



Summary

Per Axelsson, Åsa David, Kishore Kamath, Carl Lönnbark and Viktor Thell*

The authors work at the Bank Analysis and Policy Department and the Economic Analysis Office at FI.

The FI Analysis series is presented at internal seminars at FI. The reports are approved for publication by an Editors' Board.

*The authors thank Björn Bargholtz, Johan Berg, Maria Blomberg, Henrik Braconier, Gunnar Dahlfors, Magnus Karlsson, Jorma Kyrö, Stefan Palmqvist and participants at seminars held at Finansinspektionen for valuable feedback.

FI uses so-called stress tests to analyse how unfavourable macroeconomic scenarios can impact the solvency of the Swedish banking system. An important component in these stress tests is the potential credit losses facing the banks. In this FI Analysis, we describe the method that FI used to estimate such credit losses in the stability report in the spring of 2020 and that can be used for similar objectives going forward.

We estimate credit losses based on historical relationships between credit losses and macroeconomic variables during the period 2007–2017. An important goal during the development of the methodology has been to be able to estimate credit losses for important regions and different lending categories. This means that the stress tests reflect the regions and segments where a bank is active, and the result in the form of total credit losses is impacted by the composition of a bank's lending portfolio. This facilitates the analysis of credit risk, both in total lending and in different lending categories. Based on the banks' risk exposures, we have chosen the following regions: Sweden, other Nordic countries, Baltic countries, and other countries. The lending categories are mortgages, consumer credit, loans to small and medium-sized enterprises, loans collateralised by commercial real estate, and loans to other corporates.

To illustrate how the models work, we use a macroeconomic scenario developed during the spring of 2020. Then, Sweden was experiencing a sharp economic downturn due to the COVID-19 pandemic and the measures the authorities were implementing to stop the spread of the virus.

The scenario is based on a sharp fall in GDP. Real estate prices and other real economic and financial variables also develop negatively in the scenario. Over the two years of the scenario, we estimate the total credit losses to 2.4 per cent of the major banks' lending to the public. Significant credit losses occur in all lending categories, but the loss ratios are highest for loans not collateralised by property for both households (consumer credit) and corporates. In our estimates, the credit losses as a percentage of total lending are larger than the losses that occurred between 2008 and 2010 but significantly smaller than the losses in the crisis in the 1990s.

Because crises occur infrequently and vary in nature, there is a significant degree of uncertainty associated with these types of analysis. Therefore, the results should be interpreted with caution and not be viewed as forecasts.



Stress tests of the banks' resilience

Finansinspektionen (FI) uses so-called stress tests to analyse how unfavourable macroeconomic scenarios can impact the solvency of the Swedish banking system. The objective of this FI Analysis is to present a method to estimate credit losses in stressed scenarios. In many situations, credit losses are the most important dimension of how the banks are managing a downturn. If the provisions for credit losses increase sharply, an otherwise profitable bank could report a loss. This can either immediately or in the long run threaten the bank's existence, and by extension financial stability.

In order to be able to better understand the results and assess the banks' resilience to different types of shocks, we need to be able to estimate credit losses for individual regions and lending categories.¹ This means that the different parts of the banks' balance sheets are impacted differently depending on the scenario that is used. This also means that the stress tests can reflect the segments where a bank is active, i.e., that the results in the form of total credit losses are affected by how the bank's lending is distributed between different segments. This enables us to better analyse the credit risk for both lending as a whole and different parts of the banks' lending. However, the method is not able to consider differences in the credit risk for a specific segment, neither between banks nor over time.²

In this FI Analysis, we start by presenting the banks' credit risks when lending and how the credit risks are related to credit losses and capital requirements. We then describe the underlying data and how the credit loss models work. We then illustrate our models based on the scenario that FI used in its stability report from the spring of 2020 (FI, 2020b) as a result of the spread of COVID-19 and measures to handle the pandemic. Finally, we discuss potential development areas to estimate credit losses following a shock.

Credit risk associated with lending

Banks assume when granting loans that not all customers will be able to make their interest and amortisation payments. They are therefore exposed to credit risks. In order to limit the credit risk associated with lending, the bank may require collateral when the loan is issued, for example in the form of real estate. Some credit losses can still be expected, though, and these can be viewed as a cost that must be covered when the banks set their prices.³ This cost is captured in the bank's income statement through provisions. Provisions are when expected losses are reported before any final losses are realised. In

¹ This expands the approach that was used in an earlier cooperation between FI and the Riksbank where credit losses were estimated at the aggregate level instead of for specific lending categories. See IMF (2017).

² See Aranki, et al. (2020) for a method that uses data at the lending level together with information about the counterparties' financial position.

