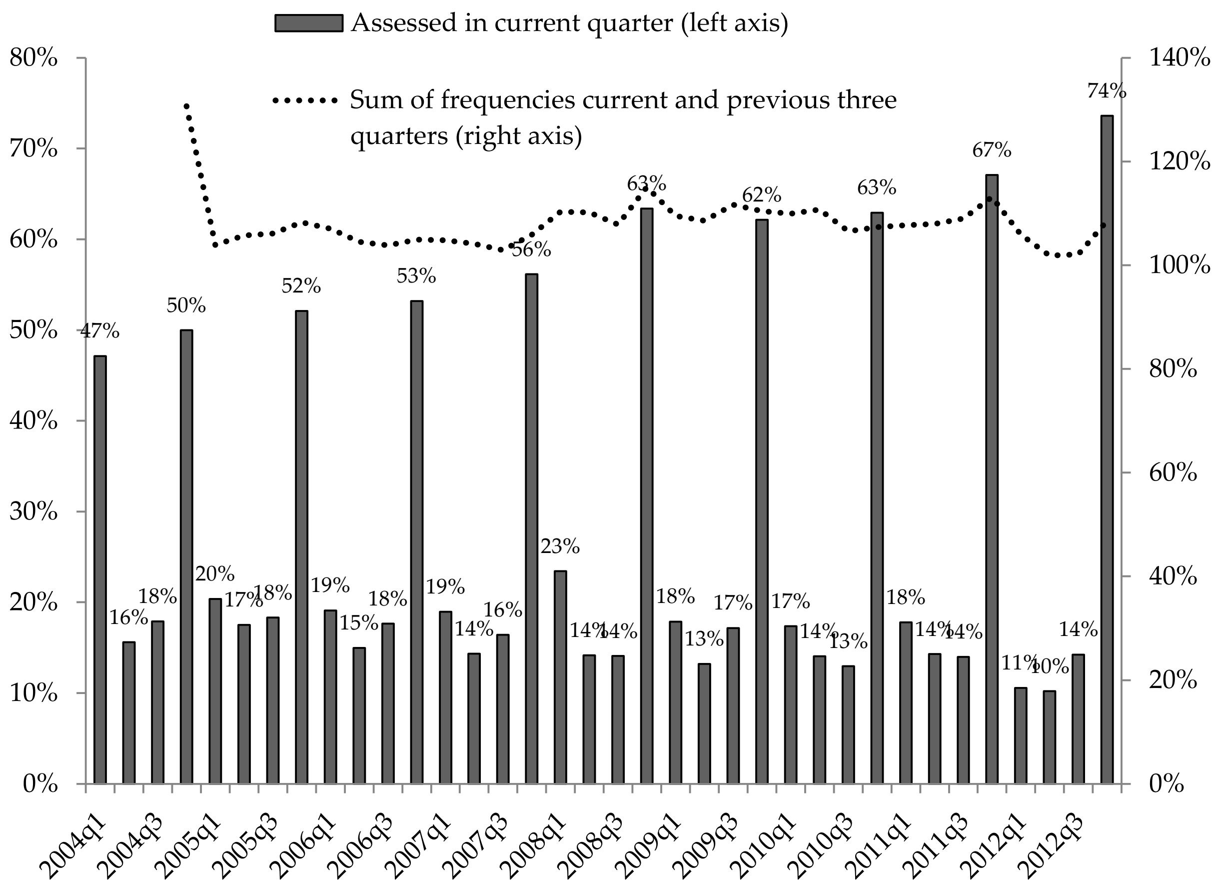


Table 1. Variable definitions

This table lists the definition for the variables used in the analysis

Variable	
Internal rating group	The Internal rating aggregated up to the 7 main steps
Limit	Granted credit limit in 1000 SEK
Internal limit	The max amount the loan officer is entitled to lend to the firm without further internal approval
Outstanding balance	Outstanding credit balance
Outstanding balance / Limit	Outstanding credit balance devided by the firms granted credit limit in 1000 SEK
Slack	The ratio is; (Internal limit - granted credit limit) / Internal limit
Collateral	The bank's own internal updated estimate of the value of the assets pledged in 1000 SEK
Days since review	The number of days elapsed between two consecutive reviews by the loan officer
Total sales	Total sales in 1000 SEK
Total assets	Total assets in 1000 SEK
Total tangible assets	Total tangible assets in 1000 SEK
Return on capital	The ratio is; profits / the book value of capital
Return on assets	The ratio is; operating profits / average total assets
Gross margin	The ratio is; (earnings before interest, taxes, depreciation and amortization) / sales
Net margin	The ratio is; (earnings before taxes and amortization) / sales
Credit score	Credit bureaus' ordinal rating with x steps
Employees	Number of employees employed by the firm
Leverage	The ratio is; total debt / total assets
Default	Dummy variable that is one if the borrowers' payment is past due over 90 days

Table 2. Summary Statistics

This table lists the variables used in this study and presents some summary statistics for each variable for the entire sample. All variables are obtained from the bank's customer and loan files. Observations of default are the quarterly observations of average default rates. For all other variables, observations are firm-quarters.

Variable	Mean	Median	Standard deviation	Observations
Internal rating	12.9	13.0	3.6	1,706,000
Internal rating group	4.7	5.0	1.2	1,706,000
Limit (in 1000 SEK)	13,000	165	2,880,000	5,812,000
