STAFF MEMO

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NO. 10 | 2020

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NORGES BANK

ISSN 1504-2596 (online)
ISBN 978-82-8379-173-0 (online)

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December 17, 2020

Abstract

Loans to non-financial enterprises are the main source of banks' losses. Analyses of banks' losses on corporate loans are therefore important in the assessment of financial stability. This paper presents Norges Bank's framework for estimating losses on corporate loans built up from microdata for each firm and loan in each bank. Losses are estimated using a stepwise process. First, we estimate revenue developments at industry level and simulate the effect on firms' future financial statements. This is then used to project firms' bankruptcy probabilities using Norges Bank's bankruptcy probability model (KOSMO). Finally, the bankruptcy probabilities are linked to data on banks' exposures and credit losses are estimated. The estimates will be included in Norges Bank's assessment of vulnerabilities and risks in the Norwegian banking system. In addition to being included in a general risk assessment, the framework can be used in stress testing and in the assessment of new areas of risk, such as climate risk.

Key words: credit risk, bankruptcy probability, credit losses, bank losses

*The views and conclusions expressed in this publication are the authors' own and do not necessarily reflect those of Norges Bank. This paper should not be reported as representing the views of Norges Bank. We thank Henrik Borchgrevink and Torbjørn Hægeland for useful comments and input. Corresponding author: Ida Nervik Hjelseth, ida-nervik.hjelseth@norges-bank.no

1 Introduction

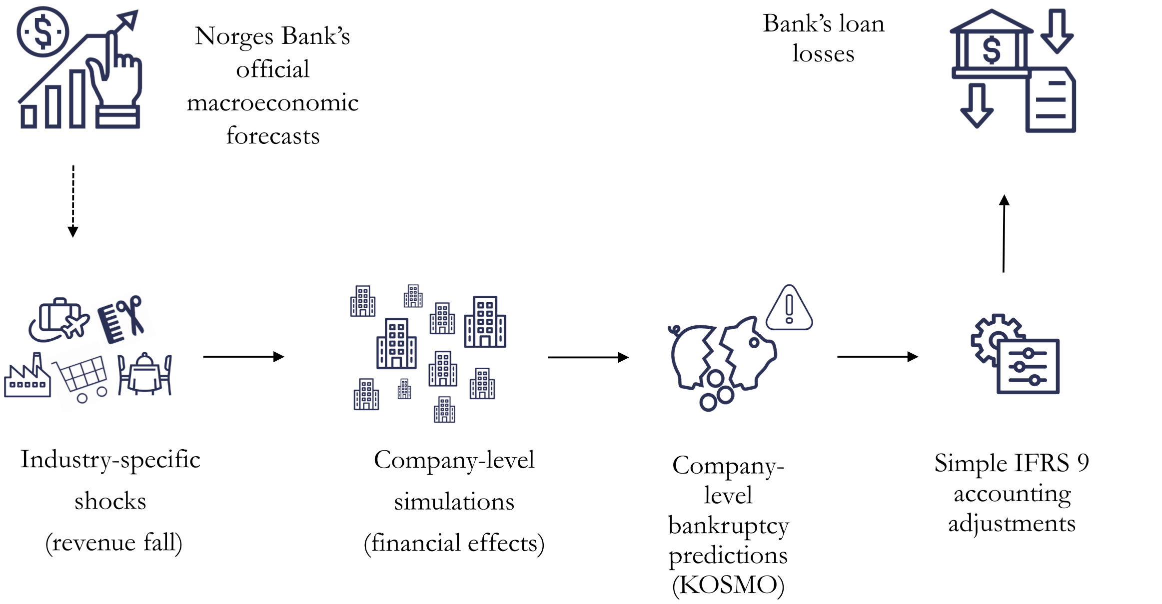
Loans to non-financial enterprises are the main source of banks' losses. Experience from Norway and abroad has shown that banks' credit losses are as a rule higher on corporate loans than on household loans, including during banking crises (see Kragh-Sørensen and Solheim (2014)). About 40 percent of banks' total lending is to non-financial enterprises. In order to assess risks and vulnerabilities in the banking system, it is important to be able to assess the risk of losses on banks' corporate loans. Analyses of banks' losses on lending to the corporate sector are therefore important in the assessment of financial stability (see Norges Bank (2018)).

This paper presents a framework to estimate banks' losses on loans to non-financial enterprises built up from microdata (see Chart 1 for a schematic presentation). The framework combines insights from a broad range of models and analyses developed by Norges Bank over many years with new analyses of credit losses after the outbreak of the Covid-19 pandemic. The method is based on non-financial enterprises' financial statements and banks' exposure reporting.

Norges Bank has long conducted analyses based on Norwegian firms' annual financial statements (see for example Bernhardsen and Larsen (2007)). Since 2019, Norges Bank has had access to Finanstilsynet's (Financial Supervisory Authority of Norway) database of banks' corporate exposures. We use this data set to link estimates of bankruptcy probability based on an individual firm's annual financial statements to banks' credit exposure to that firm. The data set is presented in Section 2.

Norges Bank conducts extensive macroeconomic forecasting. This is done at a relatively aggregated level. Micro-based analyses have the advantage of allowing us to analyse at a detailed industry level and take industry-specific challenges into account. Based on forecasts for output in the economy, we develop estimates for revenue decline by industry. We then assume that the impact of industry-level revenue decline varies at firm level and simulate a unique financial effect for each firm. How macroeconomic forecasts are translated into micro-based estimates for each firm is described in Section 3.

Chart 1: Illustration of framework for developing estimates of banks' losses on loans to the corporate sector



The simulated financial effect on individual firms is then used to project firms' future financial statements, which are included in the projection of individual bankruptcy probabilities generated by Norges Bank's bankruptcy probability model, KOSMO (see Hjelseth and Raknerud (2016)). The model uses accounting variables, firms' credit ratings and macroeconomic indicators to predict bankruptcy probabilities. Bankruptcy probabilities are also adjusted to take account of technical accounting rules for loss provisions. (See Section 4 for a description of projections of firms' bankruptcy probabilities.)

Some industries, such as oil service and international shipping, are not included in the bankruptcy probability model. We have limited access to these industries' financial statements as many of the firms are registered abroad. For oil service and international shipping, our analysis is therefore based on banks' credit exposure data, and we conduct loss assessments based directly on banks' portfolios in accordance with a few simple rules. The method is described in Section 6 and our conclusions are presented in Section 7.

2 Data and sample

This analysis primarily uses two data sources:

1. Annual financial statements for Norwegian limited companies that provide data on firms' financial position.

2. Finanstilsynet's credit exposure database that provides data on banks' lending to individual firms.

In addition, the database for banks' and financial undertakings' reporting to the Norwegian authorities (ORBOF) provides information on banks' balance sheets and financial results.

2.1 Annual financial statements from the Brønnøysund Register Centre and Norges Bank's bankruptcy probability model (KOSMO)

Norges Bank has a database containing the annual financial statements of all firms required to keep accounting records that were registered with an organisation number in the Norwegian business register in the period 1999-2019. The Bank also has data on bankruptcies and company-specific information, such as industry codes and number of employees. The data are reported to the Brønnøysund Register Centre and are delivered by Bisnode together with Bisnode's own credit ratings.

The financial statements database is the primary data source for Norges Bank's bankruptcy probability model KOSMO, which we use to estimate credit risk (see Hjelseth and Raknerud (2016)). The model estimates individual bankruptcy probabilities for each firm using bankruptcy data, financial statement data and credit ratings at firm level, as well as macroeconomic indicators at industry level. In the current version of the model, parameters are estimated on financial statement data and credit ratings for the period 1999-2017 and macroeconomic data for 2000-2018. KOSMO only includes Norwegian limited companies with bank debt and does not include self-employed persons or foreign borrowers.

KOSMO consists of six different models, one for each industry group in KOSMO. Different macroeconomic indicators are used for each industry group. Although parameter estimates are based on KOSMO's industry classification, the model is nonetheless flexible as industry groups can subsequently be reclassified, thereby adjusting the framework to focus on different industries depending on the economic situation. In this analysis, we estimate losses on loans to nine industries (see Table 1). This industry classification separates out industries that we have considered particularly severely affected during the Covid-19 pandemic. The industries separated out and added to the original KOSMO industries are tourism, personal services and transport.

