

# STAFF MEMO

## How does IFRS 9 affect banks' impairment recognition in bad times?

NO 9 | 2019

HENRIK ANDERSEN  
IDA NERVIK  
HJELSETH



NORGES BANK

Staff Memos present reports and documentation written by staff members and affiliates of Norges Bank, the central bank of Norway. Views and conclusions expressed in Staff Memos should not be taken to represent the views of Norges Bank

© 2019 Norges Bank

The text may be quoted or referred to, provided that due acknowledgement is given to source.

ISSN 1504-2596 (online)

ISBN 978-82-8379-123-5 (online)

**NORGES BANK**  
**STAFF MEMO**  
NO 9 | 2019

HOW DOES IFRS 9 AFFECT  
BANKS' IMPAIRMENT  
RECOGNITION IN BAD  
TIMES?

# How does IFRS 9 affect banks' impairment recognition in bad times?

NORGES BANK  
STAFF MEMO  
NO 9 | 2019

HOW DOES IFRS 9 AFFECT  
BANKS' IMPAIRMENT  
RECOGNITION IN BAD  
TIMES?

Henrik Andersen and Ida Nervik Hjelseth<sup>1</sup>

*IFRS 9 has changed the way banks recognise credit losses. Under IFRS 9, credit impairment shall be based on more forward-looking assessments by including recognition of expected credit losses. The purpose of this memo is to analyse how IFRS 9 affects the path of Norwegian banks' credit losses in bad times. We analyse the effects of IFRS 9 by calculating and comparing the paths of banks' credit losses under IAS 39 and IFRS 9 in the period 2001–2017. Our results suggest that IFRS 9 may increase impairment losses both immediately prior to and during bad times with increased credit risk.*

IFRS 9, IAS 39, credit losses, enterprises, credit risk.

## 1. Introduction

After the financial crisis erupted in 2008, the accounting rules for banks' impairment recognition were criticised by the G20 leaders, authorities and investors (see Cohen and Edwards (2017) and Stefano (2017)). International Accounting Standard (IAS) 39 permitted banks to recognise credit impairment only if there was objective evidence of a loss event. According to critics, banks' impairment recognition was thus “too little, too late”.

European authorities responded to the criticism by introducing new accounting rules, International Financial Reporting Standard (IFRS) 9, from January 2018. Under IFRS 9, credit impairment shall be based on more forward-looking assessments by including recognition of expected credit losses. IFRS 9 is also intended to facilitate banks' management of credit risk.

Under IFRS 9, loans are to be assigned to one of three stages for impairment purposes (Chart 1). For fresh loans, a provision for expected credit losses (ECL) over the next 12 months must be recognised at origination (Stage 1). If the credit risk of a loan increases significantly,

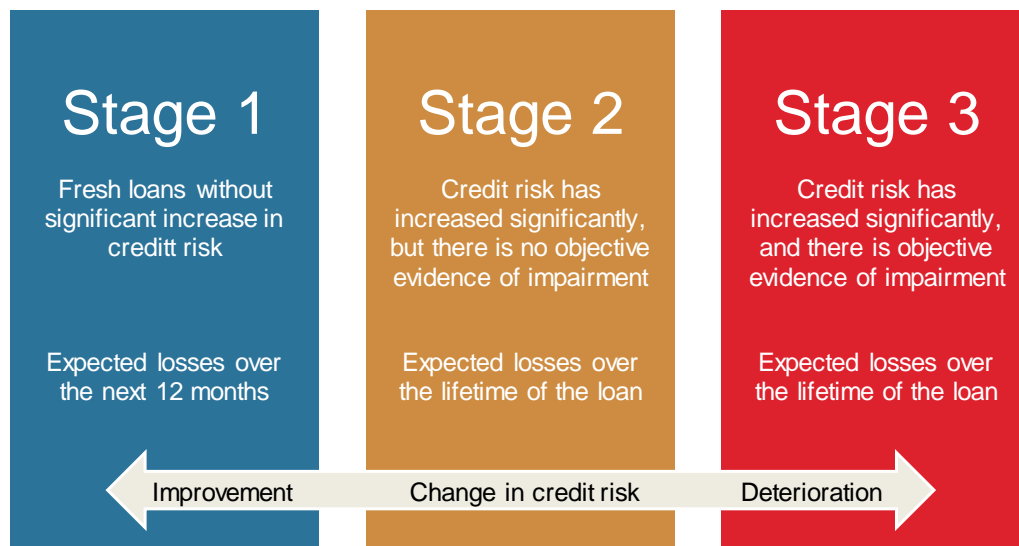
---

<sup>1</sup> The views and conclusions expressed in this publication are those of the authors and do not necessarily represent those of Norges Banks. We would like to thank Henrik Borchgrevink, Sigurd Galaasen, Karsten Gerdrup, Roar Hoff (DNB), Torbjørn Hægeland, Ragnar Juelsrud, Sverre Krog (DNB), Kjell Bjørn Nordal, Haakon Solheim, Norman Spencer, Nicolas Stefano and Sindre Weme for valuable comments and input.

banks must recognise a provision for lifetime credit losses (Stages 2 and 3). Banks define their own criteria for indications of a “significant increase in credit risk” (SICR), but both the external auditor and Finanstilsynet (Financial Supervisory Authority of Norway) are responsible for overseeing how banks apply IFRS 9.

Whether a loan is reclassified to Stage 2 or 3 depends on whether there is objective evidence of impairment. A loan is reclassified to Stage 2 if there is a significant increase in credit risk but no objective evidence of impairment. Reclassification from Stage 2 to Stage 3 requires objective evidence of impairment, eg that a loan has been non-performing for at least 90 days. Since Stage 3 requires objective evidence of impairment, this stage largely corresponds to credit losses measured on an individual basis under IAS 39.

Chart 1 Impairment recognition under IFRS 9



Source: E&Y (2017)

Implementation of IFRS 9 had limited effects on Norwegian banks' capital adequacy.<sup>2</sup> This may be because Norwegian banks' estimated credit risk was low when IFRS 9 was introduced. The introduction resulted in total impairment losses at the 30 largest Norwegian banks that were 7 percent higher at the beginning of 2018 than at year-end 2017 (see Finanstilsynet (2018)).

Several studies show that IFRS 9 may result in higher credit losses than IAS 39 when credit risk increases, because unlike under IAS 39, banks

<sup>2</sup> Norwegian banks may apply the transitional arrangements for IFRS 9, so that the effects on capital adequacy can be phased in during the period 2018-2022 (see Ministry of Finance (2017)). Only four banks in Norway are applying the transitional arrangements (see Finanstilsynet (2018)).

must to a larger degree recognise a provision for ECL over the entire life of a loan. In this situation, banks' capital ratios may fall faster and more sharply than under IAS 39 (see Norges Bank (2017)). Krüger et al (2018) performed a counterfactual analysis of a US bond portfolio over the period 1991–2013. The analysis shows that IFRS 9 may increase the fall in banks' capital adequacy in a downturn. Plata et al (2017) concluded the same, after having simulated the credit portfolios of the 14 largest banking groups in Spain. A model-based analysis by Abad and Suarez (2017) also shows that IFRS 9 may increase banks' capital needs in bad times, if expected losses rise quickly. The analysis shows that banks will then tighten lending more, which can amplify the fluctuations in the economy.

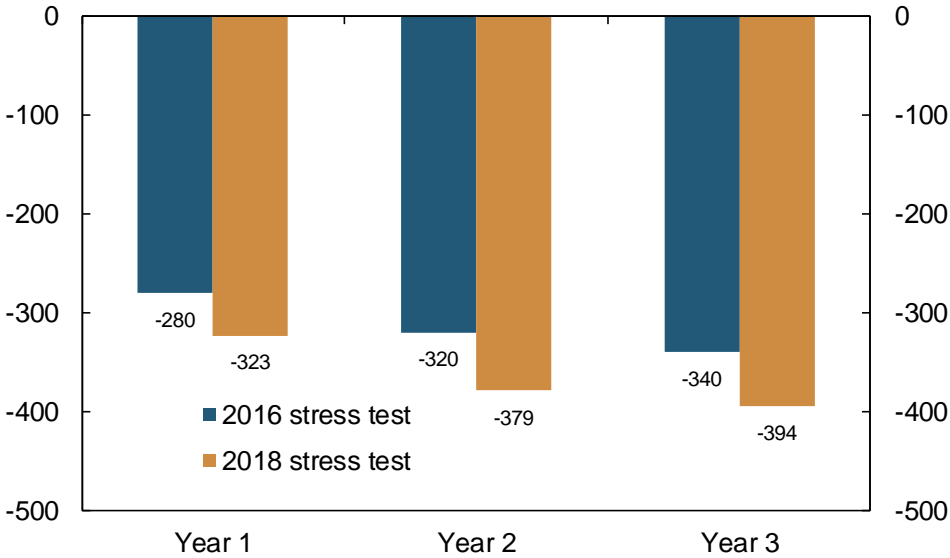
Other studies are less conclusive on how IFRS 9 will affect banks' impairment recognition. Gaffney and McCann (2018) analyse the effect of IFRS 9 on Irish residential mortgage loans and argue that IFRS 9 may lead to a smoother pattern for credit impairment, because IFRS 9 credit losses may increase earlier in a cyclical downturn than those under IAS 39. This will reduce the need to recognise impairment later in the downturn. On the other hand, a model-based analysis by Grünberger (2012) shows that the cyclical nature of impairment recognition under both IFRS 9 and IAS 39 may be broadly the same if banks cannot predict future changes in credit risk. Chae et al (2018) find that provisions for expected losses on US residential mortgages become more volatile if they are only based on information available to banks.

