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New microdata for loan defaults provide better estimates of banks' credit losses

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New microdata for loan defaults provide better estimates of banks' credit losses

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Abstract

Loans to non-financial firms are the main source of banks' losses. In order to assess credit risk, Norges Bank has long used models to assess firms' bankruptcy probability. However, the banks' credit losses are more closely linked to firms that default on their loans. Defaulting loans are only partly comprised of loans to firms that go bankrupt. Loan defaults are therefore likely a better indicator of banks' losses than bankruptcies. Microdata on both credit losses and loan defaults have historically been limited, especially compared to microdata on bankruptcies. Improved access to microdata for loan defaults allows us to analyse the relationship between loan defaults and bankruptcy at the micro-level. We find a strong correlation between loan default and bankruptcy, but that the relationship varies across industries and the analysis period. In particular, the Covid-19 pandemic marks a difference in this relationship. We use analysis insights to develop a model that estimates default probabilities, and to estimate new loan defaults going forward. Finally, we show how to use this exercise to improve estimates of banks' corporate loan losses. These estimates will form part of Norges Bank's assessment of credit risk in the Norwegian banking system.

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1 Introduction

When assessing risks and vulnerabilities in the financial system, it is important to have thorough analyses of the risk of losses associated with the banks' corporate loans. Around 40 percent of the banks' lending is to non-financial firms, and historically, these loans have accounted for the majority of the banks' losses.

Norges Bank has long used bankruptcy probability models to analyse risk of losses on corporate loans, utilising ample access to data on bankruptcies. However, banks' credit losses are not only limited to firms that go bankrupt. Significant losses may also arise if firms that do not go bankrupt default on loans. Although banks' loss assessments are relatively complex[1], loan defaults are probably a better indicator of credit losses than bankruptcies. The challenge has been limited microdata for both credit losses and loan defaults. Several analyses[2] have therefore used a "rule of thumb" that states that the bankruptcy rate is about half as large as the loan default rate.[3]

Improved access to microdata for banks' corporate loans, including information on loan defaults over the past six years, makes it possible to analyse the relationship between bankruptcy and loan default at the micro-level. We use a sample of these data to estimate a model for the probability of default, based on estimated bankruptcy probabilities from one of Norges Bank's bankruptcy probability models. We argue that the model follows actual loan defaults better than the rule of thumb described above. We use the model to estimate new loan defaults going forward and show how this exercise can contribute to improved estimates of banks' credit losses at the micro-level.

In Section 2 we describe the data and sample included in the analysis, and in Section 3 we describe the relationship between bankruptcy and loan default across years and industries. Section 4 describes how we go from bankruptcy probabilities to default probabilities and presents a model for default probability. We then use this model to estimate new loan defaults and credit losses on banks' corporate loans in Section 5. Section 6 concludes.

[1]See box on page 23 in "Financial Stability Report 2024 H1" for a review of accounting rules for impairment recognition under the current framework

[2]See Bernhardsen and Larsen (2007), Andersen and Hjelseth (2019) and Hjelseth et al. (2024).

[3]The relationship is based on a simple statistical model for misclassification documented in Bernhardsen (2001) and Bernhardsen and Syversten (2009).

2 Data and sample

We use data from different sources to analyse the relationship between loan defaults and bankruptcy. This Section provides an overview of the different data sources and the data sample used in the analysis.

2.1 Data

We mainly use microdata for banks' lending, loan defaults and loan loss provisions (LLPs) from Finanstilsynet's (The Financial Supervisory Authority of Norway) exposure database (ENGA) and Finanstilsynet's specification of credit losses (STU) reporting. In addition, we use bankruptcy data from the Register of Mortgaged Movable Property and estimated bankruptcy probabilities from Hjelseth et al. (2022).

2.1.1 Microdata for banks' lending, loan defaults and provision rate

The banks in the Norwegian banking sector report data on their corporate exposures (ENGA) to Finanstilsynet. We have annual data for the period 2017 to 2023, and use information on loans per firm per bank (drawn loans), as well as the banks' assessment of the probability of default, $P(D)$.[4] We define a loan as defaulted if the reported $P(D)$ is very high, i.e. it exceeds 90 percent, found experimentally to be the best measure to capture actual loan defaults.

Finanstilsynet also collects a quarterly survey in which banks are required to specify recognised credit losses, loan defaults, and write-downs on loans by industry. From this data source, we use loan default data from 2018 to 2023 to cross-check the data from ENGA, and information on industry-specific write-downs and loan defaults for the first and second quarters of 2024 to calculate a industry-specific provision rate at default. The provision rate at default, often referred to as the loss-given-default (LGD) ratio, is the proportion of the defaulted loans that banks set aside as credit losses. We use this to estimate LLPs on defaulted loans going forward.

2.1.2 Bankruptcy data

We use bankruptcy data from the Register of Mortgaged Movable Property for the period from January 2016 to September 2024. As in our bankruptcy probability models, both an-

[4] The banks report one exposure per firm per year. For simplicity, we refer to this as one loan per firm per year, even though an exposure may consist of several loans.

nouncements of compulsory dissolution and announcements of bankruptcy are included in the definition of bankruptcy. The data is provided by Dun & Bradstreet.

2.1.3 Bankruptcy probability data

We use estimated probabilities of bankruptcy, $P(B)$, from the bankruptcy probability model documented in Hjelseth et al. (2022). We refer to this model as *KOSMO 2*. The model estimates the probability of firms going bankrupt in year t based on accounting data and payment remarks for year $t-1$ and macroeconomic indicators for year t. In the model, the year of bankruptcy is defined as the year in which the firms's activity ceases. This means that firms are classified as bankrupt in year t if year $t-1$ is the last year the firm is registered as active, and the bankruptcy is registered in year t or year $t+1$.

