Bad times, good credit

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Abstract. Banks' limited knowledge about borrowers' creditworthiness constitutes an important friction in credit markets. Is this friction deeper in recessions, thereby contributing to cyclical swings in credit? Alternatively, is the depth of this friction reduced in recessions, as tough times reveal information about firm quality? We test these alternative hypotheses using internal ratings data from a large, Swedish bank. This banks' ability to sort borrowers by credit quality is best in recessions, and worst in good times. Our results suggest 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 firms -- funding operations, working capital, new investment, and acquisitions. The flow of corporate credit is highly cyclical: in recessions, the volume of new credit is low and loan spreads are high. There is a long-standing concern that depressed credit flows in recessions reflect a low supply of credit due to some friction in credit markets, and that this friction 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 and Japelli 1993 and Hertzberg, Liberti and Paravisini 2011), and the use of covenants in debt contracts (Smith Warner 1979). Information frictions have been identified as important to both quantities (Garmaise and Natividad 2013) and prices (Ivashina 2009) in credit markets.

Given the well-established importance of information frictions, it may seem natural to ask how they contribute to credit market cycles.[2] Information frictions can potentially be more or less severe in cyclical downturns, and theory provides no unambiguous direction.

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[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, recent evidence for cyclical supply is diverse. Dell'Ariccia, Detragiache, and 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.

[2] Information frictions include asymmetric information between borrower and lender about borrower quality (Stiglitz Weiss 1981), asymmetric information between banks (Dell'Arricia and Marquez 2006), and ex-ante uncertainty about an individual project's future payoff (Townsend 1979, Gale and Hellwig 1985).

On the one hand, some theories suggest that information problems between lenders and borrowers are *less severe in downturns*. Such countercyclicality of information frictions can be the result of several underlying mechanisms. Banks may exert more effort in recessions (Ruckes 2004) or face fewer hard-to-classify new borrowers in recessions (Dell'Ariccia and Marquez 2006); loan officers can also become more risk averse in bad periods (Cohn, Engelmann, Fehr, and Maréchal 2015) or see their skills deteriorate in low default periods because there is less feedback (Berger and Udell 2004) .

On the other hand, another set of models suggests information frictions are *more severe in bad times*. Kurlat (2013), for example, finds that a reduction in investment opportunities increases information frictions, which generates a feedback to growth. Ordonez (2013) and Guerrieri and Shimer (2014) also model economies where worsening information frictions contribute to cyclical downturns.

Prior evidence on the cyclical properties of banks' information is mostly of an indirect nature. On the one hand, Dilly and Mählmann (2015) document that initial credit ratings of corporate bonds issued in recessions are more accurate than the initial ratings of bonds issued in better times, consistent with *lower* information frictions in bad periods.[3] Brown, Kirschenmann and Spycher (2016) find that loan officers were better at predicting micro-enterprise losses in the financial crisis than in the preceding expansion.

On the other hand, there is empirical evidence suggesting that the information frictions banks face are pro-cyclical. Kashyap, Stein and Wilcox (1993) and Becker and Ivashina (2014) show that bank lending is more cyclical than bond issuance. If loans are subject to greater information frictions than bonds are, then the observed greater cyclicality of bank lending could be a consequence of cyclical variation in information frictions. Alternatively, banks reluctance to lend could also reflect banks' capital needs (Holmström and Tirole 1997), suggesting that other frictions than those between banks and their borrowers are at work.

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

Prior evidence thus offers some indirect support for both the pro-cyclicality- and counter-cyclicality of information frictions. However, that evidence is also consistent with other explanations than information frictions.

In this paper, we examine more directly how the quality of banks' information about their borrowers varies through the cycle. We use data from one, large Swedish bank and examine how the predictive ability of its borrower credit quality assessments varies. Our data provides detailed information on the bank's borrowers through two business cycles, allowing us to separately examine the financial crisis and a second, less severe recession.

The bank we study follows the Basel 2 Internal Ratings Based (IRB) approach and employs an internal rating system to summarize information about the credit quality of its borrowers. Our key test consists of comparing the precision of internal ratings over the cycle. We find a strong negative correlation between the predictive power of ratings and a range of macro-economic performance measures such as GDP growth, the stock market index, and the consumer confidence index. The internal ratings are better able to predict defaults in recessions than at other times. Regression analysis confirms that ability of banks' internal ratings to predict defaults is greater during recessions. This finding is robust to using different measures of informativeness. Lower default rates of highly rated firms relative to lower firms provide further support for this finding.

Our results are not driven by adverse selection. First, the panel of firms is very stable due to the fact that the Swedish banking sector is highly concentrated and characterized by strong bilateral relationships.[4] Second, to quantify the extent to which adverse selection might influence our findings, we develop a simple structural model of firms' credit choices to analyze the

[4] In a sample 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 (less than one year as customers) is 10%, and the number of exits from our sample is only 3% (over the entire sample period).

importance of exit behavior. We find that the theoretical limit for how much of the variation in signal precision over the business cycle can be explained by exits is 6%.[5]

Our results imply that the bank we study is best able to predict loan defaults in business cycle downturns, a pattern consistent with information frictions being pro-cyclical, i.e. weaker in recessions.[6]

Our findings are not about lending decisions or loan standards. Our tests only examine the quality of the bank's information about clients, not how that information is used.

Another alternative explanation for our results, which would work against our conclusion, is that credit granting decisions by banks drive the cyclicality of information quality. Since borrowers with better ratings are more likely to be granted credit (or otherwise be offered better terms) cyclical variation in credit decisions could affect future default risk in the pool of borrowers, possibly in different ways over the cycle.[7] In our regression tests we therefore always control for credit amounts. Our results also hold when we restrict the sample to borrowers receiving no new credit. We therefore conclude that variation in credit decisions (flows) does not drive our results.

A third possible concern may be that regulation can affect how banks assign ratings. The banking industry in Sweden, as elsewhere around the world, has been subject to new regulation during our sample period. Could this in some way drive our finding that the precision of bank credit information varies with the business cycle? Recent reforms in banking regulation have increased the implicit cost of assigning low ratings, because low ratings raise the capital

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[5] Credit markets where relationships play a smaller role, and where borrowers have more choices, offer much more 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).

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

[7] How obtaining new credit impacts on a firm's default risk is likely to vary over time. 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).

requirements when banks use the internal ratings-based approach for capital.[8] This generates an incentive to improve ratings (Behn Haselmann and Vig 2014), which might make them less precise, by adding noise.

In Sweden, the Basel II rules were introduced in February 2007, allowing the largest banks to use the internal ratings-based approach model after an approval procedure. Transitional rules, however, meant that the old 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 Basel II rules were expected to generally raise requirements on both large corporates and SME's (Finansinspektionen 2006). To the extent that ratings would have become noisier over the 2007-2009 period, this would have led to a deteriorating performance of internal bank ratings, at the exact time when we find that the ratings precision improves. We therefore conclude that regulation is unlikely to explain our results.[9]

Given that the quality of borrower information is greatest in recessions, we next attempt to differentiate between the various theories of pro-cyclical information problems. In particular, we assess a prediction of Dell'Arriccia and Marquez (2006). In their theory, more new borrowers enter the bank's pool of clients in good times, thereby reducing the precision of internal ratings. We find that our results are qualitatively and quantitatively unchanged when we analyze new and old borrowers separately. Our results are therefore not driven by shifts in the mix of new and old borrowers. In a similar fashion we verify the effect of variation in the industry composition of the borrower pool and find this neither drives our results.