The European Systemic Risk Board (ESRB) points out that IFRS 9 may result in greater discipline in banks' loss recognition and greater transparency regarding loan quality (see European Systemic Risk Board (2017)). This may reduce uncertainty regarding the quality of banks' assets and improve the market's confidence in banks during downturns. In another report, the ESRB points out that the effects of IFRS 9 on financial stability will depend on whether banks can anticipate a downturn sufficiently far in advance, to allow them to adapt without tightening lending (see European Systemic Risk Board (2019)). The ESRB also points out that the effects of IFRS will depend on banks' incentives to recognise credit losses in good times and on whether other market participants will be able to replace a potential reduction in the supply of bank credit.

In 2018, the European Banking Authority (EBA) conducted a stress test of 48 large European banks, including DNB (see EBA (2018)). This was the first EBA stress test that included effects of IFRS 9. Compared with a similar stress test in 2016, banks' average capital adequacy fell more in the 2018 stress test, and this difference increased most in the first year

of the stress scenario (Chart 2).<sup>3</sup> Higher credit losses can explain why capital adequacy falls more in the 2018 stress test.<sup>4</sup> The increase in losses reflects effects of IFRS 9 and a deeper downturn in the adverse scenario than in 2016.<sup>5</sup> In the 2018 stress test, it was assumed that banks could anticipate developments in credit risk over the entire stress horizon. In a situation where credit risk increases over several years, under IFRS 9, banks will have to take into account the entire increase as soon as it becomes known. In that case, losses may rise sharply.

Chart 2 Cumulative change in average capital adequacy<sup>1)</sup> for the banks in the EBA stress test. Basis points



1) Without IFRS 9 transitional arrangements.

Source: EBA (2016, 2018)

Like the EBA, the Bank of England conducted its first stress test incorporating effects of IFRS 9 in 2018 (Bank of England (2018)). The stress test was conducted in collaboration with seven large UK banks and building societies. With IFRS 9, a larger share of losses were recognised in the first years of the stress horizon. In the 2018 stress test, 80 percent of aggregate losses were recognised in the two first years of the adverse scenario, a 16 percentage point increase compared with the stress test in 2017. Capital adequacy also fell faster in the 2018 stress test owing to IFRS 9. As with the EBA stress test, banks were able to anticipate developments in credit risk over the entire stress horizon.

<sup>3</sup> Impacts vary substantially across banks.  
<sup>4</sup> Credit losses in isolation pulled down average capital adequacy by 425 basis points in the 2018 stress test. In the 2016 stress test, the negative contribution from credit losses was 370 basis points.  
<sup>5</sup> In the 2016 stress test, EU GDP was 7.1 percent lower than the baseline at the end of the stress horizon. By comparison, this gap was 8.3 percent in the 2018 stress test.

In this memo we perform a counterfactual analysis of what credit losses would have been under IFRS 9 from 2001, where our assumptions are adapted to the reported practices of the largest Norwegian banks. Estimated paths for credit losses under IAS 39 and IFRS 9, which are calculated using the same data set and consistent assumptions, form the basis for our assessments of how the transition from IAS 39 to IFRS 9 may affect the path of banks' impairment losses. Section 2 addresses the parts of the standard that are relevant for the analysis in this memo. Section 3 provides an overview of the data set we use, while Section 4 describes the methods and assumptions underlying the analysis. Section 5 evaluates the results of our calculations, and Section 6 discusses challenges these calculations pose. Section 7 concludes.

## 2. IFRS 9 and banks' practices

The effects of IFRS 9 will depend on the banks' assessment of SICR.<sup>6</sup> Under the standard, this assessment shall be based on several elements (EY (2016)). Changes in the probability of default (PD) shall be a key component of the assessment of SICR. In this assessment, the banks shall use the change in the default risk occurring over the expected life of the loan (lifetime PD).<sup>7</sup> At the same time, the standard permits use of an estimate of the probability of default over the next 12 months (12-month PD) if there are no indications that it is necessary to assess PD over the expected life of the loan.<sup>8</sup> For example, indications that lifetime PD should be used may be a payment obligation or change in the regulatory environment which results in a significant change in the borrower's ability to meet its debt obligations beyond the next 12 months.

The assessment of SICR shall also include a qualitative assessment of other relevant information not used in the PD estimate. Finally, the assessment shall also consider other indicators that signal a significant increase in credit risk. Under IFRS 9, there is a rebuttable assumption that a significant increase in credit risk has occurred when contractual payments are more than 30 days past due.

It is crucial that our assumptions correspond to practices at the Norwegian banks under IAS 39 and IFRS 9 when analysing the effects of IFRS 9 on Norwegian banks' credit losses. The largest Norwegian banks use changes in PD as the primary criterion in their assessment of

---

<sup>6</sup> Krüger et al show that IFRS 9 will result in lower loss provisions if banks' SICR thresholds for reclassifying a loan from Stage 1 to Stage 2 are high than if they are low. Chae et al (2018) shows that banks' ECL recognition may also be affected by banks' models for calculating ECL.

<sup>7</sup> See paragraph 5.5.9 of IFRS 9 (International Financial Reporting Standards (2014)).

<sup>8</sup> See paragraph B5.5.13 of IFRS 9 (International Financial Reporting Standards (2014)).

SICR. Sparebanken Vest uses changes in 12-month PD to classify its loans under IFRS 9. For most of their loans, the largest SpareBank1 banks<sup>9</sup> do likewise.<sup>10</sup> DNB uses lifetime PD for all its loans in its assessment of SICR.

Banks shall define their own criteria for the level of and change in a loan's lifetime PD that is indicative of a significant increase in credit risk, but both the external auditor and Finanstilsynet are responsible for overseeing banks' practices in assessing SICR. The largest Norwegian banks reclassify loans from Stage 1 to Stage 2 if PD has increased by 100-150 percent since origination (Appendix Table A1).<sup>11</sup> In addition, DNB reclassifies loans from Stage 1 to Stage 2 if PD has risen by at least 7.5 percentage points, regardless of the percentage increase. Moreover, some Norwegian banks require an increase in PD of at least 0.6 percentage point, while others require an increase in PD to a level of at least 0.6 percent.

### 3. Data

We use several data sources to analyse the effect of IFRS 9 on banks' credit losses. We use estimated bankruptcy probabilities from Norges Bank's bankruptcy probability model to derive PD (see Section 4 for a description of the model). The model estimates bankruptcy probabilities using bankruptcy data, financial reporting data and credit ratings at enterprise level and macroeconomic indicators at industry level. Our bankruptcy and financial reporting data come from the Brønnøysund Register Centre and have been provided by Bisnode along with Bisnode's own credit ratings. The data set for the bankruptcy probability model contains financial reporting data for all Norwegian limited companies with bank debt over the period 1999–2018. The model uses GDP for mainland Norway, office rental prices and swap rates as macroeconomic indicators. The indicators are calculated on the basis of data from Statistics Norway, CBRE and Thomson Reuters.

We also use data from Norwegian banks in our estimations of credit losses. Norges Bank's bank statistics<sup>12</sup> contain data back to 1987 on banks' total losses, impairment losses on both a collective and individual basis and loans to the corporate market. Banks' quarterly and annual

---

<sup>9</sup> SpareBank 1 SR-Bank, SpareBank 1 SMN, SpareBank 1 Østlandet and SpareBank 1 Nord-Norge.

<sup>10</sup> These banks use lifetime PD from simulation models to classify loans to commercial property landlords. For remaining exposures they use 12-month PD.

<sup>11</sup> The EBA requires an increase in PD of at least 200 percent in its stress testing guidelines (see European Banking Authority (2017)). Their guidelines permit banks to keep loans with PD below 0.3 percent in Stage 1, even if PD has risen by 200 percent or more.

<sup>12</sup> See banks' and financial institutions' financial reporting to Norwegian authorities (ORBOF): <https://www.ssb.no/innrappoter/naeringsliv/orbof> (in Norwegian only).



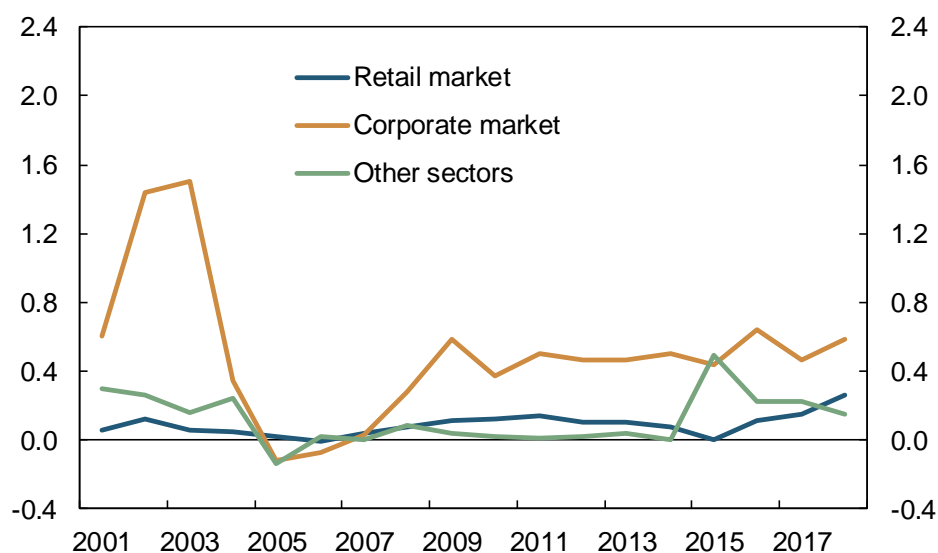
reports provide information on how IFRS is applied and data on loans and impairment broken down by Stages 1, 2 and 3 under IFRS 9.