2.2 Data sample

In the analysis we use two different data samples. In the discussion of bankruptcy probabilities in Section 4.1 and in the calculation of the estimates in Section 5, the sample of firms is the same as in KOSMO 2. This means that the sample is limited to Norwegian-registered, non-financial limited firms with bank debt in the following industries: fishing and aquaculture, manufacturing, retail trade, construction, real estate development, commercial real estate and services.[5] Oil-related industries, international shipping, power supply and agriculture and forestry are not covered by the model and are therefore also excluded from the sample. The sample accounted for approximately 80 percent of loans to Norwegian non-financial firms at the end of 2023. See Hjelseth et al. (2022) for a more detailed description of the data sample in KOSMO 2.

For the remainder of the analysis, the data sample is further restricted to the loan exposures from a selection of nine large banks, which we consider to have high-quality reporting of $P(D)$ over time.[6] This sample covers just under 60 percent of the banks' total lending to non-financial firms at the end of 2023.

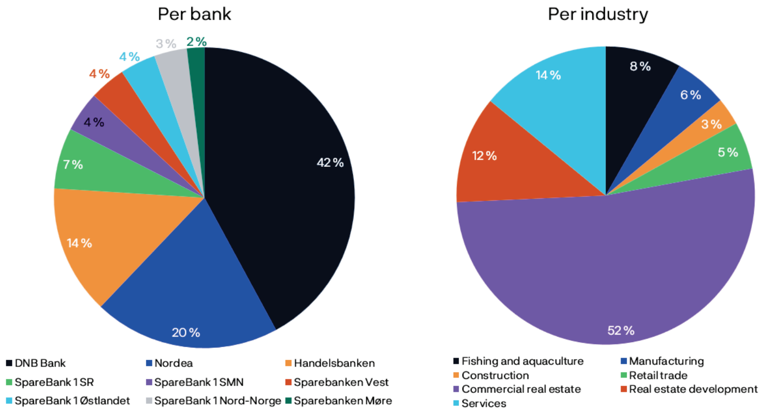
Chart 1 shows the distribution of loans in the latter data sample at the end of 2023, broken down by the banks and industries included in the sample. DNB Bank is the largest

[5]KOSMO 2 estimates six models, while in this analysis we divide into seven industries. The difference is that KOSMO 2 estimates bankruptcy probabilities for commercial real estate and real estate development in the same model.

[6]The nine banks are DNB Bank, SpareBank 1 SR, SpareBank 1 Nord-Norge, SpareBank 1 SMN, Sparebanken Vest, Nordea, Handelsbanken, SpareBank 1 Østlandet and Sparebanken Møre. These banks accounted for almost 70 percent of total lending to Norwegian non-financial firms at the end of 2023.

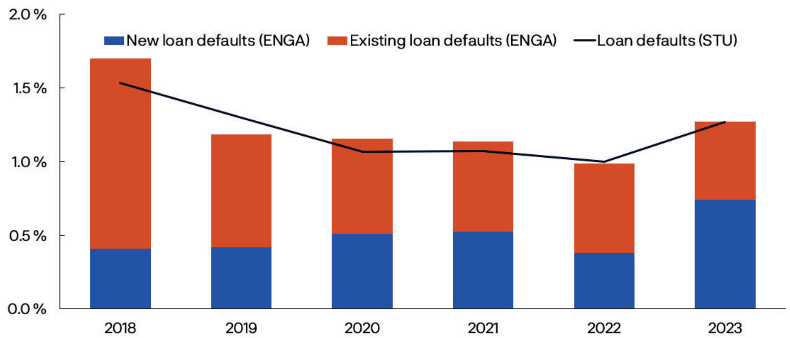
bank, with just over 40 percent of the loans in the sample. The largest industry is commercial real estate, which accounts for just over half of the loans in the sample.

Chart 1: Share of loans per bank and industry in the data sample at the end of 2023



Sources: Finanstilsynet and Norges Bank

Chart 2: Loan defaults as a share of total loans to Norwegian non-financial firms in nine large banks



Sources: Finanstilsynet and Norges Bank

Chart 2 shows the development in loan defaults in the latter data sample from the two data sources, ENGA and STU. The Chart illustrates that the development in loan defaults is quite similar in the two data sources, with only minor deviations in 2018 and 2019. In the Chart, we also differentiate between new and existing loan defaults, where new loan defaults are identified by the first year a loan defaults. Existing loan defaults are defaults that have been identified as loan defaults in previous years. Our analysis focuses on new loan defaults as these are most relevant for new losses in banks' loan portfolios. Since data from 2017 is used to detect loan defaults occurring in 2018, we only present results from 2018 onwards in the analysis.

3 Relationship between bankruptcy and loan default

3.1 Almost all firms that go bankrupt have defaulted loans

A firm defaults on a loan when it has liquidity problems. To go bankrupt, the firm must be considered insolvent, i.e. the value of its assets is less than the sum of its liabilities.

It is natural that loan defaults occur more frequently than bankruptcies among firms with loans. Liquidity problems can be temporary. There may also be cases where it is more profitable for a bank to negotiate with a firm experiencing payment problems rather than allowing it to go bankrupt. Similarly, it is reasonable to assume that firms that have loans and go bankrupt have also defaulted on their loans.

