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, or is the depth of the friction reduced, as bad times reveal information about firm quality? We test these alternative hypotheses using internal ratings data from a large Swedish cross-border bank and credit scores from a credit bureau. The ability to classify corporate borrowers by credit quality is greater during bad times and worse during good times Soft and hard information measures both display countercyclical patterns. Our results suggest that information frictions in corporate credit markets are intrinsically counter-cyclical and not due to cyclical variation in monitoring effort.

Keywords: Credit markets, corporate loans, information frictions, internal ratings, 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 of Berkshire Hathaway

1. Introduction

Credit is the main form of financing for firms—funding operations, working capital, investment, and acquisitions. The flow of credit to firms 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: some friction reduces the availability of loans at bad times, thereby exacerbating business cycles (see e.g., Bagehot 1873).[1] In this paper, we examine if one important friction – variation in the quality of lenders' information about borrowers – drives cyclical swings in the credit supply.

Information frictions are perceived as central to understanding many features of credit markets, including the formation of long-term relationships between borrowers and lenders (Petersen and Rajan 1994, Agarwal and Hauswald, 2010), the existence of credit registries (Pagano and Japelli 1993; Hertzberg, Liberti and Paravisini 2011), the use of covenants in debt contracts (Smith and Warner 1979) and the calibration of financial incentives to loan officers (Agarwal and Ben-David 2018). Information frictions have been identified as important to both quantities (Garmaise and Natividad 2013) and prices (Ivashina 2009) in credit markets.

[1] Recent evidence for cyclical variation in the credit 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. Jiménez, Ongena, Peydró and Saurina (2017) show that supply effects stemming from bank balance sheet strength drive credit in crisis times, while demand effects originating in firm balance sheet strength affect credit in both good and crisis times

Given the well-established importance of information frictions, it is natural to ask if they also contribute to credit market cycles.[2] Information frictions can potentially be more or less severe in cyclical downturns, and available theories point in both directions.

On the one hand, some theories suggest that information problems between lenders and borrowers are *less severe in downturns*. Such counter-cyclicality 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.

In this paper, we examine directly how the quality of banks' information about their corporate borrowers varies throughout the cycle. We use data from one large Swedish cross-border bank matched with a national credit register that has been used in, among others, Cerqueiro et al. (2016) and Nakamura et al. (2018) and examine how the information content of its borrower credit quality assessments (i.e., the ability to predict future defaults and bankruptcies) varies over time. Our data provides detailed information on the bank's corporate borrowers through two business cycles, allowing us to separately examine the financial crisis and a second, less severe recession. We do not study *how* information frictions affect either lending decisions or lending standards.

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

Our tests only examine the quality of the bank's information about clients, not how that information is used.

The bank we study follows the Basel II Internal Ratings Based (IRB) approach and employs an internal rating system to summarize information about the credit quality of its borrowers. A key element in our tests consists of comparing the precision of internal ratings over the cycle. First, 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. Then we show that internal ratings have greater accuracy in predicting defaults during recessions than at other times. Moreover, we observe that defaults are more concentrated among firms to which the bank assigned poor ratings during a recession than in good times, providing further support to the notion that information quality is countercyclical. Regression analysis confirms that the ability of the bank's internal ratings to predict defaults is greater during recessions. This finding is robust to using different measures of borrower information and various subsets of borrowers. In addition, we establish that soft information - included in internal ratings - is a more powerful predictor of defaults than hard information during bad times.

We attempt to differentiate between the different theories of pro-cyclical information problems that could explain our finding of countercyclical information quality.

First, we assess a testable implication of Dell'Ariccia 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 find that variation in the industry composition of the borrower pool does not drive our results either.

We also consider Ruckes's (2004) theory, which suggests that banks will exert more effort in times when defaults are costlier (i.e., recessions). We use information on the timing of the bank's revisions of borrower ratings instead of effort data and find that monitoring activity is not cyclical. Increased monitoring activity in recessions is therefore not driving our findings.[3]

Last, we examine Berger and Udell's (2004) mechanism: loan officer skills deteriorate (and lending institutions forget lessons learned in recessions) as time passes, resulting in progressively lower quality of credit analysis in expansions. By exploiting data on mechanical credit scores, which do not rely on skill, we reveal a similar variation in the precision of mechanical credit scores as for loan officers' ratings. This suggests a deterioration of skills cannot drive all of the time series patterns.[4]

Our findings suggest that the improvement in the bank's sorting ability and the reduction in information frictions in corporate credit markets during recessions are robust and intrinsic properties, i.e., inherent to the data, and not driven by bank actions such as loan officer effort as soft and hard information measures both display similar countercyclical patterns. Overall, 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.[5] Our findings do not lend support to theories in which information frictions in credit markets play a role in recessions, but are broadly consistent with models of poor lending decisions in expansions.[6] [7]

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[3] 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.

[4] It is still possible that the bank's credit model has been estimated to predict defaults *in bad times* rather than defaults in general. This does not explain why mechanical credit scores produced by a credit bureau also perform better in recessions.

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

[6] 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.

[7] 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.

Our paper complements the literature that sees information frictions as key to credit markets and is closely related to the line of research that investigates why credit markets are cyclical. We show that information frictions between banks and their borrowers cannot explain the cyclicality of credit flows, and in fact work in the opposite direction. As a consequence, other frictions must be driving the observed patterns in the supply of corporate credit. Such frictions may be located in the financial system: a low loan supply in recessions (see Kashyap, Stein and Wilcox 1993; Becker and Ivashina 2014) 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] 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 paper is also related to the literature on credit ratings, which, like internal ratings, measure credit risk. Dilly and Mählmann (2015) document that ratings agencies' incentive conflicts vis-à-vis investors are stronger in boom periods and lead to a bias and lower quality of initial ratings for corporate bonds. In boom times, rating agencies hold a more optimistic view than bond markets and boom bond ratings are more heavily downgraded, consistent with the notion that information frictions are *less severe* in bad times.

The remainder of this paper is organized as follows. Section 2 describes the data and variables. Section 3 presents our main results. Section 4 offers some robustness tests. Section 5 concludes.

2. Data and variables

For our analysis, we use a comprehensive database of all corporate accounts of a major Swedish cross-border bank that followed the international standards of Basel Committee's IRB approach for classification of its borrowers (henceforth, "the bank"). The database contains all loan files the bank maintains for each borrower in Sweden at a monthly frequency between 2004:01 and

[8] 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).

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. Although our panel is un-balanced in a strict sense, it displays most features of a balanced panel because of very low entry and attrition rates for borrower relationships. Of 16,702 firms in our main sample, only 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.

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.[9] We summarize our data set 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 used in our baseline regressions (equation 1).

2.1 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 2018). Only borrowers to which the bank has a total exposure above a certain pre-determined threshold are assigned an internal rating by a loan officer.[10] Smaller borrowers only have an automated behavioral rating that is not available to us. Borrowers with an IR represent between 70% and 80% of loans outstanding, depending on the year. Although loan officers are required to review client files and update client information at least once a year, IR values are stable over time: on average, 2% of firms change category from one quarter to next. We assign the different rating grades values from one to twenty-one, where one is the worst rating (highest default risk).

[9] Nakamura and Roszbach (2010) describes the credit bureau's modeling.

[10] This threshold does not vary over the business cycle. To protect the identity of the bank, we cannot publish the threshold.

We follow conventions in international banking regulation and use the occurrence of a borrower default in the next 12 months as the baseline outcome measure in our tests of information quality. The bank's internal default variable equals one when any payment is over 90 days past due.[11] 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 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 firm, the share of loans that are secured with collateral, the average loan maturity, and the average interest rate for each IR category.

Banks' decision making could potentially be based on different metrics than their internal ratings or on some soft information to which we lack access. We therefore construct an alternative measure of the bank's assessment of a borrowers' creditworthiness, that should incorporate such information. We call this "credit slack"and base it on the bank's (privately known) borrower specific willingness to lend more than it is currently doing, i.e., an internal lending limit. This measure is available for more borrowers than IR. We refer to Appendix 1 for details on the construction of credit slack. Some of the results using credit slack that we refer to in Section 3 and Section 4 will be presented in Appendix 2.

[11] This definition of loan follows international standards.

