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Predicting Credit Deterioration: Internal Default Models versus Lending Rates

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Abstract

This paper examines how accurately Swedish banks' internal probability of default (PD) models under IFRS 9 accounting rules predict changes in the borrowing firms' credit risk levels. Using a sample of matched bank lending and firm-level data, we find that PDs align well with aggregate transitions to an elevated risk level, but explain little of the variation across individual borrowers. Lending rates, in contrast, provide limited information on moderate distress levels but are more predictive of severe credit events. The findings suggest that PDs capture both risk assessment and accounting conventions in a non-linear and complex pattern, highlighting the importance of combining regulatory and market-based indicators when monitoring credit risk.

Keywords: Probability of Default, Bankruptcy, Financial Distress

JEL: G33, L25

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1 Introduction

When a bank lends to a firm, the bank is required to estimate the risk of default on the loan in the next twelve months, according to the Basel accords. These probabilities of default (PDs) are relevant not only for banks, but also for any agencies who are interested in the riskiness of different firms in the economy, as well as for authorities assessing the aggregate risks that banks are taking with their lending (Stepankova & Teply, 2023). A firm's risk of defaulting can be influenced by factors such as a high debt-to-asset ratio, low return on equity, and low earnings (Campbell et al., 2008; Jacobson et al., 2013; Tian et al., 2015; Miao et al., 2018; Banerjee & Kharroubi, 2020). Furthermore, all firms are at risk of idiosyncratic shocks, such as sudden changes in the health of the CEO (Bennedsen et al., 2020).

The implementation of the IRFS9 accounting framework, and the risk modeling that is accompanied with it, has already changed the behavior of banks. Lending to small and medium sized enterprises has been reduced Ertan (2025), and firms who see their credit risk increased experience a reduction in available credit (Buchetti et al., 2025) which in turn could lead to procyclical lending dynamics (Suarez, 2018). If banks respond to increased capital requirements by decreasing risky lending, rather than increasing their equity, this could in turn decrease capital available for investments (Behn et al., 2016; Gropp et al., 2019).

In this paper, we use registry data on Swedish firms, in combination with detailed bank information of almost all lending to firms, to compare what best predicts the firms loan being categorized in different risk levels or going bankrupt: the banks' PDs or their lending rates. To the best of our knowledge, this paper is unique in evaluating both the predictive power the pricing of loan riskiness and the internal modeling that is required under IFRS9. We find that for the lowest levels of financial stress the PDs are better predictors than the lending rates. However, the predictive power is non-linear with an inverted U-shape, where the predictive power declines following a peak in PDs of about 25%. We argue that this is because PDs incorporate more information than just a statistical probability, including accounting conventions and banks' internal rules. PDs are also better predictors at the aggregated level, with a relatively low predictive power for the individual firm.

In contrast, the banks' lending rates have less predictive power for lower levels of financial risk, but are better at predicting higher levels of financial risk. The predictive power of the lending rate is also non-linear, with higher lending rates having an increasing predictive power, perhaps due to both selection and to high lending rates directly contributing to bankruptcy by increasing the firms' capital costs. While the notion that banks set a lending rate that corresponds to the riskiness, it is important to connect banks pricing of lending to the aggregate financial risks in the economy (González-Aguado & Suarez, 2015; Gilchrist & Mojon, 2018). Public agencies who monitor the bankruptcy-risk in the economy can therefore benefit from including the lending rates as a monitoring variable.

2 Institutional setting

Banking is regulated through frameworks such as the Basel III accord and is shaped through accounting standards such as the IFRS 9. The IFRS 9 is an international accounting standard that has a significant impact on banks, particularly in how they manage and report financial instruments and credit losses. It was introduced in 2018 and replaced the previous standard, the IAS 39 (IFRS Foundation, 2025). The purpose of introducing the new standard was to prevent credit losses being either underreported or reported too late. With IFRS 9, a forward-looking model was introduced for credit loss recognition. This means that banks must now estimate future credit losses and not just recognize them when they occur. The introduction of IRFS 9 seems to have reduced lending to small and medium sized firms, due to the higher risks associated with such firms (Ertan, 2025).

Under IFRS 9, PDs are central to measuring expected credit losses and represents the risks that financial assets will default. The PD framework includes a particular definition regarding what constitutes a default. The expected credit losses framework divides financial assets, such as loans, into three stages based on changes in credit risk. Loans in stage 1 are considered "performing assets", which means that there has been no negative change in the credit quality of the loan since its initial recognition. For these loans, banks are to estimate the expected credit losses for the next twelve months i.e. the likelihood that they will default within the next year. For loans in stage 2 ("under-performing") and stage 3 ("impaired"), banks must instead estimate expected credit losses for the remaining maturity. A loan is moved from stage 1 to stage 2 if there is a significant increase in the credit risk (SICR) of the loan. A loan could pass through each stage in a sequential order, e.g. from stage 1 to stage 2 and stage 3, but it could also go straight from a stage 1 loan to a stage 3 if the banks deem that the increase in credit risk is sufficiently high (Bank for International Settlements, 2017). When banks have downgraded a loan from e.g. stage 1 to stage 2, they could be reluctant to withdraw the downgrade even if the firm's situation improves (Buchetti et al., 2025).

However, in IFRS 9 there is no definition of what is considered a significant increase in credit risk. Instead, banks must define the SICR threshold themselves and use internal models for calculating the PD of each loan. The choice of the SICR threshold directly affects the share of stage 2 loans and thereby has a large impact on banks' expected credit losses (Leventis et al., 2011; Krüger et al., 2018). A change in the PD is often the indicator for whether a loan moves into a different stage. However, qualitative judgment could also be used to move a loan into a different stage.

3 Data

We combine fine grained lending data on bank loans from all major Swedish banks from the Sveriges Riksbank's database Krita with registry data on all Swedish firms for the period 2019-2023 from the firm database Serrano[1]. Notably, we use the banks' own PD estimates for each firm, according to the capital requirement regulation (EU regulation 575/2013). If a

[1] We exclude interbank lending and firms in the government sector.

firm has several different loans, including loans from different banks, we aggregate the data at the firm level and use the mean PD and lending rate. Since the firm data is based on the firms' annual reports, we extract the loan information from the last available date (December 31st) to correspond as best as possible with the information that the firm has submitted in their annual reports. We use the firms' largest loan to identify the relevant bank for each firm. Descriptive statistics are presented in Table 1 and Figure A1. Data on the loan status is from the Krita database whereas the bankruptcy status is from the Serrano database.

For several firms, there is information about the bank's lending rate of the loan, despite the loan being equal to zero. These lending rates typically represent a standard lending rate for e.g. a credit line that the firm has not utilized at that time. While this lending rate could be a relevant price signal of the riskiness of the firm, it could also just reflect a standardized rate. We exclude these observations in the main regressions and hence only include firms with a non-zero loan in the main regression, returning to these firms in the robustness checks.