Table 1: Categories of loans

Category	Quantity
Healthy loans*	247 675
Defaulted loans	8 110
Of which: Not bankrupt	4 612
Of which: Bankrupt	3 498
Bankrupt, but not default	121
Total number of loans	255 906

*We define healthy loans as loans that are neither registered as defaulted nor bankrupt in our dataset.

As expected, table 1 confirms that loan defaults occur more often than bankruptcies among firms with loans.[7] The table also confirms that almost all bankrupt firms are found among firms with loan defaults. Only 3 percent of the loans to firms that have gone bankrupt can be found among non-defaulting loans.[8]

[7] In the table, each loan is counted once per year. Both new and existing loan defaults are included, so the same loan default is counted several times if it exists over several years. Similarly, bankruptcies can also be counted multiple times.

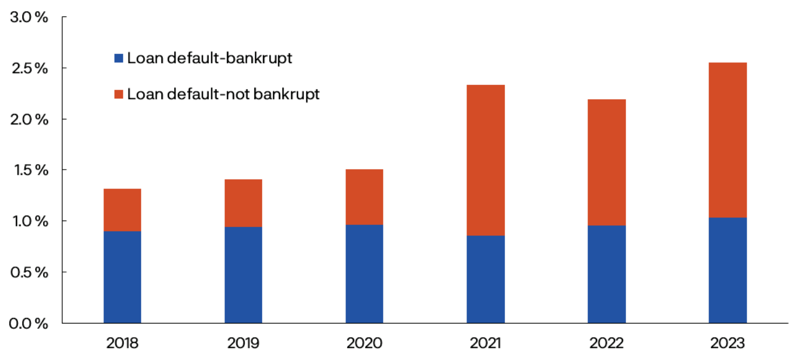
[8] Some of the loans to firms that have gone bankrupt, but not defaulted according to our definition, have missing $P(D)$. Some of these loans may have defaulted, but we do not capture them. In this *Memo* we will only consider the bankruptcies among defined defaulted loans.

3.2 The relationship between bankruptcy and loan default has varied over the analysis period

We find that the Covid-19 pandemic marks a clear distinction in the relationship between loan default and bankruptcy.

Firstly, there have been markedly fewer bankruptcies in relation to loan defaults after the pandemic, see Chart **3**. In the period from 2018 to 2020, almost 70 percent of firms in default went bankrupt, while from 2021 to 2023 this ratio fell to around 40 percent. The drop in bankruptcy rate is consistent among loan defaults in all industries, likely reflecting the measures taken during the pandemic, especially that bankruptcy petitions were put on hold for a longer period by the Norwegian Tax Administration. This contributed to abnormally low bankruptcy numbers during the pandemic. Firms also had the opportunity to postpone their payments of, among other things, VAT for a period of time, which was frequently used by weaker firms, see Hjelseth et al. (2021). Since the path from non-payment of public taxes and fees to bankruptcy is often short, this may also have contributed to fewer bankruptcies during the pandemic. The measures may have led to both bankruptcies and loan defaults being lower than they would otherwise have been, but they probably had the greatest effect on bankruptcies.

Chart 3: Fewer bankruptcies relative to loan defaults after the pandemic
Number of new loan defaults as a share of total number of loans broken down by whether the firm has gone bankrupt or not

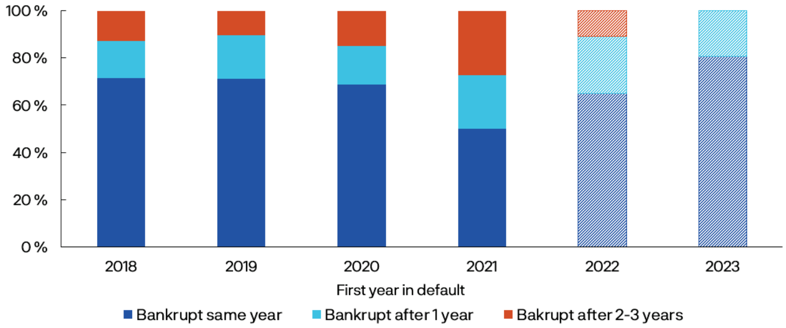


Sources: Brønnøysund Register Center, Dun & Bradstreet, Finanstilsynet and Norges Bank

Secondly, the time it takes from loan default to bankruptcy also seems to have changed since the pandemic. It is natural to think that loan defaults occur well before bankruptcy and can therefore identify problems in firms at an earlier stage than bankruptcies, see for example Blanco et al. (2023). However, before the pandemic, in the period between 2018 and

2020, 70 percent of bankruptcies occurred in the same year as the loan default first occurred, see Chart 4. Therefore, during this period, the time from loan default to bankruptcy has been shorter than one might typically expect.[9] After the outbreak of the Covid-19 pandemic, the time it takes from loan default to bankruptcy has widened. In 2021, only 50 percent of bankruptcies occurred in the same year as the loan default first occurred. This change is probably also due to the measures taken during the pandemic, as described above.

Chart 4: The time from loan default to bankruptcy has increased after the pandemic
Share of firms that go bankrupt in the same year, one year after and two to three years after the first year in default



Sources: Brønnøysund Register Center, Dun & Bradstreet, Finanstilsynet and Norges Bank

We do not yet have complete data on how many firms went bankrupt two to three years after loan default in 2022 and 2023, meaning that we cannot know exactly how long it will take on average from loan default to bankruptcy in 2022 and 2023. However, preliminary figures indicate that it has also taken longer than before the pandemic, shown by shaded bars in Chart 4. Even missing large parts of the data in 2022 for the red portion of the bar in the Chart (bankruptcy two to three years after loan default), the dark blue portion of the bar (bankruptcy in the same year as loan default) is still lower than before the pandemic. The bar for 2023 in Chart 4 lacks the red portion completely, and some of the light blue. It is therefore natural to assume that the dark blue portion will fall when these data points are included.