We also assess Ruckes' (2004) theory about banks' exerting more effort in times when defaults are costlier (i.e., recessions). Our data allows a very rough examination of his prediction. We test this using information on when the bank revises each borrower's ratings and find that

[8] Under the IRB approach, banks' own ratings are inputs into determining capital requirements.
[9] During our sample period, no other reform of similar broad importance for internal ratings was introduced.

monitoring activity is not cyclical, albeit highly seasonal. We therefore have no evidence that increased monitoring in recessions is driving our findings.[10]

Berger and Udell (2004) suggest another mechanism could explain our findings. They argue that loan officer skills deteriorate as lending institutions forget the lessons they learned as time passes since their last loan bust, resulting in an easing of credit standards over time. We observe, however, a similar variation in precision for mechanical third party credit scores as for bank ratings which involve judgment. This suggests a deterioration of skills is not driving our results. Our observation leaves open the possibility that the bank's credit model aims to predict defaults in bad times. This would be similar in spirit to Ruckes' model, but with the mechanism going through credit model design instead of through effort intensity. This would also leave unexplained why mechanical credit scores produced by a credit bureau also perform better in recessions.

An explanation that appears consistent with all our findings is that it is the nature of environment itself, rather than bank actions that differs between recessions and expansions and reduces information frictions in corporate credit markets in recessions.

Overall, our results are consistent with the literature that sees information frictions as key to credit markets. Importantly, the information problem we study – a bank's limited information about true credit risk -- appears most severe in good times. Our findings do not match with theories where information frictions in credit markets play a role in recessions, but are more consistent with models of poor lending decisions in expansions.[11]

Our paper is related to research on why credit markets are cyclical. If information frictions do not help explain cyclical credit flows, and in fact work in the opposite direction, other frictions

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[10] A more direct test of effort, in the context of US construction loans is provided by Lisowsky, Minnis and Sutherland (2016), who show that banks collected fewer financial statements from small borrowers in bad times.

[11] Our results do not speak to uncertainty about *aggregate* states (see e.g. Bloom 2007, Caballero and Simsek 2013, Fajgelbaum, Schaal and Taschereau-Dumouchel 2014, and Gilchrist, Sim and 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.

must be even more cyclical to be able to explain the 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).[12] Another category of explanations involves agency problems between lenders and borrowers. Agency problems can become more severe in recessions if corporate losses reduce equity values (Bernanke and Gertler 1989) or if asset values fall (Kiyotaki and 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 apply to the corporate credit market. Information frictions may have different cyclical properties in other financial markets. Equity markets, for example, may experience increased information asymmetries in crises. Given the key role of corporate credit markets for funding investment and operations, the results we present here are nevertheless important.

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 structure of the bank's own risk measurement. The panel is almost balanced, reflecting very low turnover of borrower relationships. Our main sample contains 16,702 firms of which 523 exit at some point. This means that 3.1% of firms ever exit during the whole nine year sample, corresponding to an average exit rate of around 0.35% per year.

[12] Different kinds of evidence that financial institutions' capital and willingness to bear risk are important to cycles is provided by, e.g., Becker and Ivashina (2014), Benmelech, Meisenzahl and Ramcharan (2016), Chodorow-Reich (2014), Ivashina and Scharfstein (2010), Jiménez, Ongena, Peydró and Saurina (2012), and Khwaja and Mian (2008).

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 credit bureau's assessment of the firms' credit risk.[13] We summarize our dataset in two tables: Table 1 lists all variables and their source data set, and Table 2 presents descriptive statistics for each variable for the sample.

1.1 Borrower and loan data

The bank's main measure of credit quality is the internal rating (IR). 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. Borrowers with an IR represent between 70 and 80% of loans outstanding, depending on the year. IR values are stable over time: on average, 2% of firms change category from one quarter to next. We assign the rating variable's different grades values from one to 21, where one is the worst rating (highest default risk).

The key outcome measure in our tests of information quality will be the occurrence of a borrower default in the next 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 in the next 12 or 24 months as an alternative dependent variable. Bankruptcy is less frequent than default 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).

In Table 3, we report data demonstrating how firms differ across IR (grouped into bins for expositional purposes). The table shows average default and bankruptcy rates and loss given default. Both default and bankruptcy rates, at either horizon, are highest for the bin with IRs

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

between one and three. The worst rated borrowers also have the highest loss given default rates. These borrowers are thus much riskier than better-rated firms but cover only a small part of the bank's loan portfolio. Most of the bank's credit losses are therefore caused through defaults of firms with a somewhat better rating. The default risk of relatively safe firms is therefore 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 are secured with collateral, the average loan maturity and the average interest rate for each IR category.

In our baseline specification we will use the untransformed IR variable as an explanatory variable. However, Table 3 illustrates how default rates rise in a convex fashion with falling IR. Using rating categories linearly in regressions may thus be econometrically inefficient. Allowing a completely flexible form, e.g. through separate dummy variables for each category, would however complicate interpreting whether ratings are better or worse at predicting default in recessions. To allow for both an easy interpretation and a non-linear relationship between ratings and default rates, we estimate a 5th degree polynomial in IR (with only time FE), to generate a default prediction that fits the 12 month default rate. We will call this variable the "Internal Rating polynomial".[14]

As an alternative to using IR, we have also used another measure of the bank's assessment of a borrowers' creditworthiness which we call "credit slack". This measures is based on the bank's (privately known) lending limit and is available for more borrowers than IR. Results obtained using credit slack confirm our IR results and are available in the online appendix.

1.2 Macro data

We construct an indicator variable for recessions based on stock market and GDP growth. For GDP we use the seasonally adjusted, real growth rate, measured at quarterly frequency; for the stock market we use the 12 month return on the OMX30 stock market index, a market value-weighted price index of the 30 most actively traded stocks on the Stockholm Stock Exchange.

[14] The definition is $0.41xIR - 0.083xIR^2 + 0.0064xIR^3 - 0.00022xIR^4 - 0.0000029xIR^5$. A second, third or fourth order polynomial looks very similar over the relevant range: $IR \in \{1,2,..,21\}$.

The two time series variables are highly positively correlated with each other (0.73) and with consumer confidence measures of the business cycle (0.70 and 0.51 for GDP growth and stock market return, respectively). The recession indicator takes value one when either the trailing 12 month stock return or 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).

1.3 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. Internal rules require loan officers to review each client's file at least once every 12 months. The average time between two monitoring events is slightly above 10 months and it varies from 1 to 24 months. Long time gaps are rare: only 2.1% of firm-month observations exceed the 12 month limit since their last reported monitoring.

2. Empirical results

In this section, we report tests of competing hypotheses regarding the cyclical properties of banks' internal credit ratings. We employ a range of tests that aim to capture how informative bank internal ratings are about default risk.

A natural starting point is running predictive regressions with internal ratings (IR) as independent variable, assessing the extent to which default risk differs between borrowers with different values of internal ratings. We can compare the estimated coefficient on IR in expansions and recessions as a direct way of assessing how much ex-ante default risk can be expected to differ for borrowers with different values of internal ratings. A caveat is that we need to make our measure scale-free in the sense of not mechanically producing higher coefficients in periods of high average defaults. We achieve this by using a probit regression model instead of OLS. Probit coefficients are essentially multiplicative, so are not mechanically affected by whether they are estimated in high or low default risk periods. Another advantage of probit models over linear probability models is that they are better at fitting the very small probabilities of defaults and bankruptcy in some rating categories).

In the following sections we attempt to answer the question if "borrowers with different IR differ in terms of default risk?[15] We assess the magnitude of these differences using three statistics; coefficient size, the variation in R-squared over the cycle (either on its own, or in terms of additional R-squared over and above hard information variables) the ratio of default probability for poorly rated firms relative to the overall default rate measure. The latter is a scale-free, simple, non-parametric measure of informativeness. All three test statistics are presented below.

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. We estimate probit regressions as follows:

$$\text{Default}_{t+s} = \text{IR}_t + \text{Controls}_t + \text{Time Fixed Effects} \qquad (1)$$

We estimate equation (1) for defaults within twelve or twenty-four months ($s = 12$ or $s = 24$).[16] Control variables capturing accounting-based measures of firm performance as well as the firm's credit bureau score and various characteristics of the loan contract are included.