Table 1: Industrial classification

Industrial classification KOSMO	NACE (SN 2007)	Macroeconomic indicator
Fishing and aquaculture	03	Salmon prices
Manufacturing and mining	05, 07- 08, 09.9, 10-33	GDP mainland Norway
Construction	41-43	GDP mainland Norway
Retail, accommodation and food service activities	45-47, 55-56	GDP mainland Norway
Commercial real estate	68	Office rents, 10-year swap rates
Service activities and transport (excl. international shipping)	49.1-49.4, 50.102, 50.109, 50.202-50.203, 50.3-50.4, 51-53, 58-63, 69-75, 77-82, 84-97	GDP mainland Norway

Industrial classification Staff Memo	NACE (SN 2007)	Macroeconomic indicator
Fishing and aquaculture	03	Salmon prices
Manufacturing and mining	05, 07-08, 09.9, 10-33 (excl. 30.113 and 30.116)	GDP mainland Norway
Construction	41-43	GDP mainland Norway
Retail	45-47	GDP mainland Norway
Tourism	55-56, 79	GDP mainland Norway
Commercial real estate	68	Office rents, 10-year swap rates
Transport (excl. international shipping)	49.1-49.4, 50.102, 50.109, 50.202-50.203, 50.3-50.4, 51-53	GDP mainland Norway
Personal services	85.5-85.6, 93-96	GDP mainland Norway
Commercial services	58-63, 69-75 (excl. 71.122), 77-78, 80-82	GDP mainland Norway

2.2 Finanstilsynet's exposure database (ENGA) and banks' and financial undertakings' financial reporting to the Norwegian authorities (ORBOF)

Finanstilsynet has collected credit exposure data from Norwegian banks since the mid-2000s. Finanstilsynet's exposure database (ENGA) initially included only the largest exposures, but was expanded in 2014 to cover all exposures. Banks are required to report credit exposure data as at 31 December for all their corporate customers (see Finanstilsynet (Online)). The data include the size of approved exposures and loans drawn, as well as sector and industry code. In addition to data on total lending, the reporting includes data that Finanstilsynet uses in its supervision activities, such as banks' assessment of probability of default (PD) and loss-given-default (LGD) for the exposure and the value of any collateral. Banks are also required to register credit loss provisions made under IFRS 9 rules.

Because it uses organisation numbers, ENGA gives us a direct link between individual firms and banks' lending, which means that when we assess a company's credit risk, we can also see which banks are exposed to this risk. ENGA is therefore important for a sound microdata-based analysis of banks' risks. In the analyses in this paper, we have used ENGA reporting as at 31 December 2019.

We make loss estimates based on exposure data for eight of the nine banks[1] included in Norges Bank's macro stress test (DNB Bank, SpareBank 1 SR, Sparebanken Vest, SpareBank 1 SMN, Sparebanken Sør, SpareBank 1 Østlandet, SpareBank 1 Nord-Norge and Sparebanken Møre) and three branches of foreign banks (Nordea, Danske Bank and Handelsbanken). We limit the sample in ENGA to the sectors Norwegian non-financial enterprises and corporate exposures registered under a foreign sector. Loss estimates for the industries included in KOSMO will further limit the sample to exposures to firms with an available bankruptcy probability.

ENGA is a large and complex data set. In our loss estimate calculations, we use reported data for loans drawn, industry codes, banks' own PD and LGD assessments and credit loss provisions. The quality of reporting for loans drawn and industry codes generally appears to be good. Banks' own PD reporting is only used to rank lending to oil service and international shipping. Credit loss provision reporting has only been included recently and is the part of the data set that is subject to the greatest uncertainty. Given the uncertainty, some of the results in this analysis must be interpreted with caution.

We cross-check the data in ENGA against the ORBOF statistics, which are prepared by Statistics Norway in collaboration with Finanstilsynet and Norges Bank (see Statistics Norway (Online)).

[1] Sbanken is not included in this analysis as the bank does not have exposures to the corporate sector and therefore does not report to ENGA.

ORBOF is based on balance sheets and financial statement data from financial institutions. Norges Bank has access to reported data from each bank. There are somewhat larger discrepancies between ORBOF and ENGA for the foreign branches than for the Norwegian banks, which may affect our results.

In addition to using ORBOF as a cross-check, we also follow the reporting of recognised losses in the analysis. Banks report their impairment losses on a quarterly basis. The estimate for 2020 has been continuously assessed and updated in light of banks' actual impairment losses. Impairment losses are only reported aggregated for each bank and not at industry level. However, Finanstilsynet collects impairment loss data by industry on an annual basis.

3 From projected macroeconomic developments to estimated financial effect on individual firms

This section describes how we proceed from Norges Bank's official projections for macroeconomic developments to estimates of individual firms' financial developments. First, we describe how we proceed from official macroeconomic projections to the estimated revenue decline at industry level. Then we explain how we use the industry-level revenue decline to estimate the financial effect on individual firms.

3.1 From macroeconomic developments to falls in revenue at industry level

We develop an estimate for the fall in revenue at industry level based on Norges Bank's projections in *Monetary Policy Report* 3/2020 (Norges Bank (2020)).

Our estimates of the fall in revenue at industry level are based on Norges Bank's projections for total output growth for mainland Norway in 2020 and 2021, as well as unpublished output projections broken down by some main industries. The industry-level projections are short-term projections two quarters ahead. We use these projections and the overall GDP projection for 2021 as a basis for the more detailed estimates of revenue decline. We proceed as follows:

- Our starting point is annual output growth for 2020 based on actual output in the main industries for the first and second quarter and Norges Bank's estimates for the third and fourth quarters.

- We use these quarterly estimates to make projections for 2021. We assume that developments in 2021 follow the same trend as developments in Norges Bank's estimates for the last two quarters in 2020, at the same time as we should arrive at approximately the same result as the official annual growth projection for overall output in 2021. We adjust the pace of growth in each industry on a discretionary basis.

- The fall in revenue is assumed in principle to be equal to the fall in output. The impact of price effects on revenue is also taken into account on a discretionary basis, particularly in industries where revenue is largely dependent on commodity prices.

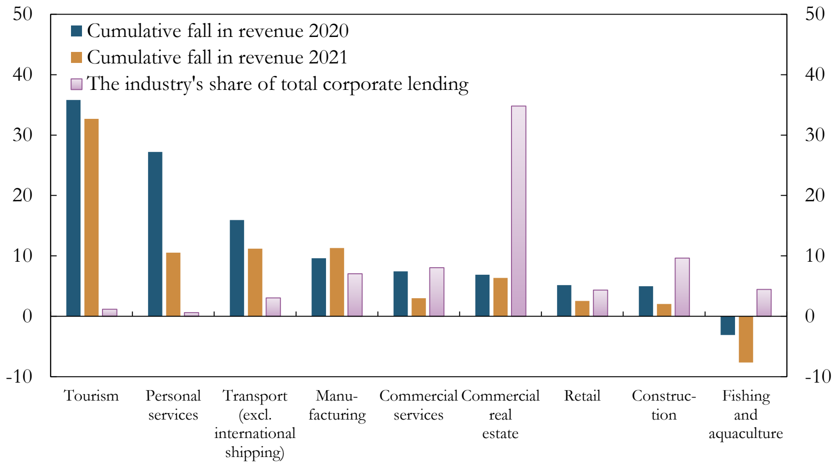
- Estimates for each industry at the five-digit level, according to the Norwegian standard for industrial classification (SN2007), are based on each main industry's estimated output in 2020 and 2021. The severity of the impact of the pandemic can differ widely across five-digit industries in a main industry grouping. We use, for example, detailed industry data on financial support under the government compensation scheme for 2020, survey responses and judgement to distribute the overall fall in revenue in the main industry in cases where a finer calibration at the five-digit level is necessary.

Chart 2 shows estimates of the average accumulated percentage fall in revenue[2] in the nine industries studied in this paper and the share of banks' corporate lending each industry accounts for. The estimated fall in revenue between 2019 and 2020 is thus used for 2020, while the accumulated estimated fall in revenue between 2019 and 2021 is used for 2021. This is because for both years we use data from end-2019 for further calculations. We estimate the steepest fall in revenue for the tourist industry, followed by personal services and transport. These three industries only account for about 5 percent of banks' total corporate lending. In comparison,

[2] Average fall in revenue in each five-digit industry, $\bar{S}$, is weighted by revenue in the industry and aggregated up to the relevant main industry. Estimated falls in revenue for large five-digit industries will therefore contribute most to the estimated fall in revenue in the aggregated industry, as shown in this chart.

we estimate a more moderate fall in revenue for commercial real estate (CRE), the industry to which banks are most exposed.

