Bad times, good credit

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Abstract. Asymmetric information between lenders and borrowers is understood to be a key friction in credit markets. Can amplified information problems explain why the supply of corporate credit contracts in recessions and crises? Alternatively, asymmetric information may be reduced by economic slowdowns. We test these opposing views of information frictions in the credit market using data on lending from a large bank, through two business cycles. We find that this banks' ability to sort borrowers by credit quality is best in bad times. This suggests that information frictions are counter-cyclical in corporate credit markets.

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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

In recessions, and especially in financial crises, bank loans are hard to get for households, corporations and other borrowers.[1] Why does the supply of bank credit vary through time, and why is the availability of loans so cyclical? There are fundamentally two explanations for this. The first explanation involves the lenders: low loan supply in recessions may reflect the impairment or weakness of the financial institutions that intermediate loans (Holmström and Tirole 1997). The second category of explanations involves frictions in the credit market itself. Credit markets are understood to suffer from agency problems and from information frictions. Both problems may be worse in recessions (Bernanke and Gertler, 1989, and Stiglitz and Weiss, 1981, respectively). Sorting through these mechanisms is important for understand the role of the financial system is business cycles and has important implications for monetary policy and bailouts (bailouts and other support for the financial system is more relevant for the credit supply to the companies if balance sheet weakness is the culprit than if information problems are to blame). In this paper, we investigate empirically the second mechanism, specifically the cyclicality of information problems, in corporate credit markets.

The critical role of information and information asymmetries in corporate credit markets can be inferred from the existence of intermediaries (Leland and Pyle 1977) and credit registries (Pagano and Japelli 1993) as well as from the critical role played by relationships and reputations in credit markets (Diamond 1991). Garmaise and Natividad (2010) show that improving banks' information about borrowers increases their willingness to lend. Given that information frictions appear important to business lending, the idea that information frictions

[1] Gilchrist, Yankov and Zakrajsek (2009), Dell'Ariccia, Detragiache, Rajan (2008) and Greenwood and Hanson (2013) show how credit conditions are related to business cycles. 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. Kashyap Stein Wilcox (1993) and Becker and Ivashina (2014, 2015) document that changes in debt composition reflecting lending contractions.

could be more severe in bad times, and thus generate cyclicality, seems plausible. Kurlat (2013) models a macro economy where lower investment opportunities can increase AI problems, generating feedback to growth. Both Ordonez (2013) and Guerrieri and Shimer (2014) also model economies where worsening AI is the driver of cyclical downturns.

On the other hand, several theories predict that AI between banks and borrowers is worse in booms. Banks may be better able to sort firms on credit risk in bad periods because the incentives to screen borrowers are counter-cyclical (Ruckes 2004). Berger and Udell (2004) argue that loan officer skills may deteriorate in booms, possibly reducing the quality of the bank's credit decisions. Indeed, Dilly and Mählmann (2013) document that initial credit ratings of corporate bonds issued in recessions are more accurate than those initial ratings issued in better times, consistent with *less* AI in bad periods.[2] Dell'Ariccia and Marquez (2006) develop a model where booms are characterized by less need to screen new borrowers. Finally, credit officers may exert more effort because credit risk information is more valuable in recessions or because they themselves are more risk averse (Cohn, Engelmann, Fehr and Maréchal 2015).

Thus, there are several arguments consistent with both pro- and counter-cyclical AI in corporate credit markets, and indirect evidence consistent with both. Can credit flow data help settle the question? Financing with bank loan is likely more reliant on overcoming asymmetric information than financing with bonds. Indeed, bank lending is more cyclical than arm's-length credit (Kashyap Stein Wilcox 1993; Becker Ivashina 2014, 2015). This could reflect cyclical variation in the amount of asymmetric information. Alternatively, these cyclical swings in bank lending could also reflect other factors holding back bank lending (as in Holmström Tirole 1997), so this is not conclusive.

We aim to test more directly how the extent of information frictions changes over the business cycle, by examining one Swedish bank's ability to assess the credit quality of its corporate

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

clients. We use a data set on the bank's loans and borrowers through two business cycles, and test whether the banks' internal metrics of credit quality work better or worse in bad times.

The bank employs an internal rating system that assesses the credit quality of borrowers, using an ordinal scale. We compare the precision in these internal ratings over time by regressing an indicator for future defaults on ratings.

This method faces an econometric challenge in that borrowers with better ratings are more likely to be granted more credit (or be charged less interest or otherwise be offered better terms), and these credit decisions can affect future default risk, possibly in different ways over the cycle.[3] Therefore, we need to separate the predictive power of ratings from the effect of credit decisions (which rely on the ratings) on future credit quality. We try to address this challenge by controlling for the amount of credit a firm is granted. In other words, for two similar borrowers, with the same amount of credit outstanding, is the one with a better internal rating less likely to default? In our sample, the answer is yes. We find a strong negative correlation between the predictive power of ratings and macro-economic performance (GDP growth, stock market index, consumer confidence index). Thus, the bank appears better able to predict default in business cycle downturns. This is consistent with information frictions being pro-cyclical, i.e. weaker in recessions.[4]

We consider several alternative explanations to our interpretation of the results. A key concern is whether or not Internal ratings are "real". Perhaps the bank's decisions are based on different metrics, or some soft information to which we lack access? If so, perhaps the real metrics used to make lending decisions exhibits different cyclicality? 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 "slack" and use it as an alternative measure of the bank's assessment of a borrower. Credit slack

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

[4] Default is defined as missed payments (interest or amortization) by at least 60 days. We have also used bankruptcy as a dependent variable. Although this is much rarer, our results are similar.

reflects new credit the loan officer responsible for the firm *could grant* without consulting a credit committee (the next hierarchical level in the bank's commercial credit organization). 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 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 the extent of information frictions is highest in bad times.

We also consider whether the mix of borrower is more challenging in good times (e.g., because there are more new borrowers), but this does not affect our results, which hold for both new and old clients. Similarly, the industry mix does not appear to explain the time series patterns we observe.

Could our results reflect higher monitoring and screening efforts by the bank, in a more difficult information environment? We test this using data on when the banks revises borrower ratings. Such monitoring activity is highly seasonal, but not cyclical. Thus, we see no sign of increased monitoring effort in recessions.[5]

Our results are related to the literature on the role of information frictions in business cycles. Kurlat (2013), Guerrieri and Shimer (2014) and Ordonez (2013) propose models where asymmetric information problems in financial are worse in bad times. These theories, broadly speaking, do not fit our findings for corporate credit. Our results do imply that worse asymmetric information in credit markets in bad times should not be considered a stylized fact. It is important to make the distinction between cross-sectional uncertainty and uncertainty about aggregate states. Our results are not as directly related to recent work on aggregate uncertainty (see e.g. Bloom 2007, Caballero and Simsek 2013, Fajgelbaum, Schaal and

[5] Note that settling what causes the better ratings precision in bad times issue is not key to the overall interpretation of our results. Even if banks work harder to achieve the good precision in downturns, the implication remains that credit provision in bad times is not limited by more severe information frictions.

Taschereau-Dumouchel 2014, and Gilchrist, Sim and Zakrajšek 2014). In particular, it may be the case that uncertainty is high in recessions, but that sorting corporate borrowers by credit quality is, in fact, easier. Also, asymmetric information in different part of the financial system may have different cyclical properties: for example, asset markets, and the market for bank equity, may experience wider asymmetries in crises. Given the key role of corporate credit markets for funding investment, the results presented here are nevertheless of great potential importance.