Results for both horizons, with and without controls, are reported in Table 4. Panels A and B each use a different transformation of the rating variable. In each specification, the bank's

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[15] One drawback with t-statistics is that they tend to be higher in large samples, or, put differently, even small effects can be precisely estimated in large samples. Small differences in default risk may not be economically interesting in this setting.

[16] 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.

information variables are significant and have the expected, negative sign, i.e., better quality borrowers have lower default probability.

In columns one and four of Panel A, we first leave out all controls except for time fixed effects to determine if IR, on its own, predicts default. Both columns show it indeed does. In columns two and five we next include control variables, 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 and isn't captured in the "hard" control variables. The rating variable (IR) again predicts default, and has 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-grade increase in the rating, slightly less than one standard deviation (3.6), reduces the likelihood of default from 1.50% to 1.19%, or a 21% reduction.

In panel B, we repeat the tests of panel A using a fourth degree polynomial in IR. We refer the data section for details. The magnitude of the estimated coefficient on IR polynomial is significantly different from zero, both with and without control variables. A one standard deviation increase in IR around the median IR (13) is associated with a 1.2% reduction of the default likelihood (from 1.04% to 1.02%). Because of the shape of the IR polynomial, this effect is much larger for riskier firms. Dropping from the second worst into the worst IR group (from IR=5 to IR=2), while holding all control variables fixed, default probability increases from 4.9% to 16.3%. Transitioning from the third worst to the second worst IR group (i.e., from IR=8 to IR=5) is associated with an increase from 2.0% to 4.9%, while moving from the fourth worst to the third worst IR group (i.e., from IR=11 to IR=8) is associated with an increase from 1.18% to 1.97%.

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 bureau 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 frictions that are our primary object of interest. Our main tests investigate the time-series variation in the informativeness of IR. We first use several non-parametric and graphical techniques to visually assess the informativeness of IR, and then turn to regression-based estimation of the time-series properties of IR.

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 plots 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 occur for firms with high ratings. In such a case the accuracy curve will be close to the upper left corner. Random assignment of ratings (i.e. uninformative ratings) would produce an accuracy curve along the 45 degree line because defaults are equally likely at all ratings levels. We construct accuracy curves for ratings at year end for all years in the sample, with a 12 month forward default horizon, and plot these annual curves in Figure 2. Clearly, ratings have 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, however. Moreover, 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

As described earlier, our sample of firms is largely stable over time, with few firms dropping out of the panel. To deal with any 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):

$$\hat{S}(t_k) = \frac{n_k - h_k}{n_k} \tag{2}$$

where t_k is the kth lowest survival time, n_k is the number of "at risk" observations at time t_k , i.e., 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.[17] Figure 3 displays the 12 and 24 months survival rates for the four intermediate internal rating groups, obtained by combining three adjacent IRs into one group, quarter by quarter until 2011q1. We exclude the weakest rating category to keep the scale small enough so that changes are visible. Borrowers with the best ratings have the lowest default frequencies in all periods, while the two strongest categories show little visible variation. Survival rates display a clear business cycle pattern with rates falling for all categories during both recessions. During downturns the difference in survival rates between rating categories tends to increase. In other words, the difference in default risk between firms positioned in 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.

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

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 groups of approximately equal size, one consisting of the three highest ratings and another containing the next three grades. [18] We drop the lowest rating category, where default is imminent for most firms. Results are qualitatively unchanged, however, with this category included. We define the default ratio as the default frequency for the weak group divided by the default frequency for the overall sample as follows:

$$Default\ ratio = \frac{\frac{D_{weak}}{N_{weak}}}{\frac{D_{weak}+D_{strong}}{N_{weak}+N_{strong}}} \quad (3)$$

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 default ratio becomes one. The lower bound for the ratio is therefore equal to one.[19] Second, 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 ranging from one (no information) to two (very good information).

[18] 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.

[19] 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.

We plot the quarter by quarter default ratio in Figure 4, while dropping IR category 7.[20] The average default ratio in expansions is 1.42 and 1.60 in recessions. 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).[21] 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 degree of precision in bank 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 essence is public information available to any bank and thus a hard signal. The IR variable performs better than credit score, with the former having an overall default ratio of 1.47 and credit scores an overall default ratio of 1.51 in the same period. The difference (0.25) is significantly different from zero.[22] Interestingly, the precision of the credit score variable is *also* counter-cyclical: the average default ratio based on credit scores alone is 1.44 in expansions and 1.53 in recessions (the difference between expansions and recessions is 0.09, half the difference using IR). One interpretation of this symmetry between hard and soft information measures is that the problem of predicting defaults is inherently easier in recessions. This would explain why even a mechanical procedure of sorting firms, where there is no role for effort decisions and no learning by credit officers, could perform better in bad times.

Can sample selection have affected 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. Although this appears unlikely a priori, we develop a simple model of firms' credit choices over a one-year period to assess this possibility. We consider a sample equally split

[20] Firms with IR = 7 are often already in default, and are not really a prediction challenge. Results are similar with these firms.
[21] The t-stat using Newey-West standard errors which allow for four auto-correlation terms is 5.0.
[22] Assuming time series independence, the t-stat is 12.9, and allowing for four auto correlation terms, the t-stat is 8.7.

between good and bad ratings, and 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. Next, we use the model to compute if the time series changes in the default ratio can be driven by changes in selection over time. Exits in the model are calibrated to 2% 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, as well as a default ratio of 1.6. Initially, sample exits are assumed no different from non-exits, and then calculate what default rates among exits, if any, could drive the default ratio down to 1.42 (the ratio during expansion periods). Under 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 will also be the default rates both in exit and non-exit samples. To be able to reduce the default ratio in the remaining sample to 1.42, the default rates of the exit firms would have to change. 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. We therefore conclude that while selection may contribute to the difference between good and bad times, it can only account for a small part of the differences we observe at a business cycle frequency, at most $\frac{1.60-1.59}{1.60-1.42} \approx 5.6\%$.[23]

Using the relative default ratio involves two caveats. 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 type 2 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

[23] We do not deal formally with the scope for selection bias in regression-based 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 (not just two broad groups) and with many control variables.

specifications which deal with both these concerns by allowing for 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. We consider both coefficient magnitudes and explanatory power as capture by R-squared. By filtering out information captured in these variables, we implicitly focus on the soft component of the bank's information. To track time-series variation in the predictive precision of IR we adjust regression (1) by allowing the coefficients on bank's information (IR) to differ each quarter. This amounts to 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 IR. Second, this variation is correlated with the business cycle both the statistical power and the magnitude of coefficient estimates are higher during the 2008-2009 recession, and again during the second recession starting in 2011, than during the expansionary periods. These results suggest that the bank's internal information is better able to sort borrowers by credit quality at times when the economy is weak, as captured by coefficient size in probit regressions.

An additional measure of internal ratings' ability 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. While coefficient magnitudes reflect the magnitude of the difference in default risk between borrowers of different level of IR, comparisons of R-squared reflect what fraction of total variation in default risk can be explained by IR. Thus, these metrics are complementary.

To examine the variation in explanatory power, 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.[24] On the one hand, the credit score corresponds closest to the standard notion of hard information, since it is a numerical variable, publicly available for a nominal 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. Because we use probit regressions for our regression tests, we report the Pseudo R-squared measure for completeness.

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%.[25] 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 than out of recessions, but the difference is small. Finally, we look at the marginal contribution to the explanatory power that internal ratings offer over and above credit scores, i.e. the difference in R-squared between a model with credit scores alone and one that also includes internal ratings. On this measure as well as the one reported above, we find that the bank information appears more important in recessions.