Chart 2: Estimated cumulative fall in revenue compared with 2019 for different industries and banks' lending to each industry as share of banks' total corporate lending. Percent



Sources: Finanstilsynet and Norges Bank

3.2 From falls in revenue at industry level to financial effect on individual firms

In this section, we first show how we model the effect of the fall in revenue on firms' financial statements. The fall in revenue per five-digit industry is used to estimate how much revenue in NOK each firm loses. We take into account that some of the revenue decline can be recouped by cutting costs. For example, many of the firms affected can reduce their workforce through lay-offs, and inputs are also reduced when sales fall.

Since economic shocks rarely affect all firms equally, we introduce additional heterogeneity in the analysis. Rather than applying the same shock to all firms in a five-digit industry, we simulate draws of falls in revenue and costs from different distributions. The method and assumptions applied in the simulation are described in the next section.

Finally, in the calculation of the effect on firms' financial statements, we have also taken into account the government compensation scheme under which firms that met certain criteria could apply for financial support during the Covid-19 pandemic, and we show how the effect of the scheme is captured in the analysis.

Net fall in revenue per firm

Our calculation of the financial effect of a given fall in revenue on a firm is based on an estimated net fall in revenue, N. We assume that a firm has some capacity to cut variable costs as revenue falls, while fixed costs cannot be changed.

We use financial statement data on a firm's revenue, variable and fixed operating costs, and operating profit to estimate N. According to the financial statements:

$$\text{Revenue} = \text{variable operating costs} + \text{fixed operating costs} + \text{operating profit}$$

We define net fall in revenue, N as:

$$\begin{aligned}\text{N} = &\text{ Revenue after fall in revenue} \\ &- \text{variable costs after fall in revenue} \\ &- \text{fixed costs before fall in revenue} \\ &- \text{operating profit before fall in revenue}\end{aligned}$$

Technically, we model net fall in revenue as follows:

$$N = (1-\sigma)I - ((1-(1-\nu)\sigma)(I-D-\phi A)+\phi A) - D \tag{1}$$

where I is revenue, D is operating profit and A is the accounting item «other operating costs». The parameter $\sigma \in [0,1]$ is the percentage fall in revenue. Our financial statement data do not include specific data on fixed or variable operating costs. We therefore assume that fixed costs represent a certain share, $\phi \in [0,1]$, of other operating costs, A. The parameter $\nu \in [-1,1]$ denotes the degree of reduction in variable costs, given σ. The lower the ν, the greater a firm's capacity to reduce its variable costs $(I - D - \phi A)$.[3]

If $N > 0$, ie net increase in income, we set $N = 0$.

Simulation of net fall in revenue

Rather than allowing the fall in revenue for all firms, σ, to be equal to the fall in revenue in their five-digit industries, $\bar{S}$, and allowing ν and ϕ to be the same for all firms, we simulate the shock by drawing falls in revenue, σ, degree of reduction in variable costs, ν, and share of fixed costs, ϕ, from different beta distributions. A beta distribution is a continuous probability distribution defined by the interval $[0, 1]$.

For the fall in revenue, $\bar{S}$ will represent the average distribution for each five digit-industry. (See Appendix A.1 for further specification of the choice of parameters for beta distributions.)

The number of draws is set to 100 because this analysis uses average bankruptcy probability for each firm across the 100 draws. Increasing the number of draws would not appreciably change the result. In other contexts, it may be appropriate to use other outcomes. In a stress test, for example, the focus would be on tail probability and increasing the number of draws would then be relevant.

Cash support for 2020

At the beginning of April 2020, the Norwegian authorities adopted a compensation scheme allowing firms with a substantial fall in revenue related to Covid-19 to apply for cash support to cover unavoidable fixed costs. The general scheme lasted six months from March until August. The calculation of the firm-level fall in revenue in this analysis takes into account that firms can apply for and receive financial support under the scheme provided that they meet certain

[3] When $(1 - (1 - \nu)\sigma) < 0$, the whole expression is set to 0. This means it is not possible to reduce variable costs below 0.

criteria.[4]

This analysis assumes that qualified firms receive cash support and allows T to be equal to total cash support received between March and August. See Appendix A.2 for a more detailed description of how we have modelled cash support in the analysis.

For a firm that receives cash support, T, the net fall in revenue will be reduced. To estimate falls in revenue when the compensation scheme is included, N^T, we can add T in equation 1:

$$N^T = (1-\sigma)I - ((1-(1-\nu)\sigma)(I-D-\phi A)+\phi A) - D + T \tag{2}$$

It is only in 2020 that $T \geq 0$. For 2021, we assume that $T = 0$ for all firms.

4 Bankruptcy probability for individual firms

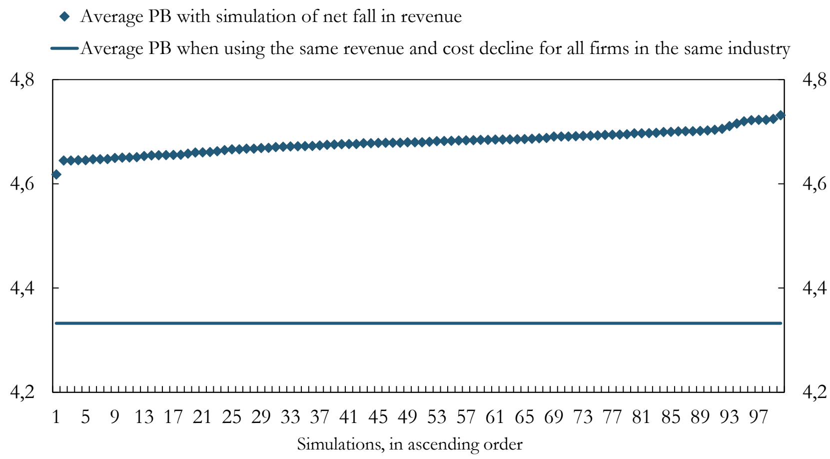
Norges Bank's bankruptcy probability model (KOSMO) is a logit model that estimates the probability of bankruptcy, PB, for individual firms based on accounting variables, macro variables and individual credit ratings (see equation (1) in Hjelseth and Raknerud (2016)). In Section 4.1, we show how we project these variables, while in Section 4.2, we describe various alternative paths for developments in estimated bankruptcy probabilities for 2020-2022. Finally, in Section 4.3, we explain how we take account of technical accounting rules for loss provisions in our estimated bankruptcy probabilities.

Our bankruptcy probability estimates are based on the simulated falls in revenue for 2020 and 2021, N_{20}^T and N_{21}, as described in Section 3.2. With the convexity characteristics of the logit function for $PB < 0.5$ (where almost all estimated PBs are to be found), substantial negative shocks lead to relatively larger increases in bankruptcy probability than the corresponding reduction when other firms experience a smaller-than-average shock. As a result, the average

[4] The authorities also adopted a scheme for government-guaranteed bank loans. However, the effect of such loans on firms' bankruptcy probability is not unequivocal. We have not adjusted for access to such loans in the analysis, but refer to the Special Feature on page 56 in *Financial Stability Report* 2020 on the impact of the scheme on banks' risk of credit losses.

estimated PB will be higher for all simulations than the average PB without a simulated fall in revenue and degree of cost reduction (see Chart 3 for an illustration).

Chart 3: Illustration of difference in PB with and without simulation exercise. Percent



Source: Norges Bank

4.1 Projection of firms' accounting variables, credit ratings and macroeconomic developments

The firm-specific accounting variables, REG, included in the prediction of bankruptcy probability for a firm in KOSMO are:

- Return on assets, $RoA = \frac{\text{earnings before tax+interest expenses}}{\text{total assets}}$
- Equity ratio, opening balance, $ER = \frac{\text{shareholders' equity, opening balance}}{\text{total assets, opening balance}}$
- Total assets deflated by GDP deflator, RA, in logarithmic form, $\ln(RA)$. and quadratic logarithmic form, $\ln(RA)^2$

The simulated net falls in revenue, N_{20}^{T} and N_{21}, affect the variables through earnings before tax, shareholders' equity and total assets. (See Appendix B.1 for a more detailed description of how the accounting variables are projected.)