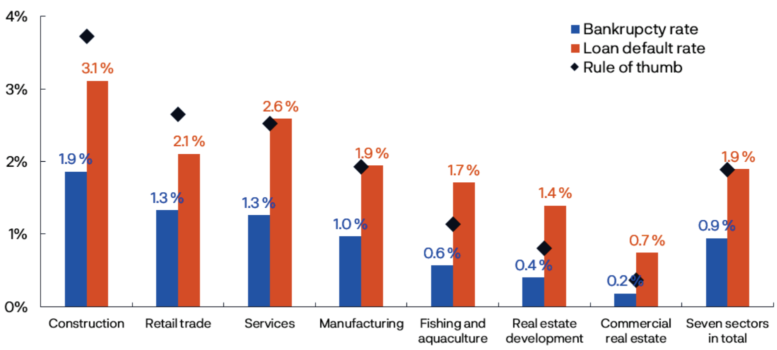
[9]It usually takes some time from a firm experiencing problems to becoming insolvent and filing for bankruptcy, see for example Statistics Norway (2020). Hjelseth and Raknerud (2016) finds that there are often two years between the last available annual accounts and the actual bankruptcy registration.

3.3 Half of firms with loan defaults also go bankrupt, but the relationship varies across industries

In Section 1 we mentioned that in the absence of data on loan defaults, several previous Norges Bank analyses have used a rule of thumb that suggests the bankruptcy rate is roughly half the loan default rate. In this Section, we use our data to test this rule of thumb.

The blue bars in Chart 5 represent the number of loans to firms that have gone bankrupt relative to the total number of loans in each industry, as well as the overall total. The black diamonds indicate what the loan default rate will be if the rule of thumb is applied, while the red bars show what the actual loan default rate is. We measure the loan default rate as the rate of new loan defaults, so that we only count each defaulted loan once, as for bankruptcies.

Chart 5: The relationship between bankruptcy and loan default varies across industries
Number of loans to bankrupt firms and number of new defaulted loans as a share of total loans



Sources: Brønnøysund Register Center, Dun & Bradstreet, Finanstilsynet and Norges Bank

We find that the rule of thumb holds quite well when looking at all loans combined. In total, 0.9 percent of loans have been to firms that have gone bankrupt, while the loan default rate has been 1.9 percent. However, we see that the relationship between bankruptcy and loan default varies across industries.

The rule of thumb is fairly accurate for services and manufacturing, while in retail trade and construction the loan default rate has been lower than the rule of thumb suggests.

The loan default rate is lowest in fishing and aquaculture, real estate development and commercial real estate, but these industries nevertheless have three to four times as many loan defaults as bankruptcies. One of the reasons for this is probably that these firms are more prone to encountering liquidity problems rather than solvency issues. In recent times, banks have typically imposed strict equity ratio requirements when lending to real estate development and commercial real estate. This means that the firms that receive loans are more solid than they otherwise could have been.

Another possible reason for the relatively fewer bankruptcies in these industries could be that banks have a greater vested interest in preventing these firms from going bankrupt due to the often large size of the loans. In the case of large loans, banks risk large losses in the event of bankruptcy, as the sale of assets may have to take place in unfavourable market conditions, resulting in lower-than-usual sale prices. By restructuring the debt and keeping the firm alive, the loss could potentially be smaller than if the firm had gone bankrupt.

Overall, these results show that, when assessing loan default risk, it is important to take into account that the relationship between loan default and bankruptcy varies across industries.

4 From probability of bankruptcy to probability of default

The aim of this analysis is to improve estimates of bank loan defaults and corporate loan credit losses using new data on loan defaults. Since Norges Bank already has well-established bankruptcy probability models, we want to use these to predict the risk of loan default.[10]

In the previous Section, we described the relationship between bankruptcy and loan default during the period for which we have data. If we had used the rule of thumb to estimate the probability of loan default based on estimates of the probability of bankruptcy, it would have doubled for all industries. However, the insights from Section 3 indicate that there is a lot of variation in the relationship between bankruptcy and loan default.

In this Section, we first present estimated bankruptcy probabilities from KOSMO 2 and show that these probabilities also signal which firms will default on loans but not go bankrupt. We then estimate this effect in a model for the probability of default without bankruptcy, $P(D|\bar{B})$. Finally, we combine the predictions from the two models into the model of main interest – the model for the overall probability of default, $P(D)$.

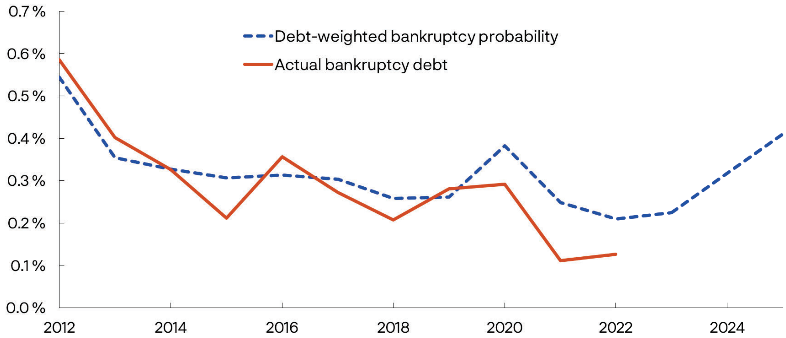
[10] As the dataset for loan defaults increases in size, it may be advisable to develop models for default probability that are independent of the already estimated bankruptcy probability models.