Parametric estimates of cyclicality

Next, we test if 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:

$$\text{Default} = \{(\text{IR})\}\times\{\text{Recession dummy}\} + \text{IR} + \text{Controls} + \text{Time F.E.} \quad (4)$$

The results are reported in Table 6 and confirm that the differences in patterns between good times and bad times shown in Figure 4 are statistically significant.[26] The magnitudes of the

[24] Results are qualitatively similar with more controls.
[25] 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).
[26] We use 12-month default as dependent variable from this point on. Results are similar with 24 months.

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

Business cycles may hit different parts of the economy differently so in column (2) we cluster errors by sector instead of firm. This has little impact in significance. We next repeat results for the polynomial in IR in columns (3) and (4). Results are very similar.

The results in Table 6 imply that the bank's is best at predicting defaults in recessions, as suggested by the quarter-by-quarter regressions in Figure 5, and consistent with the R-squared comparisons in Table 5. Together, this set of results points to better predictive power of financial the internal bank ratings during recessions. As Figure 5 shows, the pattern is visible both in the deep but brief recession associated with the global financial crisis and in the shallower, more prolonged recession that followed a few years later. We conclude that information about borrowers is not less precise, and likely more precise, in bad times.

In the next section, we address possible identification concerns and try to distinguish between the alternative theories of counter-cyclical bank information quality.

2.3 Robustness tests

In this section, we address a number of possible concerns and questions about our main results. First, we examine the cyclical properties of the predictive power of the credit bureau score. Second, we check if our results reflect the impact of greater credit flows for better rated borrowers on short run default risk. Third, we compare two possible mechanisms that may produce better information for the bank in recessions: cyclical variation in the mix of old and new borrowers.

Hard information over the cycle

A key robustness test involves allowing not just the internal rating, but also other variables, to have time-varying coefficients. A key variable is the credit bureau score, since it is constructed mechanically using a large amount of data, making it a good example of "hard" data in the sense of Stein (2002). In Table 7, we allow the coefficient for both IR and credit bureau score to differ in recessions (column 1) and then for both IR polynomial and credit bureau score (column 2). The interaction between the recession indicator and credit bureau score is positive and significant in both regressions. Recall that a high value on the score corresponds to high risk. The results suggest that both "hard" and "soft" information better predict defaults in recessions than in better times. Notably, this is consistent with the pattern in Figure 4 above, where the default prediction based on credit bureau score alone does better in recessions.

The observed cyclicality in the precision of hard information is a significant finding for several reasons. First, many of the theories about cyclical information quality information often concern bank productivity or effort in information production (e.g., Dell'Arriccia and Marquez 2006 as well as Ruckes 2004). These theories cannot explain why a mechanical measure like the credit bureau score works best in recessions. Perhaps the problem of predicting default is fundamentally easier in bad times.

New credit

We first consider a possible mechanical problem with our results. Firms with better IR may be less likely to default because they obtain more credit from their bank. In the short run, new credit almost surely reduces the default probability; the long run impact is more ambiguous, since the additional credit will have to be repaid, increasing the amount of future commitments on which default is possible. Such a mechanism could provide an alternative interpretation of our results, implying that the precision of the bank's information might not truly 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 attempt to control for this in our baseline specifications. However, because the default variable "looks 12 months ahead", current IR could be predictive of new loans to be granted during this time period. To test is this is quantitatively important we drop any firm receiving new credit in the next 12 months from our bank (column 1 and 2) or any bank (2 and

3) in auxiliary regressions. Results for this subset are presented in Table 8.[27] 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 driven by new credit flows; the variation in the predictive power of IR is indeed 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

Another concern may be that banks exerts more effort in bad times, and so produce 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.[28]

In Figure 6, we plot the fraction of firms being subject to an evaluation by quarter. The figure displays pronounced seasonality in the monitoring 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 the overall frequency of assessments by year. The increasing activity in the last quarter of each year is offset by reduced activity in the other three quarters. Although the evidence against cyclical variation in screening intensity is weak, we cannot detect differences in monitoring frequency for different business cycle states. Banks may increase

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[27] 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).

[28] Note that this information on monitoring frequency cannot help detect if loan officer skills deteriorate in booms, as Berger and 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 and Maréchal (2015).

intensity of screening (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 improved ability to detect risk in recessions is not mechanically driven by reassessing borrowers more often.[29]

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, throughout 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 at first sight unlikely enough to plausibly explain the large differences in precision through the cycle that we found.

To make sure this assessment is correct, we re-estimate regressions for existing clients only. The results in Table 9 make clear that the cyclicality patterns for new borrowers are similar to those for the full sample. The bank is better able to predict default among *existing* borrowers in recessions. Thus, we can conclude that the patterns we observe are not an artifact of time-

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[29] 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.

variation in the mix of old and new bank clients.[30] We conclude that the Dell'Arriccia and Marquez (2006) mechanism does not appear quantitatively important in our data.

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's industry and size composition. In particular, small firms are more opaque and may be less well understood by the bank because 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 could possible that they affect the bank's inferred 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 10, 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.

In additional robustness tests not reported here we run separate regressions 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 variation in the industry and size composition of defaults does not contribute to our cyclicality results.

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

3. Conclusions

The supply of corporate bank loans is highly pro-cyclical. In principle, this could reflect information frictions between lenders and borrowers, which become worse in recessions. In general, assessing borrowers' creditworthiness is a key challenge facing lenders. Could the magnitude of this challenge be cyclical, making it harder to assess cross-sectional variation in risk, thus contributing to low lending volumes in recessions? Our empirical results suggest that this explanation of loan supply cycles is unknot supported in data covering the loan portfolio of a large Swedish bank over two recessions. Instead, we find the opposite: corporate borrower defaults are in fact easiest to predict in recessions. This is true using hard information measures, which are easily collected and quantified, as well as soft information, which is harder to collect and quantify.

Our results suggest that cyclical patterns in the quality of bank borrower assessments do not reflect the composition of borrowers, e.g., the arrival of new, unknown firms. We also rule out that our results are contaminated by reverse causality related to the extension of new loans. Instead, our findings appear most consistent with cyclical changes information environment. It is simply easier to predict defaults in bad times.

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. They also agree with work on related questions in smaller banks (e.g. Brown, Kirschenmann and Spycher 2016 and Lisowsky, Minnis and Sutherland 2016). A working hypothesis is that the pattern we find applies to corporate credit in general.

A key implication of our findings relate to the 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.