1. Data and variables

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

We supplement the bank's data with annual accounting information from Statistics Sweden and information from the Swedish leading credit bureau that includes the firms payment histories and the credit bureaus assessment of the firms credit risk through their ordinal credit score.[6]

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

1.1 Borrower and loan data

In Table 3, we report data for firms with different internal ratings (IR). IR is the bank's own measure of the borrower's creditworthiness. The credit risk model used to assign ratings is

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

based on multiple data sources including credit ratings from a credit bureau, borrower income statements, balance sheet information and other (soft) information (Nakamura and Roszbach 2010). Only borrowers to which the bank has a total exposure above a certain pre-determined threshold are assigned an internal rating. In our raw data, 70-80% of firms are assigned an IR each year, representing that vast majority of lending. IR values are stable over time, and on average 98% of firms remain in the same category from one quarter to next.

Our key outcome measure is default in 12 or 24 months. Where default is equal to one when any payment is over 90 days past due. Occasionally, defaults are quickly resolved at limited cost, and we also use bankruptcy filings as an alternative dependent variable. Bankruptcy is rarer but typically more severe, and in our data bankruptcies constitute a subset of default events.

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

As an alternative to IR, we use a second measure of the borrowers' creditworthiness, "credit slack", defined as the amount of credit the loan officer is allowed to extend without further internal approval (this is not communicated directly to the firm). We define this measure as:

$$Slack = \frac{Internal\ limit - granted\ credit}{internal\ limit} \qquad (1)$$

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 credit committee.

1.2 Monitoring

We collect measure of the bank's monitoring activity. These monitoring measures are based on the frequency with which the bank revises either the client's credit limit, reassesses collateral, or makes other important changes. The average time between monitoring events is slightly above 10 months and it varies from 1 to 24 months. The revision outcome may be a change in the collateral value, the loan spread, the internal limit, and/or the internal rating.

1.3 Macro data

We use three variables to capture the evolution of the macro economy. The first indicator is quarterly GDP growth.[7] We also collect data on consumer confidence, a survey-based index designed to capture sentiment about the Swedish economy. The index is based on household monthly surveys run by the Swedish National Institute for Economic Research. The variable has an average value of 100 (based on data back to 1996) and a standard deviation of 10. Values over 100 indicate a stronger than normal economy and values below 100 indicate a weaker than normal economy.[8] The third indicator we use is the return over the last 12 months of the OMX Stockholm 30 Index. This is a market value-weighted price index of the 30 most actively traded stocks on the Stockholm Stock Exchange.

Figure 2 illustrates the three indicators 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 in 2011 (negative growth in 2011Q3). The three indicators are strongly correlated (the lowest pair-wise correlation is 0.70, between GDP growth and consumer confidence). Based on these time-series variables, we classify 2008Q1-2009Q3 and 2011Q1-2011Q3 as recessions.

2. Empirical results

In this section, we test the competing hypotheses regarding the cyclical properties of banks' information.

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[7] See http://scb.se/

[8] For more details about the indicator see http://www.konj.se/1425.html.

2.1 The relationships between internal ratings, slack and default

We start by documenting the basic relationship between the bank's two measures of creditworthiness and borrowers' likelihood of default. We estimate regressions as follows:

$$\text{Default} = \text{Slack (or IR)} + \text{Controls} + \text{Time Fixed Effects} \qquad (2)$$

We estimate (2) using Probit or OLS, for defaults within twelve or twenty four months.[9] We estimate with and without a set of firm and time controls.[10] Results are reported in Table 4, panel A for Slack and panel B for IR. In all specifications, the bank's information variables are significant and of the expected sign. In columns one and five, we include no controls except time fixed effects: the regressions ask if slack, on its own, predicts default. Indeed, it does. We next include controls, asking whether slack can predict default beyond the hard information captured in historic accounting data and credit bureau scores. This is close to asking whether the internal rating variable is also based on soft information. Again, the answer is yes, and the coefficient is highly significant. In the OLS specification a one unit change in slack reduces the likelihood of default by 0.2% in the next twelve months (in the probit regression, the estimated effect is similar, but smaller for safe firms and larger for risky firms). For comparison, the control variable with the strongest predictive power is the credit score, where a one standard deviation change is associated with a 0.2% increase in the default risk.

In panel B, we repeat the tests for IR. The magnitude of the estimated coefficient on IR is slightly larger throughout: using the coefficient in column (4), a one step increase in IR is associated

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

[10] The control variables 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 value, and time fixed effects.

with a 0.4% reduction of the default likelihood. This coefficient is identified mainly from observations in categories 4-7, where the majority of borrowers are.[11]

The results show that both slack and IR are economically and statistically significant predictors of default. The connection between future defaults and both of the variables capturing the bank's assessments of its borrowers suggest (a) that the bank can indeed predict defaults and (b) that both measures (ratings and slack) capture meaningful parts of the bank's internal information. Additionally, since we control for a fairly large set of accounting-based variables and the credit bureaus score, the residual effect of IR and slack can reasonably be considered "soft" information in the sense of Berger at al (2005). We next turn the cyclical patterns that are our primary interest.

2.2 Information over the business cycle

Our main tests concern time-series variation in the informativeness of slack and IR. We first use several different non-parametric and graphical techniques to assess the informativeness of the two bank variables, and then turn to regression-based estimation.

IR accuracy curves

To measure the performance of the IR variable, we first use Moody's (2003) concept of 'accuracy curves'. An accuracy curve sorts firms by ratings (in our case IR), and then plots the proportion of defaults accounted for by firms with up to that rating (y-axis) against the proportion of firms up to that rating (x-axis). High precision means that most defaults are in low ratings and few defaults in high ratings, which means the curve is close to the upper left corner. Random assignment of ratings (i.e. uninformative ratings) produces an accuracy curve along the 45 degree line (as defaults are equally likely at all ratings levels). We construct accuracy curves for ratings at year end for all years, with 12 month default, and plot the annual curves in Figure 3. Clearly, there is a lot of predictive power in ratings. Additionally, recession years (recall that

[11] If we allow the effect of to vary, the incremental increase in default risk when going from category 3 to 2 or from 2 to 1 is a much larger.

calendar years 2008, 2009 and 2011 contain negative growth quarters) are fairly high. 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 sample variation, but the visual comparison doesn't work well for too many curves at once. We next consider a way of plotting precision over time.

Survival rates by rating over time

Our sample of firms is largely stable over time, but some firms drop out of the panel. To deal with possible bias caused by selection on disappearance, we use Kaplan-Meier survival rates to examine the fine time-series variation in default rates across the various internal ratings. The Kaplan–Meier estimator is the nonparametric maximum likelihood estimate of S(t) that is a product of the form

$$\hat{S} = \prod_{t_i \leq t} \frac{n_i - losses_i}{n_i} \tag{3}$$

where n_i is the number of survivors less the number of losses (censored cases). Survival is defined as the absence of default. It is only those surviving cases that are still being observed (have not yet been censored) that are "at risk" of an (observed) default. Figure 4 shows survival rate for the four intermediate internal rating categories at 12 and 24 months horizons, respectively.[12] As expected, borrowers with the best ratings have the lowest default risk (highest survival rate). There is clear time variation in the survival rates, and it appears to line up with the business cycle as follows: in both the two recessions, survival rates fall for all categories. Importantly, the difference between the survival rates of the categories increases in downturns. Both the difference and the ratio between default rates are cyclical. We next operationalize the idea of comparing default rates across categories.

Relative default risk

[12] We choose to show the intermediate ratings because in 'extreme' ratings either almost all default or no firm defaults which worsens the depiction of the intermediate ratings.