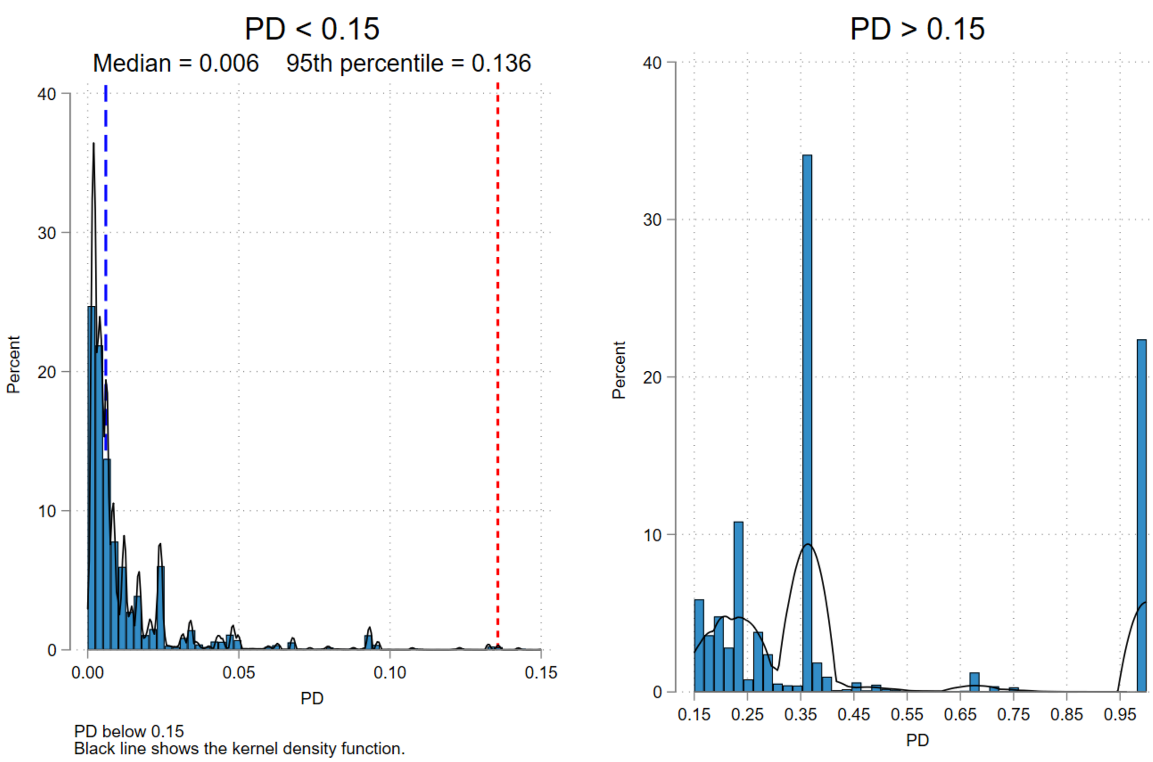
Table 1. Summary statistics

	Observations	Mean	Median	Std. Dev.	Min	Max
Bank debt	939666	11010	190	137937	0	2.93e+07
PD	797346	.036	.0064	.121	0	1
Lending rate	938065	.0416	.0347	.0389	0	.395
Loan in stage 2	1227810	.0991	0	.299	0	1
Loan in stage 3	1227810	.0093	0	.096	0	1
Bankruptcy dummy	1227810	.00866	0	.0926	0	1
No. employees	1161517	10	1	124	0	22586
Sales	1122724	39921	2230	935274	-250	2.89e+08

Notes: Summary statistics. Firm-year observations. Bank debt and sales are denominated in thousand SEK.

The distribution of PDs is extremely skewed, as evident from Figure 1, with a median value of 0.006 and a 95^{th} percentile of 0.136. The pattern is similar if we exclude PDs from credit lines that have not yet been utilized. For the distribution above 15% there are two spikes: one at 36.2% and one at the PD being equal to 1. Of the 13,678 observations of the PD being equal to 36.2%, 12,625 are from a single bank suggesting that this number is used as some type of internal accounting practice. Likewise, of the 9,110 observations of the PD being equal to 1, 7,351 are from loans in stage 3. Hence, these PDs might not reflect a genuine measurement of the probability of risk, but rather internal models in the bank. In the initial regressions, we therefore restrict the sample to observations with a PD below 35%.

Figure 1. Distribution of PDs. Leftmost panel shows the distribution of PDs below 15%, rightmost shows the distribution of PDs above 15%. The blue line shows the median value, the red line the 95th percentile of the distribution.



4 Empirical Approach

To investigate if banks' PDs are good predictors of the firms' riskiness, we run several OLS and logit regressions using an indicator for whether the firm's loan is in stage 2, stage 3, as well as the firm being in bankruptcy, as a binary dependent variable.

$$Y_{it} = \alpha_i + \beta X_{it-1} + \tau_t + \epsilon_{it} \quad (1)$$

where Y_{it} is a dummy variable equal to one if the firm's loan is in stage 2, stage 3 or the firm goes bankrupt. Our main independent variable X_{it-1} is either the firm's PD or lending rate, lagged one year. In a subset of regressions, we include a year fixed effect τ_t to remove any business cycle effects that could be due to the rapid increase in lending rates during the period we study. This is also equivalent of using the spread between the central bank lending rate and the lending rate charged by banks. Finally, ϵ_{it} is the error term. Standard errors are clustered at the firm level in all regressions.

It would be conventional to include firm fixed effects. However, this would remove almost all variation in our data, since the variation we are interested in is not mainly the change in a single firm's PD or lending rate, but rather the difference in levels of PDs and lending rate between firms. Furthermore, many firms have PDs and lending rates that are stable over time and these observations would be eliminated if we included firm fixed effects. Therefore we use a combination of pooled OLS and pooled logit regressions.

Since banks could be reluctant to change an IFRS 9 category when it has been increased (Buchetti et al., 2025), we condition all regressions on the firm's loan not being in the category that is estimated. For example, in all regressions where the dependent variable is a loan being in stage 2 in t, we condition on the previous observation not being in stage 2 in t_{-1} etcetera.

5 Results

We start by testing the predictive power of PDs and lending rates on the least risky indicator, namely if the firm's loan is in stage 2. This is done by running pooled OLS and logit regressions both with and without year fixed effects, using both PDs and lending rates, for a total of 8 separate regressions. We restrict the sample to observations with a PD below

35% for both the PD and lending rate regressions, in order to ensure that the two groups are comparable. For the logit regressions, we show the average marginal effects instead of the odds-ratios.

The results in Table 2 shows that the PD is clearly significant with an OLS coefficient slightly above 1.4 and the logit coefficient slightly above 0.6. Hence, a one percent increase in the PD increases the probability of being in stage 2 with 1.4 or 0.6 percentage points, depending on the estimation technique. This is in line with the theoretical prediction that the one percent increase in PD should correspond to a one percent increase in the actual probability. The OLS results for PDs are higher than for the lending rates, with the logit lending rate coefficients being higher for lending rates than for PDs. Including time fixed effects has a limited effect on the results. R^2 and Pseudo-R^2 is around 2% for the PD regressions and 0.2% for the lending rate regressions. Since we exclude firms with a zero lending rate, we have fewer observations in columns 5-8 compared to 1-4.

Turning instead to IFRS stage 3 in Table 3, the coefficients and R^2 decrease in size but follow a similar pattern as the stage 2 regressions. OLS coefficients for PDs are higher than for lending rates, but logit coefficients are higher for lending rates. The Pseudo-R^2 is higher for the PD regressions compared to the stage 2 regressions, whereas the R^2 is lower compared to Table 2.

For bankruptcy in Table 4, all coefficients for the PD regressions decrease in size, but the lending rate coefficients, R^2 and pseudo-R^2 increase compared to the stage 3 regressions. PDs therefore seem to be the best predictors for whether firm's loan is in stage 2 and to a lesser extent stage 3, whereas the lending rate is preferable for predicting bankruptcy.

Table 2. IFRS stage 2

Dependent var: Dummy for IFRS stage 2								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Lagged PD	1.416***	1.416***	0.673***	0.673***				
	(0.024)	(0.024)	(0.009)	(0.009)				
Lagged lending rate					0.886***	0.899***	0.698***	0.703***
					(0.015)	(0.015)	(0.011)	(0.011)
Constant	0.049***	0.045***			0.046***	0.048***		
	(0.000)	(0.001)			(0.000)	(0.001)		
Observations	606,715	606,715	606,715	606,715	492,255	492,255	492,255	492,255
R-squared	0.017	0.018			0.009	0.010		
Year FE		✓		✓		✓		✓
Pseudo R-squared			0.0208	0.0224			0.0154	0.0165

Notes: This table reports the results of OLS and logit regressions with the firms loan in Stage 2 as the dependent variable.

$$Stage2_{it} = \alpha_i + \beta_1 X_{it} + \tau_t + \epsilon_{it}$$

where the X_{it} is either the effect from the firms PD or lending rate, lagged one year. Depending on the specification we include year fixed effects, τ_t. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3. IRFS stage 3