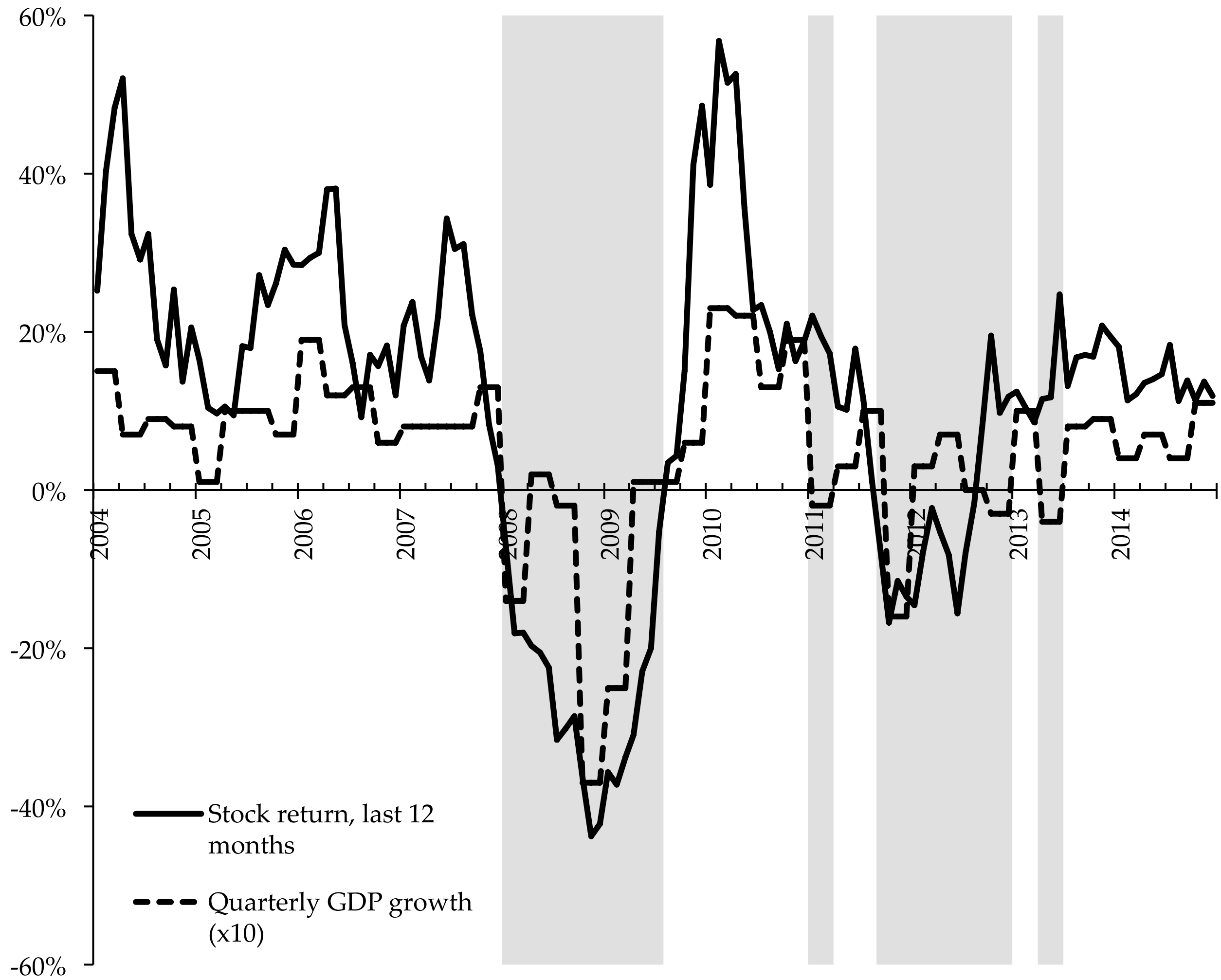


Figure 2. Accuracy of internal ratings by year, 2004-2011

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).

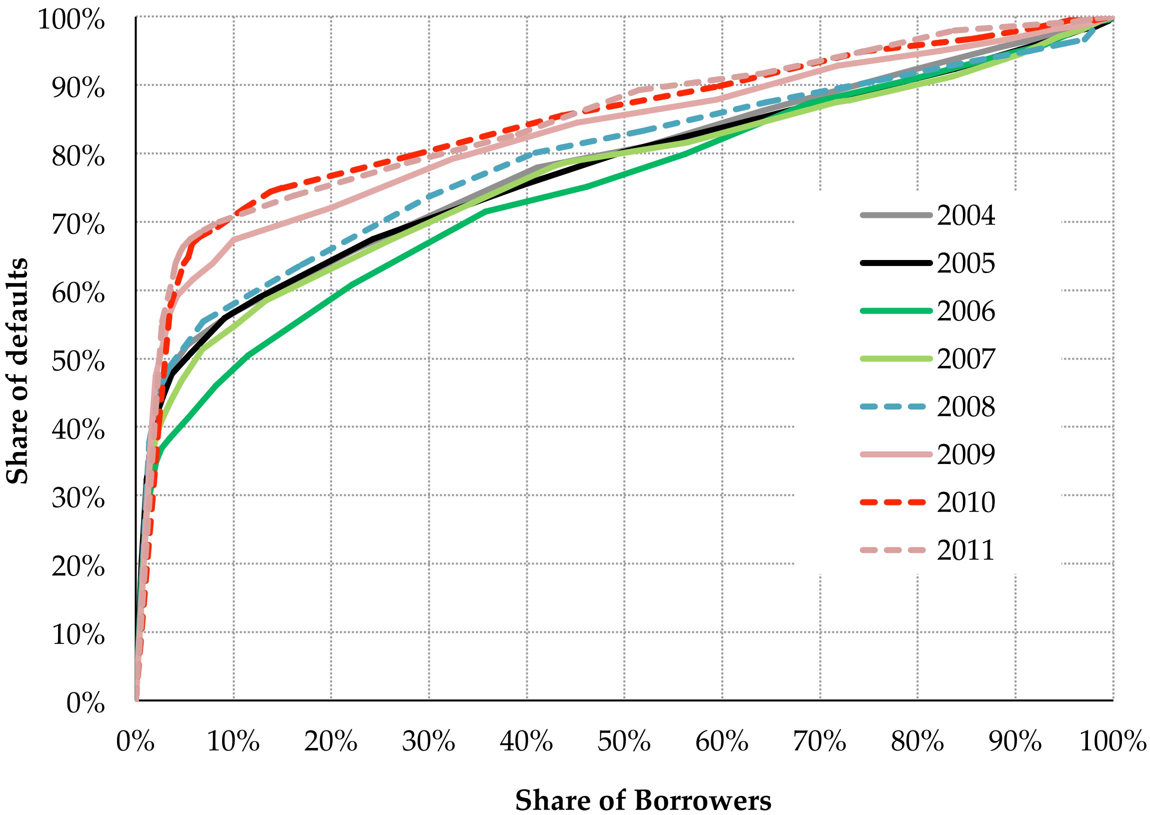
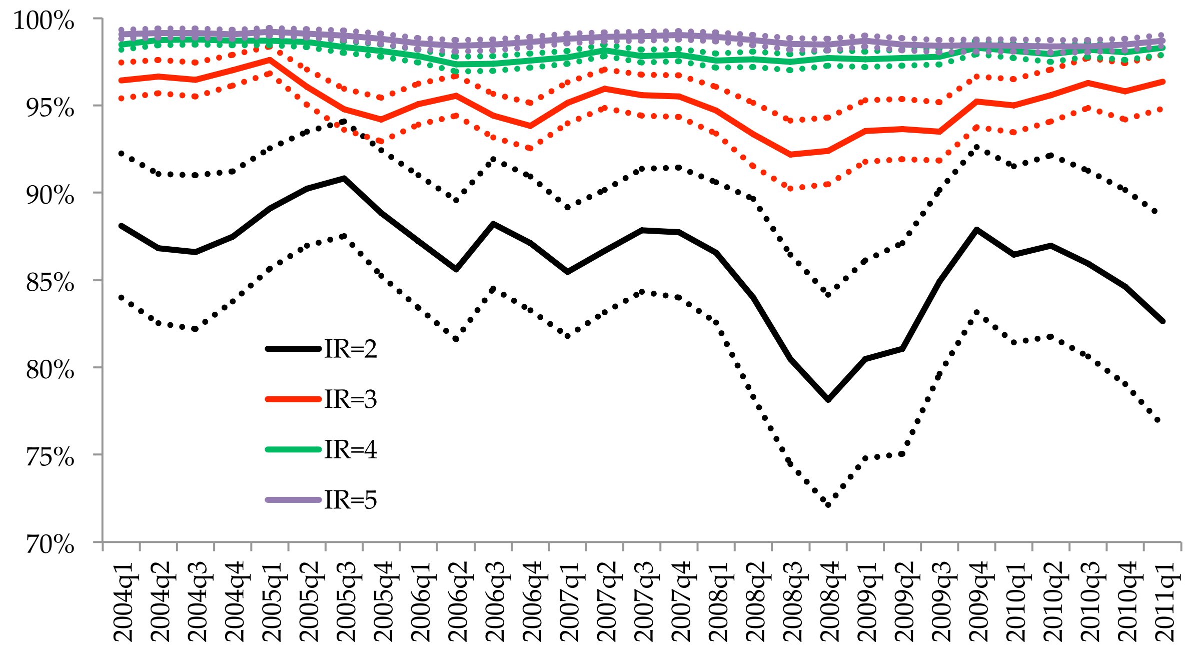