We next turn to an explicit comparison of defaults across internal ratings. To facilitate the comparison, we combine ratings into two categories, the three highest and the next three (we drop the lowest category where default is imminent for most firms, but results are similar with this category included). The two groups are of equivalent size.[13] We then calculate the ratio of the 12 month forward-looking default rates for the weak group to the default rate for the overall sample.[14] The ratio is:

$$default\ ratio = \frac{\frac{D_{weak}}{N_{weak}}}{\frac{D_{weak}+D_{strong}}{N_{weak}+N_{strong}}} \tag{4}$$

Where D measures the number of defaults and N the number of firms at risk, and where *strong* and *weak* indicates the two groups of observations (better and worse ratings, respectively). The default ratio has several attractive properties. First, if the rating system is uninformative, the default frequency will be the same for the two ratings categories, and the default ratio becomes one (in the perverse scenario where defaults are more frequent for better rated firms, the ratio is below one). If all defaults occur in the weaker category, the best outcome, the ratio simplifies to $\frac{N_{weak}+N_{strong}}{N_{weak}}$, i.e. the ratio of sample size. Since we construct the two groups size to be of similar size, this ratio is close to two. Taken together, this means that the ratio has a natural scale from one (no information) to two (very good information).

This methodology captures defaults among highly rated firms, but pays no attention to non-defaults among poorly rated firms. This choice is sensible if the former category of "mistakes" is much more costly than the second, which seems plausible.

We plot the default ratio in Figure 5, quarter by quarter. Recession quarters are shaded in gray. We calculate separate averages for expansions (1.41) and recessions (1.56). The difference is 0.15, and based on the time series standard deviation of the ratio, this is significantly different from zero (t-stat of 4.01). In other words, defaults are more concentrated among firms the bank has

[13] We have also varied the methodology by using the finer categories to make the groups even more closely equal in size. The cutoff then varies one sub-category by quarter. The results are very similar.

[14] We can use Kaplan-Meier survival adjusted default rates, but this makes very little difference.

assigned poor ratings during recession. This result confirms that the bank's ability to assess credit risk appears strongly cyclical.

Semi-parametric and parametric estimates of cyclicality

One caveat to all the tests presented above is that they are unconditional, so the result does not rule out that the information in IR is available in other observable variables (such as firm accounting data). In other words, the apparent precision in bad period may come from hard or soft information. We next turn to regression-based estimates, which allow controlling for firm level characteristics capturing hard information.

We follow adjust regression (1) to allow the coefficients on bank's information (slack and IR) to be different each quarter. This is a semi-parametric approach: the time series pattern is capture by a large number of quarterly coefficients on each information variable. For clarity, we plot these graphically in Figure 6, using 12-month default predictions (patterns are the same for 24 months). Several patterns are clear in the figure. First, there is considerable time series variation in the predictive power of the measures we use to capture the bank's information set. Second, the variation is highly correlated with the business cycle: in the pre-crisis period, when credit markets were very strong and business performed well, the slack variable is insignificant in some quarters. The power peaks in the depth of the 2008-2009 recession, then fades somewhat and finally seems to increase again in the second recession in 2011. These results suggest that the bank's is better able to sort borrowers by credit quality at times when the economy is weak.

A more explicit test of the cyclicality of bank information can be constructed by testing for the coefficient on interactions of information variables with business cycle variables. To do this, we adjust the default regressions by adding interactions of slack and IR with the business cycle variables:

$$\text{Default} = \{\text{Slack (or IR)}\} \times \{\text{Time series variable}\} + \text{Slack (or IR)} + \text{Controls} + \text{Time F.E.} \quad (5)$$

Results are reported in Table 5, for Slack in Panel A and for IR in Panel B.[15] The table confirms that the patterns in Figure 5 are statistically significant: five of the six interaction coefficients are statistically significant. The magnitudes of the interaction estimates are economically meaningful: a one percentage-point drop in growth corresponds to an increase in the coefficient on slack of 0.06, which is about a fifth of the average effect of slack (0.28, from Table 4, Panel A, Column 2). Put differently, if growth is five percentage points higher than typical, the regression implies that the bank's information becomes useless (this thought experiment corresponds to a point estimate outside of the actual growth experienced during our sample period, which ranges from -3.8% to 2.8%, and should not be taken literally). The regression tests confirm that the predictive power of the bank's measure of borrower credit quality is most precise in the worst times. Our results are subject to alternative explanations, which we turn to next, with a series of robustness tests.

2.3 Robustness tests

In this section, we address a number of possible criticisms and questions about our main results. Several of these consider various ways in which our results could reflect some mechanical difference in monitoring frequency or accuracy, rather than the difficulty of assessing borrowers. We also consider variation in the borrower pool and the role of bank lending policy.

Monitoring frequency

Is it possible that the bank exerts more effort in bad times, and so produces a better signal, despite a more difficult information environment? Before addressing the intensity of monitoring, it is worth pointing out that most macro-economic mechanisms of interest depend on the precision of banks' information, not how hard that information is to come by. To be more concrete: if banks have better information about their borrowers in bad times, then information frictions cannot explain cyclical corporate lending (even if this better information is costly). Thus, counter-cyclical monitoring intensity is not an alternative to, but a possible mechanism, for our findings. Therefore, we examine whether or not the bank measurably exerts more effort.

[15] We use 12-month default as dependent variable from this point on. Results are similar with 24 months. When interacting information variables with the survey indicator, we divide the interaction with 100 for scaling reasons.

We use data on when a borrower has been assessed. In Figure 7, we plot the fraction of firms getting assessed by quarter. There is strong seasonality with a large peak in the fourth quarter of each year. This seasonality appears to be increasing over time. Importantly for our purposes, there appears to be no time pattern in total rate of assessments by year. The increasing activity in the last quarter of each year is offset by falling rates in the other three quarters. Thus, we cannot detect differences in monitoring frequency for different business cycle states. As an additional robustness test (not reported), we have estimated our regressions using only fourth quarter observations or only observations with fresh reviews. Results are very similar: slack and IR have the most ability to predict default when the business cycle is weakest.

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 there are more new borrower in good times, could this drive our results of weaker prediction in good times (this is the mechanism of Dell'Arriccia and Marquez 2006)? We assess this by re-estimating our regressions for new and old clients separately. On average, around 10% of borrowers are new in any six month period. The highest share of new borrowers are in the first half of 2006 (17.6%) and early 2007 (14.1%), while the lowest in the second half of 2011 (7.4%) and late 2012 (6.9%). Thus, some cyclicality is apparent. When we re-estimate Table 5 regressions for old clients only, cyclicality patterns are similar to the full sample. We report regressions in Table 6. Thus, we conclude that the patterns we observe do not reflect the mix of old vs. new bank clients, and hold for existing borrowers alone.[16]

Borrower size and industry

Another possible concern with our results concerns the sample composition in terms of industry and firm size. Some groups of firms may be harder to assess, and theses may be a larger fraction of firms in good times. In particular, small firms may be less well understood by the bank: they

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

have less detailed accounting data and finding out their performance is worth less to the bank. Additionally, the relevant information may be soft and thus harder to capture in the metrics we use.

Perhaps the bank's information measures are less precise in booms because small firms (like new borrowers) are more important in our sample. We can address this by looking only at large firms. In Table 7, we report regression results (similar to Table 5) for firms with 10 employees and up. These firms represent most of the credit volume in our sample (but only a third of firms). Results are similar in magnitude and significance to the results for the full sample.

A similar concern may be raised for the industry composition of our borrower sample. To address this, we estimate regressions separately (not reported) 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.

New credit

Finally, an important possible concern with our results is that firms with better slack and IR are less likely to default because they get more credit from the bank. A (short run) reduction in default probability after receiving a loan seems possible. This provides an alternative interpretation of our results. By including controls for the level of credit a firm has from the bank (and leverage from all sources), we attempted to control for this in our baseline specification. However, the default variable looks 12 or 24 months ahead (depending on the regression). Current IR and slack could predict new loans after the point of measurement but before the future point when we measure default. A simple way to test whether this is important is to drop any firm receiving new credit in the next 12 or 24 months. Results for this subset is presented in Table 8.[17] Coefficients are similar to the main specification, although

[17] 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)

slightly smaller. We conclude that the effects we capture do not appear to be mediated by new credit flows, but that variation in the predictive power of slack and IR likely reflect variation in the banks ability to assess credit risk.