In addition to the bank's internal risk assessments, we also use an external risk assessment, made by the credit bureau. This rating is generated for all Swedish incorporated firms by a statistical model that uses only hard information that is available from government agencies like district courts and the tax authority. The credit bureau ratings are available to loan officers at near zero cost.[12]

2.2 Macro data

Sweden has no official recession dating committee nor does it publish an official recession indicator. We therefore 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. 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).

2.3 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

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[12] Generally, we think of public information as being a subset of all hard information, while private information can consist of both hard and soft information. In the remainder of this paper we will only use the concepts hard and soft.

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.

3. 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, to assess the extent to which internal ratings have a basic ability to predict loan defaults and default risk differs between borrowers with different values of internal ratings. Later, we compare the estimated coefficient on IR in expansions and recessions as a 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. [13]

In Section 3.1 we document the basic relationship between the bank's internal measure of borrower creditworthiness and default risk.[14] In Section 3.2 we present initial, non-parametric and graphical evidence on the informativeness of internal ratings over the business cycle. In Section 3.3 we present regression analyses that confirm the counter-cyclicality of information frictions.

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[13] Probit coefficients are essentially multiplicative, and 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.

[14] One drawback of 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.

3.1 The relationship 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:

$$\text{Default}_{t+s} = \beta_1 . \text{IR}_t + \boldsymbol{\beta}_2 . \text{Controls}_t + \text{Time Fixed Effects} + e_t \qquad (1)$$

We estimate equation (1) for defaults within 12 or 24 months ($s = 12$ or $s = 24$).[15] 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.[16] In each specification, the bank's information variables are significant and have the expected negative sign, i.e., better quality borrowers have lower default probability.

In column (1), we first leave out all controls except for time fixed effects to determine if IR, on its own, predicts default. It indeed does. In columns (2) and (4) 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 column (9) we present the same regression run on a sub-sample of firms that had their rating updated in the period before. The coefficient on IR and Pseudo R2 are slightly higher than in column (2), illustrating that slow updating of ratings reduces their predictive power.

[15] 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 can be obtained from the authors. Results are qualitatively very similar to those in Table 4.

[16] Results for the 24-month horizon without controls are displayed in the Appendix Table A1.

Because default rates rise convexly as IR falls (Table 3) estimating a linear relationship between internal ratings and default may be econometrically inefficient. To allow for a more efficient, flexible, functional form, we also fit a polynomial on IR (with only time FE) and use this instead of IR in the regressions underlying column (2) of Table 4. Column (6) of Table 4 displays this regression, while column (7) presents the marginal effects. The estimated coefficient on the IR polynomial is significantly different from zero and maintains its negative sign. Although pseudo-R2's do not allow for a precise comparison, the explanatory power of the regressions does not appear to rise substantially when introducing the polynomial. The linear probit regression approach used in Table 4, columns (1) - (5) and forward is thus a reasonable approximation.[17]

In columns (6) to (8) we also test if two alternative measures of borrower quality, the credit score constructed by the credit bureau and "credit slack" have similar properties as IR. Both display the same qualitative relationship with future loan defaults and have quantitatively similar explanatory power. In Sections 3.3 and 4 we will use these alternative information measures to test if the cyclical properties of information frictions are specific to the bank's own ratings or a robust feature of a broader set up creditworthiness assessments.

The above results 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).

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[17] The polynomial does allow us to better flesh out marginal effects. A one-standard-deviation increase in IR around the median IR (13) is, for example, 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 in default probability 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%.

3.2 Information frictions 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. In Sections 3.2.1 – 3.2.3, we use several non-parametric and graphical techniques to visually assess the informativeness of IR over the business cycle and present initial evidence that information frictions are countercyclical.,

3.2.1 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 of the graph. Greater accuracy can arise because of a shift in defaults between rating grades for *a given* aggregate default rate or through a combination of a shift between rating grades and *an increase* in the aggregate default rates. A multiplicative change in default rates across rating grades would not change accuracy of the rating system. Accuracy rates are therefore unaffected by aggregate conditions that influence default rates "proportionally" across the risk spectrum. Completely 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 general. In particular, the recession years 2008, 2009, and 2011, have three of the highest accuracy ratios. At this point, we will not try to explain in detail if the increase in accuracy is driven primarily by the higher risk segment or by a broader range of borrowers. Instead we suffice by observing that the increase in accuracy can be considered as prima facie evidence that the bank's information may be more precise in bad times. Later, we will return to a measure of accuracy in a regression setting.

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.

3.2.2 Survival rates by rating grade 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 non-parametric estimate of the survival function $S(t)$ (and the corresponding hazard function) using the empirical estimator $\hat{S}(t)$:

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

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.[18] Figure 3 displays the 12- and 24-month 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.

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

3.2.3 Relative default risk

A potential concern, when comparing absolute differences in default risk, as in Section 3.2.2, is that when default rates rise, these absolute differences may increase mechanically increase, even if the sorting of risks does not improve in a relative sense. To address this concern, we next gauge the precision of the bank's borrower sorting by comparing the *relative* default rates of different rating grades over time.

For this purpose, we merge observations into two groups of approximately equal size, one consisting of firms with the three best ratings and another containing the next three grades.[19] We then define the default ratio as the default frequency for the weak group divided by the default frequency for the overall sample:

$$DR = Default\ Ratio = \frac{\frac{D_{weak}}{N_{weak}}}{\frac{D_{weak}+D_{strong}}{N_{weak}+N_{strong}}} \tag{3}$$

Here D measures the number of defaults and N_i the number of firms in group i, and *strong* and *weak* are labels for the two groups. This default ratio has two attractive properties. If the ratings are completely uninformative about default risk, the default frequency will be the same for the two ratings categories, and DR reaches its lower bound, i.e., one.[20] If the discriminatory power of the ratings is maximal and all defaults occur in the "weaker" category ($D_{strong} = 0$), DR simplifies into $\frac{N_{weak}+N_{strong}}{N_{weak}}$ and thus reaches its upper bound of two.

[19] For firms with IR = 7 default is typically imminent and prediction is therefore not a challenge. We therefore drop this category. Results are qualitatively unchanged, however, with this category included. We also varied the methodology by using finer categories based on qualifiers to internal ratings ("pluses" and "minuses") and by letting the cutoff vary by quarter, in order to make sure that the two groups are of equal size. We also used Kaplan-Meier adjusted default rates. Results are very similar.

[20] 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 then would not be below one.

In Figure 4, we show that DR is on average 1.42 during expansions and statistically significantly lower than during recessions (1.60).[21] This corresponds to the default rate among weak firms rising from 2.5 times to four times that of strong firms. In other words, in recessions, defaults are more concentrated among firms to which the bank assigned poor ratings than in good times. This result confirms that the bank's ability to assess credit risk appears strongly counter-cyclical.

The precision of bank ratings, and the gain in precision during bad times, can stem from hard or soft information, since ratings are constructed using both types of information. To discriminate between these two drivers of precision (gains), we also plot DR computed with the credit bureau's statistical credit score (CR), which is constructed using hard information only. Interestingly, the precision of CR is *also* counter-cyclical. Its average default ratio (DR) is 1.44 during expansions and 1.53 during recessions, a statistically significant increase in precision, although only half that for IR.[22] Both hard and soft information measures thus display the same countercyclical variation in precision. Our results thus suggest that changes in loan officer behavior (Ruckes, 2004; Cohn, Engelmann, Fehr and Maréchal, 2015; Berger and Udell, 2004)), such as variation in monitoring effort (Ruckes 2004), alone cannot explain the reduction of information frictions in recessions

A potential concern is that sample selection could drive these results, because from the pool of borrowers could be "unfavorable" in good times. To verify if this is feasible for entry and attrition rates that are consistent with the total turnover rate in the loan portfolio of 3% over the full sample period, we perform a numerical exercise and test the sensitivity of the default ratio to variation in the attrition rate. In Appendix 2 we show that attrition which asymmetrically affects firms in better and worse rating grades can only explain about 5% of the increase in the bank ratings' precision from 1.42 to 1.6 between expansion and recession times. Empirically realistic amounts

[21] Based on the time-series standard deviation of the ratio, the difference of 0.18 has a t-statistic of 7.30). The t-stat using Newey-West standard errors that allow for four auto-correlation terms is 5.0.

[22] Assuming time-series independence, the t-statistic is 12.9, and allowing for four auto-correlation terms, the t-statistic is 8.7.

of selection bias in our sample can thus not explain the business cycle patterns in information asymmetries we observe, even if we assume extreme selection of firms that leave our sample.[23,]

Next, we turn to regression specifications that deal with potential concerns that the absence control variables or the lack of attention for incorrectly classified non-defaults is driving our findings.[24] The regression specifications in the next section deal with both these concerns.