## 4. Methods and assumptions

We perform a counterfactual analysis in which we assess the effects of IFRS 9 by calculating and comparing banks' credit losses under IAS 39 and IFRS 9 in the period 2001–2017. The differences between the two loss paths serve to illustrate how IFRS 9 would have affected recognised credit losses in the analysis period and its potential effects during downturns with increased credit risk.

The analysis is based solely on credit losses on corporate exposures. Losses on corporate exposures have accounted for nearly three-fourths of banks' credit losses in the period (Chart 3). Moreover, losses on corporate exposures explain a very large part in the fluctuations in total credit losses.<sup>13</sup> Analyses of developments in losses on corporate exposures can therefore be used to assess developments in banks' total credit losses.

*Chart 3 Banks' losses<sup>1)</sup> on lending to the retail market, corporate market and other sectors as a share of gross lending to the respective markets. Percent. 2001–2018*



1) All banks in Norway.

2) Recognised losses excluding changes in collective impairment/unspecified loss provisions.

Source: Norges Bank

<sup>13</sup> In the period 2001–2018, the correlation between the loss ratio (losses as a share of lending) on banks' corporate lending and the loss ratio on banks' total lending was 0.97.

We focus particularly on developments in credit losses around the time of downturns in Norway. Our data set contains two economic downturns with increased credit risk. During the downturn years 2002–2003, banks' credit losses rose, especially on loans to fish farming. Banks' loss provisions also rose on lending to construction and to manufacturing and services. In the same period, several banks recognised substantial losses on lending to the Finance Credit Group, which had manipulated its accounts. Considerable credit losses resulted in breaches of capital requirements by individual banks<sup>14</sup>. Moreover, some banks<sup>15</sup> were acquired by or merged with other banks. Losses a share of lending (loss ratio) also rose somewhat during the global financial crisis in 2008–2009, but less than in 2002–2003. In Norway, the financial crisis was primarily a liquidity crisis.

## 4.1. Calculating losses under IAS 39

We calculate banks' credit losses under IAS 39 by multiplying the bank debt of companies that have gone bankrupt by an estimated loss given default (LGD). The bankruptcy year is defined in the same way as in Norges Bank's bankruptcy probability model (see Section 4.2 for a further description). Appendix B describes how we estimate LGD. The estimations yield an average LGD of almost 40 percent in the analysis period. This is broadly at the same level as the LGDs used by the largest Norwegian banks. This is also on par with LGDs derived from historical loss and default data for the period 2001–2015 (see Andersen and Winje (2017)).

Under IAS 39, loss events other than bankruptcy could result in impairment recognition of banks' loans, including restructuring owing to borrowers' financial problems. To capture these loss events, we assume that enterprises experience financial problems if they have little or no equity, at the same time as substantial asset impairment contributes to negative earnings.<sup>16</sup> With this assumption, our calculated IAS 39 losses correspond better to developments in actual credit losses. The share of total bank debt captured by this assumption is highest in 2003 and 2009, ie during the two downturns in our data set. We do not have loss data on loans to enterprises that did not go bankrupt, but experience financial

---

<sup>14</sup> Nordlandsbanken, Nettet Sparebank and Sparebanken Flora Breanger breached the 8 percent capital requirement in 2002.

<sup>15</sup> In 2003, Nordlandsbanken was acquired by DnB NOR, Enebakk Sparebank acquired by Lillestrøm Sparebank and Finansbanken merged with Storebrand Bank. In 2004, Kreditbanken was acquired by Islandbanki, and in 2005, Sparebanken Rana merged with Helgeland Sparebank.

<sup>16</sup> Enterprises are assumed to have material financial problems if the carrying amount of total assets is reduced by over 5 percent, at the same time as net profit for the year is negative and the equity ratio is under 10 percent at the beginning of the year and/or the equity ratio is negative at year-end.

problems. Hence, we assume that the banks' LGD on such loans is half of the banks' LGD on loans to bankrupt enterprises. Banks' impairment losses on loans to such enterprises are thus calculated by multiplying these enterprises' bank debt by half of the estimated LGD.

## 4.2. Calculating losses under IFRS 9

We calculate credit losses under IFRS 9 with a separate PD estimate for each enterprise in our data set. The PD estimates are used in two areas in our calculations. First, we use the PD estimates to classify loans into the three stages. Second, we use the PD estimates to calculate loan impairments in the three stages. In calculating impairment losses on loans in Stage 2, we convert the PD estimates using a simple logit model, so that they reflect lifetime PD (see Appendix C for a further description of the model). We also use the same LGD estimates we used to calculate IAS 39 losses. This ensures that the two loss paths are comparable.

We apply Norges Bank's bankruptcy probability model to derive PD (see Hjelseth and Raknerud (2016)). The model calculates a bankruptcy probability for each non-financial enterprise with bank debt registered in Norway. The estimation is done at industry level. The industries modelled cover around 75 percent of the total bank debt of non-financial limited liability companies'.<sup>17</sup>

The bankruptcy probability model calculates the probability that an enterprise will go bankrupt in year  $t$  based on annual financial statement data for year  $t-1$ , credit ratings from year  $t-1$  and macroeconomic indicators for year  $t$ . When calculating eg bankruptcy probability for 2017, we use annual financial statement data for 2016, credit ratings from 2016 and macroeconomic indicators for 2017. In the model, the bankruptcy year is defined as the year in which an enterprise's business activity ceases, ie an enterprise is classified as bankrupt entity in year  $t$  if year  $t-1$  is the last year that the enterprise is registered as active and the bankruptcy is registered in year  $t$  or year  $t+1$ . In practice, an enterprise may default on its bank loan both during the last year the enterprise is registered as active ( $t-1$ ) and during the subsequent years. The results in Section 5.1 suggest that the bankruptcy probability model satisfactorily predicts developments in corporate defaults. This indicates that bankruptcy probabilities from the bankruptcy probability model can be used to calculate 12-month PD.

---

<sup>17</sup> The model covers the industries *fishing and aquaculture, manufacturing, mining and quarrying, construction, distributive trade, hotels and restaurants, commercial real estate and services and transport.*

Bernhardsen and Syversten (2009) find that PD is around twice as high as the probability of bankruptcy. On this basis, we derive PDs by multiplying bankruptcy probabilities by 2.

### **Classification of loans in Stages 1, 2 and 3 under IFRS 9**

We apply our estimate of 12-month PD to classify each enterprise into Stages 1–3 under IFRS 9. This corresponds to practices at the largest Norwegian savings banks. Our calculated lifetime PD is generally higher than our estimates of 12-month PD, but the variation in lifetime PD is considerably less than in 12-month PD. This makes our estimates of lifetime PD fairly unsuitable for classifying loans into Stages 1–3.<sup>18</sup> However, we do use lifetime PD to calculate impairment under Stage 2.

We assume that all enterprises are classified in Stage 1 at initial loan origination, with appurtenant original 12-month PD (OPD). The bankruptcy probability model contains data for the accounting years 1999–2018 but no information on when an enterprise first takes out a loan. To obtain a satisfactory measure of OPD, we have chosen to look at all enterprises with bank debt that enter the data set from the accounting year 2000 or later. Our data set then comprises enterprises with bank debt that was either established after 1999 or enterprises without bank debt established in 1999 or earlier that have taken on bank debt after 1999. If an enterprise sharply increases its debt in one of the years after start-up, ie by 100 percent or more, this is considered new borrowing and the 12-month PD from this year is used as the OPD.<sup>19</sup> If an enterprise drops out of the data set and re-enters later, the enterprise will also be given a new OPD. Enterprises will only be included in the data set from their most recently registered OPD. That is, an enterprise's previous observations are excluded from the data set if a new OPD is registered for the enterprise.

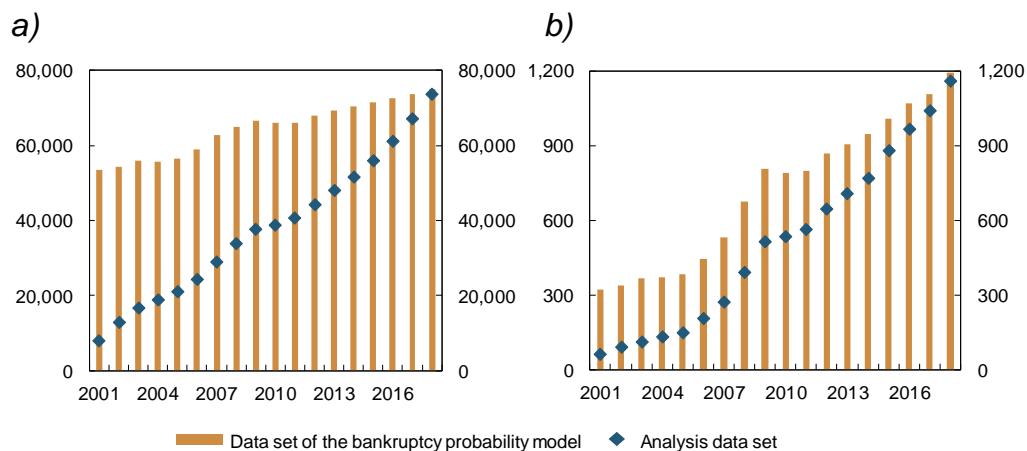
With these assumptions, the data set we use in our estimations have fewer observations than the bankruptcy probability model's data set (Charts 4a and 4b). The share of enterprises and bank debt covered by the data set is lowest early in the analysis period.

---

<sup>18</sup> If we use our estimate of lifetime PD to classify corporate exposures, the share of loans in Stage 1 is considerably higher for 2018 than has been reported by the largest Norwegian banks. In addition, few enterprises are reclassified from Stage 1 to Stage 2 during the two downturns in the analysis period. During both downturns, the share of loans classified in Stage 2 remains below the level reported by the largest Norwegian banks for 2018.