Dependent var: Dummy for IFRS stage 3								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Lagged PD	0.247***	0.247***	0.061***	0.061***				
	(0.007)	(0.007)	(0.001)	(0.001)				
Lagged lending rate					0.132***	0.135***	0.075***	0.075***
					(0.004)	(0.004)	(0.002)	(0.002)
Constant	0.000***	0.001***			0.001***	0.002***		
	(0.000)	(0.000)			(0.000)	(0.000)		
Observations	682,040	682,040	682,040	682,040	562,293	562,293	562,293	562,293
R-squared	0.015	0.015			0.003	0.003		
Year FE		✓		✓		✓		✓
Pseudo R-squared			0.0876	0.0903			0.0309	0.0325

Notes: This table reports the results of OLS and logit regressions with the firms loan in Stage 3 as the dependent variable. Firm-level clustered standard errors are reported in parentheses.

$$Stage3_{it} = \alpha_i + \beta_1 X_{it} + \tau_t + \epsilon_{it}$$

where the X_{it} is either the effect from the firms PD or lending rate, lagged one year. Depending on the specification we include year fixed effects, τ_t. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4. Bankruptcy

	Dependent var: Dummy for bankruptcy							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
Lagged PD	0.227***	0.227***	0.063***	0.063***				
	(0.007)	(0.007)	(0.001)	(0.001)				
Lagged lending rate					0.185***	0.193***	0.093***	0.094***
					(0.005)	(0.006)	(0.002)	(0.002)
Constant	0.001***	0.002***			-0.000	0.001***		
	(0.000)	(0.000)			(0.000)	(0.000)		
Observations	682,723	682,723	682,916	682,723	562,969	562,969	562,969	562,969
R-squared	0.011	0.011			0.005	0.006		
Year FE		✓		✓		✓		✓
Pseudo R-squared			0.0659	0.0674			0.0491	0.0507

Notes: This table reports the results of OLS and logit regressions with the firm entering bankruptcy as the dependent variable.

$$Bankrupt_{it} = \alpha_i + \beta_1 X_{it} + \tau_t + \epsilon_{it}$$

where the X_{it} is either the effect from the firms PD or lending rate, lagged one year. Depending on the specification we include year fixed effects, τ_t. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

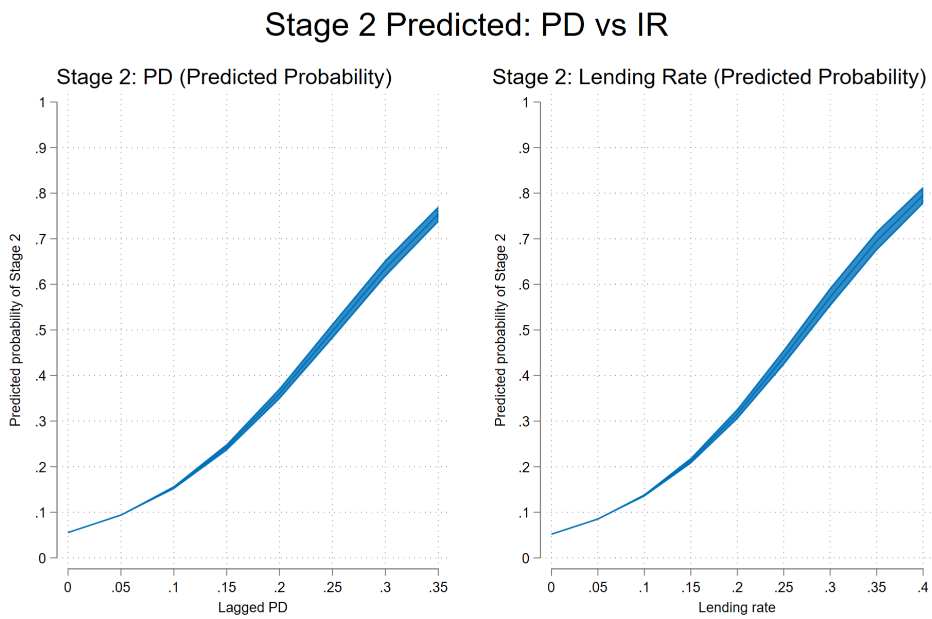
5.1 Predicted and marginal effects

To get a more nuanced view of the effects of the PDs and the lending rateds, we plot the predicted probability and average marginal probability for the logit regressions with time fixed effects, corresponding to columns (4) and (8) for both outcome variables. In Figure 2, subplot (a), both PDs and lending rates have an increasing predictive power which declines at the highest levels. Both variables have an inverted U-shape of the marginal probability, subplot (b), peaking at about 25% for the PD and for the lending rate. Hence, PDs and lending rates are primarily good predictors of a loan being in stage 2 at lower levels. This is likely due to IFRS 9 stressing that it is the derivative of the risk that is of importance when moving a loan into stage 2, rather than the level of the risk.

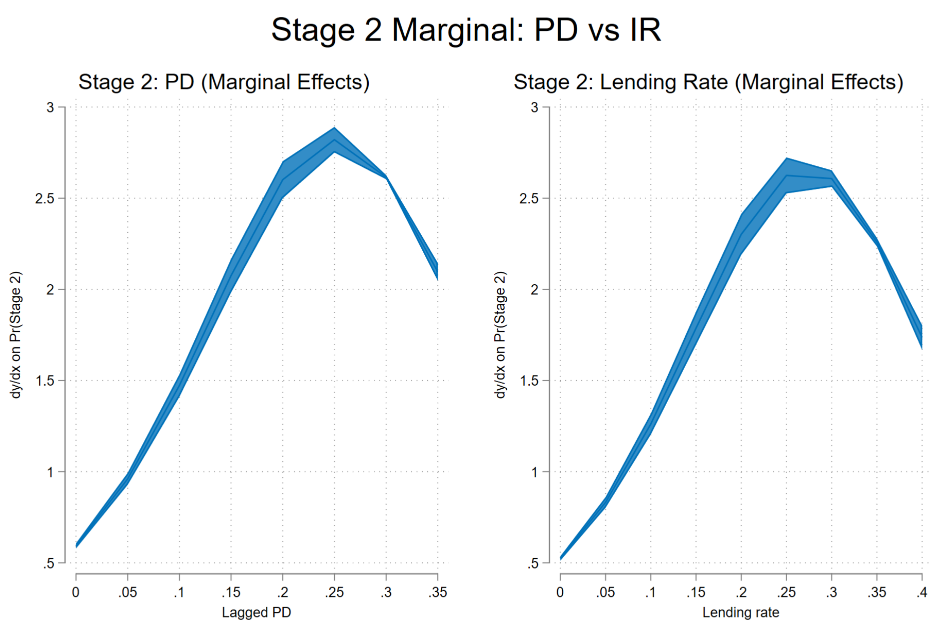
The pattern is quite different for the stage 3 regressions in Figure 3. Here, both PDs and lending rates have a convex shape in the probability, with the lending rates having a rapidly increasing effect at the end. The marginal probabilities do not have a peak and continue to increase over the entire distribution, with the lending rate increasing even more rapidly.

The results are similar for the bankruptcy outcome in Figure 4, with lending rates having a more convex relationship compared to PDs. The marginal lending rates do seem to peak at the very end of the distribution, but at a much higher level than for the PDs. For bankruptcies, higher PDs and lending rates have more explanatory power compared to predicting a stage 2 event. This is especially true for bankruptcy, as evident of the difference in predictive power of PDs and lending rates in 4, panel (a).