3.3 Semi-parametric and parametric estimates of information friction cyclicality

In Sections 3.3.1 – 3.3.3 we further study the time-series properties of IR to verify that the cyclicality of information frictions, that we found initial evidence of in Section 3.2, is robust in a regression setting.

3.3.1 Semi-parametric estimates of cyclicality

In our regressions we will use loan and borrower balance sheet variables as controls. We consider both coefficient magnitudes and explanatory power as captured 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 the 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

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[23] Even with 20% attrition, much above what we observe in our sample, selection could only generate at most around half the effect we observe.

[24] 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, comparable to Type 1 and Type 2 errors in statistics. Ignoring incorrectly classified non-defaults and focusing on incorrectly classified defaults is sensible if missed defaults are much more costly. In credit decisions, this may be a fair assumption. Second, the relative default ratio DR does not control for variation in other variables.

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 regression.

3.3.2 Parametric estimates of cyclicality

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

$$\text{Default}_{t+s} = \beta_1.\text{IR}_t + \beta_2.IR_t \times \text{Recession Dummy}_t + \boldsymbol{\beta}_3.\text{Controls}_t + \text{Time Fixed Effects} + e_t \qquad (4)$$

where we have suppressed the subscript i for firm i. The results, reported in Table 5, confirm that the differences in patterns between good times and bad times shown in Figure 4 are statistically significant.[25] The coefficients on the interaction estimates are also economically meaningful. In column (1), the coefficient on IR is estimated to be -0.071 during normal times, but -0.096 during 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 during good times but a 32% increase during a recession, taking into account that the baseline risk is higher during 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 on significance. We also re-estimate equation (4) using a polynomial instead of IR. Table 5, columns (3) – (4) show that allowing for non-linearities does not improve on capturing the business cycle properties of IR. Even when using "Credit slack" instead of IR, the results are qualitatively unchanged (column 5).

The above results imply that ratings contain more information about default risk during recessions than they do in good times. These findings are consistent with the rise in coefficient

[25] We use 12-month default as the dependent variable from this point on. Results are similar with 24 months.

size during bad times that was generated by the quarter-by-quarter regressions displayed in Figure 5.

An additional measure of internal ratings' cyclical ability to explain defaults is provided by R-squared. While coefficient magnitudes reflect the magnitude of the difference in default risk between borrowers at different levels of IR, comparisons of R-squared reflect what fraction of total variation in default risk can be explained by IR. If the information contained in IR is more useful for predicting defaults in recessions, the R-squared should be higher.

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.[26] On the one hand, the credit score corresponds most closely 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. In Table 6 we report the average R-squared for OLS regressions and pseudo R-squared for probit regressions.[27]

The first row of Table 6 shows that the R-squared from internal ratings is several times higher during recessions than outside of recessions: 11% vs. 1.3%.[28] The model fit is also considerably better using the pseudo R-squared: 23% during recessions vs. 5% outside recessions. Credit scores also generate higher explanatory power in recessions than outside 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

[26] Results are qualitatively similar with more controls.

[27] 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.

[28] Throughout, when comparing the measures of statistical fit, 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 (even if we take into account that monthly regression statistics are correlated).

well as the one reported above, we find that the bank information appears more important during recessions.

Together, this set of results points to superior information and greater predictive power of internal bank ratings during recessions. We conclude that information about borrowers is not less precise, and is likely more precise, in bad times.

4. Robustness analysis

In this section, we verify if our main results are robust to a series of alternative specifications. This also allows us to distinguish between some alternative theories of counter-cyclical bank information quality.

4.1 Do soft and hard information display the same cyclical behavior?

If the countercyclical quality of borrower information were unique to banks' internal ratings and not shared by other measures of creditworthiness, then this would cast doubt on our conclusion that information frictions are countercyclical. To verify this, we again estimate time-varying coefficients as in equation (4) using the credit bureau score instead of the internal rating. The credit bureau score 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 5, we allow first the coefficient for both IR and credit bureau score to differ during recessions (column (6)) and then for both IR polynomial and credit bureau score (column (7)). The coefficient on the interaction term between the recession indicator and the credit bureau score is positive and significant in both regressions. The results suggest that both "hard" and "soft" information predict defaults better during recessions than during 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. Many of the theories about cyclical information quality often concern bank productivity or effort in information production (e.g., Dell'Ariccia 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. That credit scores based solely on hard information, where monitoring plays no role, display the same business cycle properties makes clear that variation in effort through intensified monitoring in bad times is not the dominating driver behind the countercyclical information frictions between banks and their borrowers.

4.2 Use only updated internal ratings

Next, we verify if our results may be driven exclusively by the stickiness of the internal ratings. A possible concern could be that the predictive power of the internal ratings is driven by long-term considerations of loan officers or by long-term characteristics of the ratings. Loans officers may, for example, have been targeting longer-term behavior of loans even though ratings are explicitly intended to capture the 12-month default risk or collect (more) information at occasions where ratings are in fact updated.

We address these concerns by restricting our dataset to observations where the loan officer changed the rating in the previous period, thereby ensuring that the ratings reflect newly collected information. We then re-run the baseline regression of Table 4, column (2). The results from this regression are displayed in column (9) of Table 4.[29] We find that the results remain qualitatively unchanged but the explanatory power of the regressions rises slightly, reflecting the fact that newly updated ratings are more informative.

4.3 Exclude borrowers who were granted new credit

Third, we address a possible endogeneity concern and check whether our results reflect the impact that greater credit flows for better-rated borrowers can have on short-run default risk. Firms with better IR may be less likely to default because they later on obtain more credit from their bank. In the short run, new credit almost surely reduces the default probability; the long-run impact, however, is more ambiguous since this additional credit will have to be repaid, thus increasing the amount of future commitments on which default is possible. Such a mechanism could provide an alternative driver as well as interpretation of our finding that the accuracy of ratings varies over time. If such a mechanism were present, it would imply that the variation in

[29] We also re-ran the baseline regression for defaults over a 24-month horizon (not displayed but available from the authors upon). Results remain qualitatively unchanged.

the precision of the bank's information over the cycle is not intrinsic. By including controls for the level of credit from the bank, as well as the debt from all other sources, we had already attempted to deal with this in our baseline specifications. However, because the default variable is forward-looking, current IR could be predictive due to new loans to be granted during this time period. To test whether this is quantitatively important we drop from our sample all firms that receive new credit in the next 12 months from our bank (Table 7, columns (1) and (5)) or any bank (Table 7, columns (2) and (6)) in auxiliary regressions.[30] The coefficients are statistically indistinguishable from those in the main specification. Regressions using credit slack generate qualitatively similar results (see Appendix Table A2, column (1)).

The variation in the predictive power of IR over the cycle is therefore not driven by new credit flows; but is indeed likely reflecting variation in the banks' ability to assess credit risk.

4.4 Does the screening frequency change over the cycle?

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.[31]

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 bank's evaluations are done at the end of the year. Importantly, for our purposes, there appears

[30] Since the borrowers' credit accounts were originally expressed in euros, we allow for a 10% fluctuation in order to avoid picking up exchange rate fluctuation (a 5% cutoff delivered the same results).

[31] 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).

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 over the business cycle. Banks may increase 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 during recessions is not mechanically driven by reassessing borrowers more often.[32]

4.5 Exclude new borrowers

Finally, we consider an alternative mechanism that could produce better information for the bank in recessions: cyclical variation in the mix of old, and new borrowers. The default risk of a new borrower may be more difficult for the bank to assess than the risk of existing borrowers. If banks get relatively 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'Ariccia and Marquez 2006). This means that changes in the borrower pool could potentially be a key mechanism behind our results.

We examine this hypothesis by separating borrowers into new and old ones. We define new borrowers as those that appeared in the bank's database for the first time during the past 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%). We re-estimate regressions for existing clients only. The results in Table 7, columns (3) and (7) make clear that the cyclicality patterns for new borrowers are similar to those for the full sample. Regressions using credit slack generate qualitatively very similar results (see Appendix

[32] 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.

2). The bank is better able to predict default among *existing* borrowers in recessions. The patterns we observe are thus not an artifact of time variation in the mix of old and new bank clients.[33] We conclude that the Dell'Ariccia and Marquez (2006) mechanism does not appear quantitatively important in our data.