<sup>19</sup> Reducing this threshold value from 100 to 50 percent does not significantly affect our estimated loss paths under IFRS 9 and IAS 39.

Chart 4 Number of enterprises (a) and bank debt in billions of NOK (b) in the data set of Norges Bank's bankruptcy probability model and in the analysis data set. 2001–2018



Source: Norges Bank

We assume that an enterprise will be reclassified from Stage 1 to Stage 2 if the following two criteria are met:

- *Criterion 1:* 12-month PD must rise by at least 100 percent compared with OPD.
- *Criterion 2:* 12-month PD must rise by at least 0.6 percentage point compared with OPD.

With these two criteria, an enterprise with OPD of 1 percent will be reclassified to Stage 2 if 12-month PD rises to 2 percent or more, because the increase in 12-month PD is both at least 100 percent and 0.6 percentage point.

Regardless of whether *Criterion 1* is met, we reclassify all enterprises from Stage 1 to Stage 2 if the following criterion is met:

- *Criterion 3:* 12-month PD must rise by 5 percentage points or more compared with OPD.

With *Criterion 3*, an enterprise with OPD of 6 percent will be reclassified to Stage 2 if 12-month PD rises to 11 percent or more, because the increase in 12-month PD is at least 5 percentage points.

We reclassify an enterprise back to Stage 1 if 12-month PD falls back below the threshold values for Stage 2.

Enterprises end up in Stage 3 in the same way as loss events are registered under IAS 39. For the sake of simplicity, we assume that it is

not possible for an enterprise to be reclassified from Stage 3 to Stage 1 or 2.

### Calculating losses in Stages 1, 2 and 3 under IFRS 9

We use our estimates of 12-month PD and lifetime PD for individual enterprises and average LGD to calculate IFRS 9 losses in the three stages.

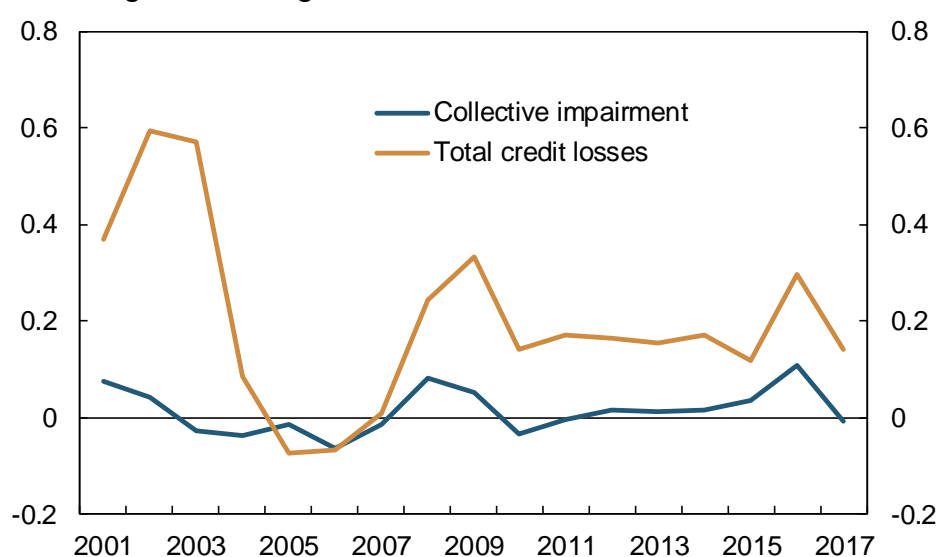
- Impairment in Stage 1 is calculated by multiplying the enterprise's bank debt by the enterprise's 12-month PD and average LGD for the year in question. If the enterprise remains at Stage 1, impairment will vary with changes in bank debt, 12-month PD and average LGD.
- Impairment in Stage 2 is calculated by multiplying the enterprise's bank debt by the enterprise's lifetime PD and LGD for the year in question. We take into account previous impairment from Stage 1 when calculating new impairment in Stage 2. If the enterprise remains in Stage 2, impairment will vary with changes in bank debt, lifetime PD and average LGD.
- We reverse Stage 2 impairment of corporate loans reclassified back from Stage 2 to Stage 1. In that case, total impairment from Stage 2 will be reversed in the year the enterprise is reclassified. If the enterprise is subsequently reclassified back to Stage 2 again, impairment is calculated anew as bank debt for that year multiplied by lifetime PD and LGD for the year in question.
- Losses in Stage 3 are calculated in the same way as IAS 39 losses: bank debt is multiplied by LGD for enterprises defined as bankrupt and with half of the LGD for enterprises identified as having financial problems. In addition, previous impairments from Stages 1 and 2 are subtracted. This ensures that calculated IFRS 9 losses on corporate exposures in Stage 3 will be at the same level as IAS 39 losses<sup>20</sup>.
- Enterprises that drop out of the data set without being classified in Stage 3 are assumed to have fulfilled their debt obligations. Earlier impairment of loans to these enterprises is reversed.

---

<sup>20</sup> Without collective impairment.

Our calculations do not include collective impairment under IAS 39. We therefore add an estimate of collective impairment to estimated IAS 39 impairment. In the period 1987–2017, banks' total collective impairment and unspecified loss provisions accounted for 10 percent of their total credit losses.<sup>21</sup> Measured as a share total credit losses, collective impairment has varied considerably over time (Chart 5). We have no data on collective impairment broken down by sector and industry. Collective impairment for the corporate market is approximated by multiplying the collective impairment of banks' total loans by a fixed share of 86 percent.<sup>22</sup>

Chart 5 Banks<sup>1)</sup> collective impairment and credit losses on total loans. Share of gross lending. Percent. 2001–2017



1) All banks in Norway.

Source: Norges Bank

We assume that banks' long-term losses do not depend on accounting rules. This makes it easier to compare the loss ratio paths under IFRS 9 and IAS 39. If the accounting rules affect the way banks monitor their borrowers, new rules can change the long-term loss level to some degree. At the same time, banks must recognise losses on loans to enterprises that default or go bankrupt, regardless of the accounting rules. Nor will cumulative losses for such a borrower depend significantly on whether or not banks have recognised impairment early. We therefore scale IFRS 9 losses by a fixed factor, so that the average

<sup>21</sup> Since IFRS 9 was introduced in January 2018, no collective impairment data are available for 2018.

<sup>22</sup> We assume that collective impairment shows the same breakdown between the corporate market and other sectors (excluding the retail market) as other recognised losses. In the period 2000-2017, the corporate market accounted for 86 percent of total recognised losses excluding changes in collective impairment/unspecified loss provisions (excluding the retail market).

loss ratio under IAS 39 and IFRS 9 is identical in the period 2001–2017.<sup>23</sup>

## 5. Results

We assess the effects of IFRS 9 by calculating and comparing banks credit losses under IAS 39 and IFRS 9, focusing in particular on developments around the time of the downturns in 2002–03 and 2008–09. The differences between the two loss paths may illustrate how IFRS 9 would have affected credit losses in the analysis period and the effects it could have during future downturns with increased credit risk.

### 5.1. Estimated IAS 39 losses

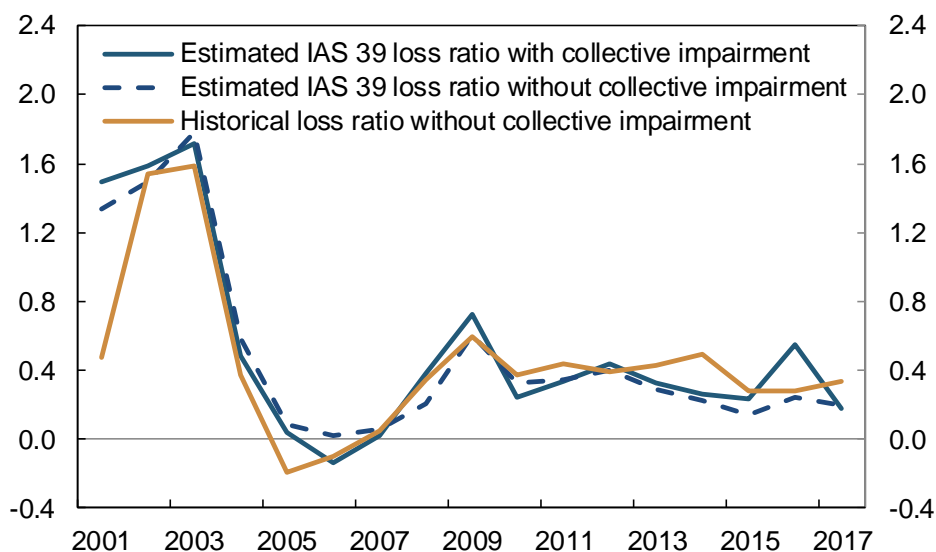
We begin by calculating banks' credit losses under IAS 39 as described in Section 4.1. Chart 6 shows that our calculations provide satisfactory estimates of developments in actual credit losses, but the path of the estimated loss ratio deviates somewhat from the historical loss ratio. There may be several reasons for this. First, there is no perfect match between Norwegian banks' corporate loan portfolios and our data set (Charts 4a and 4b). The loss ratio for the remainder of banks' corporate loan portfolios may be different from the loss ratio for the enterprises in our data set. Second, we have data on bankruptcies only, not defaults. Our measure of loss events other than bankruptcy is not a perfect measure of such loss events under IAS 39. However, the purpose of this analysis is to examine how IFRS 9 affects the path of banks' credit losses for a select loan portfolio. Estimated paths for credit losses under IAS 39 and IFRS 9, which are calculated with the same data set and consistent assumptions, forms the basis for our assessments of how IFRS may affect the path of banks' credit losses. In that case, estimated loss developments in this loan portfolio do not necessarily need to reflect loss developments in Norwegian banks' total corporate loan portfolio.