4.1 Estimated bankruptcy probabilities from KOSMO 2

The dashed line in Chart 6 shows estimated debt-weighted probabilities of bankruptcy or debt[11] at risk of bankruptcy, for the period 2012 to 2023 and projections for 2024 and 2025 for the seven industries in the analysis as a whole. The solid line shows actual bank debt in bankrupt firms (bankruptcy debt).

Chart 6: KOSMO 2 signals increased bankruptcy risk ahead

Aggregated debt-weighted bankruptcy probability from KOSMO 2 and actual bankruptcy debt as a share of total bank debt



Sources: Brønnøysund Register Center, Dun & Bradstreet and Norges Bank

We observe that the estimated debt at risk of bankruptcy closely follows the actual bankruptcy debt up until the Covid-19 pandemic. In 2020, weak macroeconomic indicators contributed to an increase in the estimated debt at risk of bankruptcy, exceeding the actual bankruptcy debt. From 2021, macroeconomic indicators improved significantly, leading to a decline in debt at risk of bankruptcy. This decrease is also linked to the reduction in the number of firms with payment remarks, see Hjelseth and Liaudinskas (2024). However, the actual bankruptcy debt fell even further, largely due to the measures implemented during the pandemic, as discussed in Chapter 3. The model also overestimates the actual bankruptcy debt in 2022. We do not yet have complete figures for bankruptcy debt after 2022[12], but given that the number of bankruptcies has slightly increased over the past two years, we expect bankruptcy debt to show an increase for 2023, which will reduce the discrepancy between the model estimates and the actual developments once again.

In 2024 and 2025, the model projects that bankruptcy debt will increase slightly, but from a low level. Increased payment remarks, somewhat weaker accounting figures and slightly

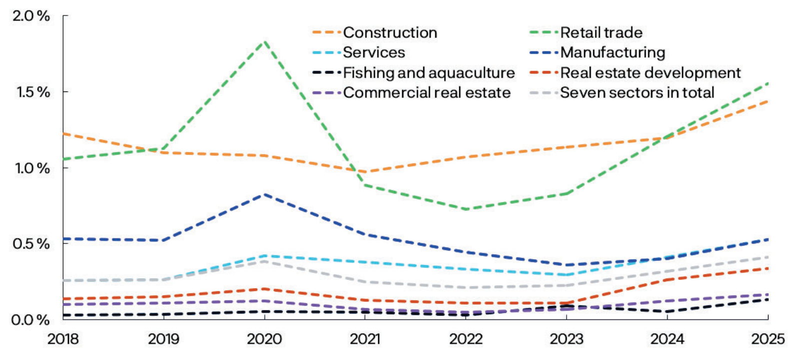
[11] Debt is here defined as long-term and short-term debt to credit institutions as shown in the annual accounts. In simplified terms, this is to be regarded as the firms' bank debt.

[12] This is due to the model's definition of bankruptcy, see Chapter 2.1.3.

weaker macroeconomic indicators all contribute to the increase in estimated debt at risk of bankruptcy.

In percentage points, the increase in estimated debt at risk of bankruptcy from 2023 to 2025 is largest within retail, followed by construction, real estate development and services, as shown in Chart 7. However, the relative increase is greatest for real estate development, followed by commercial real estate. When considering the size of bank debt in each industry, services, retail and commercial real estate account for most of the increase in the probability of bankruptcy, with around 25 percent each.

Chart 7: Bankruptcy risk is increasing in several industries
Industry-specific debt-weighted bankruptcy probabilities from KOSMO 2



Sources: Brønnøysund Register Center, Dun & Bradstreet and Norges Bank

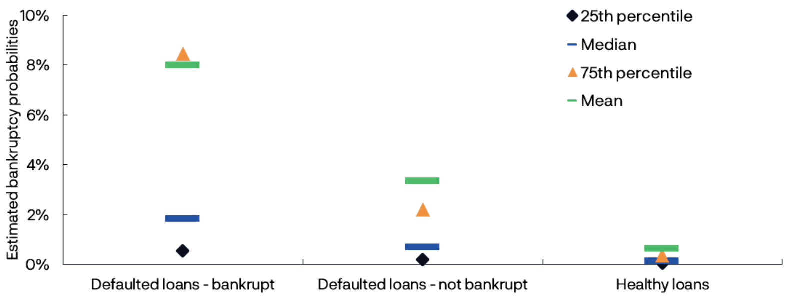
4.2 Bankruptcy probabilities can be used to predict loan defaults on loans to non-bankrupt firms

The estimated bankruptcy probabilities are, of course, intended to predict which firms will go bankrupt. If we are to use these bankruptcy probabilities to predict loan defaults, the bankruptcy probabilities must also be relevant for firms that default without going bankrupt. In other words, there must be a difference in the probability of bankruptcy between firms that default without going bankrupt and firms with healthy loans.

In Chart 8 we have linked the estimated bankruptcy probabilities to each firm with loans in the dataset and divided the firms into three categories: healthy loans, defaulted loans without bankruptcy and defaulted loans with bankruptcy.

The Chart indicates that bankruptcy probabilities are relevant for predicting loan defaults also for firms that do not go bankrupt. As expected, estimated bankruptcy rates are highest

Chart 8: Estimated bankruptcy probabilities for firms that default without going bankrupt are higher than for firms with healthy loans



Sources: Brønnøysund Register Center, Dun & Bradstreet, Finanstilsynet and Norges Bank

for firms that actually go bankrupt. At the same time, we can observe that among firms that do not go bankrupt, the probability of bankruptcy is clearly higher for firms with defaulted loans than for firms with healthy loans. We interpret these results to mean that the financial position of firms that default on their loans without going bankrupt is weak, but less weak than of firms that go bankrupt.