4.6 Variation in borrower size and industry composition

A similar mechanism that could make it harder to measure credit risk during recessions could involve cyclical changes in the firm size and industry composition of the borrower pool. 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 it is worth less to the bank to spend resources on assessing their performance and prospects.

Small firms make up a large share of our sample, and if their share is time-varying then this could 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 Table 7, columns (4) and (8), we report regression results for the subset of 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 coefficients are similar in magnitude, but are less precisely estimated compared to the full sample.[34]

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 services, and personal services. Except for financial services, which has very few borrowers, the cyclicality results are present in each industry.

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

[34] In regressions using credit slack the business cycle interaction term looses significance for large firms, suggesting that credit slack is more informative for smaller firms than for larger firms (Appendix Table A2, column 3).

4.7 Regulatory changes

A possible concern is 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 requirements when banks use the internal ratings-based approach for capital.[35] 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 corporations as well as small and medium-sized enterprises (SMEs) (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. Regulation is therefore unlikely to explain our results.[36]

5. Conclusions

The supply of corporate bank loans is highly pro-cyclical. In principle, this could reflect information frictions between lenders and borrowers becoming 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?

[35] Under the IRB approach, banks' own ratings are inputs into determining capital requirements.

[36] During our sample period, no other reform of similar broad importance for internal ratings was introduced.

Our empirical results suggest that this explanation of loan supply cycles is not supported by the data. When studying the complete corporate loan portfolio of a large Swedish cross-border bank, which follows the Basel Committee's IRB approach, covering two recessions matched with balance sheet data and credit scores from Sweden's bank-owned credit bureau, we instead find the opposite: corporate borrower defaults are better predicted during recessions. This is true using hard information measures as well as soft information, indicating that the cyclicality of information quality does not result from time-variation in loan officer effort.

Our results also suggest that cyclical patterns in the quality of bank borrower assessments do not reflect cyclical variation in the composition of the borrower pool, e.g., the arrival of new, unknown firms or the prevalence of small, more opaque businesses. We as well rule out that our results could be contaminated by reverse causality related to the extension of new loans.

Our results are based on data from a large, cross-border Swedish bank that applies the Basel Committee's IRB approach. Small banks may focus on different borrower sizes and therefore on average use different lending technologies with potentially different cyclical properties or. However, the cyclical patterns we document apply to small firms and across industries, suggesting that they may be operating broadly across banks' corporate lending.

A key implication of our findings relates 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, 2004-2014

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.

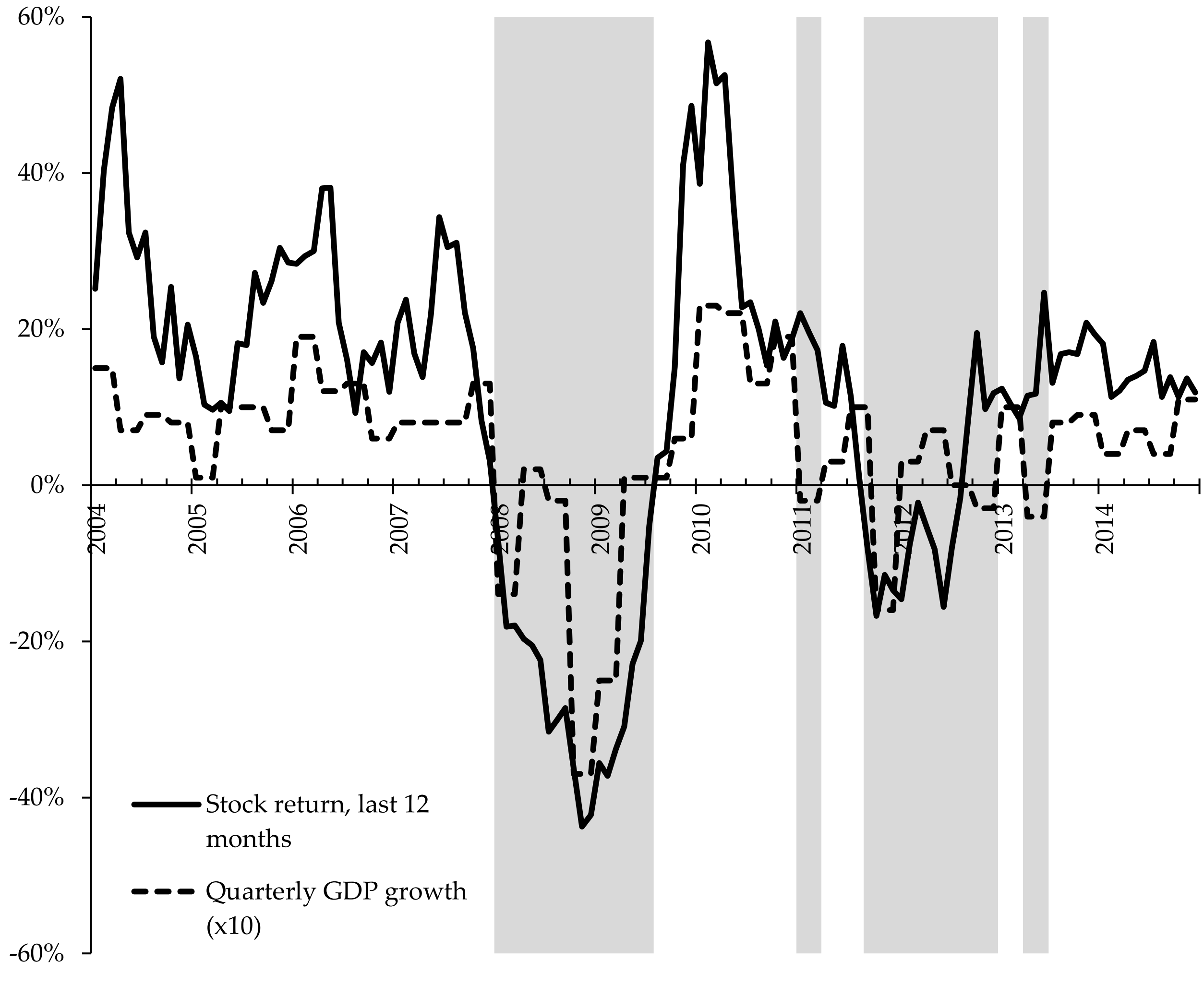


Figure 2. Accuracy of internal ratings by year, 2004-2011

This figure shows one-year cumulative accuracy profiles for the bank's internal ratings for each year from 2004 to 2011. The accuracy curve is computed using Moody's (2003) method and 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).