---

<sup>23</sup> We assume that our calculations overestimate IFRS 9 losses by a fixed proportion over time.



Chart 6 Historical loss ratios<sup>1)</sup> for banks<sup>2)</sup> loans to the corporate market and estimated loss ratio for corporate exposures under IAS 39. Percent. 2001–2017



1) Recognised losses excluding changes in collective impairment/unspecified loss provisions. Includes only industries covered by Norges Bank's bankruptcy probability model.

2) Branches of foreign banks not included, except for Nordea.

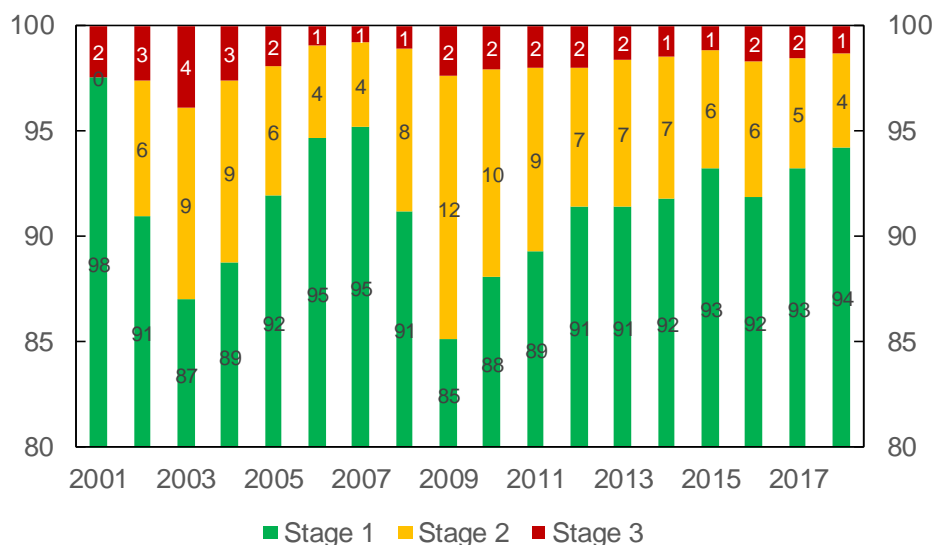
Source: Norges Bank

## 5.2. Estimated IFRS 9 losses

We calculate IFRS 9 losses with the method described in Section 4.2. Chart 7 shows the shares of bank loans classified in Stages 1, 2 and 3 with our calculations. The share of loans classified in Stages 2 and 3 rises during the two downturns with increased credit risk. The share of loans in Stage 2 peaks at 3.9 percent in 2003, while the share of loans classified in Stage 2 peaks at 12.5 percent in 2009.

The share of loans classified in Stage 1 turns out somewhat higher for 2018 than what banks reported for year-end 2018 (Appendix Table A2). This may reflect the small number of oil-related enterprises in our data set. It may also be because our calculated PDs are lower than banks' PDs. The share classified in Stage 1 is also higher than in the EBA 2018 stress test (Table A2).

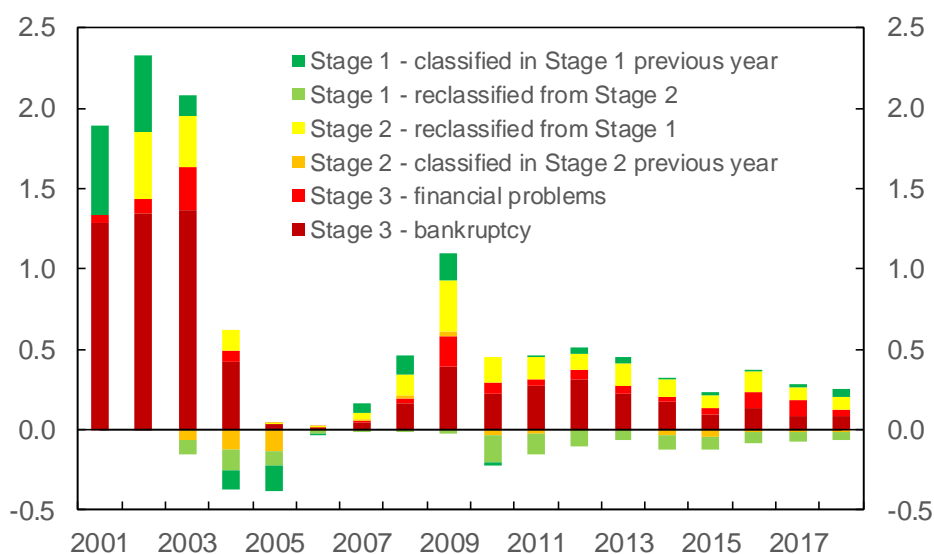
**Chart 7 Estimated classification of corporate exposures under IFRS 9. Broken down by Stages 1, 2 and 3. Percent of total bank debt. 2001–2018**



Source: Norges Bank

Chart 8 shows our estimated loss ratio under IFRS 9 broken down by Stages 1, 2 and 3. Impairment under Stage 3 accounts for most of the estimated IFRS 9 losses. This impairment is highest during the economic downturn in 2002–2003. Stage 3 impairment of loans to bankrupt companies make a particular contribution to estimated IFRS 9 losses. On average, this impairment accounts for two-thirds of total credit impairment in the period 2001–2018.

**Chart 8 Estimated loss ratio for corporate exposures under IFRS 9. Broken down by Stages 1, 2 and 3. Percent of total bank debt. 2001–2018**



Source: Norges Bank

Impairment of Stage 2 loans also accounts for a substantial share of estimated IFRS 9 losses. Stage 2 loans that had been classified in Stage 1 in the previous year contribute to higher IFRS 9 losses, especially during the two downturns with increased credit risk. This makes sense. First, banks are supposed to go from calculating impairment for expected losses over the next 12 months to impairment for expected losses over the life of these loans. Second, expected losses have risen substantially on these loans, because a SICR is required before a loan is reclassified from Stage 1 to Stage 2. On average, loans classified in Stage 2 that were also classified in Stage 2 the previous year pull down the estimated IFRS 9 losses slightly, especially in periods after the two downturns.

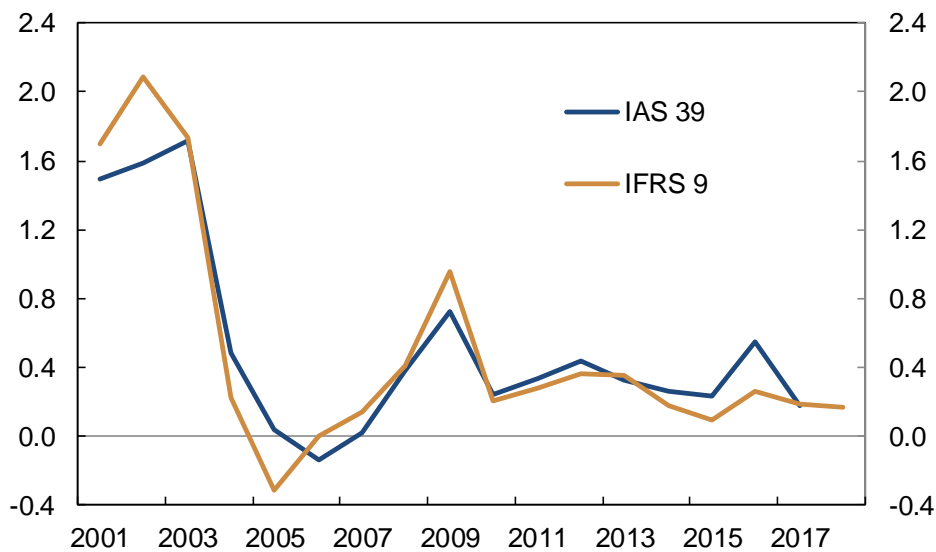
Impairment of Stage 1 loans pulls up the estimated IFRS 9 losses both before and during the two downturns. In 2001 and 2007, ie prior to the two downturns, Stage 1 impairment accounts for around a third of total IFRS 9 impairment. The reason is that expected losses on these loans rise, but not enough for them to be reclassified to Stage 2. In addition, most of banks' corporate exposures are classified in Stage 1. Loans reclassified from Stage 2 to Stage 1 generally pull down the estimated IFRS 9 losses. This makes sense, since these are loans with falling credit risk.

### 5.3. Comparison of estimated IAS 29 losses and IFRS 9 losses

Finally, we assess the effects of IFRS 9 by comparing the estimated loss ratios under IAS 39 and IFRS 9 in the analysis period. For the period 2001–2017, the calculated loss ratio under IFRS 9 averaged 6 basis points higher than the calculated loss ratio under IAS 39 including collective impairment. This reflects the fact that estimated IFRS impairment on loans classified in Stages 1 and 2 is higher than the collective impairment under IAS 39. We scale down IFRS 9 losses to get two identical average loss ratios over the analysis period. This makes it easier to compare loss ratio paths under IFRS 9 and IAS 39, with particular focus on developments around the time of the economic downturns with increased credit risk in 2002–2003 and 2008–2009. We assign the results around the financial crisis the greatest weight, because our data sample is larger at that time than during the downturn in 2002–2003.

Chart 9 shows that our estimated loss paths under IAS 39 and IFRS 9 are fairly similar. However, estimated losses under IFRS 9 are higher both immediately prior to and during the economic downturn in 2002–2003 and financial crisis in 2008–2009.