Figure 2. Predicted and average marginal effects from logit regressions with time fixed effects for Stage 2



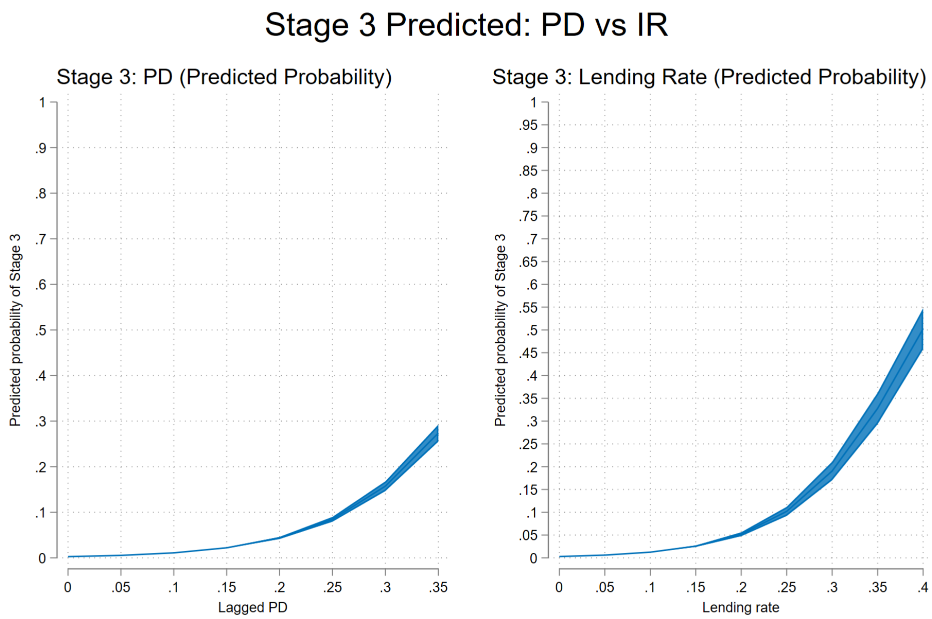
(a) Stage 2: Predicted probability



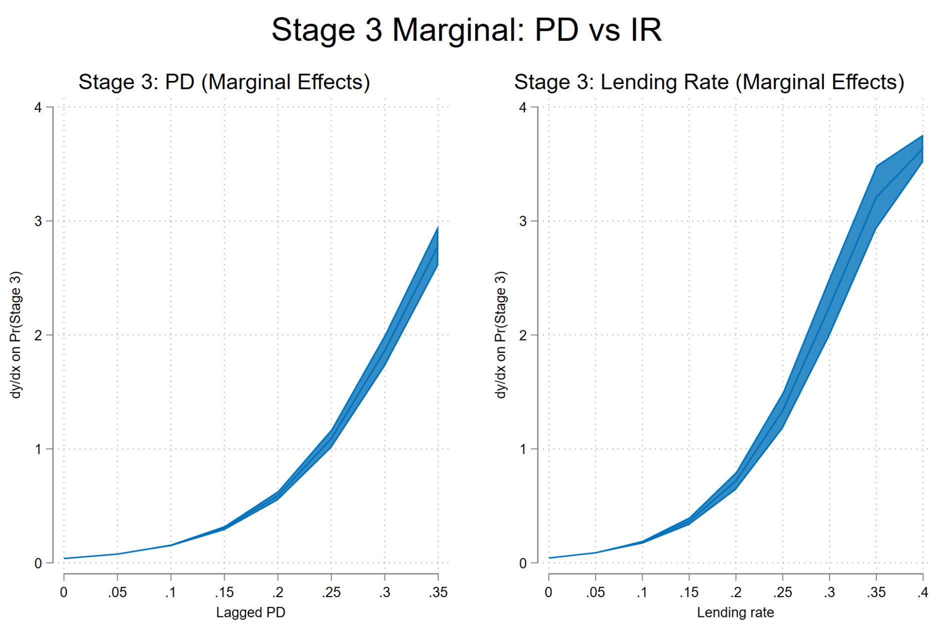
(b) Stage 2: Average marginal probability

Notes: This figure reports the predicted and marginal effects from the regressions in Table 2, columns 4 and 8. Each graph compares the effects of the PD and the lending rate on the the outcomes. The rightmost columns gives the predicted probabilities, comparing PD to lending rates. The leftmost columns predict the marginal probability.

Figure 3. Predicted and average marginal effects from logit regressions with time fixed effects for Stage 3



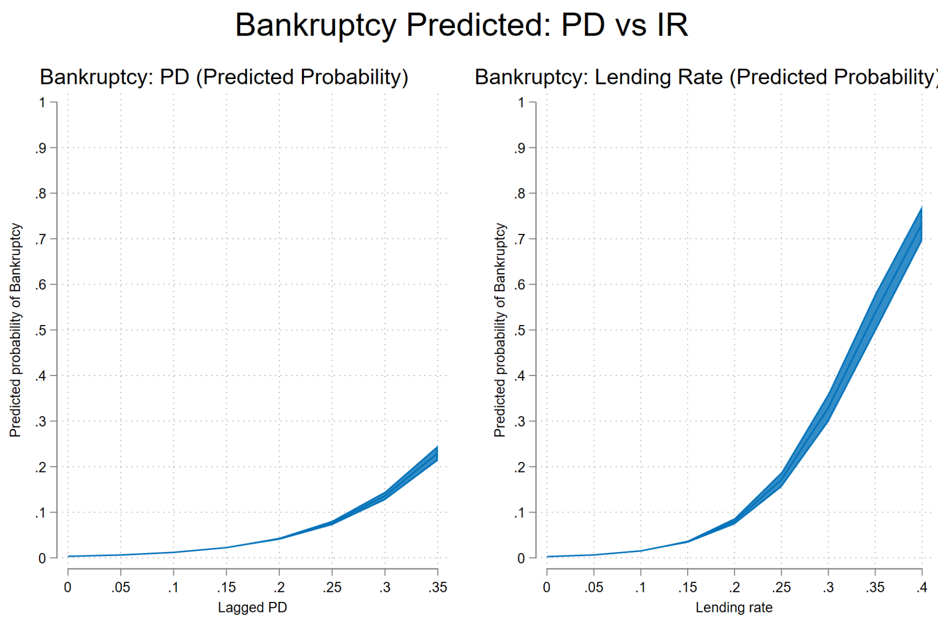
(a) Stage 3: Predicted probability



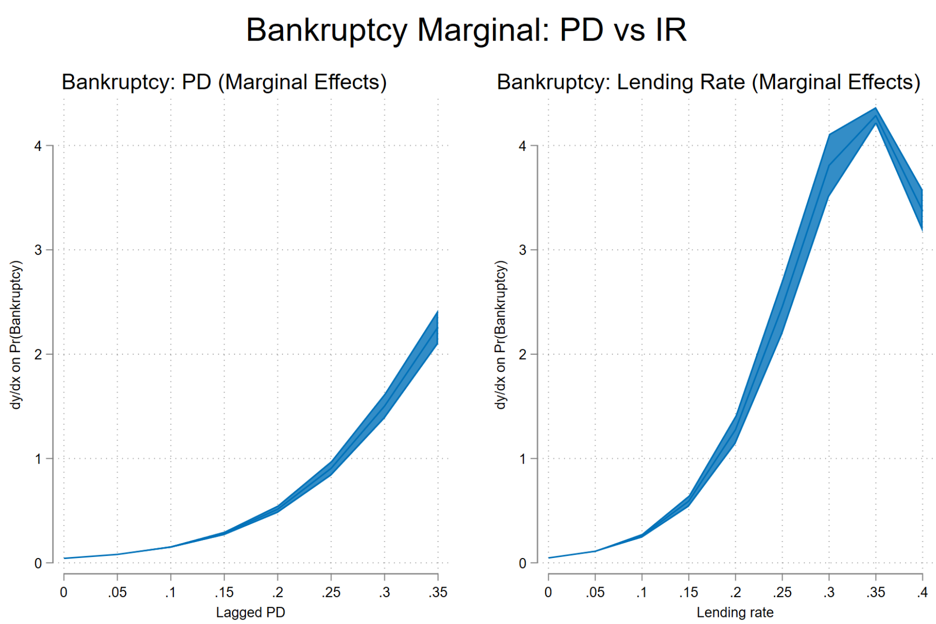
(b) Stage 3: Average marginal probability

Notes: This figure reports the predicted and marginal effects from the regressions in Table 3, columns 4 and 8. Each graph compares the effects of the PD and the lending rate on the the outcomes. The rightmost columns gives the predicted probabilities, comparing PD to lending rates. The leftmost columns predict the marginal probability.

Figure 4. Predicted and average marginal effects from logit regressions with time fixed effects for bankruptcy and any credit event.



(a) Bankruptcy: Predicted probability



(b) Bankruptcy: Average marginal probability

Notes: This figure reports the predicted and marginal effects from the regressions in Table 4, columns 4 and 8. Each graph compares the effects of the PD and the lending rate on the the outcomes. The rightmost columns gives the predicted probabilities, comparing PD to lending rates. The leftmost columns predict the marginal probability.