³ The expected loss (EL) is often formally broken down as

$$EL = EAD * PD * LGD$$

where *EAD* is the exposure at default, *PD* is the probability of default, and *LGD* is the loss given default (expressed as per cent). This differs from doubtful loans, which are called credit loss provisions for impairment.

other words, the banks assume that they will not recoup a certain percentage of every loan. They incorporate this by reporting expected credit losses in their income statement and writing down the value of assets in their balance sheet. The higher the credit risk, the higher the provisions and thus the credit losses.

Sometimes the credit losses are unexpectedly large. This occurs often when the economic development is worse than expected, for example during serious economic downturns or financial crises. One example of this type of serious economic downturn is the Swedish crisis at the beginning of the 1990s. Major credit losses can threaten the solvency of individual banks as well as the stability of the financial system as a whole, either in the long run or immediately if a bank is systemically important. In order for this not to occur, the banks are subject to requirements on how much capital they must have: enough to be able to cover unexpected losses without threatening their survival or the functions they perform in the economy.

Capital requirements are often expressed as a percentage of risk-weighted exposure amounts (REA). REA for a loan, somewhat simplified, is the amount of the loan multiplied by a risk weight that reflects the credit risk in the exposure. The higher the credit risk the higher the risk weight. The risk weights are calculated using either a standardised approach or an internal ratings-based (IRB) approach. Banks that use the IRB approach can use their own data on credit losses to estimate certain parameters in a risk-weight formula that is determined by the regulatory framework. To use the IRB approach, banks must receive authorisation from FI, and their IRB approaches are reviewed as part of FI's ongoing supervision. Two of the most important parameters estimated by the IRB approach are the probability of default (PD) and loss given default (LGD).⁴

The credit risk in the loans, in other words, affects both how large the credit losses are expected to be and the risk weights, and thus the size of the capital requirements. However, in order to prevent variations in the capital requirements over time, the risk weights must be stable over business cycles. The PD values that are used to calculate risk weights must therefore be through-the-cycle (TTC). This means that they must reflect the *average creditworthiness*⁵ in a plausible interval of variations, including severe downturns.⁶ The LGD values that are used in the calculation should be downward adjusted. This means that they must be representative of situations with sharply impaired collateral values, for example real estate prices.

After the global financial crisis, problems related to how the banks reported their credit losses came into focus, and the G20, among others, pushed for better accounting standards.⁷ In response, the International Accounting Standards Board (IASB) published the final

⁴ Banks that use the IRB approach estimate PD themselves. If the banks instead use an advanced IRB approach, they are allowed to also estimate LGD themselves.

⁵ Creditworthiness here refers to the ability to make interest and amortisation payments.

⁶ PD values that are through the cycle differ from point in time (PIT) values, which reflect the current probability of default at each instance.

⁷ The G20 is an international forum for the world's twenty largest economies. G20, Declaration on Strengthening the Financial System, London, 2 April 2009.

version of the IFRS 9 accounting standard in the summer of 2014. The new standard entered into force on 1 January 2018.⁸

IFRS 9

This new standard contains in part a new method for reporting credit losses. The reporting in the new standard is based on forward-looking loss expectations. In the previous standard (IAS 39), credit losses were reported when there was clear evidence that a loss would arise.

Credit loss provisions according to IFRS 9 are based on a three-step classification of credits:

- *Step 1* – loans with no significant increase in the credit risk since the first reporting occasion. The provision is calculated using the expected credit loss for a one-year period.
- *Step 2* – loans with a significant increase in the credit risk since the first reporting occasion. The provision is calculated using the expected credit losses for the loan's remaining lifetime.
- *Step 3* – past due loans. The provision is calculated using the expected loss for the loan's remaining lifetime.

While the calculation method itself differs between Steps 1 and 2, it is only the change in the size of the expected loss that changes when an exposure is reclassified from Step 2 to Step 3. Subsequently, the banks make provisions for all loans. Credit losses during a given period of time thus reflect changes in total provisions and realised losses that are usually called *impairment*.

An important part of this new standard is also that provisions are to consider macroeconomic outlooks. An expected economic downturn, in other words, should lead to earlier credit losses as provisions increase. Thus, the bank's financial position is affected earlier by an economic downturn than under the previous accounting standard. However, when the credit losses arise in an economic downturn is dependent on how sensitive the banks' provision models are to the macroeconomic situation.