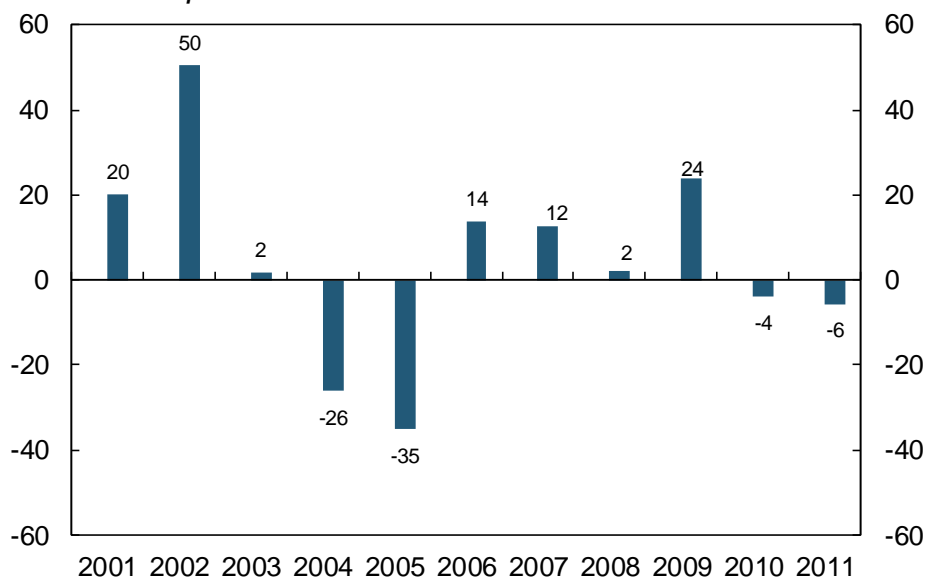
Chart 9 Estimated loss ratio on corporate exposures under IAS 39 and IFRS 9. Percent. 2001–2018



Source: Norges Bank

Prior to the two downturns, estimated IFRS 9 losses are higher than estimated IAS 39 losses. IFRS 9 losses are on average about a fifth higher than the IAS 39 losses in the last year prior to the two downturns. Chart 10 shows that IFRS 9 losses are 20 basis points higher than IAS 39 losses in the year prior to the downturn in 2002–2003. Estimated IFRS 9 losses are also higher than estimated IAS 39 losses in the two years prior to the financial crisis, 14 basis points higher in 2006 and 12 basis points higher in 2007.

Chart 10 Difference<sup>1</sup> between estimated loss ratios under IAS 39 and IFRS 9. Basis points. 2001–2011



1) Positive values mean that estimated IFRS losses are higher than estimated IAS 39 losses.

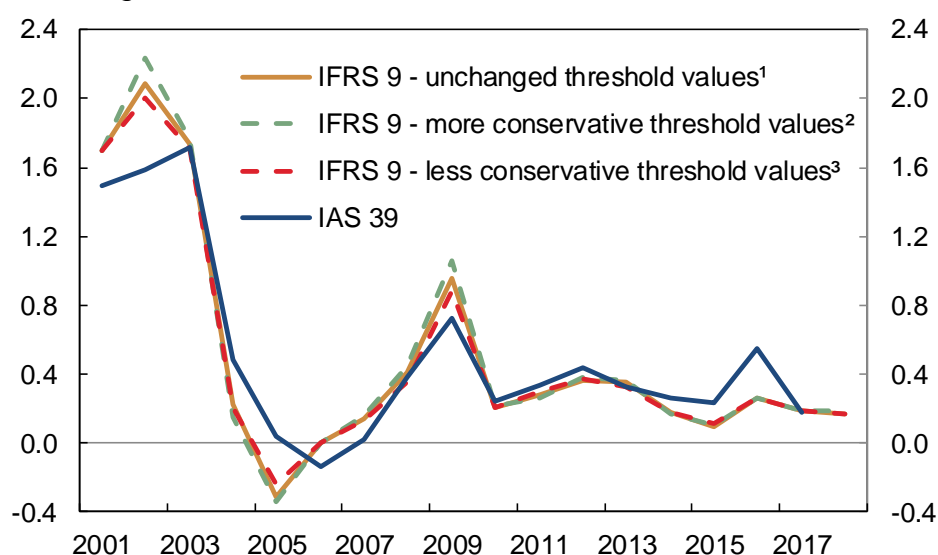
Source: Norges Bank

During the two downturns, estimated IFRS 9 losses are higher than estimated IAS 39 losses. IFRS 9 losses are on average about a fifth higher than IAS 39 losses during the two downturns. In the first and second years of the downturn in 2002–2003, IFRS 9 losses are 50 and 2 basis points higher, respectively, than IAS 39 losses. In the first and second year of the financial crisis, IFRS 9 losses are also higher than IAS 39 losses, 2 and 24 basis points, respectively.

After the two downturns, estimated IFRS 9 losses are lower than estimated IAS 39 years for a couple of years. In the two years following the downturn in 2002–2003, IFRS 9 losses are 26 and 35 basis points lower, respectively, than IAS 39 losses. In the two years following the financial crisis, IFRS 9 losses are also lower than IAS 39 losses, 4 and 6 basis points, respectively.

Our conclusions are robust to any assumptions we apply to Norwegian banks' practices in assessing SICR. Even if we apply other criteria for indications of a significant increase in credit risk, estimated IFRS 9 losses are generally higher than estimated IAS 39 losses, both immediately prior to and during the two downturns in the analysis period (Chart 11).

Chart 11 Estimated loss ratios under IAS 39 and IFRS 9 on corporate exposures with different assumptions regarding banks' practices in assessing SICR. Percent. 2001–2018



1) Threshold values for Criteria 1, 2 and 3 of 100 percent, 0.6 percentage point and 5 percentage points, respectively.

2) Threshold values for Criteria 1, 2 and 3 of 50 percent, 0.3 percentage point and 2-5 percentage points, respectively.

3) Threshold values for Criteria 1, 2 and 3 of 200 percent, 1.3 percentage points and 10 percentage points, respectively.

Source: Norges Bank

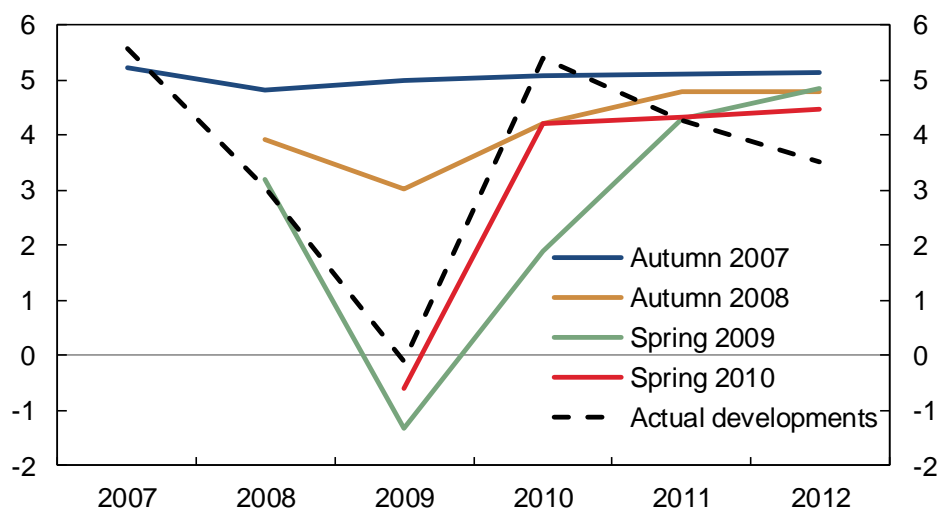
## 6. Challenges associated with our estimates

Even if our estimated loss paths under IAS 39 and IFRS 9 diverge around the time of the two economic downturns, they are, on the whole, fairly similar. This may be because our estimated losses have been calculated for a period that does not contain a sharp downturn with substantial bank losses like the banking crisis in 1988–1993. Credit risk will increase substantially on a large portion of bank loans during such a banking crisis, and a high share of these loans would likely be classified in Stage 2 under IFRS 9 before defaulting (Stage 3). In that case, the difference between IFRS 9 and IAS 39 may turn out to be considerably greater. There is also reason to believe that the effect of IFRS 9 will be stronger at the inception of a crisis if the economic outlook worsens.

Banks use a broader range of information sources to estimate impairment than the ones we use in this analysis. Both we and banks use financial reporting data for year  $t-1$ , which is reported in the course of year  $t$ , to estimate credit losses for year  $t$ . But banks also use more enterprise-specific information. In addition, banks are to use qualitative assessments and other relevant information in their analyses of SICR.

Unlike us, banks use real-time forecasts of macroeconomic variables to calculate PD and LGD. If already at the beginning of a downturn, banks forecast a sharp and prolonged contraction, banks' IFRS 9 losses will mount quickly. In such a situation, our estimated IFRS 9 losses, which are based on historical data, may vary less than credit losses estimated using forecasts. If banks do not foresee a contraction, impairment estimated using forecasts may be higher during the downturn and lower afterward. It is a challenge to predict the duration and depth of an economic downturn. For example, the International Monetary Fund (IMF) did not foresee the impact of the financial crisis on economic activity before the crisis erupted (Chart 12). Then the IMF overestimated the effects of the financial crisis in spring 2009. Applying these forecasts, recognised impairment would have been higher than real losses during the financial crisis, and some of the impairment would have been reversed after the crisis. In Norway, we find similar experience from the downturn following the oil price fall beginning in 2014. Up until March 2016, DNB forecasted that losses would be at a normalised level in the period 2016–2018. But in April 2016, DNB announced expected credit losses of up to NOK 6 billion in both 2016 and 2017, and from July 2016 to November 2017, the bank announced expected total credit losses of up to NOK 18 billion in the period 2016–2018. In the first half of 2018, the bank reversed some of its earlier impairment, and in the end, total credit losses in the period 2016–2018 were NOK 9.7 billion.