5.2 Interaction models

Since the predicted and marginal effects showed signs of non-linearity it is relevant to estimate a model that specifically incorporates these effects. We create a dummy variable for observations with a PD above 35% and incorporate these observations rather than exclude them[2]. We estimate the following model

$$Y_{it} = \alpha_i + \beta_1 X_{i,t-1} + \beta_2 \text{HighPD}_{i,t-1} + \beta_3 \Big(X_{i,t-1} \times \text{HighPD}_{i,t-1} \Big) + \tau_t + \varepsilon_{it}. \tag{2}$$

where X_{it-1} once again is either the PD or the lending rate. Due to the difficulties with modeling interaction terms in a logit model, we only estimate the model with OLS (Ai & Norton, 2003). The results for the stage 2 in Table 5 are similar for the PD coefficients in Table 2, with the PD coefficients being slightly more than double the size of the lending rate. Firms with a PD above 35% have a larger probability of being in stage 2 and a higher lending rate. However, the interaction of PD and lending rate with the high PD group is strongly negative. This suggests that banks' PD models become saturated following a certain level and that banks' pricing of lending rate risk is not related to a loan moving to stage 2.

In Table 6, the PD and lending rate coefficients are similar in size to Table 3. However, the interaction term switches sign compared to the interaction model for the stage 2 regressions. For the high PD groups, both PDs and lending rates have increasing slopes with the lending rate interaction term being more than 10 times as large as the PD interaction term. Hence, while the PD models become saturated at higher levels, additional increases in lending rates increase the probability of a loan moving into stage 3.

For the final outcome variable in in Table 7, the PD coefficients are similar in size to the stage 3 outcomes, but the interaction term is now negative, although with a size close to 0. For the lending rate regressions however, the main coefficients and the interaction term increase in size.

[2]We continue to exclude observations of lending rates where there is no corresponding loan.

The stark difference in signs and magnitude between the interaction terms of the lending rate regressions for the stage 2 and the bankruptcy suggests that banks' pricing differ between stages of risk. For modest, but slightly increased risk, banks could be willing to extend credit and engage in forbearance to avoid the firm spiraling into a worse situation (Schüle, 2007; James et al., 2021). When conditions do worsen, banks could be increasing their rates to ensure that the firms swiftly will repay their loans or seek another creditor. The high lending rates could also by themselves contribute to pushing the firms into bankruptcy (Bernanke et al., 1996; Bräuning et al., 2023). Without a clear exogenous chock it is difficult to differentiate between these theoretical mechanisms.

Table 5. Stage 2 interaction

Dependent var: Dummy for IFRS stage 2

VARIABLES	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Lagged PD	1.416***	1.416***		
	(0.024)	(0.024)		
High PD group	0.238***	0.232***	0.154***	0.156***
	(0.009)	(0.009)	(0.006)	(0.006)
Lagged PD × High PD group	-1.659***	-1.653***		
	(0.026)	(0.026)		
Lagged lending rate			0.678***	0.667***
			(0.012)	(0.012)
Lagged lending rate × High PD group			-2.218***	-2.223***
			(0.073)	(0.073)
Constant	0.049***	0.045***	0.054***	0.059***
	(0.000)	(0.001)	(0.000)	(0.001)
Observations	618,543	618,543	594,496	594,496
R-squared	0.020	0.020	0.008	0.008
Year FE		✓		✓

Notes: This table reports the results of OLS and logit regressions with the firms loan in Stage 2 as the dependent variable.

$$Y_{it} = \alpha_i + \beta_1 X_{i,t-1} + \beta_2 \text{HighPD}_{i,t-1} + \beta_3 \left(X_{i,t-1} \times \text{HighPD}_{i,t-1} \right) + \tau_t + \varepsilon_{it}.$$

where $X_{i,t-1}$ is either the effect from the firms PD or lending rate, lagged one year. $\text{HighPD}_{i,t-1}$ is a dummy variable equal to one if the firms PD is above 35%. Depending on the specification we include year fixed effects, τ_t. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6. Stage 3 interaction

	Dependent var: Dummy for IFRS stage 3			
	(1)	(2)	(3)	(4)
VARIABLES	OLS	OLS	OLS	OLS
Lagged PD	0.247***	0.247***		
	(0.007)	(0.007)		
High PD group	-0.084***	-0.084***	0.022***	0.023***
	(0.006)	(0.006)	(0.002)	(0.002)
Lagged PD × High PD group	0.038**	0.038**		
	(0.018)	(0.018)		
Lagged lending rate			0.132***	0.141***
			(0.004)	(0.004)
Lagged lending rate × High PD group			0.559***	0.549***
			(0.059)	(0.059)
Constant	0.000***	0.001***	0.001***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	694,372	694,372	675,366	675,366
R-squared	0.029	0.029	0.009	0.009
Year FE		✓		✓

Notes: This table reports the results of OLS and logit regressions with the firms loan in Stage 3 as the dependent variable.

$$Y_{it} = \alpha_i + \beta_1 X_{i,t-1} + \beta_2 \text{HighPD}_{i,t-1} + \beta_3 \left(X_{i,t-1} \times \text{HighPD}_{i,t-1} \right) + \tau_t + \varepsilon_{it}.$$

where $X_{i,t-1}$ is either the effect from the firms PD or lending rate, lagged one year. $\text{HighPD}_{i,t-1}$ is a dummy variable equal to one if the firms PD is above 35%. Depending on the specification we include year fixed effects, τ_t. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7. Bankruptcy interaction

	Dependent var: Dummy for bankruptcy			
	(1)	(2)	(3)	(4)
VARIABLES	OLS	OLS	OLS	OLS
Lagged PD	0.227***	0.227***		
	(0.007)	(0.007)		
High PD group	-0.053***	-0.053***	0.019***	0.022***
	(0.004)	(0.004)	(0.002)	(0.002)
Lagged PD × High PD group	-0.028**	-0.028**		
	(0.011)	(0.011)		
Lagged lending rate			0.325***	0.350***
			(0.007)	(0.007)
Lagged lending rate × High PD group			0.755***	0.730***
			(0.065)	(0.065)
Constant	0.001***	0.002***	-0.003***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	698,557	698,557	680,064	680,064
R-squared	0.031	0.031	0.021	0.022
Year FE		✓		✓

Notes: This table reports the results of OLS and logit regressions with the firm entering bankruptcy as the dependent variable.

$$Y_{it} = \alpha_i + \beta_1 X_{i,t-1} + \beta_2 \text{HighPD}_{i,t-1} + \beta_3 \left(X_{i,t-1} \times \text{HighPD}_{i,t-1}\right) + \tau_t + \varepsilon_{it}.$$

where $X_{i,t-1}$ is either the effect from the firms PD or lending rate, lagged one year. $\text{HighPD}_{i,t-1}$ is a dummy variable equal to one if the firms PD is above 35%. Depending on the specification we include year fixed effects, τ_t. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

5.3 Robustness results

In the previous regressions, we excluded observations of firms that had an observed lending rate but did not have a loan. These observations are typically related to firms that have an established credit line with a bank that they have not yet utilized. Since these lending rates are likely to be standardized rates rather than individual rates, they are less informative than lending rates for firms that do have a bank loan. To test this, we run all lending rate regressions with the entire sample of lending rates but utilize only observations with a PD below 35% in order ensure a maximal comparability with the main regressions. The results in Table A1-A3 follow the same patterns as the main regression results but with a smaller coefficient size. This strengthens our interpretation that these observations do not represent genuine credit risk and should not be included.

Different banks could have different models for setting lending rates and PDs. We therefore run the main regressions and include a dummy for each bank in Tables A4 - A6. The coefficients decrease in size, but the pattern between the different models remains in place. The explanatory power of the regressions increases, suggesting that different banks' models do differ in their ability to correctly predict the outcomes.

It could be the case that banks' PDs are only good estimators for bankruptcy for a certain set of firms, such as firms above a certain size or in a certain industry. We therefore interact the OLS coefficient from the model in column (2) from Tables 2-4 and plot the coefficients in Figure A2-A4. PDs do a better job at predicting bankruptcies for micro firms than for large firms, but there are also more bankruptcies in this category than there are large firms going bankrupt. Likewise, PDs do a better job in predicting bankruptcies in the sectors where bankruptcies are more common, such as restaurants and construction.