Figure 3. Kaplan Meier survival rates by internal rating

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 $\hat{S} = \prod_{t_i \le t} \frac{n_i - losses_i}{n_i}$, 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

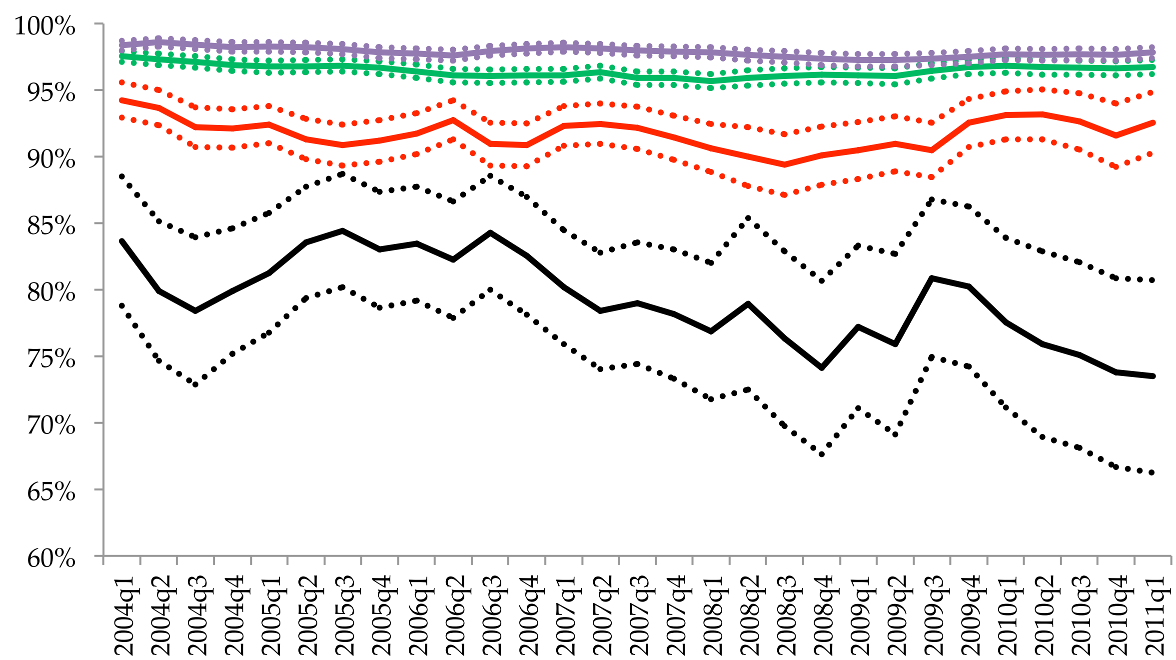


Figure 4. Default rates across ratings categories

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.

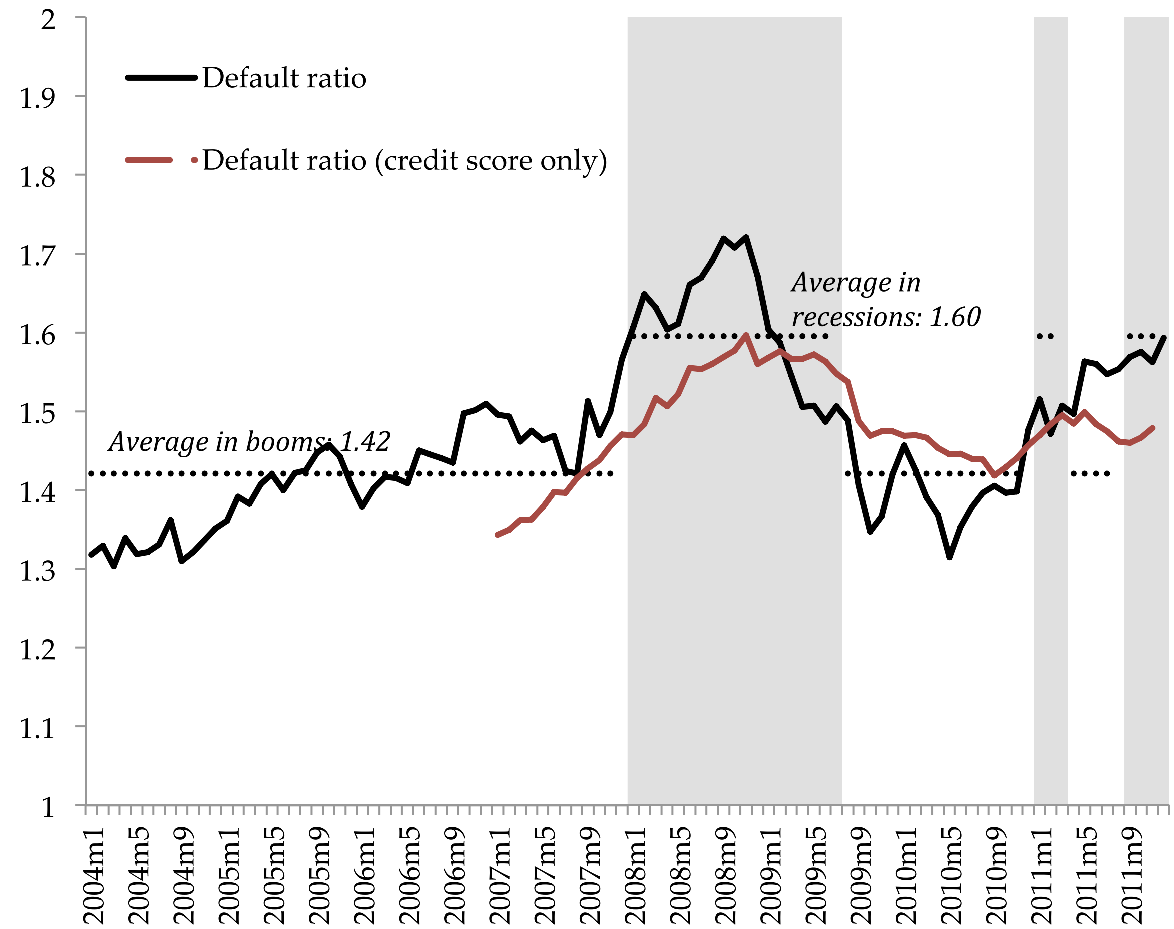


Figure 5. Predicting default over the business cycle

This figure displays the $\beta_1$coefficients from probit regressions of default twelve months ahead on internal ratings. Coefficients are from the following regression: $Default_{within\ 12m} = \beta_{1t}IR * timeF.E. + \beta_2\text{X} + \text{i.t} + \varepsilon$. 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.