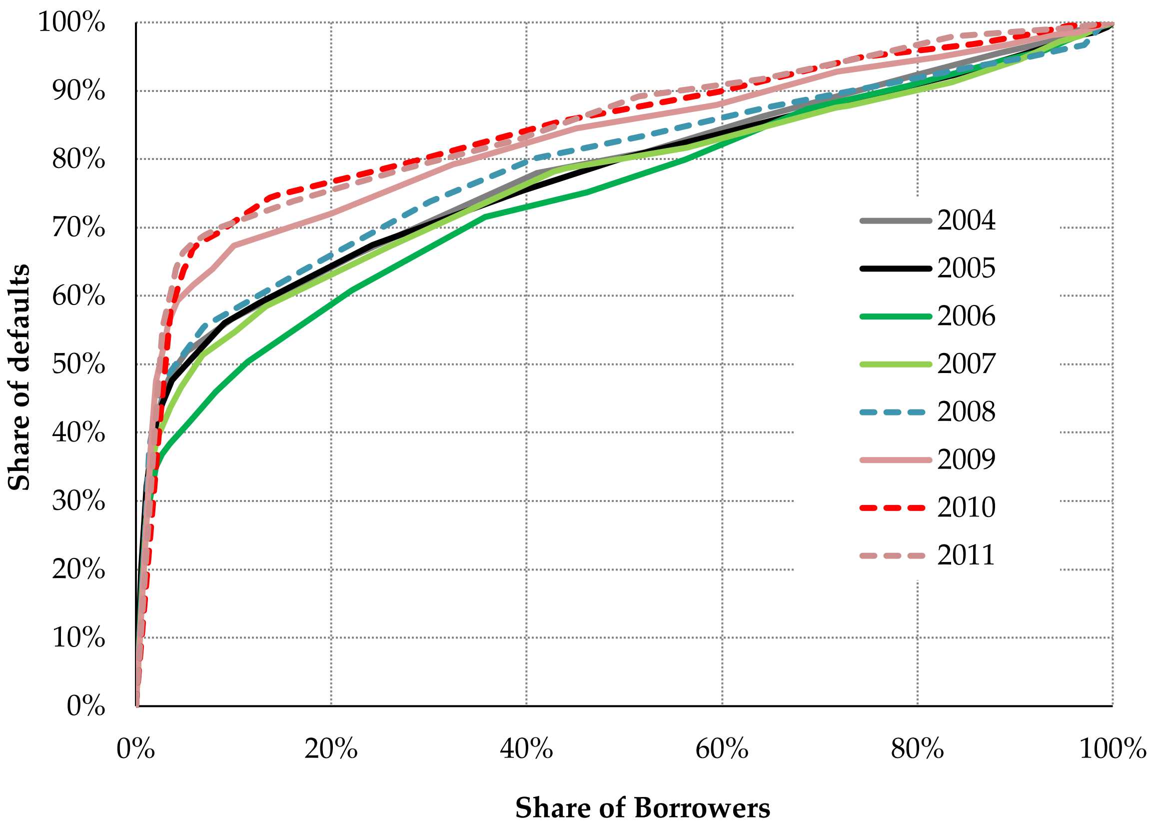
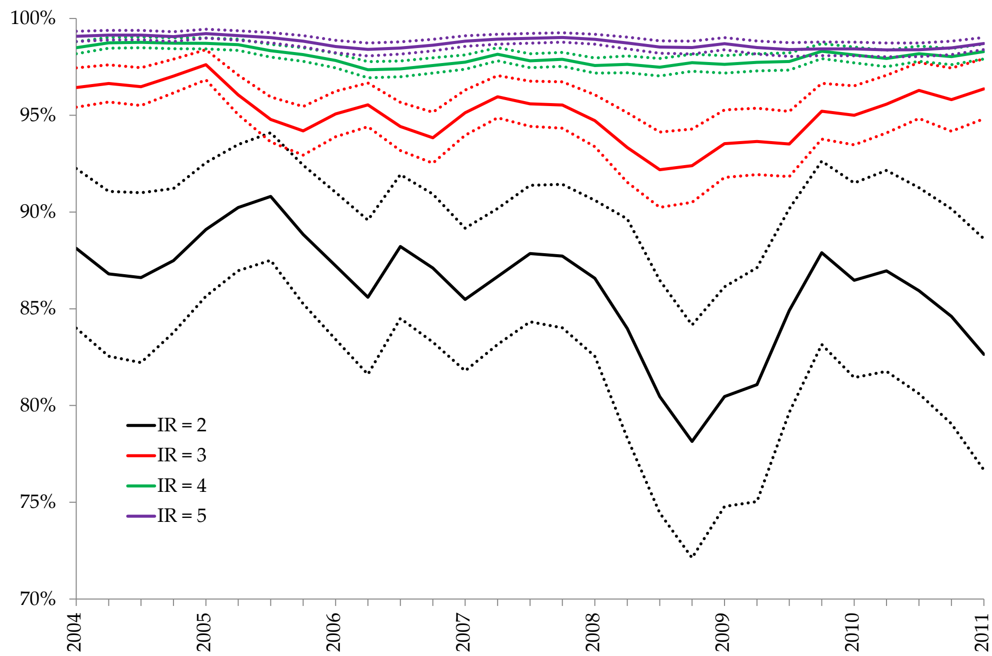


Figure 3. Kaplan-Meier survival rates by internal rating

The figure displays the survival rate, with 95 percent confidence intervals, for four 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

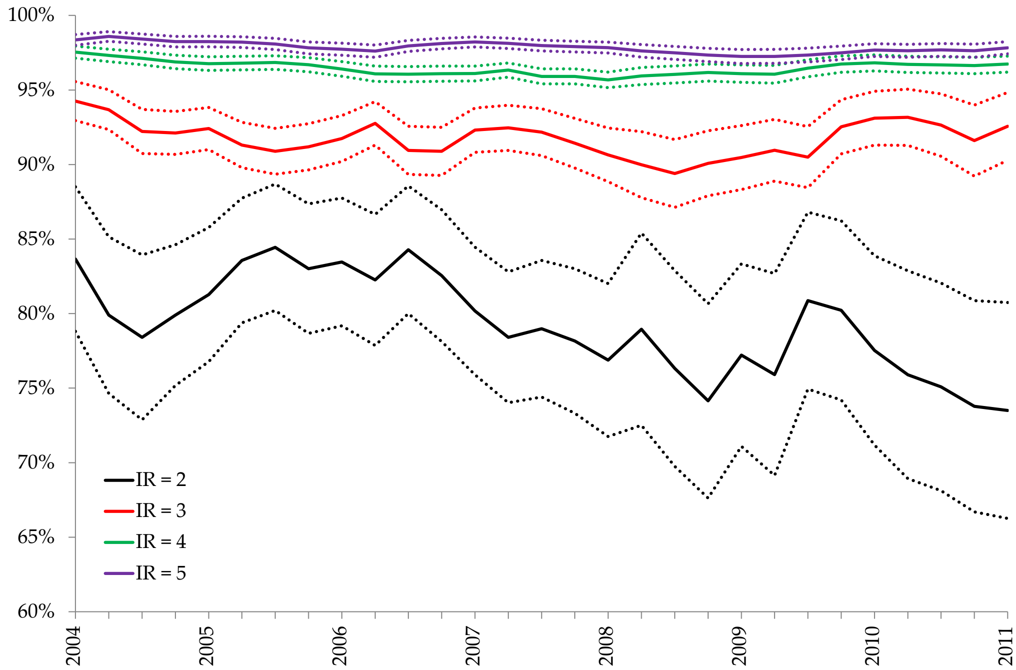


Figure 4. Default rates across ratings categories

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 the same ratio 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.

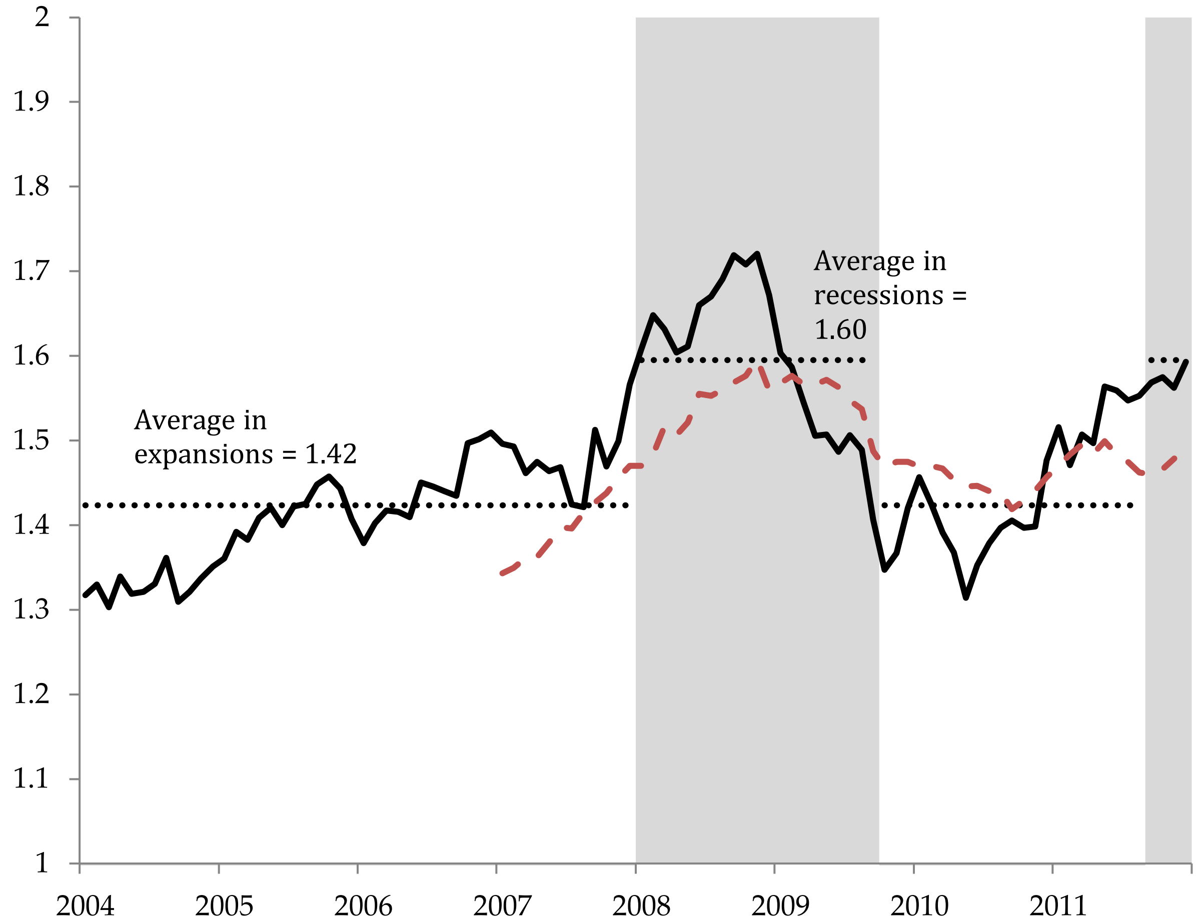


Figure 5. Predicting default over the business cycle

This figure displays the $\beta_1$coefficients from probit regressions of default 12 months ahead 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, and 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% levels, respectively. Shaded areas indicate recession periods.