Internal limit (in 1000 SEK)	24,000	600	218,000	4,293,000
Outstanding balance (in 1000 SEK	6,878	90	180,000	5,681,000
Outstanding balance / Limit	0.69	0.99	0.41	5,128,000
Collateral (in 1000 SEK)	2,617	0	34,100	5,808,000
Days since review	155.2	151.0	130.6	3,643,000
Total sales (in 1000 SEK)	87,900	3 929	1,210,000	4,916,000
Total assets (in 1000 SEK)	159,000	3 235	2,880,000	4,809,000
Total tangible assets (in 1000 SEK)	28,100	252	516,000	4,809,000
Return on capital	0.14	0.16	0.58	4,914,000
Return on assets	0.07	0.06	0.18	4,914,000
Gross margin	0.07	0.06	0.24	4,722,000
Net margin	0.03	0.03	0.24	4,721,000
UC score	1.96	0.50	5.94	3,766,000
Employees	26.4	3.0	294.6	4,809,000
Leverage	0.59	0.62	0.27	4,809,000
Default	0.02	0.0	0.1	7,166,000

Table 3. Summary statistics by internal rating

This table summarized full sample averages on credit, default and losses by internal rating (IR). Default is share of firm-quarters where a default is reported in the next 12 and 24 months respectively. Default frequency, credit-weighted reports the fraction of outstanding credit that experiences a default. Loss given default is total observed losses divided by total credit outstanding at time of default, for the whole sample. Share of aggregate credit losses refers to borrowers with an internal rating.

Panel A: Default

IR	Default wtn 12 months	Default wtn 24 months	Loss given default	Bankruptcy wtn 12 months	Share of aggregate credit losses
1-3	16.0%	24%	75%	11%	3.3%
4-6	9.2%	13%	61%	4.7%	2.4%
7-9	3.5%	6.3%	58%	1.5%	6.4%
10-12	1.4%	2.7%	55%	0.4%	17.1%
13-15	0.9%	1.7%	54%	0.1%	42.0%
16-18	0.6%	1.2%	42%	0.03%	26.4%
19-21	0.7%	1.1%	23%	0.00%	2.4%
ALL	1.5%	2.6%	51 %	0.5%	100%

Panel B: Loan Contract Characteristics

IR	Number of loans per firm (median)	Share of loans with collateral	Average loan maturity (years)	Average interest rate (per cent)
1-3	7	6%	1.95	4.567
4-6	6	9%	1.93	5.244
7-9	8	9%	2.15	4.792
10-12	13	11%	2.28	4.491
13-15	23	11%	2.04	4.094
16-18	28	18%	2.27	3.948
19-21	4	54%	2.19	3.730