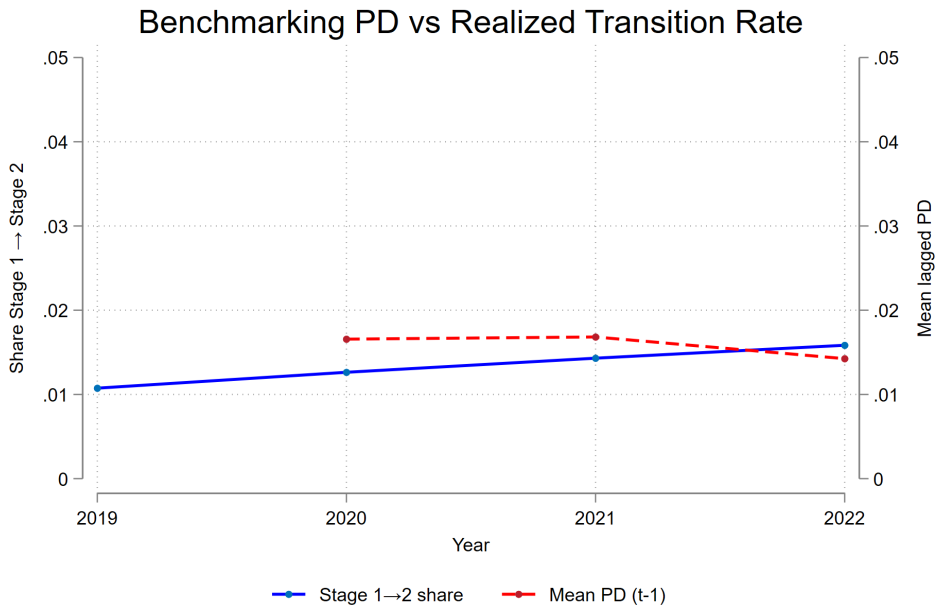
In all regressions, we have clustered the standard errors at the firm level. Changing this to clustering at industry level, for a total of 99 different industries, lead to small differences in significance. Specifically, the interaction term for the PD regressions in Table 5 becomes insignificant, suggesting that industry level shocks are important for changes in firms entering stage 3. However, the interaction term for PD in Table 7 remains significant. All regressions on lending rates remain significant, further strengthening the theory that banks price the riskiness of a loan on the firm level rather than industry level.

For firms with multiple loans, we have used the mean, unweighted, lending rate and PD for each firm. If we instead use the maximum value of PD and lending rate and re-run all regressions in Tables 2-7 the coefficients decrease slightly but remain qualitatively the same. This is consistent with the maximum value being a coarser measurement of the firm's situation. In all previous regressions, we conditioned that the loan of the firm is not in the stage that is being estimated. If we relax this restriction, all patterns remain similar but coefficients and R^2 increase significantly especially for the stage 2 regressions. This is likely due to the fact that firms whose loan enter stage 2 tends to remain there, creating serial correlation in the regression. Results are available on request.

5.4 Aggregate predictions

Even with interaction terms, the explanatory power of the stage 2 regressions was limited. Although PDs may not be accurate in predicting the change in an individual firm, the aggregate PD level could be efficient in predicting the aggregate change in loans that migrate from stage 1 to stage 2. This would be similar to having exact knowledge of the the half-life of a radioactive isotope despite that it is impossible to predict when an individual atom will decay. We therefore plot the share of loans that migrate from stage 1 to stage 2 in Figure 5 and compare that to the aggregate PD in the previous year. As before, we do not utilize the PD values above 35 %. The plot suggests that on an aggregate level, banks' PDs are close to the aggregate migration of loans from stage 1 to stage 2.

Figure 5. Macro-performance of PD and Stage 2



Notes: The blue line displays the share of all stage 1 loans that transitions into stage 2 per year. The red line displays the mean PD for the previous year.

6 Conclusion

Predicting bankruptcies and possible credit losses is of great importance both to banks themselves but also to relevant agencies. Large credit losses can lead to failing banks, with large impacts on society (Correia et al., 2025). This paper uses detailed data on firm lending to evaluate how efficient banks' own estimated PDs and their lending rates are in predicting whether the firms' loan enters stage 2, 3 or the firm entering bankruptcy. For stage 2, there is a clear increase in the probability of the loan entering stage 2 when the firm's PD increases. However, this is only true for PDs below 35%, and the marginal predictive power is declining after a peak of about 25%. This is likely a combination of accounting rules that stresses the derivative, rather than the level of risk, and internal flagging of loans at higher risk levels. Lending rates are less efficient in predicting loans entering stage 2, possibly suggesting that banks do not increase the price related to lower levels of risk. When predicting the most drastic outcome, i.e. a firm entering bankruptcy, the lending rate of the firm instead has an increasingly steep predictive power. This could both be due to an efficient pricing of risk and due to the endogeneity of high lending rates, with corresponding high capital costs, pushing the firm into bankruptcy.

Like the Holy Roman Empire which was neither Holy nor Roman nor an Empire, the probability of default is neither a purely statistical probability, a measurement of default in the typical sense of the term, nor an direct accounting rule. Instead, it is a hybrid measurement that combines probabilities, banks' internal flags and accounting rules into one measurement. This measurement is useful but requires a careful handling to extract the most information from (Novotny-Farkas, 2016).

The predictive power of the main regression is low, with the highest R^2 of any stage 2 regression being less than 3 percentage points. However, it is also uncommon that a firm's loan is in stage 2 and even more so that they go bankrupt. One way to view these results is therefore that a change in the risk attached to loan is a good example of Knightian uncertainty that is difficult to predict at the individual level (Knight, 1921). It could also be the case that Swedish banks are skilled at identifying credit risk in firms, but prefer to ration credit to these firms rather than lend to them at elevated lending rates (Stiglitz & Weiss, 1981; Kirschenmann, 2016). Recent research shows that banks in richer countries prefer lending to real estate with collateral rather than manufacturing (Dai et al., 2025). This is clear in panel (c) in A1, with roughly half of all lending going to commercial real estate. Swedish banks have, for many years, decreased their number of bank offices, possibly reducing their lending based on soft information (Kärnä et al., 2021; Amberg & Becker, 2024; Aguirregabiria et al., 2025). Likewise, bank-lending regulation has increased, leading to reduced lending to high-risk and smaller firms (Gopalakrishnan et al., 2021; Ertan, 2025). Unfortunately, our panel of bank information is too short to identify the effects of regime changes.

From a policy perspective, public agencies could benefit from using a combination of information depending on their objective. For the lower levels of financial risk, PD is the most efficient predictor, especially at the macro level. However, when predicting more serious outcomes, lending rates and especially high lending rates, are also of great interest.

References

Aguirregabiria, V., Clark, R., & Wang, H. (2025). The geographic flow of bank funding and access to credit: Branch networks, synergies, and local competition. *American Economic Review*, 115(6), 1818–1856.

Ai, C. & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics letters*, 80(1), 123–129.

Amberg, N. & Becker, B. (2024). *Banking without branches.* Technical Report 430, Sveriges Riksbank Working Paper Series.

Banerjee, R. & Kharroubi, E. (2020). The financial vulnerabilities driving firms to the exit. *BIS Quarterly Review*, (4), 57–69.

Bank for International Settlements (2017). IFRS 9 and expected loss provisioning – executive summary. Accessed: 2025-10-27.

Behn, M., Haselmann, R., & Wachtel, P. (2016). Procyclical capital regulation and lending. *The Journal of Finance*, 71(2), 919–956.

Bennedsen, M., Pérez-González, F., & Wolfenzon, D. (2020). Do CEOs matter? Evidence from hospitalization events. *Journal of Finance*, 75(4), 1877–1911.

Bernanke, B., Gertler, M., & Gilchrist, S. (1996). The financial accelerator and the flight to quality. *Review of Economics and Statistics*, 78(1), 1–15.

Bräuning, F., Joaquim, G., & Stein, H. (2023). Interest expenses, coverage ratio, and firm distress. *Federal Reserve Bank of Boston Research Paper Series Current Policy Perspectives Paper*, (96664).