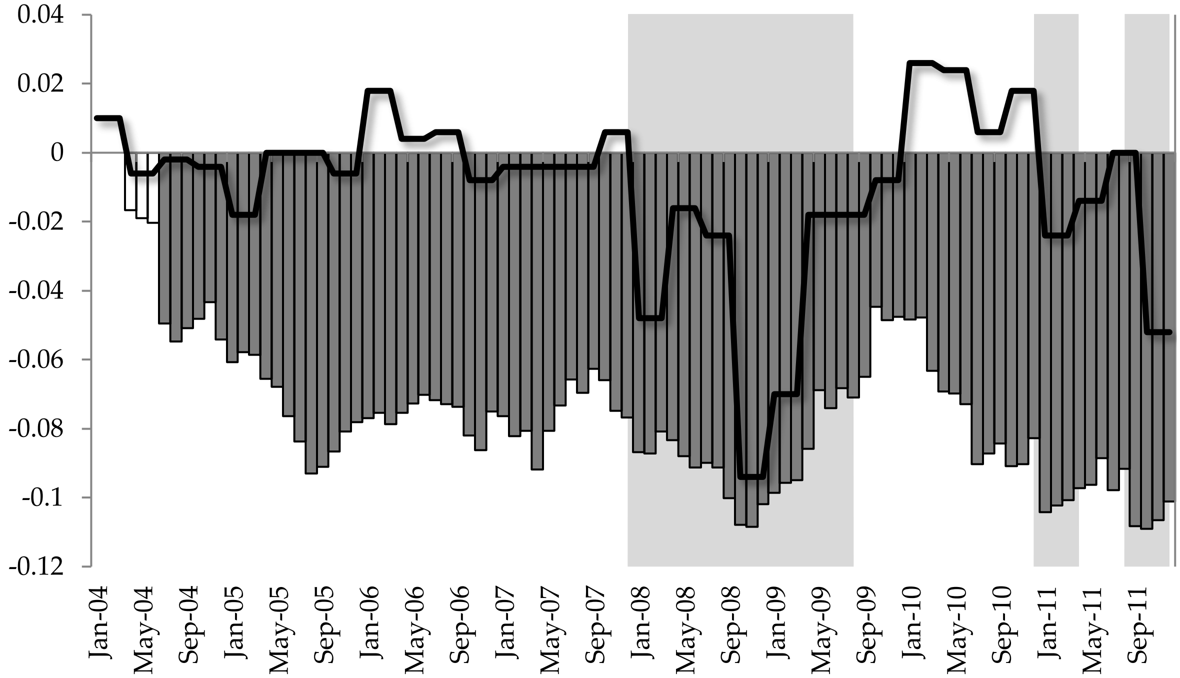


Figure 6. Proportion of borrowers being assessed by quarter

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). Nobs = 592,306.

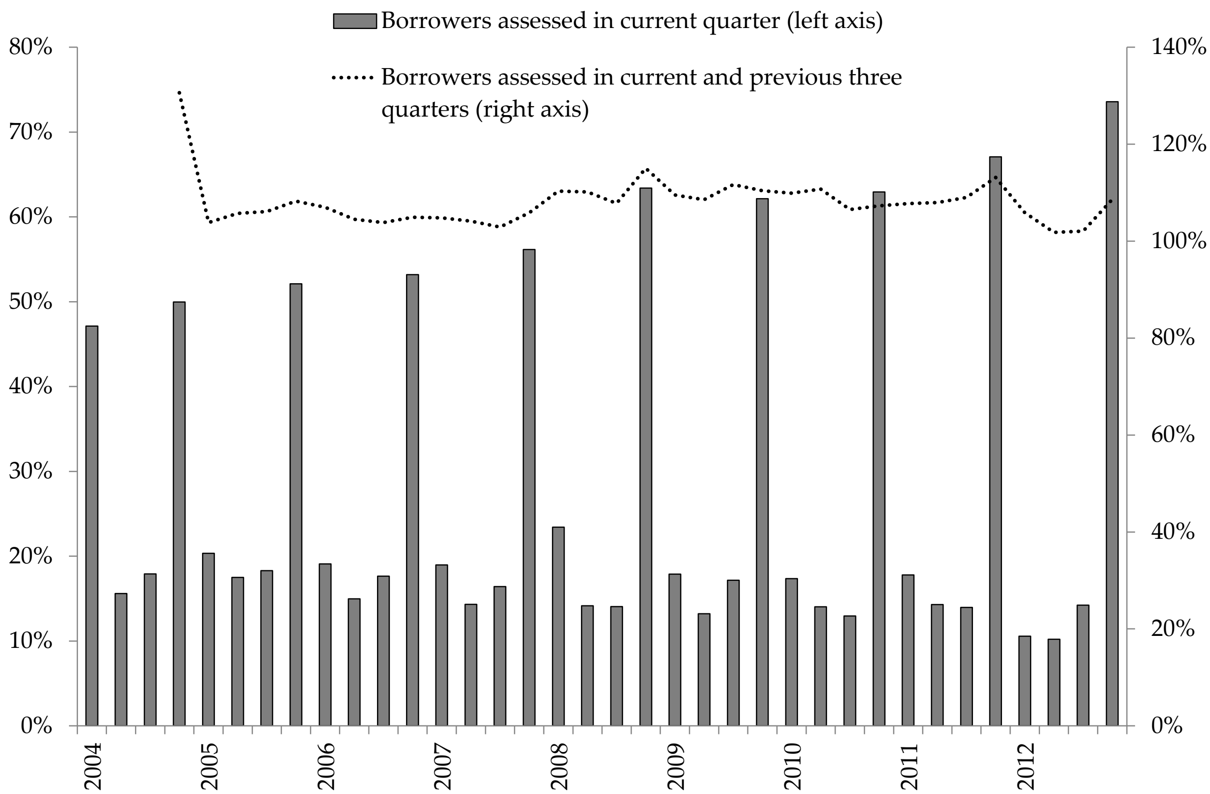


Table 1. Variable definitions

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

Variable	Freq.	Source	Definition
Internal rating raw	Monthly	Bank	A borrower's score in the bank's internal rating system, an integer from 1 to 21 (used in most analysis without controls)
Internal rating	Monthly	Bank	The internal rating aggregated up to the 7 main steps (used in the regressions)
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 firm's 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, i.e., the sample used in Table 4, column (2). In regressions without controls the number of observations is higher because we can use firms where a control variable is missing. "Days since review" is used in Figure 6. Descriptive statistics for robustness regressions are available upon request. 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	4.43	4.00	0.972	688,692
Limit (in 1,000 SEK)	30,200	3,110	191,000	688,692
Outstanding balance (in 1,000 SEK)	21,100	2,280	134,000	688,692
Outstanding balance / Limit	0.778	0.916	0.288	688,546
Collateral (in 1,000 SEK)	9,750	500	79,500	688,692
Total sales (in 1,000 SEK)	229,000	16,600	2,230,000	688,692
Total assets (in 1,000 SEK)	403,000	13,200	4,890,000	688,692
Total tangible assets (in 1,000 SEK)	83,900	3,370	913,000	688,692
Return on capital	0.158	0.172	0.527	688,692
Return on assets	0.0741	0.0650	0.124	688,692
Gross margin	0.128	0.0850	0.216	688,692
Net margin	0.0492	0.0350	0.188	688,692
UC score	1.49	0.500	4.08	688,692
Employees	66.2	9.00	517	688,692
Leverage	0.669	0.696	0.215	688,692
Default within 12 months	0.0191	0.00	0.137	688,692