Table 4. Predicting default by internal ratings

This table reports regressions default (payment overdue by 90 days or more) on credit risk measures and controls. In In Panel A, the credit variable is the bank's internal rating (IR), measured on an ordinal scale (a rating of 21 is best). In Panel B, the credit variable is a fourth order polynomial in IR. Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Panel A: Internal Rating

Dependent variable	Default wtn 12 m			Default wtn 24m		
Regression type	Probit	Probit	dy/dx	Probit	Probit	dy/dx
	(1)	(2)	(3)	(4)	(5)	(6)
Internal Rating	**-0.137*** **	**-0.078*** **	**-0.003*** **	**-0.128*** **	**-0.067*** **	**-0.005*** **
	(0.002)	(0.005)	(0.000)	(0.002)	(0.005)	(0.000)
Return on capital		**0.051***			**0.028**	
		(0.027)			(0.028)	
Return on assets		**-1.041*** **			**-0.980*** **	
		(0.148)			(0.148)	
Gross margin		**-0.336*** **			**-0.404*** **	
		(0.081)			(0.086)	
Net margin		**-0.078**			**0.095**	
		(0.081)			(0.080)	
Log (total sales)		**0.043*** **			**0.048*** **	
		(0.010)			(0.011)	
Log (total assets)		**0.036*** **			**0.032*** **	
		(0.011)			(0.012)	
Tangible fixed assets / assets		**-0.334*** **			**-0.366*** **	
		(0.054)			(0.059)	
Leverage		**0.077**			**0.170** **	
		(0.072)			(0.079)	
Outstanding loan		**0.000**			**0.000**	
		(0.000)			(0.000)	
Credit bureau score		**0.022*** **			**0.025*** **	
		(0.002)			(0.002)	
Collateral value		**-0.000**			**-0.000**	
		(0.000)			(0.000)	
Interest rate		**0.025*** **			0.019***	
		(0.005)			(0.005)	
Time fixed effects	Yes	Yes		Yes	Yes	
Number of observations	1,406,144	688,692		1,175,233	602,725	
Clusters		Borrower			Borrower	
Number of clusters	32,672	16,702		29,261	15,895	
Pseudo-R^2	0.075	0.119		0.065	0.103	

Panel B: Internal Rating polynomial

Dependent variable	Default wtn 12m			Default wtn 24m		
Regression type	Probit	Probit	dy/dx	Probit	Probit	dy/dx
	(1)	(2)	(3)	(4)	(5)	(6)
Internal Rating polynomial	-10.33***	-8.277***	-0.342***	-6.760***	-4.785***	-0.330***
	(0.274)	(0.399)	(0.018)	(0.221)	(0.312)	(0.023)
Return on capital		0.044*			0.024	
		(0.027)			(0.027)	
Return on assets		-1.081***			-1.022***	
		(0.145)			(0.145)	
Gross margin		-0.345***			-0.412***	
		(0.082)			(0.088)	
Net margin		0.064			0.088	
		(0.081)			(0.081)	
Log (total sales)		0.041***			0.046***	
		(0.010)			(0.011)	
Log (total assets)		0.030***			0.026**	
		(0.011)			(0.011)	
Tangible fixed assets / assets		-0.318***			-0.354***	
		(0.054)			(0.059)	
Leverage		0.253***			0.327***	
		(0.069)			(0.075)	
Outstanding loan		0.000			0.000	
		(0.000)			(0.000)	
Credit bureau score		0.020***			0.023***	
		(0.002)			(0.002)	
Collateral value		-0.000*			-0.000	
		(0.000)			(0.000)	
Interest rates		0.022***			0.017***	
		(0.005)			(0.005)	
Time fixed effects	Yes	Yes		Yes	Yes	
Number of observations	1,242,732	688,692		1,044,105	602,725	
Clusters		Borrower			Borrower	
Number of clusters	31,062	16,702		27,940	15,895	
Pseudo-R^2	0.075	0.123		0.056	0.104	

Table 5. R-squared over the business cycle

The table reports the average of the R squares for the regressions that were run separately for each month in 'normal' times (column one two) and recession 2008.-2009 (column thee four). The first three rows present measures of statistical fit for regressions including the explanatory variables identified in the row headings. Columns (1) and (2) present the average R squared for the linear probability models; columns (3) and (4) McFadden's Pseudo R-squared for probit models (one minus the ratio of the log likelihood with no control variables to the log likelihood with controls). The last row reports the marginal increase in R-squared and Pseudo R-squared due to IR, i.e. the difference between the row labeled "Credit Score and IR" and the row labeled "Credit Score".