Buchetti, B., Perdichizzi, S., & Santoni, A. (2025). Fast to cut, slow to restore: Bank lending responses to IFRS 9 stage migrations. *Economics Letters*, 254, 112446.

Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In search of distress risk. *Journal of Finance*, 63(6), 2899–2939.

Correia, S., Luck, S., & Verner, E. (2025). Failing banks. *Quarterly Journal of Economics.*

Dai, P., Müller, K., & Verner, E. (2025). Finance, structural change, and growth. *Available at SSRN 5079393.*

Ertan, A. (2025). Expected losses, unexpected costs? Evidence from SME credit access under IFRS 9. *The Accounting Review*, 100(4), 443–473.

Gilchrist, S. & Mojon, B. (2018). Credit risk in the euro area. *The Economic Journal*, 128(608), 118–158.

González-Aguado, C. & Suarez, J. (2015). Interest rates and credit risk. *Journal of Money, Credit and Banking*, 47(2-3), 445–480.

Gopalakrishnan, B., Jacob, J., & Mohapatra, S. (2021). Risk-sensitive basel regulations and firms' access to credit: Direct and indirect effects. *Journal of Banking & Finance*, 126, 106101.

Gropp, R., Mosk, T., Ongena, S., & Wix, C. (2019). Banks response to higher capital requirements: Evidence from a quasi-natural experiment. *The Review of Financial Studies*, 32(1), 266–299.

IFRS Foundation (2025). IFRS 9 financial instruments. Accessed: 2025-10-27.

Jacobson, T., Lindé, J., & Roszbach, K. (2013). Firm default and aggregate fluctuations. *Journal of the European Economic Association*, 11(4), 945–972.

James, C., Lu, J., & Sun, Y. (2021). Time is money: Real effects of relationship lending in a crisis. *Journal of Banking & Finance*, 133, 106283.

Kärnä, A., Manduchi, A., & Stephan, A. (2021). Distance still matters: Local bank closures and credit availability. *International Review of Finance*, 21(4), 1503–1510.

Kirschenmann, K. (2016). Credit rationing in small firm-bank relationships. *Journal of Financial Intermediation*, 26, 68–99.

Knight, F. H. (1921). *Risk, uncertainty and profit.* Hart, Schaffner and Marx.

Krüger, S., Rösch, D., & Scheule, H. (2018). The impact of loan loss provisioning on bank capital requirements. *Journal of Financial Stability*, 36, 114–129.

Leventis, S., Dimitropoulos, P. E., & Anandarajan, A. (2011). Loan loss provisions, earnings management and capital management under ifrs: The case of eu commercial banks. *Journal of financial services research*, 40(1), 103–122.

Miao, H., Ramchander, S., Ryan, P., & Wang, T. (2018). Default prediction models: The role of forward-looking measures of returns and volatility. *Journal of Empirical Finance*, 46, 146–162.

Novotny-Farkas, Z. (2016). The interaction of the IFRS 9 expected loss approach with supervisory rules and implications for financial stability. *Accounting in Europe*, 13(2), 197–227.

Schüle, T. (2007). Forbearance lending and soft budget constraints in multiple bank financing. *Journal of Institutional and Theoretical Economics (JITE)/Zeitschrift für die gesamte Staatswissenschaft*, (pp. 448–466).

Stepankova, B. & Teply, P. (2023). Consistency of banks' internal probability of default estimates: Empirical evidence from the covid-19 crisis. *Journal of Banking & Finance*, 154, 106969.

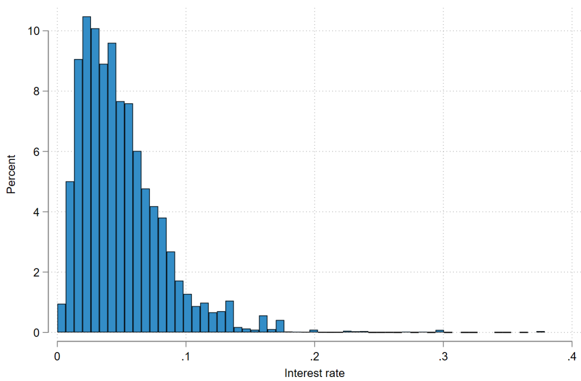
Stiglitz, J. E. & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, 71(3), 393–410.

Suarez, J. (2018). *The Procyclicality of Expected Credit Loss Provisions.* Technical report, CEPR Discussion Papers.

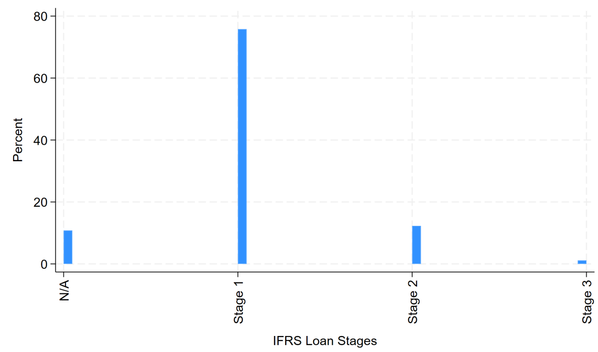
Tian, S., Yu, Y., & Guo, H. (2015). Variable selection and corporate bankruptcy forecasts. *Journal of Banking & Finance*, 52, 89–100.

Appendix

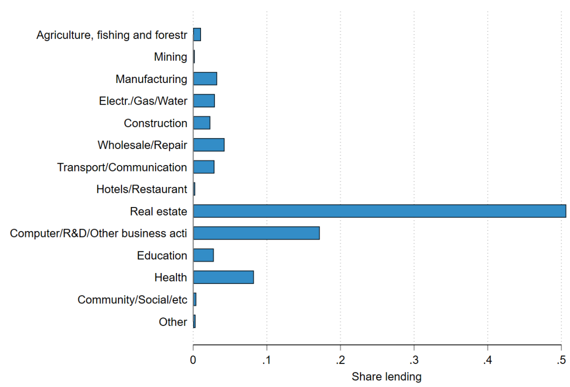
Figure A1. Descriptive statistics



(a) lending rates



(b) Loans by IFRS stage



(c) Share lending per industry

Table A1. IFRS stage 2, full lending rate sample

VARIABLES	(1) OLS	(2) OLS	(3) Logit	(4) Logit
Lagged lending rate	0.459***	0.448***	0.391***	0.380***
	(0.009)	(0.009)	(0.007)	(0.007)
Constant	0.049***	0.048***		
	(0.000)	(0.001)		
Observations	606,209	606,209	606,209	606,209
R-squared	0.005	0.005		
Year FE		✓		✓
Pseudo R-squared			0.00879	0.00962

Notes: This table reports the results of regression similar to Table 2 but includes observations for firms with an observed lending rate and no corresponding bank loan. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A2. IRFS stage 3, full lending rate sample

VARIABLES	(1) OLS	(2) OLS	(3) Logit	(4) Logit
Lagged lending rate	0.058***	0.057***	0.043***	0.042***
	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0.002***	0.003***		
	(0.000)	(0.000)		
Observations	681,481	681,481	681,481	681,481
R-squared	0.001	0.001		
Year FE		✓		✓
Pseudo R-squared			0.0153	0.0171

Notes: This table reports the results of regression similar to Table 3 but includes observations for firms with an observed lending rate and no corresponding bank loan. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A3. Bankrupt, full lending rate sample

VARIABLES	(1) OLS	(2) OLS	(3) Logit	(4) Logit
Lagged lending rate	0.089***	0.091***	0.061***	0.062***
	(0.003)	(0.003)	(0.002)	(0.002)
Constant	0.002***	0.003***		
	(0.000)	(0.000)		
Observations	682,169	682,169	682,169	682,169
R-squared	0.002	0.002		
Year FE		✓		✓
Pseudo R-squared			0.0272	0.0283

Notes: This table reports the results of regression similar to Table 4 but includes observations for firms with an observed lending rate and no corresponding bank loan. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A4. IFRS stage 2, bank fixed effects