Table 3. Summary statistics by internal rating

This table summarizes full sample averages on credit, default, and losses by internal rating (IR). Default is the share of firm-quarters where a default is reported within 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 within 12 months	Default within 24 months	Loss given default	Bankruptcy within 12 months	Share of aggregate credit losses
1–3	16%	24%	75%	11%	1.4%
4–6	9.2%	14%	61%	4.7%	0.30%
7–9	3.5%	6.3%	58%	1.5%	3.2%
10–12	1.4%	2.7%	55%	0.37%	26%
13–15	0.90%	1.7%	54%	0.097%	46%
16–18	0.60%	1.2%	42%	0.034%	19%
19–21	0.70%	1.1%	23%	0.000%	4.5%
ALL	1.5%	2.6%	51%	0.47%	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 (percent)
1–3	1	6.2%	1.9	4.6%
4–6	2	9.5%	1.9	5.2%
7–9	2	9.3%	2.1	4.8%
10–12	2	11%	2.3	4.5%
13–15	2	11%	2.0	4.1%
16–18	2	18%	2.3	4.0%
19–21	2	5.4%	2.2	3.7%

Table 4. The ability of internal ratings and other risk measures to predict default

This table reports Probit regressions with loan or borrower default (payment overdue by 90 days or more) as dependent variable regressed on credit risk measures and controls. The credit rating variable is the bank's internal rating (IR), measured on an ordinal scale (a rating of 21 is best), IR Polynomial is a fifth order polynomial fitted on IR to capture non-linearities and Credit Slack, a measure of unused credit. Regressions are run on defaults 12 or 24 months ahead, as well as on a sub-sample of observations where IR was updated in the previous period.

$default_{12m} = \alpha + \beta_1(Rating) + \beta_3 controls + \beta_3 time + \varepsilon$ where Rating ={IR, IR Polynomial, Slack}

Columns (3) and (7) report marginal effects, evaluated at the mean of the dependent variable. 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. Controls are 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, collateral.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	All obs 12M	All obs 12M	All obs Marginal effects 12M	All obs 24M	All obs 24M	All obs 12M	All obs Marginal effects 12M	All obs 12M	Updated ratings 12M
Independent variable									
IR	-0.107 ***	-0.078 ***	-0.003 ***	-0.102 ***	-0.067 ***				-0.115 ***
	(0.003)	(0.005)	(0.000)	(0.004)	(0.005)				(0.007)
IR Polynomial						-8.26 ***	-0.341 ***		
						(0.400)	(0.018)		
Slack								-0.373 ***	
								(0.038)	
Controls	NO	YES	YES	NO	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clusters	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
No. Clusters	32,672	16,702	16,702	27,940	15,895	16,702	16,702	31,117	11,842
Pseudo R2	0.083	0.119		0.660	0.113	0.123		0.105	0.171
Nobs	1,406,144	688,692	688,692	1,044,105	602,725	688,692	688,692	1,381,081	37,454

Table 5: Default prediction over the business cycle and the time-varying effects of hard vs soft information

The table reports Probit regressions of future default (at 12 month horizon) on different information measures, like the bank's internal Rating (IR), the Bureau's Credit Credit Score (CBCS), Credit Slack and IR Polynomial (a polynomial fitted to IR). The interaction recession dummy equals one if either trailing 12-month stock return is negative or nominal GDP growth is negative, or both).

$default_{12m} = \alpha + \beta_1(Rating * Recession\_dummy) + \beta_2(Rating) + \beta_3 controls + \beta_3 time + \varepsilon$ where Rating ={IR, CBCS, IR Polynomial, Slack}

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. Controls are 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample / Estimation method	All obs 12M	All obs 12M	All obs 12M	All obs 12M	All obs 12M	All obs 12M	All obs 12M
Independent variable							
IR	-0.0712 ***	-0.0712 ***				-0.0728 ***	
	(0.00550)	(0.00545)				(0.00548)	
IR x Recession	-0.0243 ***	-0.0243 ***				-0.0179 **	
	(0.00780)	(0.00790)				(0.00815)	
CBCS						0.0209 ***	0.0187 ***
						(0.00164)	(0.00172)
CBCS x Recession						0.0108 ***	0.00868 **
						(0.00403)	(0.00425)
IR Polynomial			-7.62 ***	-7.62 ***			-7.75 ***
			(0.450)	(0.530)			(0.445)
IR polynomial x Recession			-2.19 ***	-2.19 ***			-1.62 **
			(0.634)	(0.752)			(0.669)
Slack					-0.314 ***		
					(0.0428)		
Slack x Recession					-0.184 ***		
					(0.065)		
Controls	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES
Clusters	Borrower	Industry	Borrower	Industry	Borrower	Borrower	Borrower
No. Clusters	16,702	54	16,702	54	31,177	16,702	16,702
Pseudo R2	0.120	0.120	0.124	0.124	0.105	0.120	0.124
Nobs	688,692	688,692	688,692	688,692	1,381,180	688,692	688,692

Table 6: Explanatory power of hard and soft information over the business cycle
The table reports the explanatory power of regressions predicting future defaults (similar to Table 4) using the same controls as in specification (2) in Table 4. Columns (3) and (4) present the average R-squared for the linear probability models; columns (1) and (2) 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). Regressions were estimated separately for expansions (columns 1 and 3) and recessions (columns 3 and 4). The first three rows present measures of statistical fit for regressions including the explanatory variables identified in the row headings. 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."

	Probit		OLS	
Sample / Estimation method	Expansion	Recession	Expansion	Recession
Independent variable				
Internal rating (IR)	5.1	22.7	1.3	11.1
Credit score (CBCS)	5.6	5.9	3.3	5.4
IR and CBCS	7.8	23.6	5.4	13.4
Marginal contribution of IR	2.1	18.6	2.1	8.0

Table 7. Default prediction with internal ratings through the business cycle, robustness analyses

The table reports Probit regressions of future default (at 12 month horizon) on different information measures, like the bank's internal Rating (IR), and IR Polynomial (a polynomial fitted to IR). The interaction recession dummy equals one if either trailing 12-month stock return is negative or nominal GDP growth is negative, or both). "Existing customers" contains only observations for borrowers that have been a client of the bank for 12 months or more. No small firms refers to firms with 10 or more employees. "No new credit, this bank" includes only observations from firms that don't receive new credit within the next 12 months from our bank, "No new credit, all banks" includes only observations from firms that don't receive new credit from any bank within the next 12 months. 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. Controls are 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample / Estimation method	No new credit this bank	No new credit *all* banks	Existing customers	No small firms	No new credit this bank	No new credit *all* banks	Existing customers	No small firms
Independent variable								
IR	-0.0777 ***	-0.0861 ***	-0.0730 ***	-0.0602 ***				
	(0.00631)	(0.00634)	(0.00557)	(0.00731)				
IR x Recession	-0.0269 ***	-0.0135	-0.0252 ***	-0.0214 *				
	(0.00895)	(0.00883)	(0.00791)	(0.0111)				
IR Polynomial					-7.53 ***	-7.92 ***	-7.77 ***	-7.28 ***
					(0.494)	(0.514)	(0.450)	(0.639)
IR polynomial x Recession					-2.11 ***	-1.82 **	-2.25 ***	-2.51 **
					(0.700)	(0.722)	(0.633)	(1.03)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Clusters	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
No. Clusters	16 035	15 121	16 197	7 662	16 035	15 121	16 197	7 662
Pseudo R2	0.142	0,161	0,12	0.089	0.144	0,163	0,125	0.093
Nobs	455,491	377,299	661 397	325,072	455,491	377,299	661 397	325,072

APPENDIX (for online publication)

APPENDIX 1 Slack

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 it is willing 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.