Table 2: Calculation and projection of indicators

Indicator	Method of calculation	Projection
GDP mainland Norway, constant prices	Annual growth	Norges Bank's official projections for annual growth in MPR 3/2020
Rents for prime office space in Oslo, constant prices	Four-quarter change in average real rents past four quarters. Nominal rents deflated by GDP deflator	Norges Bank's estimates of quarterly rents and four-quarter CPI inflation based on information as at MPR 3/2020
10-year swap rates	Average daily listing so far this year	Current average rate
Salmon prices, frozen per kilo, constant prices	Deflated by CPI	Current real prices

Firms' credit ratings, K, are an important driver in estimating bankruptcy probability in KOSMO. Since credit ratings are an exogenous variable in the model, we do not have the direct relationship between changes in accounting variables and changes in credit ratings. We model credit ratings by assuming a simple relationship between a firm's credit rating, K, and developments in a firm's equity ratio, ER (see Appendix B.2).

KOSMO uses four different variables as indicators of macroeconomic developments, M.[5] Table 2 shows how each indicator is calculated and how it is projected.

4.2 Estimated bankruptcy probabilities

Based on the method described in Section 4.1, we estimate annual bankruptcy probabilities, PB, per firm for the period 2020-2022 in each of the 100 draws. If we follow the same time specifications as in KOSMO (alternative 1), this gives:

Alternative 1: Time specifications for accounting variables, credit ratings and macroeconomic indicators as in KOSMO.

$$\widehat{PB}_{20} \text{ depends on: } REG_{19}, K_{19}, \widehat{M}_{20}$$

$$\widehat{PB}_{21} \text{ depends on: } \widehat{REG}_{20}, K_{20}, \widehat{M}_{21}$$

$$\widehat{PB}_{22} \text{ depends on: } \widehat{REG}_{21}, \widehat{K}_{21}, \widehat{M}_{22}$$

Variables marked with a hat are estimates, either from simulations or macroeconomic projections. Variables without a hat are data observations.

[5]See Table 1 in Section 2 for the specific indicators we use for specific industries.

KOSMO is based on annual observations, which can affect the timing of bankruptcy predictions. Economic developments and changes in credit ratings through the year are interpreted as an overall movement at the end of a year. Since the Covid-19 pandemic was such a large and abrupt shock, it is also likely that bankruptcies as a result of the pandemic may occur earlier than in the more normal times on which KOSMO's estimates are based.[6] Therefore, when estimating reasonable loss developments for the coming years, we also test alternative paths for developments in bankruptcy probabilities with other time specifications (see alternatives 2 and 3 below).

In the projections in Norges Bank's *Monetary Policy Report* 3/2020 (Norges Bank (2020)), output falls sharply in 2020 followed by a recovery in 2021, resulting in relatively strong annual output growth in 2021. At the same time, at end-2021, output has only returned to approximately the same levels as in 2019. The estimation period for KOSMO does not include periods of such abrupt movements in output growth as in these projections. It is therefore likely that KOSMO will exaggerate the positive effect resulting from high output growth in 2021. We therefore test alternative 2 where macroeconomic indicators for 2020 are kept constant throughout the period.

Alternative 2: Time specifications for accounting variables and credit ratings as in KOSMO, but macroeconomic indicators for 2020 are constant through the period.

$$\widehat{PB}_{20} \text{ depends on: } REG_{19}, K_{19}, \widehat{M}_{20}$$
$$\widehat{PB}_{21} \text{ depends on: } \widehat{REG}_{20}, K_{20}, \widehat{M}_{20}$$
$$\widehat{PB}_{22} \text{ depends on: } \widehat{REG}_{21}, \widehat{K}_{21}, \widehat{M}_{20}$$

As mentioned above, a firm's credit rating is an important driver of bankruptcy probability in KOSMO. If KOSMO is followed mechanically, credit ratings given in one year are used to assess bankruptcy probability at the end of the following year. In a situation where credit ratings deteriorate early in 2021 and the period to bankruptcy is a little less than one year, it will likely be equally precise to assign credit losses to 2021 rather than to 2022. The equity ratio is also brought forward by one year so that the estimated equity ratio for 2020 is used in the loss

[6] Substantial support schemes from the authorities have, on the other hand, contributed to providing temporary liquidity relief for many firms.

estimates for 2021 and affects credit ratings in 2021. The macroeconomic indicator for 2020 is kept constant to isolate the credit rating effect in 2021 and 2022 (see alternative 3).

Alternative 3: Time specifications for credit ratings and equity ratio moved back by one year and macroeconomic indicators for 2020 remain constant through the period.

$$\widehat{PB}_{20} \text{ depends on: } REG_{19}, K_{20}, \widehat{M}_{20}$$
$$\widehat{PB}_{21} \text{ depends on: } \widehat{REG}_{20}, \widehat{K}_{21}, \widehat{M}_{20}$$
$$\widehat{PB}_{22} \text{ depends on: } \widehat{REG}_{21}, \widehat{K}_{22}, \widehat{M}_{20}$$

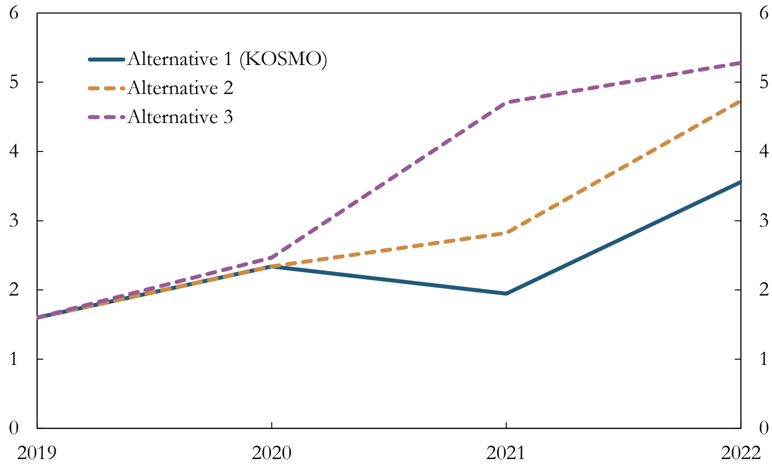
where $\widehat{REG}_{20}$ contains $\widehat{ER}_{20}$ and $\widehat{REG}_{21}$ contains $\widehat{ER}_{21}$ in this alternative.

See Appendix B.3 for a more detailed description of the three alternatives. Chart 4 shows the path for average PB for 100 draws per year in each of the alternatives. As shown in alternative 1, the strong annual output growth projection for 2021 has a pronounced effect on average PB in 2021. In our opinion, this is not realistic, given the prevailing downturn. In alternative 2, where the macro estimate for 2020 is kept constant, the largest increase in average PB does not occur until 2022. In Alternative 3, where the effect of credit ratings is brought forward by one year, the largest increase in PB is in 2021. Given the current situation and the abrupt shock to the economy caused by the Covid-19 pandemic, it is reasonable to assume a somewhat higher bankruptcy rate than in normal times. We therefore choose to base further analysis on the PB estimates in alternative 3. Paths for credit losses based on alternative 3 are shown and discussed in Section 5.

4.3 Adjustment of bankruptcy probabilities to take account of the effect of technical accounting rules for loss provisions.

The aim of this paper is to project banks' credit impairments. A key element in the new accounting rules (IFRS 9) introduced in 2018 was that impairment for each exposure should build

Chart 4: Average PBs for three different model alternatives. Percent



Source: Norges Bank

on forward-looking assessments.[7] The loss provision rules applied will depend on developments in each exposure's expected credit risk.

Under IFRS 9, loans are assigned to one of three stages for impairment loss recognition purposes. Impairment of fresh loans is based on expected credit losses over the next 12 months (stage 1). If a loan has a significant increase in credit risk, expected credit losses over the life of the loan must be recognised (stages 2 and 3). A loan is classified as stage 2 if credit risk has increased significantly but there is no objective evidence of impairment. When there is objective evidence of impairment, a loan is classified as stage 3. In purely practical terms, a loan is classified as stage 3 when it is clear that the borrower is unable to service the loan. PD on the loan will normally be set at 1 in stage 3.

The stage to which a loan is assigned determines the size of loss provisions. In stage 1, loss provisions are normally very low. In stage 2, provisions increase substantially, but it is only when a loan is classified as stage 3 that a very large share of the loan will be recognised as a loss.