Dependent variable	Default wtn 12m			
Regression type	OLS		Probit	
	Non-recession	Recession	Non-recession	Recession
Average	R –squared	R –squared	Pseudo R - squared	Pseudo R – squared
	(1)	(2)	(3)	(4)
IR	1.3%	11.1%	5.1%	22.7%
Credit Score	3.3%	5.4%	5.6%	5.9%
Credit Score and IR	5.4%	13.4%	7.8%	23.6%
Marginal increase from including IR (above Credit Score alone)	2.1%	8.0%	2.1%	18.6%

Table 6. Default prediction with internal ratings through the business cycle

The table reports regressions of future default on IR and IR polynomial, and all interacted with a recession dummy (equal to one if either trailing 12 month stock return is negative or nominal GDP growth is negative, or both): $default_{12m} = \alpha + \beta_1(IR * Recession\_dummy) + \beta_2(IR) + \beta_3 controls + \beta_3 time + \varepsilon$. Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Dependent variable	Default wtn 12m	
Regression type	Probit	Probit
Regression type	(3)	(6)
Internal Rating	**-7.622*** **	
	(0.444)	
Internal Rating x Recession dummy	**-2.215*** **	
	(0.631)	
Internal Rating polynomial		**-0.313*** **
		(0.043)
Internal Rating polynomial x Recession dummy		**-0.190*** **
		(0.065)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, interest rates, duration, collateral	
Time F.E.	Yes	Yes
Number of observations	688,692	1,381,180
Clusters	Borrower	Borrower
Number of clusters	16,702	31,177
Adjusted R^2	0.124	0.105

Table 7. Default prediction through the business cycle: borrowers that do not - or receive credit within the upcoming 12 months

This table is based on Table 6, but only includes firms that don't receive any new credit within the next 12 months from our bank (column 1 and 2) or any other bank (3 and 4). The table reports regressions of future default on IR and IR polynomial, and all interacted with a recession dummy (equal to one if either trailing 12 month stock return is negative or nominal GDP growth is negative, or both). Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

	No new credit wtn 12m our bank		No new credit wtn 12m any bank	
Dependent variable	Default wtn 12m			
Regression typs	Probit			
	(1)	(2)	(3)	(4)
Internal Rating	-0.078***		-0,086***	
	(0.006)		(0.006)	
Internal Rating x Recession dummy	-0.027***		-0,013	
	(0.009)		(0.009)	
Internal Rating polynomial		-7.531***		-7,920***
		(0.494)		(0.514)
Internal Rating polynomial x Recession dummy		-2.113***		-1,824**
		(0.700)		(0.722)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, interest rates, duration, collateral			
Time F.E.	Yes	Yes	Yes	Yes
Number of observations	455,491	455,491	377,299	377,299
Clusters	Borrower	Borrower	Borrower	Borrower
Number of clusters	16,035	16,035	15,121	15,121
Adjusted R^2	0.142	0.144	0.161	0.161

	Based on outstanding credit at our bank		Based on total outstanding credit	
Dependent variable	Default wtn 12m			
Regression typs	Probit			
	(1)	(2)	(3)	(4)
Internal Rating	-0.078***		-0,086***	
	(0.006)			
Internal Rating x Recession dummy	-0.027***		-0,013	
	(0.009)			
Internal Rating polynomial		-7.531***		-7,920***
		(0.494)		
Internal Rating polynomial x Recession dummy		-2.113***		-1,824**
		(0.700)		
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, interest rates, duration, collateral			
Time F.E.	Yes	Yes	Yes	Yes