Chart 12 Global GDP. IMF projections and actual developments. Four-quarter growth. Percent. 2007–2012



Source: IMF

Results of the most recent EBA and Bank of England (BoE) stress tests show that credit losses can rise sharply if banks use forecasts when estimating IFRS 9 losses (EBA (2018) and Bank of England (2018)). The EBA and BoE assume that banks have “perfect foresight” with regard to future developments in credit risk. In that case, banks’ estimates of PD and LGD will reflect the entire contraction at an early stage and banks’ losses will rise sharply. This was probably the case for DNB in the EBA stress test, where the bank’s capital adequacy fell by 3 percentage points in the first year, and rose by 1.5 percentage points in the two subsequent years. All banks in the stress test as a whole showed broadly the same developments as DNB in the first stress year, but for all banks as a whole, capital adequacy also fell somewhat in the two subsequent years.

The fairly similar tracks of our estimated loss paths under IAS 39 and IFRS 9 can also be explained by the fact that collective impairment appears to have some of the same effect on banks’ credit losses that are expected from IFRS 9, ie it resulted in higher impairment at the beginning of a downturn when credit risk was increasing. Collective impairment losses contributed to an increase in credit losses in the first year of the two downturns (Chart 5). Collective impairment also contributed to an increase in credit losses *prior to* the downturn in 2002–2003. Prior to financial crisis, banks reversed their collective impairment, which helped to pull down credit losses.<sup>24</sup>

<sup>24</sup> New financial reporting rules introduced in 2005 may have contributed to net reversal of collective impairment by banks prior to the financial crisis. Under these new rules, banks could reduce the carrying amount of their loans only if there was objective evidence of impairment. This would suggest a bigger difference in impairment recognition under IAS 39 and IFRS 9 prior to 2005 than after 2005. However, we find no clear signs of this in our calculations, but the difference measured in basis points between our estimated loss ratios for IAS 39 and IFRS 9 narrows somewhat after 2005 (Charts 9 and 10).

## 7. Conclusion

The purpose of this memo is to analyse how IFRS 9 affects the path of Norwegian banks' credit losses in bad times. We perform a counterfactual analysis of what losses would have been on Norwegian corporate exposures with IFRS 9 from 2001, where our assumptions are adapted to reported practices at the largest Norwegian banks. Estimated credit loss paths under IAS 39 and IFRS 9, which are calculated using the same data set and consistent assumptions, form the basis for our assessments of how the transition from IAS 39 to IFRS 9 may affect banks' impairment recognition.

Our calculations suggest that IFRS 9 may increase credit losses both immediately prior to and during economic downturns with increased credit risk. Overall, estimated IFRS 9 losses are around a fifth higher than estimated IAS 39 losses both immediately prior to and during the two downturns in the analysis period. The estimations also suggest that IFRS 9 may result in lower credit losses than IAS 39 in periods following economic downturns. If banks recognise impairment early in bad times, IFRS 9 may result in greater transparency regarding loan quality. In that case, market confidence in banks may be better than under IAS 39. On the other hand, higher losses at the beginning of a downturn may contribute to a sharper fall in banks' capital adequacy. This may weaken confidence in banks, fuel financial market turbulence and result in tighter bank lending, which will amplify the downturn. In such a situation, the impact may be significantly reduced if banks hold sufficient capital buffers.

Our conclusions are robust to the assumptions we apply to Norwegian banks' practices. At the same time, our estimated loss paths under IAS 39 and IFRS 9 are fairly similar. This may be because credit losses are calculated for a period that does not contain a pronounced downturns with substantial bank losses. Credit risk will increase significantly for a large share of banks' loans during such a crisis, and then the difference between losses under IFRS 9 and IAS 39 may be considerably greater. Nor do we use projections of economic variables to estimate IFRS 9 losses. This may contribute to less variation in estimated IFRS 9 losses than banks' practices would imply. Moreover, collective impairment also appears to have some of the same effects on banks' credit losses as are expected from IFRS 9.



## References

NORGES BANK  
STAFF MEMO  
NO 9 | 2019

HOW DOES IFRS 9 AFFECT  
BANKS' IMPAIRMENT  
RECOGNITION IN BAD  
TIMES?

Abad, J. and J. Suarez (2017): "Assessing the cyclical implications of IFRS 9, a recursive model". *Occasional Paper Series 12/2017*. ESRB. July 2017.

Andersen, H. and H. Winje (2017): "Average risk weights for corporate exposures: what can 30 years of loss data for the Norwegian banking sector tell us?" *Staff Memo 2/2017*, Norges Bank.

Bank of England (2018): "Financial Stability Report". Issue No. 44, November 2018.

Bernhardsen, E. and B.D. Syversten (2009): "Stress testing the Enterprise Sector's Bank Debt: a Micro Approach". *International Journal of Central Banking*, Volume 5, Number 3. 111-138.

Chae, S., R. Sarama, C. Vojtech and J. Wang (2018): "The Impact of the Current Expected Credit Loss Standard (CECL) on the Timing and Comparability of Reserves". *Finance and Economics Discussion Series*, 2018-020, Board of Governors of the Federal Reserve System.

Cohen B.H. and G.A. Edwards (2017): "The new era of expected credit loss provisioning". *BIS Quarterly Review*. March 2017. Side 39-56.

DNB (2018a): "DNB Group Annual Report 2017". March 2018.

DNB (2018b): "DNB Group Quarterly Report 2Q18". July 2018.

European Banking Authority (2016): "2018 EU-Wide Stress Test – Results". July 2016.

European Banking Authority (2017): "2018 EU-Wide Stress Test". *Methodological Note*. November 2017.

European Banking Authority (2018): "2018 EU-Wide Stress Test – Results". November 2018.

European Systemic Risk Board (2017): "Financial stability implications of IFRS 9". ESRB. July 2017.

European Systemic Risk Board (2019): "The cyclical behaviour of the ECL model in IFRS 9". ESRB. March 2019.

E&Y (2016): "The implementation of IFRS 9 impairment requirements by banks". Global Public Policy Committee of representatives of the six largest accounting networks, 17 June 2016.

E&Y (2017): "Financial Instruments: A summary of IFRS 9 and its effects". March 2017.

Ministry of Finance (2017): "Forskrift om endring av forskrift om beregning av ansvarlig kapital for banker, kredittforetak, finansieringsforetak, pensjonsforetak, oppgjørssentraler og verdipapirforetak" [Regulation to amend the regulation on calculation of regulatory capital for banks, mortgage companies, finance companies, pension funds, clearing houses and investment firms]. December 2017 (in Norwegian only).

Finanstilsynet (2018): "Risk Outlook – June 2018". June 2018.

Gaffney, E. and F. McCann (2018): "The cyclicity in SICR: mortgage modelling under IFRS 9". Central Bank of Ireland, *Research Technical Paper*, Volume 2018, No. 16.

Grünberger, D. (2012): "Expected loan loss provisions, business- and credit cycles". *Austrian Financial Market Authority working paper* 2013/01.

Hjelseth, I.N. and A. Raknerud (2016): "A model of credit risk in the corporate sector based on bankruptcy prediction". *Staff Memo* 20/2016, Norges Bank.

International Financial Reporting Standards (2014): "IFRS 9 Financial Instruments". July 2014.

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

Norges Bank (2017): "Financial Stability Report 2017". Norges Bank.

Plata, C., M. Rocamora, A. Rubio and J. Villar, (2017): "IFRS 9: Pro-cyclicality of provisions. Spanish banks as an illustration". *BBVA Research*, October 2017.

SpareBank1 Nord-Norge (2019): "SpareBank1 Nord-Norge Årsrapport 2018 [SpareBank1 Nord-Norge Annual Report 2018]". SpareBank1 Nord-Norge (in Norwegian only).

SpareBank1 SMN (2019): "Årsrapport 2018 [Annual Report 2018]". SpareBank1 SMN (in Norwegian only).

SpareBank1 Østlandet (2019): "Årsrapport 2018 [Annual Report 2018]". SpareBank1 Østlandet (in Norwegian only).

Sparebanken Vest (2019): "Årsrapport 2018 [Annual Report 2018]". Sparebanken Vest (in Norwegian only).

Stefano, N. (2017): "IFRS 9 Implementation". *Economic Commentaries* 8/2017, Norges Bank.

## Appendix

### A. Tables

*Table A1 Banks' minimum requirements for a change in PD and PD level for reclassifying loans from Stage 1 to Stage 2*

	DNB <sup>1</sup>	Sp. Nord-Norge	Sp. SMN	Sp. Østlandet	Sp. Vest
Increase in percent	150	150	150	150	100
Change in percentage points	0.6		0.6		
Minimum level in percent		0.6		0.6	0.6

1) DNB also reclassifies loans from Stage 1 to Stage 2 if PD has risen by at least 7.5 percentage points, regardless of the percentage of the increase.