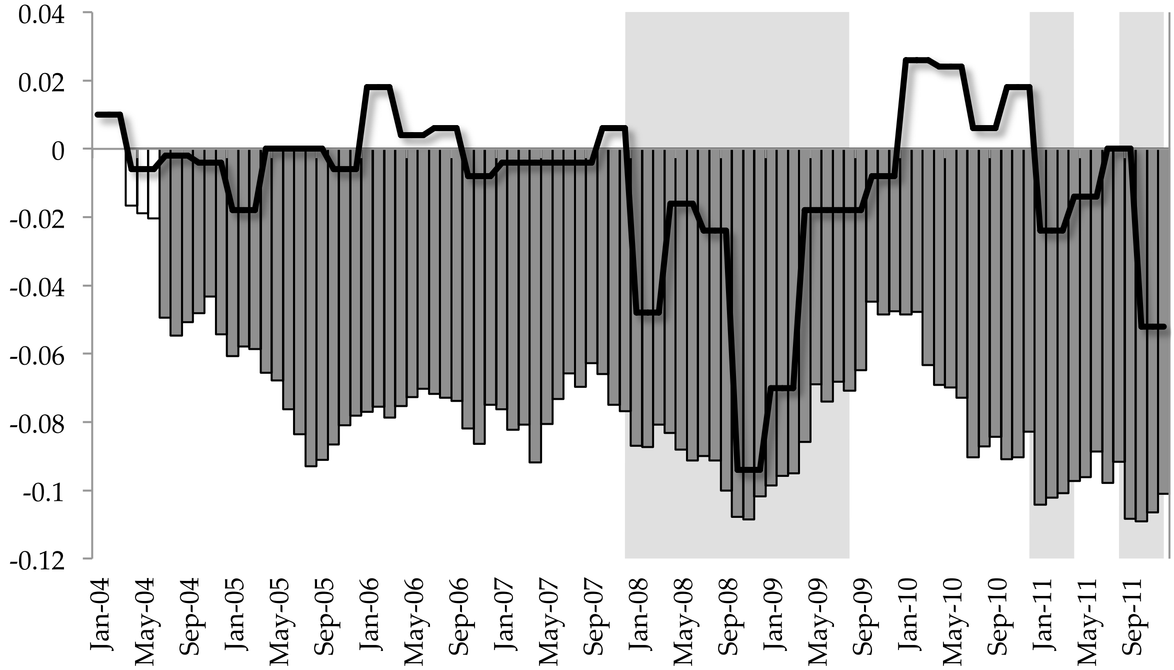


Figure 6. Proportion of borrowers being assessed by quarter

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).

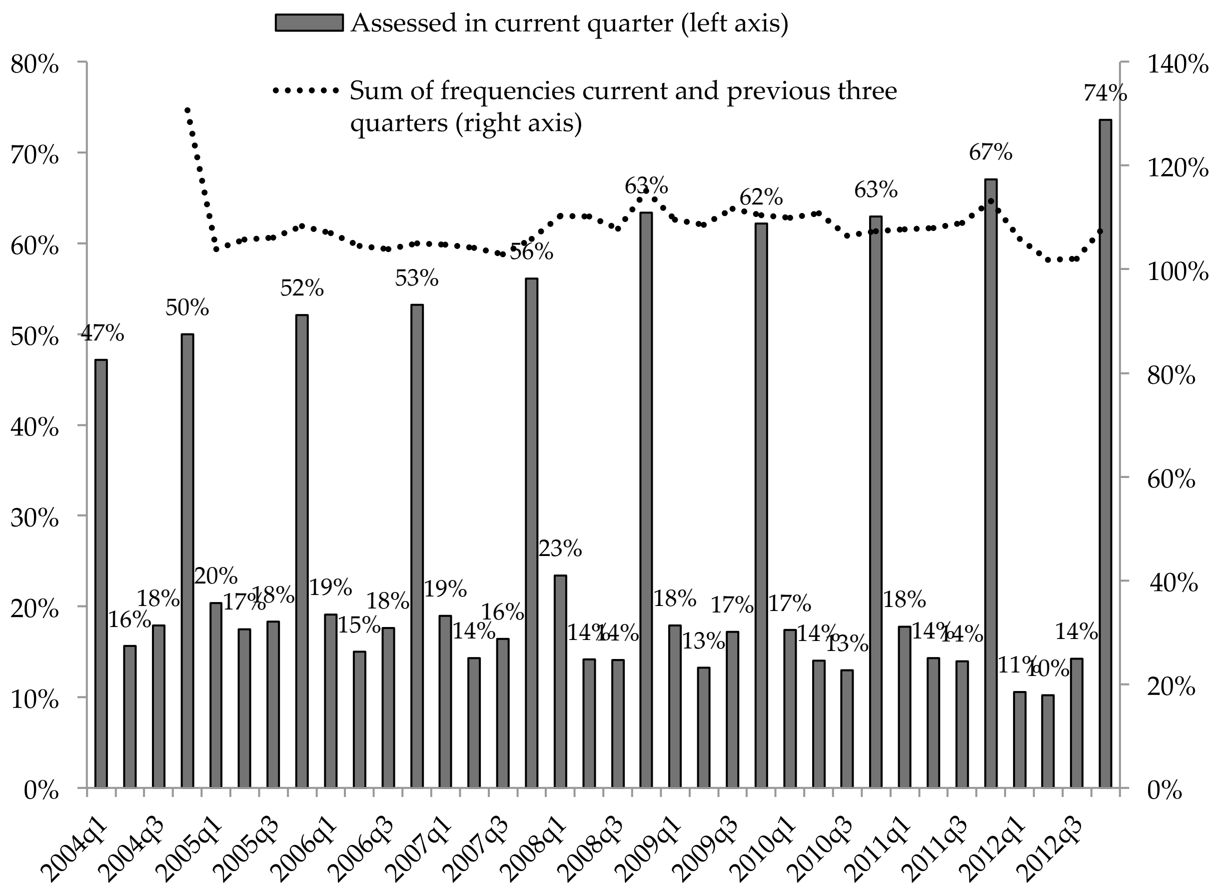


Table 1. Variable definitions

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

Variable	Freq.	Source	Definition
Internal rating (IR)	Monthly	Bank	A borrowers score in the bank's internal rating system, an integer from 1 to 21
Internal rating group	Monthly	Bank	The internal rating aggregated up to the 7 main steps
IR polynomial	Monthly	Computed	The negative of predicted future default probability. The prediction is done by fitting future default with a fifth degree polynomial.
Limit	Monthly	Bank	Granted credit limit in 1,000 SEK
Internal limit	Monthly	Bank	The maximum amount the loan officer is entitled to lend to the firm without further internal approval. In 1,000 SEK
Outstanding balance	Monthly	Bank	Outstanding credit balance
Outstanding balance / limit	Monthly	Computed	Outstanding credit balance divided by the firms granted credit limit in 1,000 SEK
Slack	Monthly	Computed	The ratio is: (Internal limit – granted credit limit)/Internal limit
Collateral	Monthly	Bank	The bank's own internal updated estimate of the value of the assets pledged in 1,000 SEK
Days since review	Monthly	Bank	The number of days elapsed between two consecutive reviews by the loan officer
Total sales	Annual	UC	Total sales in 1,000 SEK
Total assets	Annual	**SCB**	Total assets in 1,000 SEK
Total tangible assets	Annual	SCB	Total tangible assets in 1,000 SEK
Return on capital	Annual	UC	The ratio is: profits / the book value of capital
Return on assets	Annual	UC	The ratio is: operating profits / average total assets
Gross margin	Annual	UC	The ratio is: (earnings before interest, taxes, depreciation and amortization) / sales
Net margin	Annual	UC	The ratio is: (earnings before taxes and amortization) / sales
Credit bureau score	Monthly	UC	Credit bureau's risk measure (an ordinal rating)
Employees	Annual	SCB	Number of employees employed by the firm
Leverage	Annual	Computed	The ratio is: total debt / total assets
Default	Monthly	Computed	Dummy variable that is one if the borrower's 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 1,000 SEK)	13,000	165	2,880,000	5,812,000
Internal limit (in 1,000 SEK)	24,000	600	218,000	4,293,000
Outstanding balance (in 1,000 SEK)	6,878	90	180,000	5,681,000
Outstanding balance / Limit	0.69	0.99	0.41	5,128,000
Collateral (in 1,000 SEK)	2,617	0	34,100	5,808,000
Days since review	155.2	151.0	130.6	3,643,000
Total sales (in 1,000 SEK)	87,900	3 929	1,210,000	4,916,000
Total assets (in 1,000 SEK)	159,000	3 235	2,880,000	4,809,000
Total tangible assets (in 1,000 SEK)	28,100	252	516,000	4,809,000
Return on capital	0.14	0.16	0.60	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	0.23	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	0.13	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	15.9%	24.2%	74.5%	11.3%	1.4%
4–6	9.2%	13.5%	61.1%	4.7%	0.3%
7–9	3.5%	6.3%	57.9%	1.5%	3.2%
10–12	1.4%	2.7%	54.7%	0.4%	26.0%
13–15	0.9%	1.7%	53.7%	0.1%	46.1%
16–18	0.6%	1.2%	42.4%	0.03%	18.5%
19–21	0.7%	1.1%	22.6%	0.00%	4.5%
ALL	1.5%	2.6%	51.4%	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	1	6%	1.95	4.564
4–6	2	10%	1.93	5.244
7–9	2	9%	2.15	4.795
10–12	2	11%	2.28	4.495
13–15	2	11%	2.04	4.097
16–18	2	18%	2.27	3.950
19–21	2	54%	2.19	3.735