3. Conclusions

The supply of corporate bank loans is very cyclical. Could this be because information frictions are worse in recessions? Indeed, assessing borrowers' credit worthiness is a key problem facing all lenders. Could this problem be cyclical, contributing to low credit volumes in recessions? Our empirical results suggest that this information explanation of cyclicality is false. For the bank we study, we find the opposite: corporate borrower defaults are easiest to predict in recessions.

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

To what extent can our results, from a sample based on a single Swedish bank during a specific period be extrapolated? One limitation is that this is a large bank, and small banks may rely more on soft information and therefore behave differently through the cycle. However, the cyclical patterns we document hold for the bank's soft information as well as overall, suggesting that the results may generalize broadly. A working hypothesis is that the pattern we find is general to corporate lending

We find that the extent of asymmetric information in the corporate loan market is pro-cyclical: distinguishing between weak and strong potential borrowers is easiest in downturns. The large cyclical swings in corporate credit availability that have been repeatedly identified probably do not reflect meager information about borrowers.

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Figure 2. The Swedish business cycle, 2004-2013

This figure displays four time series measures of Sweden's business cycle. The consumer confidence are survey-based measures with 100 as long run mean and a standard deviation of 10. Higher values indicate a stronger economy. The last 12 months stock return of the OMX30 index and quarterly GDP growth rate are measured on the right hand axis.

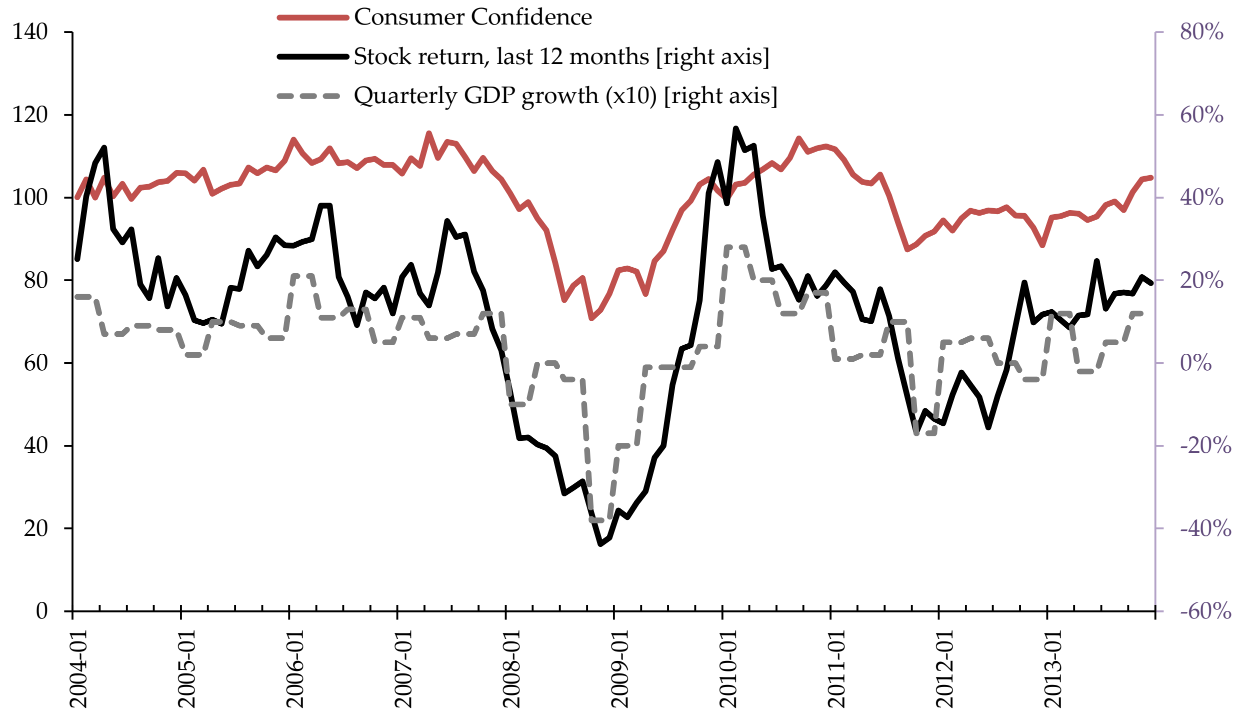


Figure 3. Accuracy of internal ratings by year, 2004-2011

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).

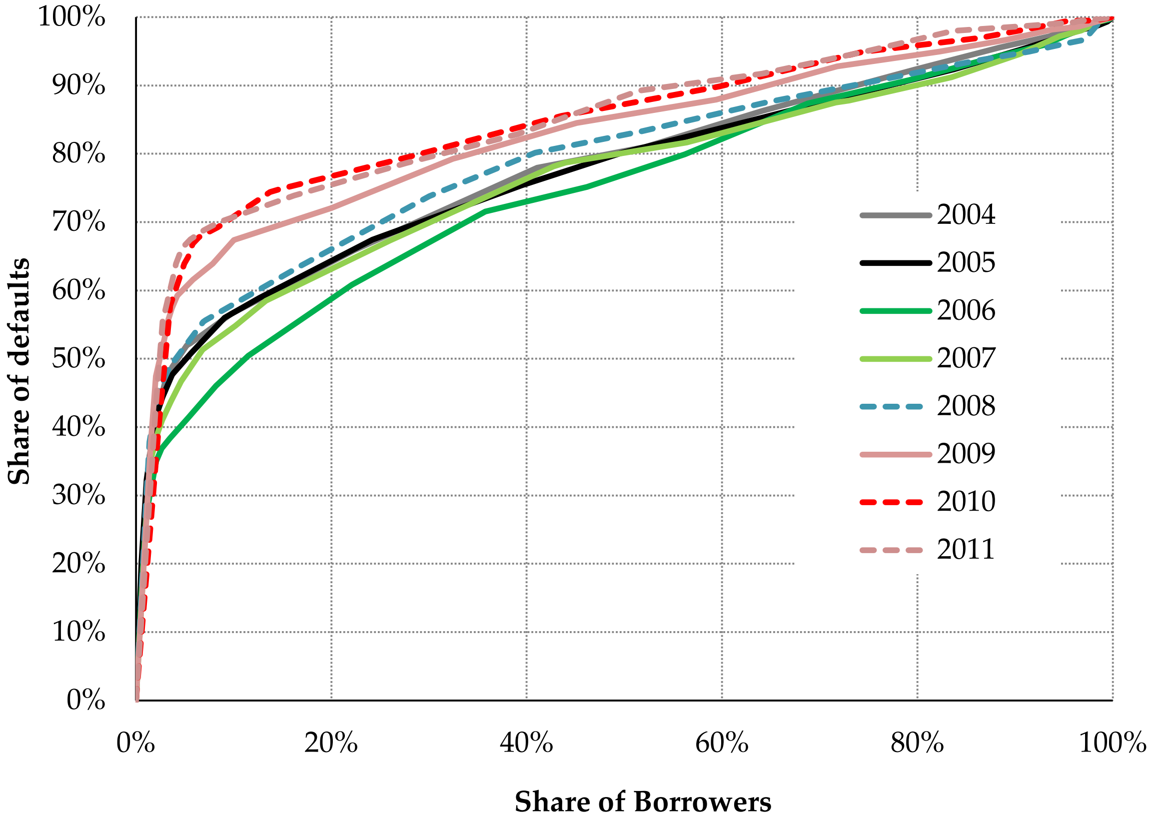
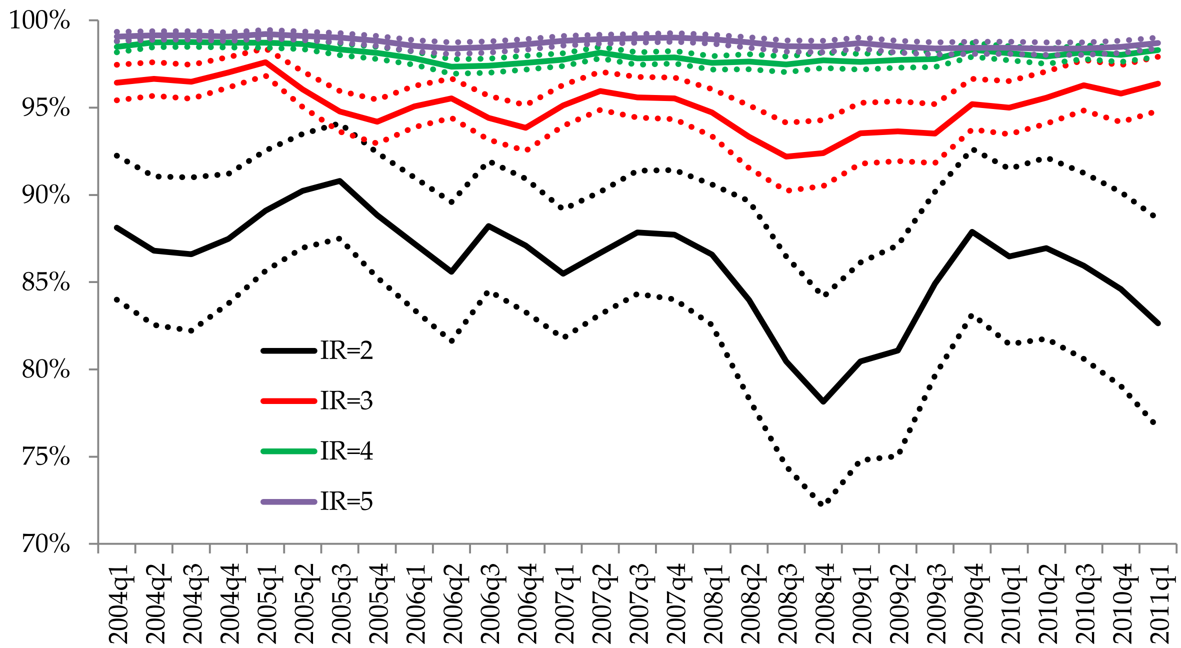