The difference in estimated probabilities of bankruptcy between firms that go bankrupt and firms that default without going bankrupt indicates that it is more appropriate to estimate the probability of default given that the firm does not go bankrupt, $P(D|\bar{B})$, rather than the overall probability of total default, $P(D)$.

4.3 Model for probability of default without bankruptcy

Since we find a significant difference in the estimated probabilities of bankruptcy between firms with healthy loans, firms with defaulted loans without bankruptcy and firms that go bankrupt, we estimate a model for the probability of default given that the firm does not go bankrupt, $P(D|\bar{B})$, see equation (1):[13]

$$P(D|\bar{B})_{i,t} = \alpha + \beta P(B)_{i,t} + \delta_t P(B)_{i,t} d_t + \gamma_t d_t + \epsilon_{i,t} \tag{1}$$

where $P(B)_{i,t}$ are estimated bankruptcy probabilities for firm, i, in year t. We take into account that the relationship between bankruptcy and loan default varies over time (see Section 3.2) by including time-fixed effects for each year, d_t. The base year is 2018 in

[13] We use OLS because it makes the results easy to interpret. The model also very rarely predicts probabilities above 1. We have also tried other modelling alternatives, such as logistic regression, without it giving better results compared to OLS.

the estimation, so that d_t is equal to 0 when $t = 2018$ and equal to 1 when $t > 2018$. d_t is included both as a separate year dummy and as an interaction with $P(B)$.[14] As the relationship between bankruptcy and loan default differs between industries, see Section 3.3, we estimate a model for each of the seven industries in the analysis.

Since bankruptcy is a one-off event, we estimate the probability of first time in default. The aim of the model is to estimate the rate of new loan defaults, and not the sum of defaulted loans, which also includes loans that are in default on the balance sheet over several years.

The coefficients from the estimation of equation (1) for the seven industries are shown in Table **2**. For example, the probability of default (given that the firm does not go bankrupt) increases by 0.06 percentage point when the probability of bankruptcy increases by 1 percentage point for a firm in construction in the base year 2018. For real estate development, the corresponding increase is 0.76 percentage point in the same year.[15] For 2023, the default probabilities increase significantly more, by 0.64 and 1.62 percentage points respectively.[16]

We also see that the probability of bankruptcy $P(B)$ is highly significant in each industry in almost all years covered by the data. The exception is for manufacturing in 2018 and fishing and aquaculture in 2018, 2022 and 2023. Here, $P(D|\bar{B})$ will be equal to the constant term for all firms.

The results are largely consistent with the findings in Section 3. The size of the coefficients of both $P(B)$ and the constant term vary widely between industries and years. In the years following the pandemic, the probability of default without bankruptcy is generally higher for a given probability of bankruptcy for all industries. Furthermore, the results indicate that the probability of default without bankruptcy is generally relatively higher in fishing and aquaculture, commercial real estate and real estate development than in the other industries.

4.4 Model for overall probability of default, MISMO

To predict the overall probability of default, $P(D)$, we derive in this Section a default probability model by adding estimated $P(B)$ and estimated $P(D|\bar{B})$ for each firm i in year t,

[14] We want the effect from the year dummies to be included only if it is strongly significant. We therefore eliminate the number of parameters in each model that are not significant at the 5 percent level using stepwise regression.

[15] In addition, the constant term of 0.3 percentage point in construction and 0.6 percentage point in real estate development must be added.

[16] In 2023, a 1 percentage point increase in $P(B)$ results in an increase in $P(D|\bar{B})$ of 0.06+0.58=0.64 percentage point in construction and 0.75+0.87=1.62 percentage points in real estate development. The constant terms are 0.3+0.6=0.9 percentage point in construction and 0.6+0.9=1.5 percentage points in real estate development.

Table 2: Estimation results for $P(D|\bar{B})$

	Fishing and aquaculture	Industry	Construction	Retail trade	Commercial real estate	Real estate development	Services
	$P(D\|\bar{B})$	$P(D\|\bar{B})$	$P(D\|\bar{B})$	$P(D\|\bar{B})$	$P(D\|\bar{B})$	$P(D\|\bar{B})$	$P(D\|\bar{B})$
Constant	0.005*	0.003**	0.003***	0.002**	0.002***	0.006***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
$P(B)$			0.062**	0.087***	1.543***	0.756***	0.098***
			(0.022)	(0.011)	(0.098)	(0.131)	(0.024)
$P(B) \times d_{2019}$	10.239***	0.278***			-0.844***	-0.724***	
	(1.314)	(0.076)			(0.112)	(0.181)	
$P(B) \times d_{2020}$	4.767***	0.258***			-1.026***	-0.700***	
	(0.689)	(0.050)			(0.128)	(0.208)	
$P(B) \times d_{2021}$	3.390***	0.394***	0.439***	0.101***	0.626**		0.445***
	(0.317)	(0.065)	(0.047)	(0.029)	(0.191)		(0.066)
$P(B) \times d_{2022}$		0.269***	0.309***	0.106***	-0.395*		0.964***
		(0.069)	(0.044)	(0.030)	(0.200)		(0.066)
$P(B) \times d_{2023}$		0.121*	0.580***	0.141***	-0.635***	0.868**	0.649***
		(0.048)	(0.045)	(0.025)	(0.138)	(0.273)	(0.056)
d_{2021}	0.010*	0.015***	0.015***	0.006***	0.003***		0.012***
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)		(0.001)
d_{2022}		0.009***	0.009***	0.005***	0.003***		0.005***
		(0.002)	(0.002)	(0.001)	(0.001)		(0.001)
d_{2023}	0.014***	0.009***	0.006**	0.008***	0.004***	0.009***	0.010***
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
N	4 804	15 611	28 626	35 572	73 715	12 555	55 004
R^2	0.047	0.010	0.023	0.009	0.011	0.008	0.014