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	**-0.099*****	**-0.078*****	**-0.003*****	**-0.098*****	**-0.067*****	**-0.005*****
	(0.003)	(0.005)	(0.000)	(0.004)	(0.005)	(0.000)
Return on capital		**0.047***			**0.027**	
		(0.026)			(0.027)	
Return on assets		**-1.017*****			**-0.944*****	
		(0.140)			(0.140)	
Gross margin		**-0.349*****			**-0.428*****	
		(0.086)			(0.093)	
Net margin		**-0.096**			**-0.134**	
		(0.083)			(0.085)	
Log (total sales)		**0.040*****			**0.044*****	
		(0.010)			(0.011)	
Log (total assets)		**0.039*****			**0.036*****	
		(0.011)			(0.012)	
Tangible fixed assets / assets		**-0.333*****			**-0.364*****	
		(0.054)			(0.059)	
Leverage		**0.075**			**0.167****	
		(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	**-10.335*** **	**-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 three 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 or sector, 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	Probit	Probit
	(1)	(2)	(3)	(4)
Internal Rating	**-0.0712*** **	**-0.0712*** **		
	(0.0055)	(0.0063)		
Internal Rating x Recession dummy	**-0.0243*** **	**-0.0243*** **		
	(0.0078)	(0.0079)		
Internal Rating polynomial			**-7.617*** **	**-7.617*** **
			(0.445)	(0.525)
Internal Rating polynomial x Recession dummy			**-2.189*** **	**-2.189*** **
			(0.634)	(0.752)
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 bureau score, interest rates, duration, collateral			
Time F.E.	Yes	Yes	Yes	Yes
Number of observations	688,692	688,692	688,692	688,692
Clusters	Borrower	Sector	Borrower	Sector
Number of clusters	16,702	54	16,702	54
Adjusted R^2	0.12	0.12	0.12	0.12

Table 7. Default prediction through the business cycle: time-varying effect of hard information

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.

Dependent variable	Default wtn 12m	
Regression type	Probit	Probit
	(1)	(2)
Internal Rating	**-0.0728*** **	
	(0.0055)	
Internal Rating x Recession dummy	**-0.0179** **	
	(0.0082)	
IR polynomial		**-7.748*** **
		(0.045)
IR polynomial x Recession dummy		**-1.620*** **
		(0.669)
Credit bureau score	**0.0209*** **	**0.0187*** **
	(0.0016)	(0.0017)
Credit bureau score x Recession dummy	**0.0108*** **	**0.0087** **
	(0.0040)	(0.0043)
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, collateral	
Time F.E.	Yes	Yes
Number of observations	688,692	688,692
Clusters	Borrower	Borrower
Number of clusters	16,702	16,702
Adjusted R^2	0.12	0.12

Table 8. 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 type	Probit			
	(1)	(2)	(3)	(4)
Internal Rating	**-0.078***** (0.006)		**-0.086***** (0.006)	
Internal Rating x Recession dummy	**-0.027***** (0.009)		**-0.013** (0.009)	
Internal Rating polynomial		**-7.531***** (0.494)		**-7.920***** (0.514)
Internal Rating polynomial x Recession dummy		**-2.113***** (0.700)		**-1.824**** (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 bureau 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	0.14	0.14	0.16	0.16
	Based on outstanding credit at our bank		Based on total outstanding credit	

Table 9. 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 type	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 bureau 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	0.12	0.13

Table 10. 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		**-7.279*** **
		(0.639)
Internal Rating polynomial x Recession dummy		**-2.510** **
		(1.026)
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 bureau score, interest rates, duration, collateral	
Time F.E.	Yes	Yes
Number of observations	325,072	325,072
Clusters	Borrower	Borrower
Number of clusters	7,662	7,662
Adjusted R^2	0.09	0.09

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

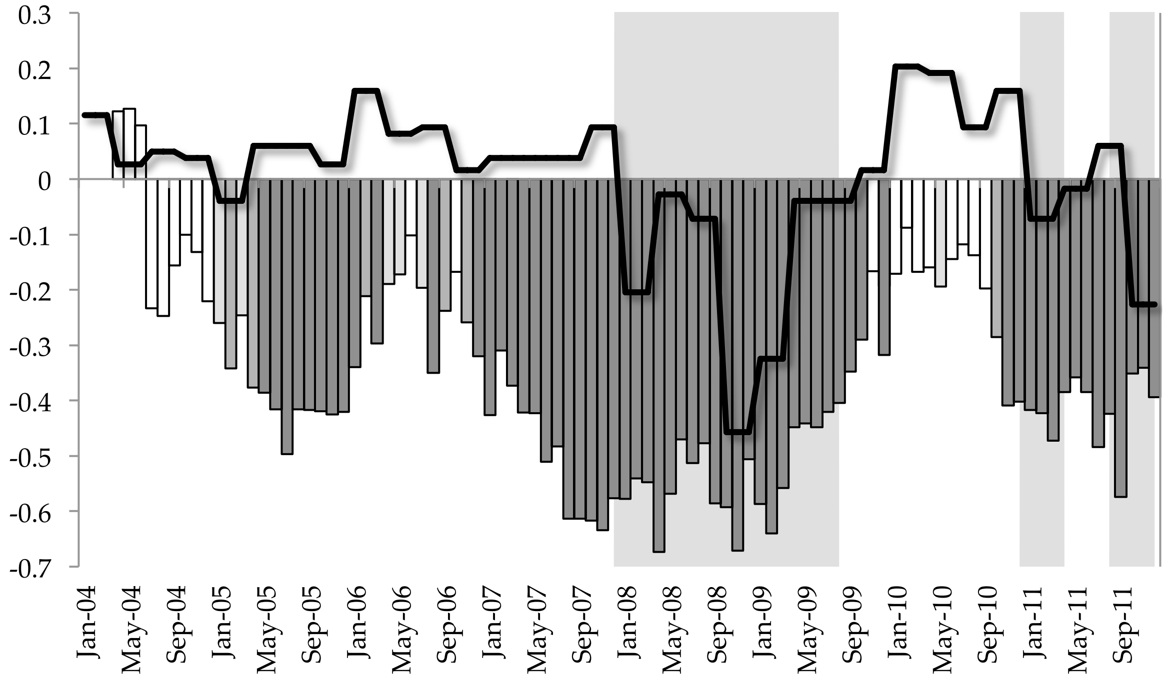


Table A1. Similar to table 4 in the paper Predicting default by Slack

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		**-0.272*** **			**-0.304*** **	
/ total assets		(0.042)			(0.048)	
Leverage		**0.618** **			**0.614** **	
		(0.051)			(0.056)	
Outstanding loan		**0.000**			**0.000**	
balance		(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 bureau 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 8 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 bureau 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 9 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 bureau 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 10 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 bureau score, collateral
Time F.E.	Yes
Number of observations	409,358
Clusters	Borrower
Number of clusters	9,397
Adjusted R^2	0.077