Figure 4. Kaplan Meier survival rates by internal rating

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

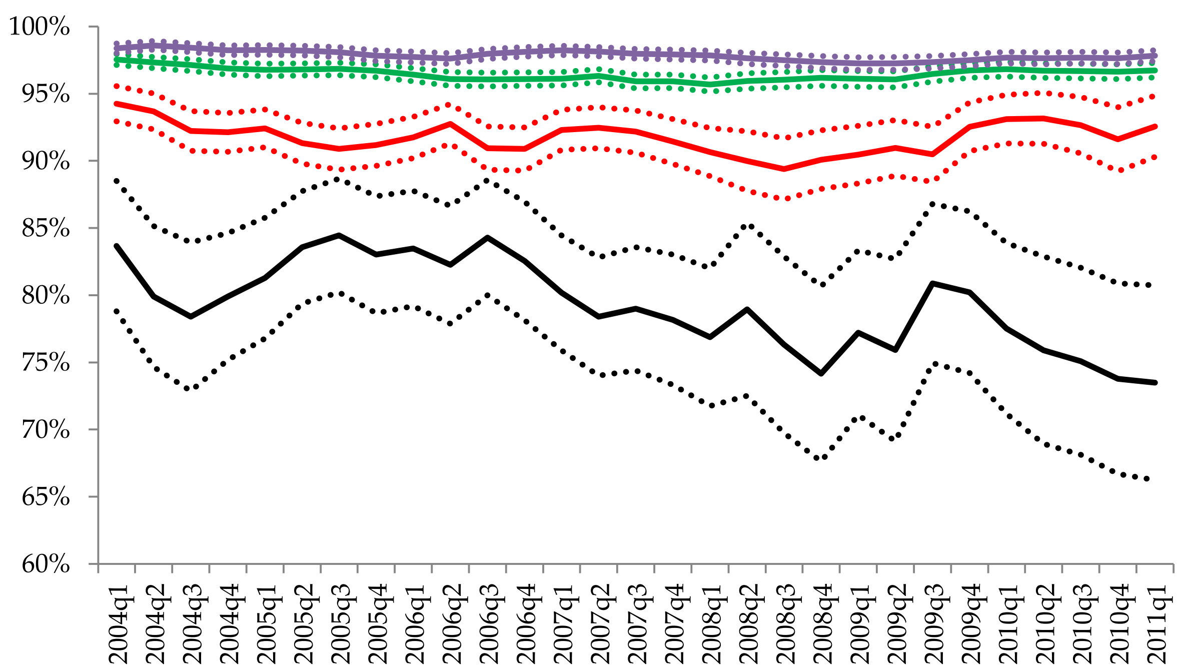


Figure 5. Default rates across ratings categories

The figure displays the 12 month default rate for the top three internal rating categories, relative to the overall default rate for the six top categories (the lowest ratings category is excluded). Shaded areas indicate recession periods (either trailing 12 month stock return is negative or nominal GDP growth is negative, or both). Dotted lines represent average ratios in recessions and expansions, respectively.