Standard errors in parentheses. Asterisks indicate significance level at: * $p < 5\%$, ** $p < 1\%$ and *** $p < 0,1\%$. Estimation period: 2018-2023. The base year is 2018. The overall coefficient for $P(B)$ is β for $t = 2018$ and $\beta + \delta_t$ for $t > 2018$. The constant term is α for $t < 2021$ and $\alpha + \gamma_t$ for $t > 2020$.

see equation (2).[17] We call this model *MISMO*.

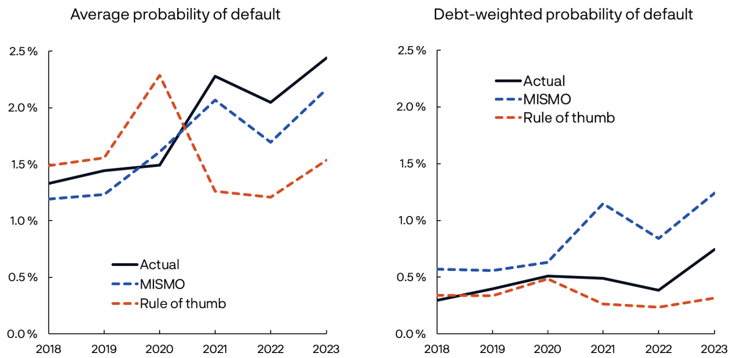
$$P(D)_{i,t} = P(B)_{i,t} + (1 - P(B)_{i,t}) \cdot P(D|\bar{B})_{i,t} \tag{2}$$

[17]The equation is derived using the general product rule, $P(D) = P(D \cap B) + P(D \cap \bar{B}) = P(D|B) \cdot P(B) + P(D|\bar{B}) \cdot P(\bar{B})$. Since $P(\bar{B}) = (1 - P(B))$ and we assume that $P(D|B) = 1$, we get equation (2).

We calculate the average $P(D)$ for each year for all firms combined using equation (2) and compare this to both the actual rate of new loan defaults and the results from the widely used rule of thumb described in Sections 1 and 3.3. Chart **9** shows both the unweighted and debt-weighted average probability of default for the seven industries combined.

The unweighted results from MISMO are more similar to the actual development in new loan defaults than the rule of thumb, especially after the Covid-19 pandemic, see left panel in Chart **9**. This reflects in particular that the extent of bankruptcy in relation to loan defaults has varied during the analysis period.

Chart 9: New estimated model for probability of default, MISMO, captures post-pandemic developments better than the rule of thumb



Sources: Brønnøysund Register Center, Dun & Bradstreet, Finanstilsynet and Norges Bank

When we weight by the firms' debt, the model estimates from MISMO are somewhat higher than the actual defaulted debt, see the right panel in Chart **9**.[18] The difference is particularly large in 2021, but this is due to the fact that the number of loan defaults was high, while the loan volume in default was not particularly high. This means that there were smaller firms than normal that defaulted on their loans this year. However, the new model better captures the increase in defaulted debt in 2023, which the rule of thumb does not do to any significant extent.

[18]We have attempted to include various specifications of loan size as an explanatory variable in the regression for $P(D|\bar{B})$. However, these variables are not always significant and it becomes more difficult to interpret the results. The inclusion of these variables does not result in a significant difference in average debt-weighted $P(D)$ compared to our chosen model specification.

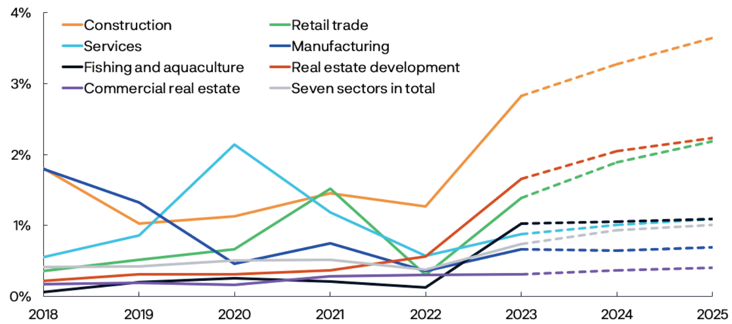
5 Estimate of new loan defaults and credit losses

In this Section, we show how we can use MISMO to estimate the rate of new loan defaults and credit losses for the current and next year.

5.1 Estimate of new loan defaults

First, we use MISMO to estimate the rate of new loan defaults this year and next year. We estimate default probabilities, $P(D)$, for 2024 and 2025 based on estimates for $P(B)$ in the same years.[19] In Section 4.4, we showed that MISMO overestimates the total debt-weighted probability of default. We therefore assume that the model overestimates the level of defaulted debt in 2024 and 2025 as well, and scale down the estimates by using the ratio between actual and estimated defaulted debt in 2023 as a scaling factor.