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 is 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 define Slack as:

$$Slack = \frac{Internal\ limit - Granted\ Credit}{Internal\ Limit} \tag{1}$$

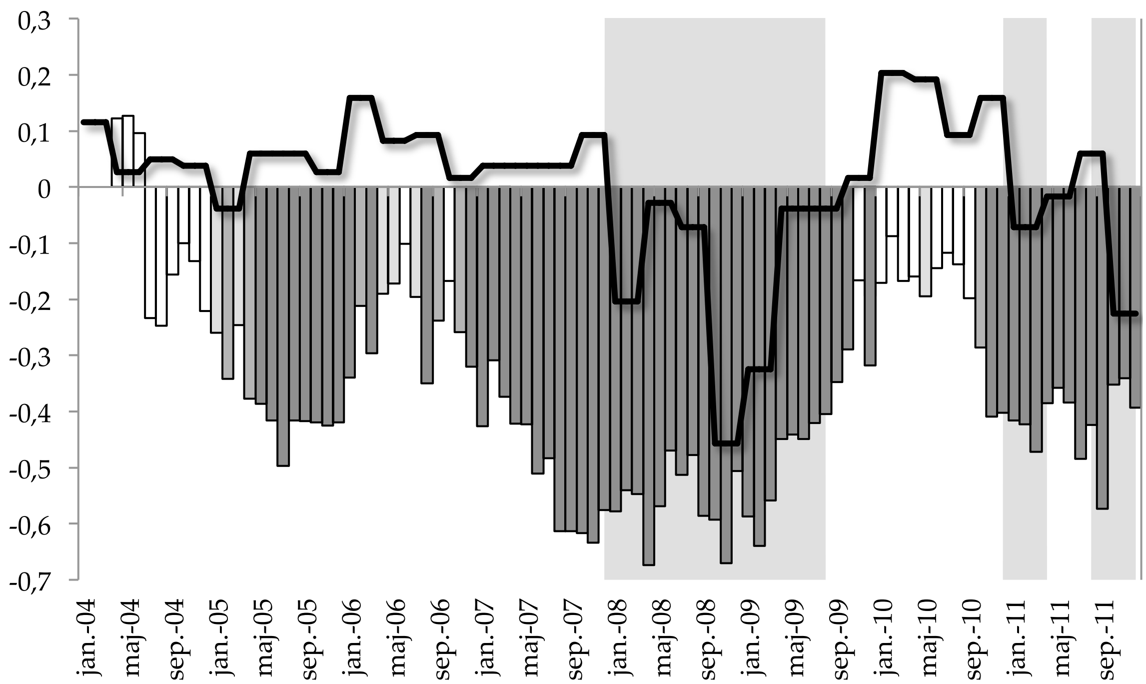
where the Internal limit is the maximum amount the loan officer is entitled to lend to the firm. The Internal limit is based on the repayment ability of the firm, and changes in this limit must be approved by a senior official or a credit committee, depending on the size of the loan.

In this appendix we present most of the analysis using slack instead of the IR. 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.

Figure A1. Predicting default over the business cycle using credit slack

This figure replicates Figure 5 for credit slack instead of IR. It 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: $Default_{within\ 12m} = \beta_{1t}Slack * timeF.E. + \beta_2 X + i.t + \varepsilon$. Controls (X) include credit bureau risk score, collateral, credit contract features, and 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% levels, respectively. Shaded areas indicate recession periods.

Credit slack, 12 months



APPENDIX 2 Potential impact of attrition in good times

To compute the sensitivity of the default ratio DR to different forms of attrition, we assume that a bank sorts borrowers into Good and Bad firms, in two states: recession and expansion. Good firms are assumed to be the ones that are less likely to default than Bad firms and each group constitutes 50% of the sample of borrowers in recession and expansion. However, we let attrition of firms in good times works against the sort.

We assume that no sample selection through attrition is operating in recessions and calibrate the model as follows. We set default rates in recessions such that the mean across the two groups (sample average), is 1.5% and the ratio of default rates DR is 1.6, as it is in the data. This implies that, in recessions, Good firms have a default rate of 0.6% and Bad firms 2.4%. In expansions, we let sample attrition affect the realized default rates. The exit rate is assumed to be 2% for both groups. Since we have around 3% turnover over the full sample period, an attrition rate of 2% during good times somewhat overstates the scope for sample selection.

To capture the possibility that in good times either fewer risky firms may be sorted into the better rating grades or more of the riskier firms with better rating grades may leave the bank, we let the source of selection be that, in expansions, relatively more of the "worse" Good firms drop out. To maintain the average 1.5% default rate in the post-selection sample (the portfolio in expansions after the attrition has taken place), we assume that the average Good firm dropping out has a 1.5% default rate. Instead of the (0.6%, 2.4%) default rates for Good and Bad firms in the overall sample, we set the default rate for firms that drop out to (0%, 3%) for Good and Bad firms, respectively. In other words, the Good firms that drop out are completely safe, whereas the Bad firms that drop out are very risky. This makes the difference in default risk between remaining Good and Bad firms (the post-selection sample) minimal. The post-selection default rate for remaining Good firms becomes $\frac{0.6\% - 0.02*0\%}{1-0.02} =$ 0.61% and that for remaining Bad firms $\frac{2.4\% - 0.02*3.0\%}{1-0.02} =$ 2.39%. The post-selection "Expansion" sample therefore has a default ratio DR of $2.39/(\frac{2.39+0.61}{2}) = 1.593$.

Selective attrition that is consistent with the moments of the portfolio can thus only explain around 5% (from 1.59 up to 1.60) of the gain in the bank ratings' precision between expansion and recession times as captured by the rise in the default ratios DR from 1.42 to 1.6 in Section 3.2.3.

Table A1. The ability of internal ratings and other risk measures to predict default

This table reports Probit regressions with loan or borrower default (payment overdue by 90 days or more) as dependent variable regressed on credit risk measures and controls. The credit rating variable is the bank's internal rating (IR), measured on an ordinal scale (a rating of 21 is best), IR Polynomial is a fifth order polynomial fitted on IR to capture non-linearities and Credit Slack, a measure of unused credit. Regressions are run on defaults 12 or 24 months ahead, as well as on a sub-sample of observations where IR was updated in the previous period.

$default_{12m} = \alpha + \beta_1(Rating) + \beta_3 controls + \beta_3 time + \varepsilon$ where Rating ={IR, IR Polynomial, Slack}

Columns (3) and (7) report marginal effects, evaluated at the mean of the dependent variable. 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. Controls are 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, collateral.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	All obs 12M	All obs 12M	All obs Marginal effects 12M	All obs 24M	All obs 24M	All obs Marginal effects 24M	All obs 24M	All obs 24M	All obs Marginal effects 12M
Independent variable									
IR Polynomial							-6.760 ***	-8.26 ***	-0.330 ***
							(0.221)	(0.400)	(0.023)
Slack	-0.165 ***	-0.373 ***	-0.015 ***	-0.150 ***	-0.417 ***	-0.026 ***			
	(0.0026)	(0.038)	(0.002)	(0.0029)	(0.041)	(0.003)			
Controls	NO	YES	YES	NO	YES	YES	NO	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clusters	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower	Borrower
No. Clusters	59,410	31,117	31,117	53,093	29,686	29,686	27,940	15,895	15,895
Pseudo R2	0.004	0.105		0.002	0.095		0.056	0.104	
Nobs	2,849,932	1,381,081	1,381,081	2,357,469	1,188,058	1,188,058	1,044,105	602,725	602,725

Table A2: Default prediction over the business cycle using "Credit Slack"
The table reports Probit regressions of future default (at 12 month horizon) on Credit Slack, a measure of of unused credit the bank is willing to grant to a firm, but which is unknown to the firm. The interaction recession dummy equals one if either the trailing 12-month stock return is negative or nominal GDP growth is negative, or both). The estimated equation is:

$$Default_{t,i} = \alpha + \beta_1 . Credit\ Slack_{t,i} + \beta_2 . Credit\ Slack_{t,i} \times Recession\ Dummy_t + \beta_3 . Controls + Fixed\ effects + \varepsilon_{t,i}$$

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. Controls are 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.

	(1)	(2)	(3)
Sample / Estimation method	No new credit 12M	Existing borrowers 12M	No small firms 12M
Independent variable			
Slack	-0.382 ***	-0.315 ***	-0.376 ***
	(0.053)	(0.044)	(0.044)
Slack x Recession	-0.155 *	-0.190 ***	-0.071
	(0.081)	(0.066)	(0.099)
Controls	YES	YES	YES
Time FE	YES	YES	YES
Clusters	Borrower	Industry	Industry
No. Clusters	30,589	30,436	9,397
Pseudo R2	0.118	0.104	0.077
Nobs	997,01	1,316,379	409,358