Number of observations	455,491	455,491		
Clusters	Borrower	Borrower	Borrower	Borrower
Number of clusters	16,035	16,035		
Adjusted R^2	0.142	0.144		

Table 8. Default prediction through the business cycle: existing borrowers

This table is based on Table 6, but the sample only contains borrowers that have been customers of the bank for at least 12 months. The table reports regressions of future default on IR and IR polynomial, and all interacted with a recession dummy (equal to one if either trailing 12 month stock return is negative or nominal GDP growth is negative, or both). Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Dependent variable	Default wtn 12m	
Regression typs	Probit	Probit
	(1)	(2)
Internal Rating	**-0.073*** **	
	(0.006)	
Internal Rating x Recession dummy	**-0.025*** **	
	(0.008)	
Internal Rating polynomial		**-7.771*** **
		(0.450)
Internal Rating polynomial x Recession dummy		**-2.247*** **
		(0.633)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, interest rates, duration, collateral	
Time F.E.	Yes	Yes
Number of observations	661,397	661,397
Clusters	Borrower	Borrower
Number of clusters	16,197	16,197
Adjusted R^2	0.120	0.125

Table 9. Default prediction through the business cycle: large and medium sized firms

This table is based on Table 6, but only contains firms with 10 or more employees. The table reports regressions of future default on IR, interacted with the recession dummy that is equal to one, if either trailing 12 month stock return is negative or nominal GDP growth is negative, or both).. Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Dependent variable	Default wtn 12m	
Regression typs	Probit	Probit
	(1)	(2)
Internal Rating	**-0.060*** **	
	(0.007)	
Internal Rating x Recession dummy	**-0.021***	
	(0.011)	
Internal Rating polynomial		**-7.213*** **
		(0.626)
Internal Rating polynomial x Recession dummy		**-2.020** **
		(0.962)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, interest rates, duration, collateral	
Time F.E.	Yes	Yes
Number of observations	325,027	325,027
Clusters	Borrower	Borrower
Number of clusters	7,662	7,662
Adjusted R^2	0.088	0.090

APPENDIX I Slack (for online publication)

One concern is whether banks' internal ratings really matter to decision making. Perhaps the bank's decisions are based on different metrics, or some soft information to which we lack access. If so, real lending decisions may exhibit cyclicality that differs from what we document for internal ratings. We address this by also studying the amount of credit the bank has decided to grant, but has not yet offered, a borrower. We call this "credit slack" and use it as an alternative measure of the bank's assessment of a borrower. In this appendix we present the results of our analysis gathered in the paper using Slack instead of the IR.

Credit slack reflects new credit the loan officer responsible for the firm *could grant* without consulting the next hierarchical level in the bank's commercial credit organization (a manager or a credit committee). Thus, from the point of view of the bank, this a credit decision (since the loan officer may grant the credit), but it is not known to – or reflected in any financial flow to - the borrower. We show that "slack" predicts defaults: of two firms with the same amount of credit, the one with lower slack is more likely to default. As for internal ratings, the predictive power of credit slack is strongest in bad times. This reinforces the conclusion that information frictions are most severe in good times

We define Slack as:

$$Slack = \frac{Internal\ Limit - Granted\ Credit}{Internal\ Limit} \quad (1)$$

where the Internal Limit is the maximum amount the loan officer is entitled to lend to the firm. The Internal Limit is based on the repayment ability of the firm, and changes in this limit must be are approved by a senior official or a credit committee, depending on the size of the loan.

Figure A1 similar to figure 5 in the paper. Predicting default over the business cycle

This figure displays the $\beta_1$coefficients from probit regressions of default on credit variables as bars. The variables credit slack Coefficients are from the following regression: $Default_{within\ 12m} = \beta_{1t}Slack * timeF.E. + \beta_2\mathrm{X} + \mathrm{i.t} + \varepsilon$. Controls (X) include credit bureau risk score, collateral, credit contract features, accounting variables. Errors are clustered at the borrower level. The line displays real GDP growth (renormalized). White bars represent coefficients that are insignificantly different from zero, while light gray, medium gray and dark gray are significant at the 10%, 5% and 1% level, respectively. Shaded areas indicate recession periods.