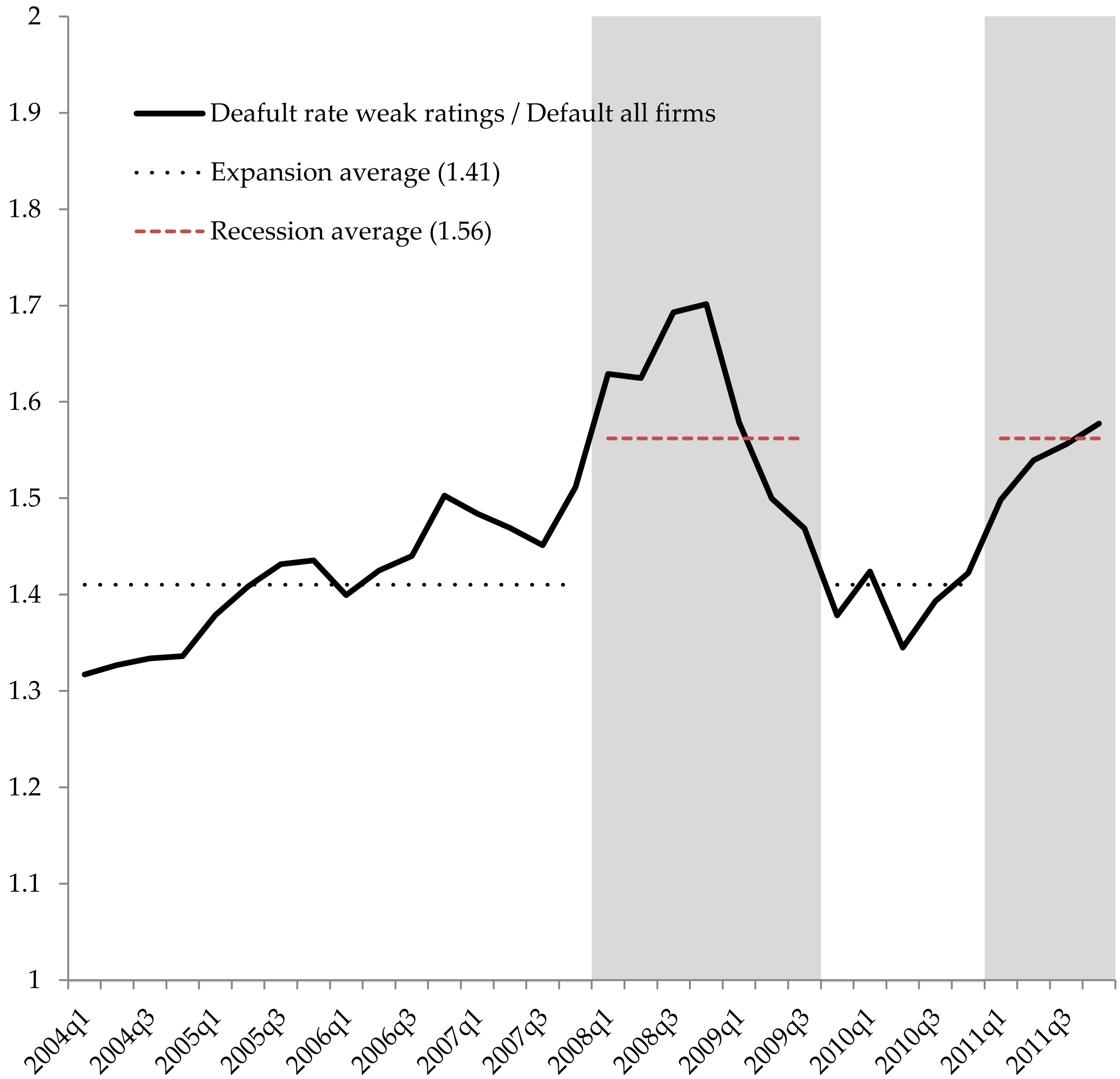
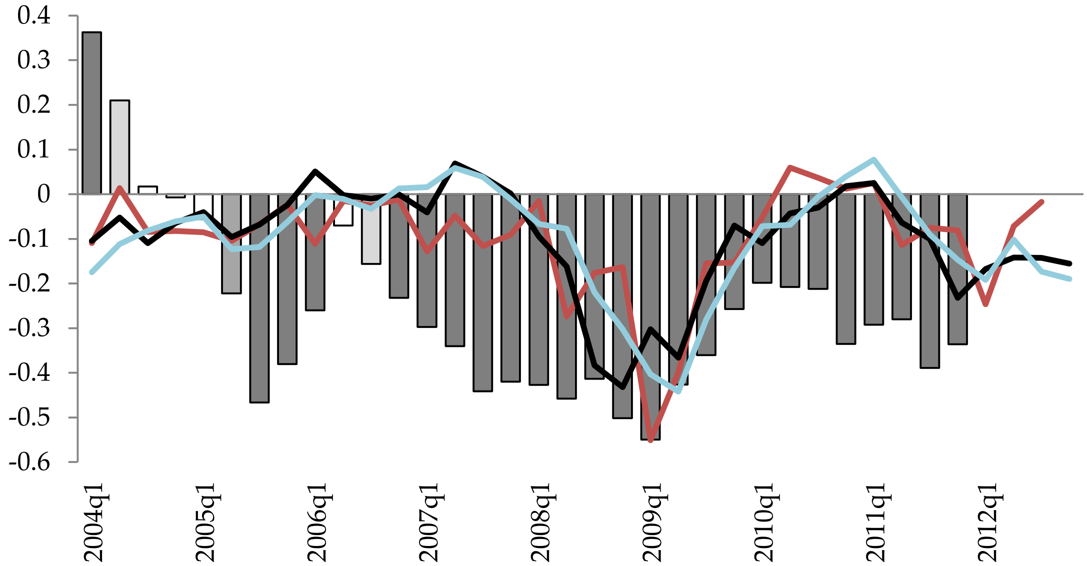


Figure 6. Predicting default over the business cycle

This figure display four business cycle indices (the lines, right scale) and the $\beta_1$coefficients (the bars, left scale) from the probit regression of default on credit slack or internal ratings (IR): $Default_{within\ 12m} = \beta_{1t}Slack\ (or\ IR) * time_{dummies} + \beta_2 X + i.t + \varepsilon$. The plotted coefficients (β_{1t}) time-varying predictive power of slack (Panel A) and IR (Panel B). Controls (X) include credit bureau risk score, collateral, and accounting variables also control fixed effect for time. Errors are clustered at the borrower level. The business cycle indicators have been 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.