We take account of IFRS 9 effects by assuming that the level of and developments in firms' PB determine the stage at which a loan is classified and PB is adjusted accordingly. We define IFRS 9-adjusted PB as PB^{adj}. The PB classification criteria and the adjustments made are set

[7] Prior to IFRS 9, banks had more commonly made forward-looking assessments through collective impairments at industry level.

out below.

- Stage 1: No adjustment of PB.[8]
- Stage 2: For PB above level 1, PB is multiplied by 5. The same applies to exposures that have PB below level 1 but that double between two periods.
- Stage 3: Loans with PB above level 2 are assumed to be in default and PB is set at 1.

The thresholds defining each stage are determined based on a calibration of exposures in the base year 2019. Level 1 and 2 are calibrated so that the share in stage 1 prior to shock is 95 percent of total lending, the share in stage 2 is about 4 percent of total lending and the share in stage 3 is about 1 percent of total lending.[9]

With this method, impairments are recognised earlier in a downturn. Thus, our analysis takes into account that some of the impairments will occur early in the period, in line with the intention of the accounting rules. For exposures in stage 3, an increase in PB will not trigger further impairment recognition. In practice, it is possible that other variables, for example assessed loss-given-default (LGD), may increase. This is taken into account in the assessment of oil service and international shipping, where impairment is assessed for individual exposures, but not for industries where our assessment is based on KOSMO estimates. Losses in a deep downturn may be underestimated as a result.

5 From bankruptcy probabilities for individual firms to banks' credit losses

To estimate banks' corporate credit losses, bankruptcy probabilities generated by KOSMO are linked to observations of banks' lending at exposure level, ENGA, as of the end of 2019. In addition to the size of each bank's credit exposure to a firm, we use data from ENGA on banks'

[8] PB is the probability of bankruptcy during a calendar year and not over several years. No adjustment is therefore necessary for stage 1.
[9] Based on calculations in Andersen and Hjelseth (2019).

assessment of loss-given-default (LGD) per exposure. Banks' own assessments of the probability of default, PD, are not used actively in our assessment of banks' losses.

Since KOSMO is based on limited companies registered in the Norwegian business register, banks' foreign exposures are not included. These are, however, included in our sample from ENGA. We have PB throughout the projection period for about 31 percent of the loans in ENGA, but this covers slightly more than 70 percent of total lending to the nine industries studied here. Exposures to firms in industries included in ENGA, but for which PB is not available, are assumed to have in sum the same share of expected losses as for exposures to firms with PB in the same industry group. Credit losses per industry per bank are thus estimated as the sum of the estimated share of losses to the industry multiplied by total lending to that industry.

5.1 Expected and estimated credit losses in the projection period

The key to explaining credit loss developments in the projection period is developments in expected losses, EL:

$$EL = PD \cdot LGD \cdot L \tag{3}$$

where L is loan volume.

Expected credit losses reflect the need for loss provision on a loan. Expected losses are not in themselves a loss prediction, but an estimate of the risk facing a bank. As we do not have estimates of actual probability of default, PD, our calculations are based on estimated bankruptcy probability, PB. In addition, banks are required under IFRS 9 to set aside extra loan loss provisions if the expected credit losses for a loan exceed certain limits, cf. the discussion on accounting provisions in Section 4.3, where PB has been adjusted to PB^{adj} to take this into account. We start by estimating so-called expected exposure, EE, which per loan i to bank b is given as

$$EEi = PB_i^{adj} \cdot LGD_{b,i} \cdot L_{b,i} \tag{4}$$

By adding up exposures across banks, we can now estimate EE per industry and per bank.

Expected exposure is a stock variable. Since PB is an estimate of the probability of bankruptcy and not the probability of default, its absolute level is not an indication of the level of a bank's expected credit losses. To estimate impairment losses in a given year, we therefore apply a transformation in two steps.

Step 1: Expected credit losses in the base year

To estimate credit losses, the level of losses in normal times must first be established. Our study is based on average historical losses on corporate loans and estimated average bankruptcy probability at industry level in the period 2010 – 2019. In this period, banks recorded average losses of about 0.3 percent on their corporate loans per year for the industries studied here. [10] We assume that 2019, our base year, can be regarded as a "normal year". We therefore assume that if expected exposure is the same as in 2019, the loss ratio, $LOSS$, for the nine industries studied here will remain constant at 0.3 percent for banks overall.

Historically, there are substantial differences in credit losses across industries and across banks. Historical credit loss reporting, however, is only available at more aggregated levels. It is not possible to estimate historical credit losses for industries that correspond exactly with the industry categories chosen in this paper. Instead, we use the relative difference in expected exposure across industries to estimate the difference in expected credit losses across industries. To obtain a more representative picture of differences in expected exposure, we base our estimates on historical volume-weighted PBs for the period 2010 – 2019. From this, we can estimate relative expected exposure for that historical period and estimate credit losses in the "normal year" 2019 per industry, n:

$$LOSS_{19,n} = 0.3\frac{\overline{EE}_{10-19,n}}{\overline{EE}_{10-19}} \tag{5}$$

where $\bar{EE}$ represents average EE for 2010-2019.

There are also likely to be systematic differences across banks for a given industry. We adjust for this based on the differences in EE in 2019 for exposures to a given industry, n and a given

[10]Source: Banks' annual credit loss reporting to Finanstilsynet and our own calculations.

bank, b, against EE for this industry across all banks:

$$LOSS_{19,n,b} = LOSS_{19,n}\frac{\overline{EE}_{19,n,b}}{\overline{EE}_{19,n}} \tag{6}$$

Step 2: Expected credit losses in the projection

If expected exposure to industry n for bank b is the same as the level in 2019 throughout the projection period, credit losses will remain constant at $LOSS19, n, b$. We assume that if EE rises between year t and year $t + 1$, the bank will record the entire increase in EE as increased credit losses in the year EE rises. This means that the loss ratio in 2020 will be given as:

$$LOSS_{20,n,b} = LOSS_{19,n,b}\frac{\overline{EE}_{n,b,20}}{\overline{EE}_{n,b,19}} \tag{7}$$

Credit losses in subsequent years will reflect the change in the previous year. The change in exposure in the previous year is added to normal losses, such that:

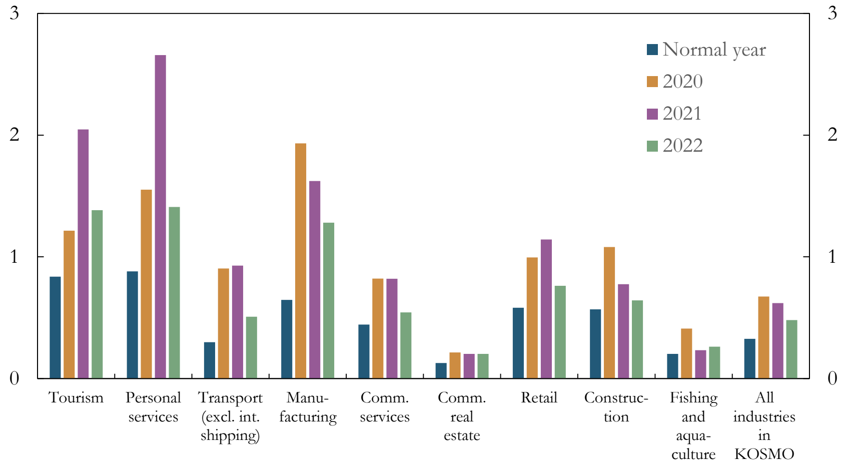
$$\begin{aligned}LOSS_{21,n,b} =& LOSS_{19,n,b}(1 + \frac{\overline{EE}_{n,b,21} - \overline{EE}_{n,b,20}}{\overline{EE}_{n,b,19}})\\LOSS_{22,n,b} =& LOSS_{19,n,b}(1 + \frac{\overline{EE}_{n,b,22} - \overline{EE}_{n,b,21}}{\overline{EE}_{n,b,19}})\end{aligned}$$

This gives us a loss ratio estimate per industry per bank for a "normal year" and the projection period 2020 – 2022 for loans with PB. These loans are assumed to be representative of the portfolio of loans to the given industries. Each bank's impairment losses in NOK for each industry can then be estimated based on the bank's total credit exposure to the given industry. Aggregate expected credit losses can also be estimated for different industry definitions. In addition, we have a basis for estimating overall credit losses in the Norwegian banking sector.