Credit slack, 12 months

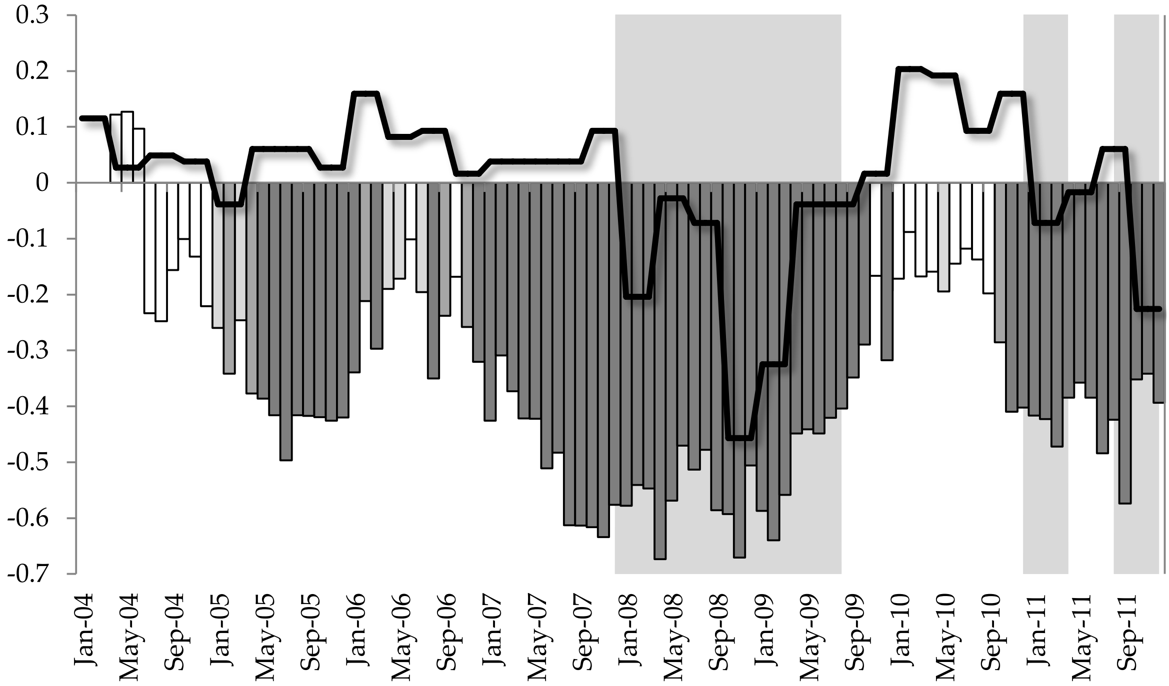


Table A1. Similar to table 4 in the paper Predicting default by Slack

This table reports regressions default (payment overdue by 90 days or more) on credit risk measures and controls. The credit risk variable is Credit Slack (amount of unused credit up to maximum the credit officer is authorized to grant as a fraction of the maximum). Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Panel C: Slack