Sources: Banks' annual reports for 2018

*Table A2 Shares of loans classified in Stages 1, 2 and 3 under IFRS 9. 2018 Q4*

	Stage 1	Stage 2	Stage 3
With our assumptions and data set	94.3%	4.5%	1.3%
DNB - corporate loans	91.3%	6.3%	2.4%
SpareBank 1 Østlandet - corporate loans	89.1%	10.4%	0.5%
Sparebanken Sør - corporate loans	84.0%	14.1%	1.9%
DNB - total loans	93.5%	5.1%	1.5%
SpareBank 1 SR-Bank - total loans	90.7%	8.0%	1.3%
Sparebanken Vest - total loans	90.9%	8.0%	1.1%
SpareBank1 SMN - total loans	89.2%	9.3%	1.4%
SpareBank1 Østlandet - total loans	93.2%	6.4%	0.4%
Sparebanken Sør - total loans	89.6%	9.6%	0.9%
SpareBank1 Nord-Norge - total loans	92.1%	7.3%	0.5%
Uvektet gjennomsnitt - total loans	91.3%	7.7%	1.0%
EBA 2018 stress test: 2017 restated	90%	7%	3%
EBA 2018 stress test: adverse scenario (2020)	80%	13%	7%

Sources: Banks' annual and quarterly reports, EBA (2018) and Norges Bank

### B. Calculating LGD

We do not have data on LGD on corporate exposures. We therefore derive a debt-weighted LGD from other data series. The expected loss ratio on an exposure can be expressed as the product of PD and LGD:

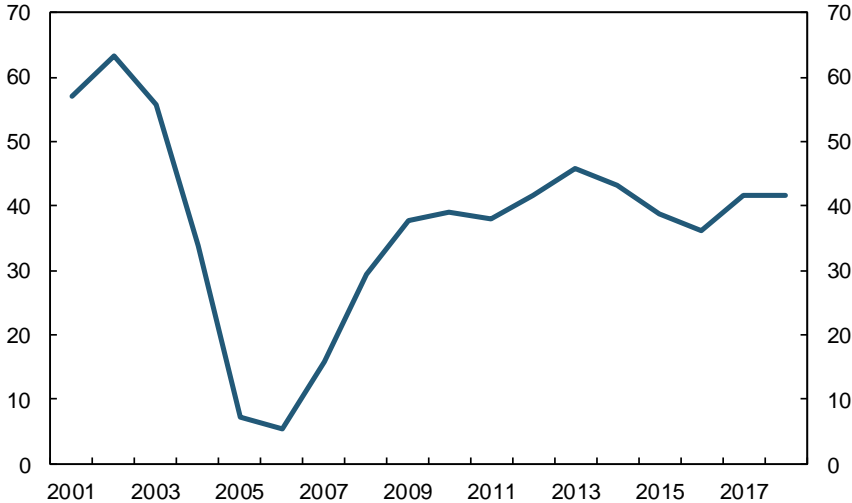
$$\text{Expected loss ratio} = PD * LGD$$

It follows that LGD can be approximated by dividing the loss ratio by PD. Approximated LGD corresponds to recognised losses as a share of expected defaults:

$$LGD \approx \frac{\text{Loss ratio}}{PD} = \frac{\left(\frac{\text{Losses}}{\text{Loans}}\right)}{PD} = \frac{\text{Losses}}{PD * \text{Loans}} = \frac{\text{Losses}}{\text{Expected defaults}}$$

We derive a debt-weighted LGD by dividing annual loss ratios by debt-weighted PDs (Chart B1).

Chart B1 Estimated annual LGD. Percent. 2001–2018



Source: Norges Bank

The calculation is based on the same historical loss ratios for corporate exposures as in Chart 6. We smooth this time series so that LGD does not turn negative in years with large reversals of earlier impairment. We calculate PD by multiplying annual, debt-weighted bankruptcy probabilities from Norges Bank’s bankruptcy probability model by 2 (see Section 4.2).<sup>25</sup>

PD and the loss ratio do not always move in tandem. In some cases, PD rises in the year before an increase in the loss ratio. In other cases, the converse is true. At times, this results in considerable fluctuations in derived LGD. Therefore, we smooth derived LGD by calculating a centred three-year moving average.<sup>26</sup>

Our method, which largely depends on the loss ratio, makes the results somewhat more robust to erroneous estimations of PD and LGD. Since the loss ratio is known and LGD is approximated on the basis of the loss ratio and PD, an overestimation of PD will lead to an underestimation of LGD and vice versa. For example, a reduction of PD by half results in a doubling of LGD.

<sup>25</sup> Average derived LGD over the analysis period is fairly similar for the different industries in the bankruptcy probability model. We have therefore calculated a single average LGD for all industries that we use for all enterprises.  
<sup>26</sup> In calculating the centred three-year average, LGD for 2018 is set equal to 2017 because loss data for 2019 are unavailable.

### C. Calculation of lifetime PD

We use a simple logit model to convert our estimates of bankruptcy probability over the coming year, so that they reflect bankruptcy probability over the entire term of the loan. For the sake of simplicity, we assume that the life of a loan is five years.<sup>27</sup> We construct a binary variable for bankruptcy in the course of the next five years, where  $b_{i,t}^5 = 1$  each year for up to five years up until and including a bankruptcy ( $b_{i,t} = 1$ ), if any:

$$b_{it}^5 = \begin{cases} 1 & \text{if } (b_{i,t} = 1 \cup b_{i,t+1} = 1 \cup b_{i,t+2} = 1 \cup b_{i,t+3} = 1 \cup b_{i,t+4} = 1) \\ 0 & \text{otherwise} \end{cases}$$

$b_{it}$  is defined in the same way as in Norges Bank's bankruptcy probability model. The relationship between  $b_{it}^5$  and  $b_{it}$  can be illustrated by some examples (Table C1). In the table, corporate loan 1 was granted five years before the enterprise goes bankrupt, and  $b_{i,t}^5$  will therefore be equal to 1 in every year. Corporate loan 2 is current for only three years before the enterprise goes bankrupt and for this loan,  $b_{i,t}^5$  will therefore be equal to 1 for three years. Corporate loan 3 is current for seven years before the enterprise goes bankrupt. In that case,  $b_{i,t}^5$  will be equal to 1 only in the last five years prior to the bankruptcy and 0 in the first two years.

Table C1 Examples of bankruptcy observations

	<i>t</i> (year)	$b_{it}$	$b_{it}^5$
<b>Corporate loan 1</b>	2002	0	1
	2003	0	1
	2004	0	1
	2005	0	1
	2006	1	1
<b>Corporate loan 2</b>	2015	0	1
	2016	0	1
	2017	1	1
<b>Corporate loan 3</b>	1999	0	0
	2000	0	0
	2001	0	1
	2002	0	1
	2003	0	1
	2004	0	1
	2005	1	1

<sup>27</sup> This is somewhat lower than the average number of years an enterprise is included in the data set of Norges Bank's bankruptcy probability model (6.5 years). On the other hand, it is somewhat higher than the average number of years an enterprise is included in the data set we use in our analysis (3.8 years).

We use the data set of Norges Bank’s bankruptcy probability model to estimate the bankruptcy probability for the entire term of the loan  $P^5_{i,t}$  using the following logit model:

$$\ln\left(\frac{P^5_{i,t}}{1 - P^5_{i,t}}\right) = \beta P_{i,t} + \mu$$

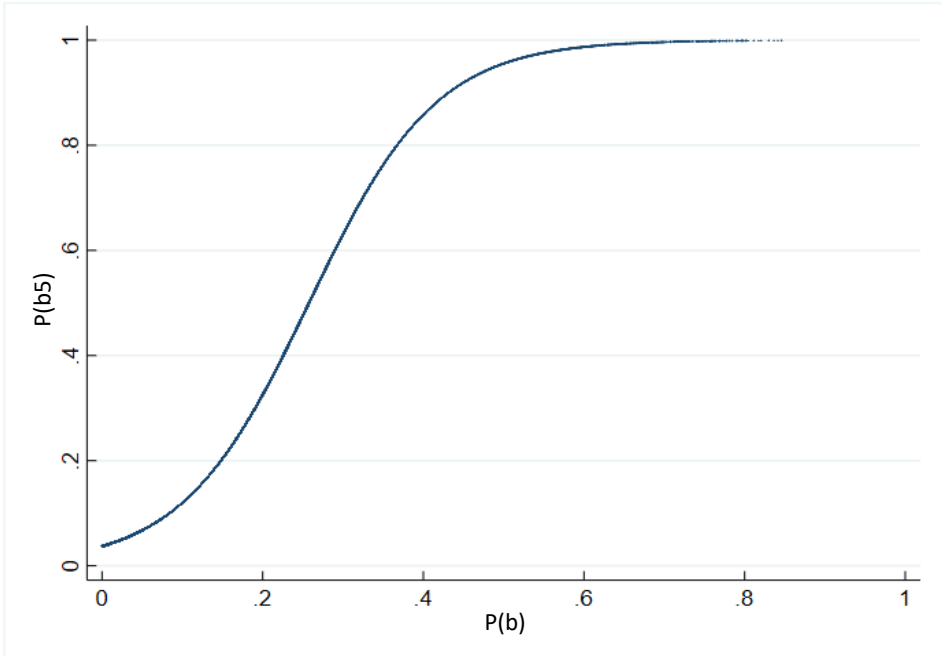
, where  $P_{i,t}$  is the “12-month bankruptcy probability” from the bankruptcy probability model and  $\mu$  is a constant term. The results are shown in Table C2 and Chart C1:

Table C2 Estimation results. Z-values in brackets

	<b>Coeff.</b>
<b><math>P(b)_{i,t}</math></b>	12.7*** (121.1)
<b><math>\mu</math></b>	-3.3*** (-399.3)
<b>Pseudo R<sup>2</sup></b>	0.1
<b>No. of obs.</b>	1 362 423

Significance level: \*\*\* 1 percent. \*\* 5 percent. \* 10 percent.

Chart C1 Estimated values for  $P(b^5)_{i,t}$  (y-axis) for every  $P(b)_{i,t}$  (x-axis)



Source: Norges Bank

Bernhardsen and Syversten (2009) find that PD is around twice as high as the probability of bankruptcy. On this basis, we derive the probability of default over the entire term of the loan, ie lifetime PD, by multiplying the estimated bankruptcy probability for the entire term of the loan by 2.