5.2 Estimated credit losses in industries with bankruptcy probabilities generated by KOSMO

Given the bankruptcy probabilities generated by KOSMO as set out in Section 4 and the transformation from PBs to losses described in Section 5.1, we have calculated loss estimates for different industry categories in a "normal year" and the years 2020 – 2022 (Chart 5). The method shows substantial differences in estimated credit losses across industries, in line with our data observations. A rise in PB leads to higher credit losses, but if PB rises for several consecutive years, the increase in credit losses is reduced as banks have already recognised some of the volume of loans as impaired.

Chart 5: Loss ratios for a "normal year" and 2020 – 2022 for industries with estimated PB. As a share of total lending to the industry. Percent



Source: Norges Bank

These industry-level loss estimates are included in a broad analysis of risk in the banking sector. The estimates are compared with banks' actual loss provisions in the course of the year and information that for various reasons is not reflected in the model. Combined with discretionary judgement, this forms the basis of the conclusions published in Norges Bank's reports.

6 Estimates of losses on exposures to oil service and international shipping

As stated in the introduction, since some industries are not covered by KOSMO, we do not have individual bankruptcy probabilities for all firms. This applies to, among others, oil service and international shipping firms. Oil service lending has in recent years been a substantial source of losses in the banking sector, and credit risk associated with this industry increased further in 2020 (see Hjelseth (2020)). In addition, international shipping is an industry where banks have often incurred losses in bad times and which has experienced shocks during the Covid-19 pandemic. The cruise industry in particular is vulnerable, and some parts of the industry are also sensitive to developments in oil demand. It is therefore important to take account of these industries in loss assessments.

Banks' exposures to oil service and international shipping total about 14 percent of corporate lending.[11] In the ENGA database, the number of credit exposures to both of these industries is relatively low. Banks' portfolios of loans to these industries are therefore fairly straightforward, and we conduct loss assessments for each bank's portfolio according to simple rules as described below.

ENGA contains information on loss provisions recognised in three stages, as prescribed in the IFRS 9 framework, for each exposure at the end of 2019 (see Section 4.3 for a brief summary of the main elements of the framework). We have used the information on recognised loss provisions to group each bank's exposures in stage 1, stage 2 and stage 3.[12] Oil service firms had already substantially written down their assets at the end of 2019. About 30 percent of the volume of banks' exposures to oil service are already in stage 3. For international shipping, only 3 percent of exposures were in stage 3 at the end of 2019.

[11] The oil service industry is not classified under its own industry code, but there are nonetheless some industry codes that almost exclusively contain oil service firms and that also cover much of the industry. In estimated losses on loans to oil service, we have included lending to firms under the following industry codes: 09.101, 09.109, 30.113, 30.116, 50.204 and 71.122. For international shipping, we include the codes 49.500, 50.101 and 50.201.

[12] As described in Section 2, there is particular uncertainty surrounding reporting of loss provisions, and the results of this analysis must therefore be interpreted with caution.

After grouping the exposures, we rank them by level of reported PD, in descending order in each stage for each bank. Since credit risk associated with both oil service and international shipping is assumed to have increased after the pandemic broke out, we move these exposures up to a higher stage using some simple rules (see below). Exposures with the highest PD are moved first.

Banks' impairment losses reflect their expectations with regard to developments ahead. Banks will primarily incur credit losses through three channels:

1. Further losses on exposures already in default, in the form of higher loss-given-default LGD.

2. Losses on new non-performing exposures (stage 3), ie a migration from both stage 1 to stage 3 and from stage 2 to stage 3.

3. Impairment based on an increase in credit risk for exposures that are not in default (stage 2). Under IFRS 9, higher credit losses must be recognised if there is any increase in the credit risk associated with an exposure and markedly higher losses in the event of a significant increase in credit risk. Impairment for these exposures will normally be limited compared with exposures in default, but could nonetheless be substantial if credit risk increases significantly for many exposures at the same time.

In addition, losses could increase somewhat if there is a general rise in PD in stage 1 and stage 2 without a reclassification of the exposure. This effect has not been taken into account here.

Table 3 describes the rules and assumptions underlying loss recognition in both industries for 2020 – 2022. In general, oil service firms are assumed to be in a far worse position than international shipping firms. Consequently, we assume both higher loss ratios and a higher share of loan migration to higher levels of risk for oil service than for international shipping. We have thereafter assumed a gradual improvement in both industries, so that annual loss provisions decline gradually from 2020 – 2022.

Table 3: Estimated recognised losses in oil service and international shipping for 2020 – 2022

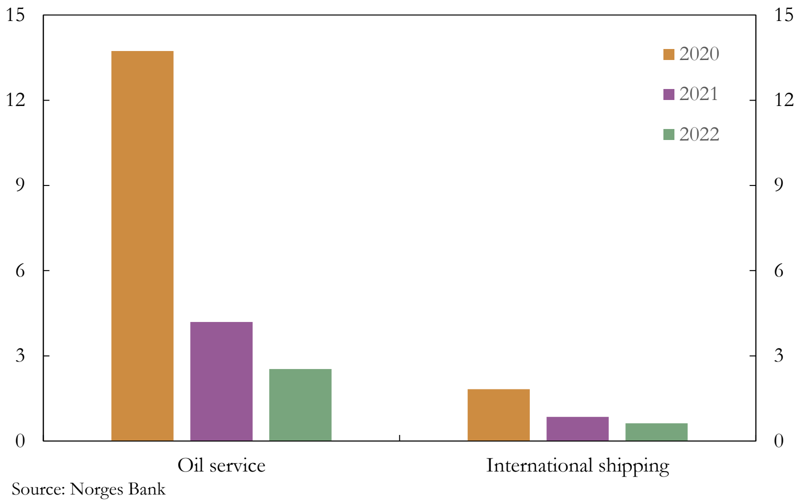
2020	Oil service	International shipping
Extra impairment losses recognised in stage 3	For exposures already in stage 3 and with an existing loss ratio lower than 50 percent, further losses are recognised so that the total loss ratio is 50 percent.	For exposures already in stage 3 and with an existing loss ratio lower than 40 percent, further losses are recognised so that the total loss ratio is 40 percent.
Reclassification of loans from stage 2 to stage 3	· Exposures with the highest PD are moved from stage 2 to stage 3 until at least 33 percent of the volume in stage 2 has been moved. · Loss ratio: 50 percent. · Already accumulated losses are deducted first.	· Exposures with the highest PD are moved from stage 2 to stage 3 until at least 2.5 percent of the volume in stage 2 has been moved. · Loss ratio: 40 percent. · Already accumulated losses are deducted first.
Reclassification of loans from stage 1 to stage 3	· Exposures with the highest PD are moved from stage 1 to stage 3 until at least 5 percent of the volume in stage 1 has been moved. · Loss ratio: 50 percent. · Already accumulated losses are deducted first.	· Exposures with the highest PD are moved from stage 1 to stage 3 until at least 1 percent of the volume in stage 1 has been moved. · Loss ratio: 40 percent. · Already accumulated losses are deducted first.
Reclassification of loans from stage 1 to stage 2	· Exposures with the highest PD are moved from stage 1 to stage 3 until at least 80 percent of the volume in stage 1 has been moved (first 5 percent to stage 3, remaining to stage 2). · Loss ratio is the average loss ratio for loans in stage 2 at end-2019. · Already accumulated losses are deducted before calculation of new losses in both cases.	· Exposures with the highest PD are moved from stage 1 to stage 3 until at least 15 percent of the volume in stage 1 has been moved (first 1 percent to stage 3, remaining to stage 2). · Loss ratio is the average loss ratio for loans in stage 2 at end-2019. · Already accumulated losses are deducted before calculation of new losses in both cases.

2021-2022	Oil service	International shipping
General assumptions in loss calculation 2021 - 2023:	· Only migration of loans is from stage 2 to stage 3. · Percentage of loan volume moved per year is given below. · Loss ratio: 50 percent. · Already accumulated losses are deducted before calculation of new losses per year.	· Migration of loans from stage 2 to stage 3. · A continued migration of loans from stage 1 to stage 2. · Percentage of loan volume moved per year is given below. · Loss ratio for loans moved from stage 2 to stage 3: 40 percent. Loss ratio for loans moved from stage 1 to stage 2 is equal to the average loss ratio for the loans in stage 2 at end-2019. · Already accumulated losses are deducted before calculation of new losses per year.
2021	20 percent of remaining loan volume in stage 2 is moved to stage 3	· 7.5 percent of remaining loan volume in stage 2 is moved to stage 3. · 10 percent of remaining loan volume in stage 1 is moved to stage 2.
2022	15 percent of remaining loan volume in stage 2 is moved to stage 3.	· 5 percent of remaining loan volume in stage 2 is moved to stage 3. · 5 percent of remaining loan volume in stage 1 is moved to stage 2.