In summary, a severe economic downturn will result in an increase in the credit risk in the banks' lending. This, in turn, will lead to an increase in credit losses through a decline in the repayment capacity of the bank's customers, a drop in value of the collateral issued for the loans, or a combination of the two. The implementation of the IFRS 9 accounting standard means that the losses will arise earlier in a stressed scenario than they would have under IAS 39. The total losses in principle could remain the same, however, though this applies on the condition that the horizon for the stressed scenario is long enough for the increase in the credit risk to have materialised into credit losses

⁸ IFRS is an international regulatory foundation that publishes accounting standards. International Accounting Standards Board (2018) contains a more detailed description of IFRS 9. The formula varies somewhat depending on the exposure category.

and for the expected credit losses that are not realised to have shown a higher creditworthiness so the provisions are reclassified as Step 1.

Method for estimating credit losses

In this section, we describe the method we developed to estimate how the banks' credit losses could develop in stressed macroeconomic scenarios. The total effect in the banks' capital ratios of a change in their credit risk consists of both the effect on the banks' capital (from the credit risk being realised as credit losses, as discussed here) and the effect on REA (from potential changes to the banks' cycle-adjusted credit risk parameters). Our method does not include lending to other financial institutions or states.⁹ Our models are estimated using data for the major banks Handelsbanken, Nordea, SEB and Swedbank.¹⁰ But when we apply the scenario to the models, we do so for the three major Swedish banks Handelsbanken, SEB and Swedbank and show their aggregate results. The next section summarises the underlying data and its segmentation.

DATA AND SEGMENTATION

When we developed our model, it was important to be able to analyse credit losses in different regions and for different lending categories. This makes it easier to analyse the credit risk more deeply and precisely, but it also facilitates comparisons with the banks' own stress tests or other organisations' stress tests that are conducted or presented at the portfolio level. It also facilitates a more detailed analysis of the correlation between credit losses and REA changes under stress.

By analysing different regions, we are better able to capture regional differences in macroeconomic events and their correlation to losses. For example, this simplifies the analysis of whether an individual region is hit harder than others in a scenario. Even if the sensitivity in the model for a given outcome will be the same between regions, we can adjust for existing differences in risk levels between different regions. We have started with the countries where the banks have the largest exposures and organised the data into four regions: Sweden, Other Nordics, Baltics, Other countries.¹¹

By analysing different lending categories in the regions, we are able to better capture the risks between different types of lending and how they relate to the macroeconomy. For example, the creditworthiness of mortgage portfolios can be more dependent on the development in housing prices and the labour market than lending to large corporates. In addition to the relative sensitivity to different types of economic development, the underlying level of credit risk can also vary between different types of lending. If a bank has a large share of exposures in

⁹ These are normally called institution and sovereign debt exposures. These exposures constitute on average around one-fifth of the Swedish major banks' total exposures.

¹⁰ We use data at the consolidated level. Nordea is included since it was a Swedish bank during the period of analysis and still is a systemically important bank for the Swedish financial system.

¹¹ Nordics includes Denmark, Finland and Norway (and excludes Iceland). Baltics includes Estonia, Latvia and Lithuania. Other countries includes other major countries where Swedish banks have large exposures: Germany, Russia and the UK.

Table 1. Share of aggregate lending per lending category, Q4 2019
Percentage of exposures

	Sweden	Other Nordics	Baltics	Other countries	Sum
Mortgages	36	4	2	2	44
Consumer credit	3	1	1	0	5
CRE	17	5	1	4	26
SME	2	1	0	0	4
Other corporates	8	5	2	6	21
Sum	67	15	5	13	100

Source: FI.

Note: Refers to the average for the three major Swedish banks.

portfolios with higher credit risk, this influences our estimates of the size of the stressed total credit losses.

For each region, we use five lending categories (sectors): three for exposures to non-financial firms and two for exposures to households.

The categories for corporate loans are loans collateralised by commercial real estate (CRE)¹², loans to small and medium-sized enterprises (SME) without collateral in CRE, and loans to other corporates, primarily large corporates without collateral in CRE.

The two categories for lending to households are mortgages and consumer credit. We define consumer credit as all non-mortgage loans to consumers, for example unsecured loans, revolving credits, and loans collateralised by assets other than real estate. Swedish mortgages constituted the largest segment in 2019 with 36 per cent of the banks' lending (Table 1). The lending categories' share of the total lending varies by bank. For example, the bank with the largest share of Swedish mortgages had 50 per cent of its lending to this segment, while the bank with smallest share had 26 per cent.

We have chosen these lending categories and regions based on both relevance and availability of data. With *relevance* we mean, for example, how the creditworthiness in the lending categories covary with various macroeconomic factors. For example, we have two different lending categories for households. This means that credit losses for mortgages can be influenced more by housing prices than losses linked to consumer credit.