Dependent variable	Default wtn 12m			Default wtn 24m		
Regression type	Probit	Probit	dy/dx	Probit	Probit	dy/dx
	(1)	(2)	(3)	(5)	(6)	(7)
Credit slack	**-0.165*** **	**-0.373*** **	**-0.015*** **	**-0.150*** **	**-0.417*** **	**-0.026*** **
	(0.026)	(0.038)	(0.002)	(0.029)	(0.041)	(0.003)
Return on capital		**0.053*** **			**0.055*** **	
		(0.016)			(0.017)	
Return on assets		**-0.977*** **			**-0.969*** **	
		(0.087)			(0.091)	
Gross margin		**-0.297*** **			**-0.336*** **	
		(0.069)			(0.073)	
Net margin		**-0.199*** **			**-0.194*** **	
		(0.072)			(0.074)	
Log (total sales)		**0.023*** **			**0.027*** **	
		(0.008)			(0.009)	
Log (total assets)		**0.050*** **			**0.052*** **	
		(0.009)			(0.010)	
Tangible fixed assets / total assets		**-0.272*** **			**-0.304*** **	
		(0.042)			(0.048)	
Leverage		**0.618** **			**0.614** **	
		(0.051)			(0.056)	
Outstanding loan balance		**0.000**			**0.000**	
		(0.000)			(0.000)	
Credit bureau score		**0.027*** **			**0.028*** **	
		(0.001)			(0.001)	
Collateral value		**-0.000**			**-0.000**	
		(0.000)			(0.000)	
Time fixed effects	Yes	Yes		Yes	Yes	
Number of observations	2,849,932	1,381,180		2,357,469	188,058	
Clusters	Borrower			Borrower		
Number of clusters	59,410	31,177		53,093	19,686	
R^2 or Pseudo-R^2	0.004	0.105		0.002	0.095	

Table A2 (similar to table 6 in the paper). Default prediction with credit slack through the business cycle

The table reports regressions of future default on Slack, and all interacted with a recession dummy (equal to one if either trailing 12 month stock return is negative or nominal GDP growth is negative, or both): $default_{12m} = \alpha + \beta_1 Slack * Recession\_dummy) + \beta_2 (Slack\ ) + \beta_3 controls + \beta_3 time + \varepsilon$. Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Dependent variable	Default wtn 12m
Regression type	Probit
Slack	**-0.071*** **
	(0.005)
Slack x Recession dummy	**-0.025*** **
	(0.008)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, interest rates, duration, credit bureaus score, collateral
Time F.E.	Yes
Number of observations	688,692
Clusters	Borrower
Number of clusters	16,702
Adjusted R^2	0.120

Table A3, similar to table 7 in the paper. Default prediction through the business cycle: borrowers that do not - or receive credit within the upcoming 12 months

This table is based on Table 6, but only includes firms that don't receive any new credit within the next 12 months. The table reports regressions of future default on Slack, and all interacted with a recession dummy (equal to one if either trailing 12 month stock return is negative or nominal GDP growth is negative, or both). Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Dependent variable	Default wtn 12m
Regression type	Probit
Slack	**-0.382*** **
	(0.053)
Slack x Recession dummy	**-0.155***
	(0.081)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, interest rates, duration, credit bureaus score, collateral
Time F.E.	Yes
Number of observations	997,010
Clusters	Borrower
Number of clusters	30,589
Adjusted R^2	0.118

Table A4 similar to table 8 in the paper. Default prediction through the business cycle: existing borrowers

This table is based on Table 6, but the sample only contains borrowers that have been customers of the bank for at least 12 months. The table reports regressions of future default on Slack, and all interacted with a recession dummy (equal to one if either trailing 12 month stock return is negative or nominal GDP growth is negative, or both). Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Dependent variable	Default wtn 12m
Regression type	Probit
Slack	**-0.315*** **
	(0.044)
Slack x Recession dummy	**-0.190*** **
	(0.066)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, interest rates, duration, credit bureaus score, collateral
Time F.E.	Yes
Number of observations	1,316,379
Clusters	Borrower
Number of clusters	30,436
Adjusted R^2	0.104

Table A5, similar to table 9 in the paper. Default prediction through the business cycle: large and medium sized firms

This table is based on Table 6, but only contains firms with 10 or more employees. The table reports regressions of future default on Slack and IR, interacted with the recession dummy that is equal to one, if either trailing 12 month stock return is negative or nominal GDP growth is negative, or both).. Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Dependent variable	Default wtn 12m
Regression type	Probit
Slack	**-0.376*** **
	(0.044)
Slack x Recession dummy	**-0.071**
	(0.099)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, interest rates, duration, credit bureaus score, collateral
Time F.E.	Yes
Number of observations	409,358
Clusters	Borrower
Number of clusters	9,397
Adjusted R^2	0.077