Discretionary adjustments have been made in the calculations where the underlying data is inadequate or seems unreasonable. As banks have already reported credit losses up to the end of 2020 Q3, we have used available reporting of credit losses at corporate level to check that our estimates do not differ substantially from those reported so far in 2020.

Given assumptions about loss ratios for the different IFRS 9 stages described above and in Table 3, we have estimated total credit losses for oil service and international shipping for 2020 – 2022 (Chart 6). Using this framework, losses on loans to oil service are estimated at about 14 percent of total lending to the industry in 2020. Losses are estimated to be substantially lower in 2021 and 2022, but losses as a share of lending to the industry are still higher than estimated losses on loans to all other industries in Chart 5. For international shipping, estimated losses are considerably lower, with a loss ratio of just below 2 percent in 2020 and a gradual decrease thereafter.

Chart 6: Estimated losses on loans to oil service and international shipping. As a share of lending to the industry. Percent



7 Conclusion

We have presented a framework for estimating banks' losses on corporate loans based on microdata. The framework utilises detailed microdata for Norwegian firms and data on banks' corporate exposures and brings together insights gained from a broad range of models and analyses Norges Bank has developed over many years.

The framework is a stepwise process. First, we estimate revenue developments at industry level and simulate the effect on firms' future financial statements. This is then used to model firms' bankruptcy probabilities for each firm using Norges Bank's bankruptcy probability model (KOSMO). Finally, the firm's bankruptcy probabilities are linked to data on banks' lending at exposure level. Losses for the period 2020 – 2022 are estimated based on calculations of historical loss ratios and changes in expected losses as a result of changes in bankruptcy probabilities through the projection period.

Industries with a large share of foreign firms are only represented to a limited extent in KOSMO. Two important industries to which this applies are oil service and international shipping. For these industries, exposures are assessed for impairment on an individual basis.

The framework provides a basis for a unified, microfounded assessment of the risk of losses on banks' exposures to the corporate sector. The estimates will be included in Norges Bank's overall assessment of risks and vulnerabilities in the Norwegian banking system. So far, the method has been applied to a set of large banks, with a primary focus on industries that were particularly vulnerable during the Covid-19 pandemic in 2020. We will test and continue to develop the framework in our further work. In addition to being included in a general risk assessment of the Norwegian banking system, the framework can be used in stress testing and in the assessment of new areas of risk, such as climate risk.

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Appendix

A Specification of simulation of net fall in revenue and modelling of cash support

A.1 Simulation of net fall in revenue

We draw falls in revenue, σ, degrees of reduction in variable costs, ν, and shares of fixed costs, ϕ from beta distributions with two parameters, α and β, which control the shape of the distribution. The beta distribution is a continuous probability distribution defined by the interval $[0, 1]$, where the mean of the distribution, μ, is given by $\mu = \frac{\alpha}{(\alpha+\beta)}$. We perform the following draws [13]:

1. For the fall in revenue, σ, $\mu = \bar{S}$, where $\bar{S} \in [0, 1]$, ie the percentage fall in a firm's revenue in the draw will on average be the same as the average percentage fall in revenue in the industry to which the firm belongs.

2. For the share of fixed costs, ϕ, $\mu = 0.5$, ie we assume that fixed costs make up on average half of the accounting item «other operating costs», A. This is reasonably in line with the average size of "unavoidable costs" reported by firms that have received support under the compensation scheme.

3. We assume that firms on average adjust their variable costs in proportion to the fall in revenue. The degree of reduction in variable costs, ν, should therefore on average be 0. ν is a normalisation of $\dot{\nu}$, given by $\nu = 2(\dot{\nu} - 0.5)$, where $\dot{\nu}$ is drawn from a beta distribution where $\mu = 0.5$.

We set $\beta = 4$ in the three draws. The shape parameter α is given by $\alpha = -(\mu\beta)/(\mu - 1)$. When $\mu = 0.5$ and $\beta = 4$, the distribution is symmetrical around 0.5, with $\alpha = \beta = 4$. A symmetrical distribution seems reasonable for falls in variable costs and the share of fixed costs, ν and ϕ. With a $\beta = 4$, there will be fewer observations of ν and ϕ close to the extreme values 0 and 1 in

[13] We use the "rbeta" function in Stata to perform the draws.

the distribution than with lower levels of β.

The distribution of σ will vary since $\mu = \bar{S}$ varies by industry. We are interested in capturing firms with large falls in revenue. In most industries, the fall in revenue, $\bar{S}$, is lower than 0.5. A $\beta = 4$ then represents a balance between the share of firms with σ higher than $\bar{S}$ and how high σ could be.[14]

A.2 Modelling of cash support

The compensation scheme adopted by the authorities in April allowed firms with large falls in revenue to apply for cash support to cover unavoidable fixed costs. Firms were eligible for support for those months in which the fall in revenue exceeded a certain level, and the scheme was in place from March until August. Firms were eligible for support in months where revenue was at least 30 percent (20 percent for March) lower than what was considered normal revenue for that month.

We assume that firms qualifying for the scheme receive an estimated amount of cash support. We model the cash support as follows:

- As the scheme varies from month to month, the estimate of support for month m, t_m, varies according to month.
- The scheme provides compensation for a certain share of fixed costs, a_m. For $m = \{\text{March, April, May}\}$, firms receive compensation for 90 or 80 percent of fixed costs, depending on whether or not they were required to close by the authorities. For $m = \{\text{June, July}\}$, the compensation rate is 70 percent and in $m = \{\text{August}\}$ the rate is 50 percent for all firms.
- The fall in revenue, σ, is the total fall in revenue for the whole year. The compensation scheme is based on the monthly fall in revenue. We simplify and assume that developments

[14] The rbeta Stata function does not generate draws when $\alpha < 0.5$. For low levels of $\bar{S}$, ie where $\bar{S} \cdot \beta/(\bar{S} - 1) < 0.5$, we set σ at $\bar{S}$.

in intensity, i, in the fall in revenue is the same for all firms and that the intensity varies over the cash support period:

Month	March	April	May	June	July	August
Intensity, i_m	1,5	1,7	1,3	1,2	1,0	0,9

To qualify for cash support, the monthly fall in revenue, σ_m, must be $\sigma \cdot i_m \geq 0.2$ when $m = \{\text{March}\}$ and $\sigma_m = \sigma \cdot i_m \geq 0.3$ when $m = \{\text{April, May, June, July, August}\}$. σ_m cannot be higher than 1.

- Firms not required to close by the authorities have to pay a deductible, E_m, in March and April of NOK 10 000 and NOK 5 000 respectively. There is no deductible after this period. E_m is therefore deducted from the estimated support, t_m, for $m = \{\text{March, April}\}$.
- There are upper and lower limits on payouts. If the estimated support, t_m, is more than NOK 30 million, the amount above NOK 30 million is halved. t_m cannot exceed NOK 80 million for $m = \{\text{March, April, May}\}$, NOK 70 million for $m = \{\text{June, July}\}$ and NOK 50 million for $m = \{\text{August}\}$. If $t_m < 5000$, no cash support will be awarded and t_m=0.
- Some firms are not eligible for cash support, such as firms in the financial sector, oil and gas production, electricity production and distribution, airlines and private childcare. Eligible firms must also have at least one registered employee.[15] We set $t_m = 0$ for firms that are not eligible for cash support.

Given the conditions described above, monthly cash support can be expressed as follows:

$$t_m = (1/12) \cdot \sigma_m \cdot a_m(\phi A + c) - E_m \tag{8}$$

where c = net interest expenses and ϕA is fixed operating costs.

As support is estimated monthly, the sum total of support can be calculated, T:

$$T = \sum t_m, \text{ where } m = \{\text{March, April, May, June, July, August}\} \tag{9}$$

[15]There are some exceptions for sole proprietors, among others. However, this analysis is restricted to limited companies, and a condition specifying that the firm must have a minimum of one employee to qualify for cash support is therefore regarded as reasonable.