Chart 10: MISMO estimates indicate somewhat higher rate of new loan defaults in 2024 and 2025
New loan defaults as share of total loans



Sources: Brønnøysund Register Center, Dun & Bradstreet, Finanstilsynet and Norges Bank

Chart **10** shows actual new loan defaults relative to total lending to each industry for the period 2018 to 2023 and our projections for 2024 and 2025. Given our assumptions, the projections indicate that the overall rate of new loan defaults for the seven industries in the

[19] In the estimates, we assume that the year dummies have the same effect for 2024 and 2025 as they had in 2023. This assumption is uncertain and the results must be interpreted with caution. It is difficult to predict what the relationship between bankruptcies and defaults will be in the future, which makes it difficult to say what the effect of the year dummies for 2024 and 2025 should be. We do not yet have complete data for new loan defaults for 2024, but we observe that the total stock of defaulted loans for the industries included in the analysis has remained steady or increased so far this year, see "Financial Stability Report 2024 H2". Bankruptcies have increased slightly so far this year, but it will require a major increase for bankruptcies to make up the same proportion of defaulted loans as before the Covid-19 pandemic. Therefore, we believe that the effect from the year dummies is likely to be closer to what it was in 2023 than in the years before the pandemic. We will gain more insight into this as we get data for the next few years.

analysis will increase slightly, from 0.7 percent in 2023 to 0.9 and 1 percent in 2024 and 2025 respectively. In comparison, KOSMO 2 estimates an increase in bankruptcy debt from 0.2 percent in 2023 to 0.3 and 0.4 percent in 2024 and 2025 respectively.

Furthermore, MISMO estimates higher loan defaults for construction relative to retail trade than KOSMO 2 estimates for bankruptcy debt. Construction accounts for 10 percent of the increase in defaulted debt, despite the industry comprising only 3 percent of bank debt.

MISMO also estimates relatively high loan default rates in real estate development. The industry holds 10 percent of bank debt, but accounts for 20 percent of the increase in defaulted debt from 2023 to 2025. In KOSMO 2, the contribution is only 10 percent.

MISMO estimates only a slight increase in new loan defaults for fishing and aquaculture, manufacturing and commercial real estate. Even though commercial real estate accounts for about half of the bank debt in the data sample, the industry accounts for 20 percent of the increase in defaulted debt from 2023 to 2025.

5.2 Estimate of credit losses

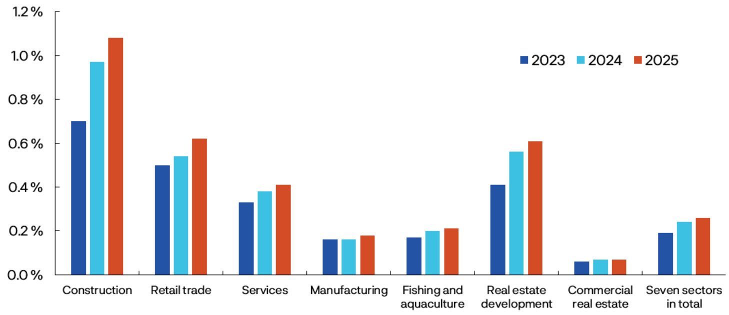
We can also use the estimates of new loan defaults from MISMO to make simplified estimates of losses on corporate loans in the banks. In the event of new loan defaults, banks set aside proportions of the loans as loan loss provisions (LLPs), often referred to as the loss-given-default (LGD) ratio. These new LLPs are usually the underlying driver of the development in credit losses. At present, Norges Bank does not have its own model for estimating LGD ratios. To estimate the LLPs for the new loan defaults, we assume an LGD ratio equal to the average LGD ratio for 2024 Q1 and Q2 for each industry.

In the projections, new LLPs relative to total corporate loans will therefore increase slightly in 2024 and 2025 compared with 2023, see Chart **11**. The increase is greatest in construction and real estate development, while the increase in other industries is limited.

There is considerable uncertainty surrounding the estimates, and banks' loss assessments are naturally more complex than what we have taken into account in this analysis. Nonetheless, the model estimates are well in line with the firm-level analyses in "Financial Stability Report 2024 H2" and Norges Banks' overall assessment of banks' risk of losses, and they also provide an improved basis for estimating annual credit losses from microdata.

Chart 11: Model estimates indicate some increase in banks' corporate credit losses in 2024 and 2025

LLPs for new loan defaults as share of total loans



Sources: Brønnøysund Register Center, Dun & Bradstreet, Finanstilsynet and Norges Bank

6 Conclusions

When assessing the credit risk associated with banks' corporate loans, Norges Bank has long used models that calculate the probability of bankruptcy. However, bankruptcies are not the same as loan defaults or credit losses, and access to such microdata has historically been very limited.

Improved access to microdata for loan defaults has enabled us to analyse the relationship between loan defaults and bankruptcy at the micro-level. We have found that there is a strong correlation, but that the relationship varies across industries and time. In particular, the Covid-19 pandemic marks a change in the relationship between loan defaults and bankruptcy. Based on this insight, we have developed a model for the probability of default based on already estimated bankruptcy probabilities. We argue that the model provides a better fit to actual loan defaults than a previously used rule of thumb.

We use the model to estimate the rate of new loan defaults this year and next year. With assumptions about the loss-given-default ratio, the model provides an estimate of the loan loss provisions (LLPs) for new loan defaults, which are usually the underlying driver of the development in credit losses.

The model is an important contribution to estimates of annual losses on corporate loans at the micro-level and will form part of Norges Bank's assessment of credit risk in the Norwegian banking system. As the dataset for loan defaults increases in size and we gain new insights, we will seek to further develop the model for probability of default.

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