A. Slack, 12 months



B. Internal Rating, 12 months

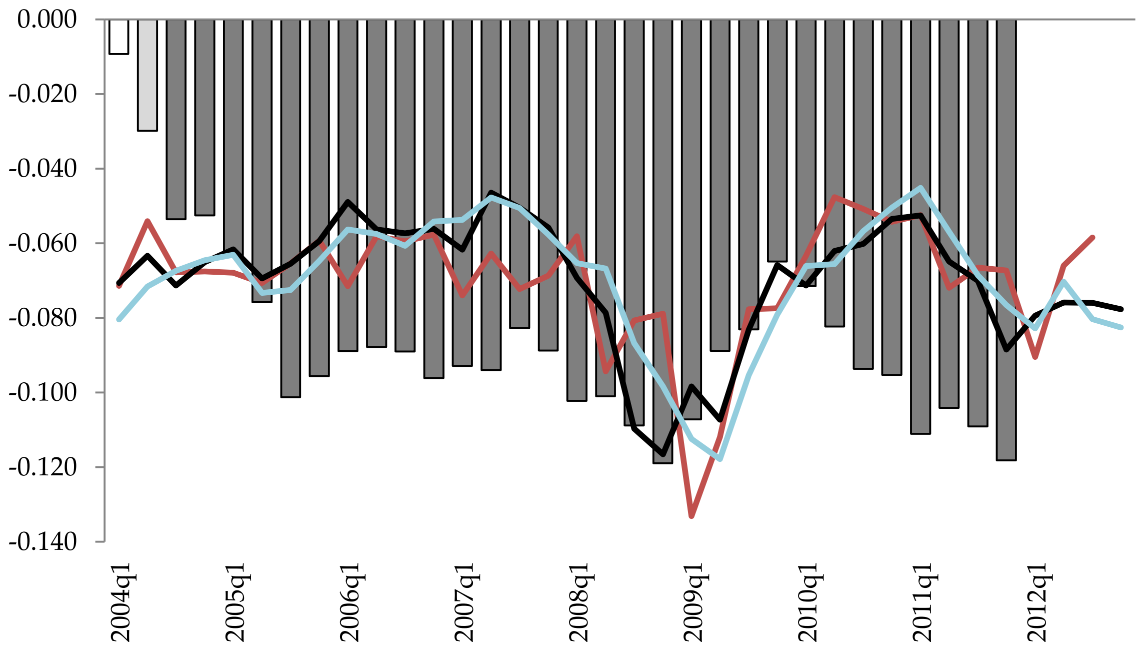


Figure 7. Proportion of borrowers being assessed by quarter

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

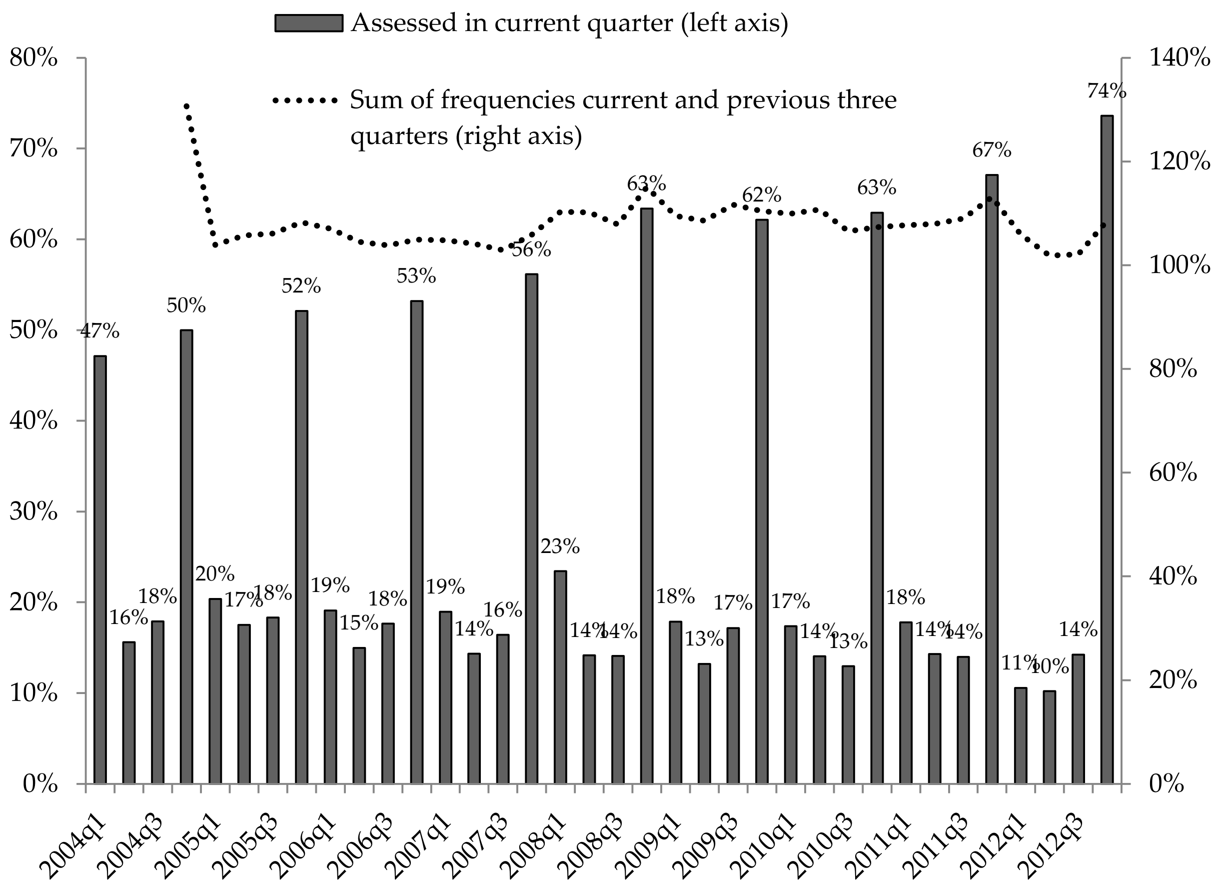


Table 1. Variable definitions

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

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

Table 2. Summary Statistics

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

Variable	Mean	Median	Standard deviation	Observations
Internal rating	12.9	13.0	3.6	1,706,000
Internal rating group	4.7	5.0	1.2	1,706,000
Limit (in 1000 SEK)	13,000	165	2,880,000	5,812,000
Internal limit (in 1000 SEK)	24,000	600	218,000	4,293,000
Outstanding balance (in 1000 SEK	6,878	90	180,000	5,681,000
Outstanding balance / Limit	0.69	0.99	0.41	5,128,000
Slack	0.21	0.06	0.27	3,327,000
Collateral (in 1000 SEK)	2,617	0	34,100	5,808,000
Days since review	155.2	151.0	130.6	3,643,000
Total sales (in 1000 SEK)	87,900	3 929	1,210,000	4,916,000
Total assets (in 1000 SEK)	159,000	3 235	2,880,000	4,809,000
Total tangible assets (in 1000 SEK)	28,100	252	516,000	4,809,000
Return on capital	0.14	0.16	0.58	4,914,000
Return on assets	0.07	0.06	0.18	4,914,000
Gross margin	0.07	0.06	0.24	4,722,000
Net margin	0.03	0.03	0.24	4,721,000
UC score	1.96	0.50	5.94	3,766,000
Employees	26.4	3.0	294.6	4,809,000
Leverage	0.59	0.62	0.27	4,809,000
Default	0.02	0.0	0.1	7,166,000

Table 3. Summary statistics by internal rating

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

Rating	Default wtn 12 months	Default wtn 24 months	Loss given default	Share of bank's aggregate credit losses	Number of loans per firm (median)	Share of loans with collateral	Average loan maturity (years)	Average interest rate (per cent)
1	59.1%	68.2%	80.3%	5.5%	7	6%	1.95	4.567
2	12.3%	18.8%	56.4%	4.3%	6	9%	1.93	5.244
3	4.4%	7.8%	64.7%	9.7%	8	9%	2.15	4.792
4	1.9%	3.4%	56.8%	14.5%	13	11%	2.28	4.491
5	1.2%	2.1%	55.1%	24.3%	23	11%	2.04	4.094
6	1.0%	1.7%	51.6%	19.7%	28	18%	2.27	3.948
7	1.1%	2.0%	35.1%	22.0%	4	54%	2.19	3.730

Table 4. Predicting default using credit slack and internal ratings

This table reports regressions of future default on Slack, which is defined as available credit up to the bank's internal limit (the amount of credit that the loan officer can grant without a new credit check), as a fraction of the internal limit. Internal rating is the bank's measure of credit risk, on an ordinal scale: Where a rating of seven is the best rating (the assessment of lowest default risk). Default is defined as payment over due by 90 days. In Panel A, all firm-years are pooled, and in Panel B regressions are run separately by IR category. 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: Slack

Dependent variable	Default, 12 m				Default, 24 m			
Regression type	Probit	Probit	OLS	OLS	Probit	Probit	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit slack	-0.165***	-0.279***	-0.006***	-0.008***	-0.150***	-0.329***	-0.008***	-0.016***
	(0.026)	(0.031)	(0.001)	(0.001)	(0.029)	(0.035)	(0.001)	(0.002)
Return on capital		0.076***		0.007***		0.078***		0.010***
		(0.017)		(0.001)		(0.018)		(0.000)
Return on assets		-1.230***		-0.058***		-1.214***		-0.088***
		(0.083)		(0.004)		(0.087)		(0.007)
Gross margin		-0.225***		-0.009***		-0.259***		-0.016***
		(0.071)		(0.002)		(0.072)		(0.004)
Net margin		-0.253***		-0.008***		-0.257***		-0.013***
		(0.073)		(0.002)		(0.073)		(0.000)
Log (total sales)		0.042***		0.001		0.044***		0.001*
		(0.008)		(0.000)		(0.008)		(0.0001
Log (total assets)		0.031***		0.002***		0.039***		0.004***
		(0.008)		(0.000)		(0.008)		(0.001)
Tangible fixed assets / total assets		-0.140***		-0.006***		-0.169***		-0.012***
		(0.039)		(0.001)		(0.043)		(0.002)
Leverage		0.001**		0.000		0.001**		0.000
		(0.000)		(0.000)		(0.000)		(0.002)
Outstanding loan balance		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Credit bureau score		0.033***		0.003***		0.034***		0.005***
		(0.001)		(0.000)		(0.001)		(0.000)
Collateral value		-0.000		-0.000**		-0.000		-0.000*
		(0.000)		(0.000)		(0.000)		(0.000)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	2,849,932	1,815,687	2,849,932	1,815,687	2,357,469	1,555,806	2,357,469	1,555,806
Clusters	Borrower				Borrower			
Number of clusters	59,410	34,026	59,410	34,026	53,093	32,431	53,093	32,431
R^2 or Pseudo-R^2	0.004	0.082	0.001	0.024	0.002	0.076	0.000	0.032