B Projection of firms' accounting variables and credit ratings and estimated bankruptcy probabilities

B.1 Projection of firms' accounting variables

As described in Section 4.1, the following accounting variables are included in the prediction of bankruptcy probability for a firm in KOSMO:

- Return on assets, $RoA = \frac{EBT+IE}{A}$
- Equity ratio, opening balance, $ER = \frac{E}{A}$
- Total assets deflated by the GDP deflator, RA, in logarithmic form, $\ln(RA)$ and squared $\ln(RA)^2$

EBT is earnings before tax, IE is interest expenses, A is total asset and E is shareholders' equity.

Note that KOSMO uses the firm's equity ratio at the beginning of year t, which is the same as the equity ratio at the end of year $t-1$, and other accounting variables at the end of year t.

In Section 3.2 we define net fall in revenue, N, as:

$$N = (1-\sigma)I - ((1-(1-\nu)\sigma)(I-D-\phi A) + \phi A) - D$$

Our estimation of N_{20}^T is based on firms' annual accounts for 2019.[16] As we use the same annual accounts to estimate N_{21}, N_{21} is estimated as the cumulative effect of the annual shocks to revenue in 2020 and 2021. N_{20}^T and N_{21} are thus given by:

$$N_{20}^T = (1-\sigma_{20})I_{19} - ((1-(1-\nu)\sigma_{20})(I_{19}-D_{19}-\phi A_{19}) + \phi A_{19}) - D_{19} + T$$
$$N_{21} = (1-\sigma_{21})I_{19} - ((1-(1-\nu)\sigma_{21})(I_{19}-D_{19}-\phi A_{19}) + \phi A_{19}) - D_{19}$$

[16] For companies that have not yet submitted their annual accounts for 2019 and that are not registered as bankrupt or deregistered, we use the annual accounts for 2018.

where T is the sum of total cash support received from March to August 2020.

The simulated net falls in revenue, N_{20}^T and N_{21}, affect the accounting variables above through earnings before tax, EBT, shareholders' equity, E, and total assets, A. Earnings before tax is equal to operating profit plus net financial items (financial income less financial expenses), ie:

$$EBT_t = D_t + F_t$$

In the projections we assume that net financial items, F, are the same as in the accounting year 2019 in all years, ie $F_{19} = F_{20} = F_{21}$. For simplicity, we have assumed that taxes are equal to 0 and that no dividends or other transfers are paid out in 2020 and 2021. This means that we assume that EBT for 2020 and 2021 are recognised directly against shareholders' equity in the following way:

$$E_t = E_{t-1} + EBT_t$$

If $N_t = 0$, we leave the shareholders' equity unchanged from the previous year, $E_t = E_{t-1}$. Given the assumptions described above, projected accounting variables, with fall in revenues and cash support, are calculated as given below. Variables marked with a hat are projections, whereas variables not marked with a hat are actual observations.

$$\begin{aligned}
\widehat{RoA}_{20} &= \frac{EBT_{19} + \widehat{N}_{20}^T + IE_{19}}{A_{19} + EBT_{19} + \widehat{N}_{20}^T} \\
\widehat{RoA}_{21} &= \frac{EBT_{19} + \widehat{N}_{21} + IE_{19}}{A_{19} + 2 \cdot EBT_{19} + \widehat{N}_{20}^T + \widehat{N}_{21}} \\
\widehat{ER}_{19} &= \frac{E_{19}}{A_{19}} \\
\widehat{ER}_{20} &= \frac{E_{19} + EBT_{19} + \widehat{N}_{20}^T}{A_{19} + EBT_{19} + \widehat{N}_{20}^T} \\
\widehat{ER}_{21} &= \frac{E_{19} + 2 \cdot EBT_{19} + \widehat{N}_{20}^T + \widehat{N}_{21}}{A_{19} + 2 \cdot EBT_{19} + \widehat{N}_{20}^T + \widehat{N}_{21}} \\
\widehat{RA}_{20} &= \frac{A_{19} + EBT_{19} + \widehat{N}_{20}^T}{\text{GDE deflator}_{19}} \\
\widehat{RA}_{21} &= \frac{A_{19} + 2 \cdot EBT_{19} + \widehat{N}_{20}^T + \widehat{N}_{21}}{\text{GDP deflator}_{19}}
\end{aligned}$$

As in KOSMO, the new estimated accounting variables are truncated at the 2nd and 98th percentile to exclude extreme outcomes.

B.2 Projection of firms' credit ratings

KOSMO also includes a category variable for the firm's credit rating, K. The credit ratings are from Bisnode and are based on information about accounts, overdue payments and the firm's ownership structure. Bisnode's credit rating system comprises five categories: AAA, AA, A, B and C, where AAA is the highest and C is the lowest credit rating.

The last credit rating given in year t, K_t, is included in the prediction of bankruptcy probability in year $t+1$ in KOSMO.[17] Since credit ratings are an exogenous variable in the model, we do not have the direct relationship between changes in accounting variables and changes in credit ratings. We model credit ratings by assuming a simple relationship between a firm's credit rating, K, and developments in the firm's equity ratio, ER:

$$\Delta\widehat{ER}_t = \widehat{ER}_t - ER_{19}, \text{ where } t = 20, 21$$

$\Delta\widehat{ER}_t$ is thus the difference in a firm's equity ratio before and after the fall in revenue for 2020 and 2021 respectively.

- If $\Delta\widehat{ER}_t < -0.05$, $\widehat{K}_{t+1}$ is moved down one category from K_{20}, at most down to C
- If $\Delta\widehat{ER}_t < -0.20$, $\widehat{K}_{t+1}$ is moved down two categories from K_{20}, at most down to C

Credit ratings for firms registered as "no credit rating" are not changed.

[17] Note that even though the information from accounting variables for year t is included together with credit ratings for year t, which are partly based on accounting data, there is no direct correlation between these in estimating KOSMO. Accounting data for year t are not available when the credit ratings for year t are set.

B.3 Estimated bankruptcy probabilities

A more detailed description of all the variables included with time specifications in the three alternatives described in Section 4.2. Variables marked with a hat are projections, either from simulations or macroeconomic projections. Variables not marked with a hat are actual observations.

Alternative 1

$$\widehat{PB}_{20} \text{ depends on: } RoA_{19}, ER_{18}, \ln(RA_{19}), \ln(RA_{19})^2, K_{19}, \widehat{M}_{20}$$
$$\widehat{PB}_{21} \text{ depends on: } \widehat{RoA}_{20}, ER_{19}, \ln(\widehat{RA}_{20}), \ln(\widehat{RA}_{20})^2, K_{20}, \widehat{M}_{21}$$
$$\widehat{PB}_{22} \text{ depends on: } \widehat{RoA}_{21}, \widehat{ER}_{20}, \ln(\widehat{RA}_{21}), \ln(\widehat{RA}_{21})^2, \widehat{K}_{21}, \widehat{M}_{22}$$

Alternative 2

$$\widehat{PB}_{20} \text{ depends on: } RoA_{19}, ER_{18}, \ln(RA_{19}), \ln(RA_{19})^2, K_{19}, \widehat{M}_{20}$$
$$\widehat{PB}_{21} \text{ depends on: } \widehat{RoA}_{20}, ER_{19}, \ln(\widehat{RA}_{20}), \ln(\widehat{RA}_{20})^2, K_{20}, \widehat{M}_{20}$$
$$\widehat{PB}_{22} \text{ depends on: } \widehat{RoA}_{21}, \widehat{ER}_{20}, \ln(\widehat{RA}_{21}), \ln(\widehat{RA}_{21})^2, \widehat{K}_{21}, \widehat{M}_{20}$$

Alternative 3

$$\widehat{PB}_{20} \text{ depends on: } RoA_{19}, ER_{19}, \ln(RA_{19}), \ln(RA_{19})^2, K_{20}, \widehat{M}_{20}$$
$$\widehat{PB}_{21} \text{ depends on: } \widehat{RoA}_{20}, \widehat{ER}_{20}, \ln(\widehat{RA}_{20}), \ln(\widehat{RA}_{20})^2, \widehat{K}_{21}, \widehat{M}_{20}$$
$$\widehat{PB}_{22} \text{ depends on: } \widehat{RoA}_{21}, \widehat{ER}_{21}, \ln(\widehat{RA}_{21}), \ln(\widehat{RA}_{21})^2, \widehat{K}_{22}, \widehat{M}_{20}$$