	Dependent var: Dummy for IFRS stage 2			
VARIABLES	(1) OLS	(2) Logit	(3) OLS	(4) Logit
Lagged PD	0.131***	0.078***		
	(0.005)	(0.002)		
Lagged lending rate			0.239***	0.213***
			(0.012)	(0.011)
Constant	0.027		0.027	
	(0.018)		(0.017)	
Observations	538,281	538,281	606,766	606,766
R-squared	0.024		0.025	
Year FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Pseudo R-squared		0.0486		0.0486

Notes: This table reports the results of regression similar to Table 2 but includes bank fixed effects dummy. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A5. IRFS stage 3, bank fixed effects

	Dependent var: Dummy for IFRS stage 3			
	(1)	(2)	(3)	(4)
VARIABLES	OLS	Logit	OLS	Logit
Lagged PD	0.220***	0.033***		
	(0.007)	(0.001)		
Lagged lending rate			0.083***	0.055***
			(0.004)	(0.002)
Constant	0.009		0.008	
	(0.008)		(0.008)	
Observations	603,722	601,979	680,166	678,420
R-squared	0.034		0.003	
Year FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Pseudo R-squared		0.124		0.0357

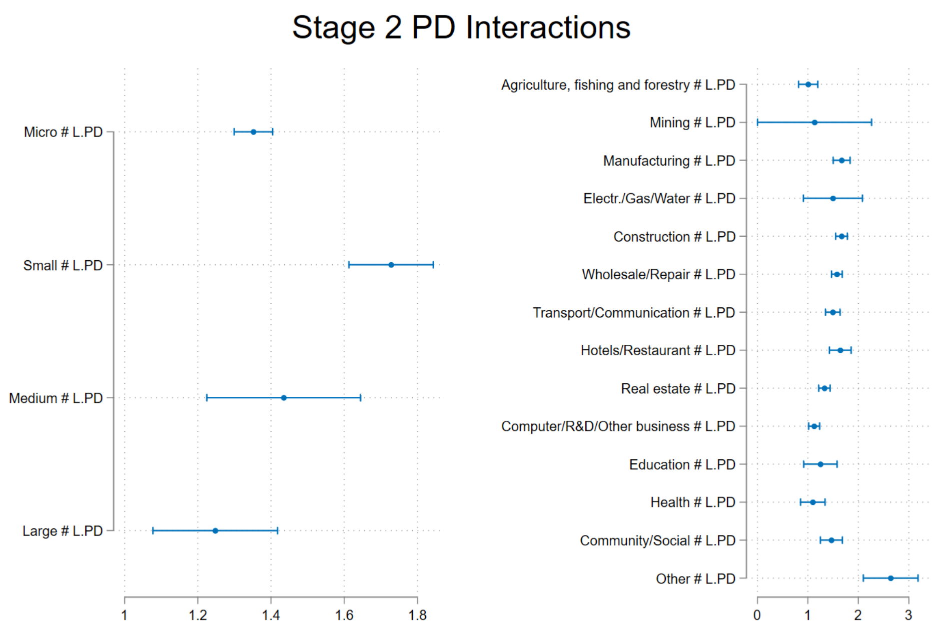
Notes: This table reports the results of regression similar to Table 3 but includes bank fixed effects dummy. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A6. Bankrupt, bank fixed effects

	Dependent var: Dummy for bankruptcy			
	(1)	(2)	(3)	(4)
VARIABLES	OLS	Logit	OLS	Logit
Lagged PD	0.115***	0.016***		
	(0.004)	(0.000)		
Lagged lending rate			0.114***	0.068***
			(0.004)	(0.002)
Constant	-0.000		-0.001***	
	(0.001)		(0.000)	
Observations	606,885	604,902	683,224	681,151
R-squared	0.029		0.005	
Year FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Pseudo R-squared		0.133		0.0649

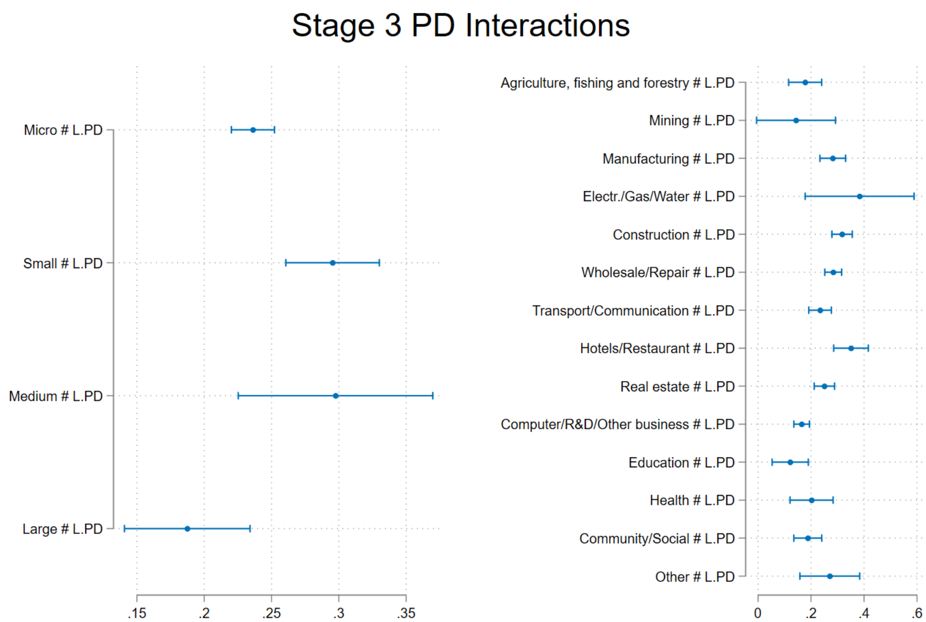
Notes: This table reports the results of regression similar to Table 4 but includes bank fixed effects dummy. Firm-level clustered standard errors are reported in parentheses. *,**, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Figure A2. Stage 2 PD interactions



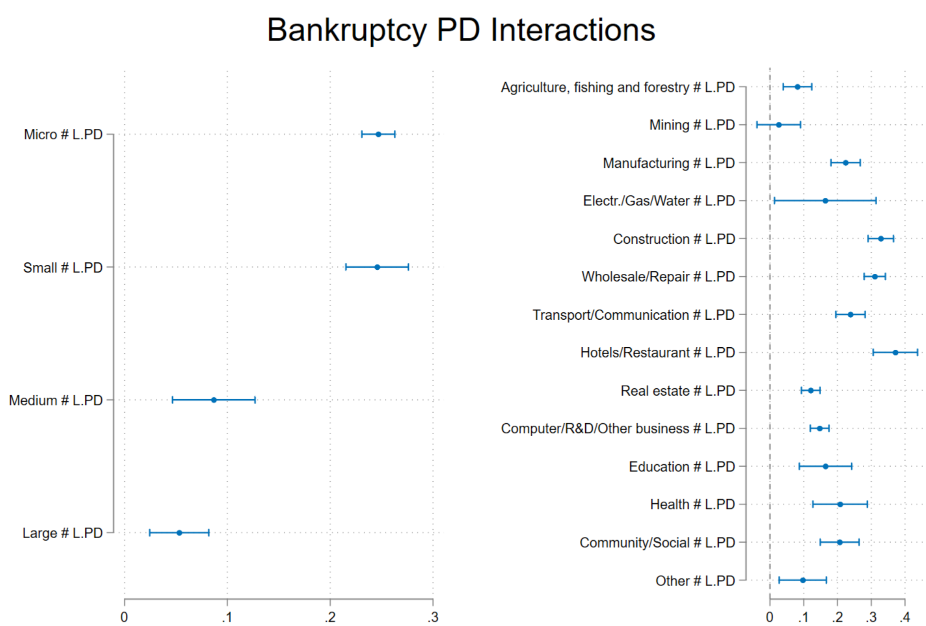
Notes: This table reports the results of regression 2 where the PD is interacted with a single digit industry dummy. Confidence intervals based on firm-level clustered standard errors.

Figure A3. Stage 3 PD interactions



Notes: This table reports the results of regression 3 where the PD is interacted with a single digit industry dummy. Confidence intervals based on firm-level clustered standard errors.

Figure A4. Bankruptcy PD interactions



Notes: This table reports the results of regression 4 where the PD is interacted with a single digit industry dummy. Confidence intervals based on firm-level clustered standard errors.

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