Panel B: Internal Rating

Dependent variable	Default, 12 m				Default, 24 m			
Regression type	Probit	Probit	OLS	OLS	Probit	Probit	OLS	OLS
	-1	-2	-3	-4	-5	-6	-7	-8
Internal Rating	-0.099***	-0.080***	-0.004***	-0.004***	-0.098***	-0.073***	-0.007***	-0.005***
	(0.003)	(0.004)	(0.000)	(0.000)	(0.004)	(0.005)	(0.001)	(0.000)
Return on capital		0.039		0.005**		0.026		0.004
		(0.027)		(0.000)		(0.028)		(0.004)
Return on assets		-0.993***		0.062***		-0.975***		-0.092***
		(0.139)		(0.009)		(0.141)		(0.014)
Gross margin		-0.282***		-0.010***		-0.341***		-0.020***
		(0.077)		(0.003)		(0.081)		(0.005)
Net margin		-0.024		0.001		0.062		0.000
		(0.076)		(0.003)		(0.075)		(0.005)
Log (total sales)		0.043***		0.001***		0.049***		0.002***
		(0.009)		(0.000)		(0.010)		(0.001)
Log (total assets)		0.027***		0.002***		0.025**		0.003***
		(0.010)		(0.000)		(0.010)		(0.001)
Tangible fixed assets / assets		-0.330***		-0.014***		-0.349***		-0.024***
		(0.051)		(0.002)		(0.055)		(0.004)
Leverage		0.005**		0.000***		0.004*		0.001
		(0.002)		(0.000)		(0.002)		(0.001)
Outstanding loan		0.000		0.000		0.000		0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Credit bureau score		0.022***		0.003***		0.026***		0.005***
		(0.002)		(0.000)		(0.002)		(0.000)
Collateral value		-0.000		-0.000*		-0.000		-0.000
		(0.000)		(0.000)		(0.000)		(0.000)
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	1,406,144	785,144	1,406,144	785,144	1,175,233	685,393	1,175,233	685,393
Clusters	Borrower				Borrower			
Number of clusters	32,672	17,980	32,672	17,980	29,261	17,037	29,261	17,037
Pseudo-R^2	0.075	0.103	0.013	0.029	0.065	0.088	0.018	0.037

Table 5. Default prediction with credit slack and internal ratings through the business cycle

The table reports regressions of future default on Slack and IR, interacted with business cycle variables

$$default_{122m} = \alpha + \beta_1((Slack\ or\ IR) * Bus.cycle.index) + \beta_2(Slack\ or\ IR) + \beta_3 controls + \beta_3 time + \varepsilon$$

Robust standard errors, clustered by borrower, are reported under coefficient estimates. * indicates a coefficient different from zero at the 10% significance level, ** at the 5% level, and *** at the 1% level.

Panel A: Slack

Dependent variable	Default, 12 m		
Regression type	Probit	Probit	Probit
	(1)	(2)	(3)
Slack x GDP growth	6.165***		
	(1.830)		
Slack x One year stock market return		0.396***	
		(0.102)	
Slack x Consumer confidence			0.536***
			(0.204)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, collateral		
Time F.E.	Yes	Yes	Yes
Number of observations	1,815,687	1,815,687	1,815,687
Clusters	Borrower	Borrower	Borrower
Number of clusters	34,026	34,026	34,026
Pseudo R^2	0.09	0.09	0.09

Panel B: Internal ratings

Dependent variables	Default, 12m		
Regression type	Probit	Probit	Probit
	(1)	(2)	(3)
IR x GDP growth	0.243		
	(0.232)		
IR x One year stock market return		0.042***	
		(0.014)	
IR x consumer confidence			0.050*
			(0.028)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, collateral		
Time F.E.	Yes	Yes	Yes
Number of observations	785,144	785,144	785,144
Clusters	Borrower	Borrower	Borrower
Number of clusters	17,980	17,980	17,980
Pseudo R^2	0.10	0.10	0.10

Table 6. Default prediction through the business cycle: existing borrowers

This table is based on T5, 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 IR, interacted with business cycle variables. 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: Slack

Dependent variable	Default, 12m		
Regression type	Probit	Probit	Probit
	(1)	(2)	(3)
Slack x GDP growth	6.029***		
	(1.856)		
Slack x One year stock market return		0.378***	
		(0.103)	
Slack x Consumer confidence			0.496**
			(0.208)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, collateral		
Time F.E. interacted with slack	Yes	Yes	Yes
Number of observations	1,726,365	1,726,365	1,726,365
Clusters	Borrower	Borrower	Borrower
Number of clusters	33,283	33,283	33,283
Pseudo R^2	0.09	0.09	0.09

Panel B: Internal ratings

Dependent variables	Default, 12m		
Regression type	Probit	Probit	Probit
	(1)	(2)	(3)
IR x GDP growth	0.265		
	(0.235)		
IR x One year stock market return		0.042***	
		(0.015)	
IR x consumer confidence			0.051*
			(0.026)
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 bureaus score, collateral		
Time F.E. interacted with slack	Yes	Yes	Yes
Number of observations	753,820	753,820	753,820
Clusters	Borrower	Borrower	Borrower
Number of clusters	17,404	17,404	17,404
Pseudo R^2	0.10	0.10	0.10

Table 7. Default prediction through the business cycle: large and medium sized firms

This table is based on Table 5, but only contains firms with 10 or more employees. The table reports regressions of future default on Slack and IR, interacted with business cycle variables. 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: Slack

Dependent variable	Default, 12m		
Regression type	Probit	Probit	Probit
	(1)	(2)	(3)
Slack x GDP growth	6.939**		
	(3.076)		
Slack x One year stock market return		0.393**	
		(0.169)	
Slack x Consumer confidence			0.650*
			(0.348)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, collateral		
Time F.E. interacted with slack	Yes	Yes	Yes
Number of observations	453,682	453,682	453,682
Clusters	Borrower	Borrower	Borrower
Number of clusters	9,397	9,397	9,397
Pseudo R^2	0.09	0.09	0.09

Panel B: Internal ratings

Dependent variable	Default, 12m		
Regression type	Probit	Probit	Probit
	(1)	(2)	(3)
IR x GDP growth	0.346		
	(0.309)		
IR x One year stock market return		0.052***	
		(0.019)	
IR x consumer confidence			0.056
			(0.038)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, collateral		
Time F.E. interacted with slack	Yes	Yes	Yes
Number of observations	356,144	356,144	356,144
Clusters	Borrower	Borrower	Borrower
Number of clusters	7,836	7,836	7,836
Pseudo R^2	0.10	0.10	0.10

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 T5, but only includes firms that don't receive credit within the next 12 months. The table reports regressions of future default on Slack and IR, interacted with business cycle variables. 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: Slack

Dependent variable	Default, 12m		
Regression type	Probit	Probit	Probit
	(1)	(2)	(3)
Slack x GDP growth	4.026***		
	(2.330)		
Slack x One year stock market return		0.289**	
		(0.135)	
Slack x Consumer confidence			0.317
			(0.296)
Controls	Return on capital, return on assets, gross margin, net margin, log (total sales), log (total assets), tangible fixed assets / total assets, leverage, outstanding loan balance, credit bureaus score, collateral		
Time F.E. interacted with slack	Yes	Yes	Yes
Number of observations	1,363,282	1,363,282	1,363,282
Clusters	Borrower	Borrower	Borrower
Number of clusters	32,371	32,371	32,371
AdjustedR^2	0.049	0.049	0.053

Panel B: Internal ratings

Dependent variables	Default, 12m		
Regression type	Probit	Probit	Probit
	(1)	(2)	(3)
IR x GDP growth	0.201		
	(0.260)		
IR x One year stock market return		0.041***	
		(0.016)	
IR x consumer confidence			0.014
			(0.026)
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 bureaus score, collateral		
Time F.E. interacted with slack	Yes	Yes	Yes
Number of observations	531,126	531,126	531,126
Clusters	Borrower	Borrower	Borrower
Number of clusters	17,129	17,129	17,129
Adjusted R^2	0.049	0.049	0.053