To estimate credit losses, we use data from two main sources: the standardised financial reporting framework (FINREP) for the years 2014–2017 and a survey of the banks by FI concerning years 2007–2013.¹³

FINREP has information about the banks' lending for each sector in each country on a quarterly basis. This data also contains information about accumulated provisions in the same dimensions. Data from the survey that FI conducted includes exposures and credit loss levels in approximately the same countries and sectors as FINREP, but measures them annually instead of quarterly.¹⁴

¹² This differs from the normal definition of commercial real estate as firms within the real estate investment and development sector.

¹³ FI's survey data of annual credit losses from the three major Swedish banks and Nordea spans the period 2007–2011 for three of the banks and 2007–2013 for one of the banks. The difference in loss ratios between regions and lending categories for 2012–2013 for the bank is used to extrapolate the values for the other banks. This assumption does not drive the results since the credit losses were low during these years and the years immediately before and after. For FINREP, the corporate segments loans to small and medium-sized enterprises and loans collateralised by commercial real estate overlap one another. However, we make the assessment that this has not had a crucial impact on the results. Data from the survey where there was no overlap contains the largest variation in credit loss levels at the same time as the time period includes the financial crisis and thus influences the estimates the most.

¹⁴ In the survey, Russia and the Ukraine belong to the same category as the Baltics. Other countries include all countries and not just Germany and the UK, which represented the majority of the exposures. Losses for consumer credit are also not reported by country.

For data from FINREP, we calculate a well-established proxy variable for credit losses.¹⁵ We define this proxy as the change of accumulated provisions over the most recent four quarters divided by a four-quarter moving average for the exposures. For 2007–2013, we use the data on credit losses and exposures to calculate the credit loss ratios.¹⁶

CREDIT LOSS MODELS

To systematically capture the correlation between macroeconomic variables and the banks' credit losses, we estimate an equation for each lending category (for example, *Small and medium-sized enterprises*).¹⁷ In each equation, we use the four banks' volume-weighted credit loss ratios per region and quarter.¹⁸

We aggregate credit losses across banks for two reasons. First, this limits the importance of historical credit losses for individual banks. For example, larger losses for an individual bank during the financial crisis does not necessarily mean that the credit risk is higher for that bank ten years later. Or that a bank that historically has had small credit losses has a significantly lower credit risk even today and will never experience large credit losses.

Second, the aggregate credit losses make the estimates more sensitive to each segment, and the underlying relationship to the macroeconomy, rather than to bank-specific losses.

We use all regions at the same time in the estimates for each lending category. We do this to take advantage of more experiences from macroeconomic outcomes and credit losses than what each individual region has experienced during the period for which we have data. This is important since the aim is to calculate credit losses in a difficult and stressed macroeconomic and financial environment. In several regions, including Sweden, such a situation has not occurred during our sample period. However, we take into consideration systemic regional differences with regard to credit risks. Such differences can arise, for example, due to different countries having different bankruptcy legislation or to regional economic development. For example, the models generate larger losses for lending in the Baltics than in Sweden, all else equal.

We choose macroeconomic explanatory variables based on two criteria. First, we limit the variables to those that often are included in stressed macroeconomic scenarios, for example those developed by the European Systemic Risk Board (ESRB), in order to make relevant comparisons using the credit loss models.¹⁹ This also means that the data is available for all regions, which would not have been the case with more specific variables that are dependent on data reporting in

15 A proxy variable is a variable that attempts to estimate the value of another variable that cannot be observed or measured. The difference between the proxy and the credit losses reported in the income statement consists of write-offs and recoveries.

16 For this period, we use the annual data points to interpolate quarterly observations.

17 Technical details regarding the models are provided in Appendix 1.

18 This type of dimensionality of data is often called panel data since it captures both time dimensions and cross-sectional dimensions.

19 See, for example, ESRB (2018).

each specific region. Second, we decide on a definitive model based on statistical significance and economic interpretation. We expect, for example, that credit losses will increase during economic downturns.²⁰

The most prominent variables in the various equations are the annual change in employment and annual GDP growth. Historically, credit losses are relatively low for a large span of economic outcomes, while much larger losses arise if the economic development is sufficiently weak.²¹ Credit losses' non-linear relationship to economic outcomes makes the modelling more challenging. This is particularly the case when the history we use to estimate losses, for most of the regions, does not contain any period of very weak economic development. But to consider that the losses tend to be disproportionately large for very adverse economic outcomes, we also include the squared change in GDP in the models, i.e., the change of GDP multiplied by itself. In addition to unemployment and GDP, the model includes the following variables: long-term interest rates, the three-year change in the relationship between the private sector's total debt and GDP, and the change in prices of housing and commercial real estate. The exact combination of variables that is used for each lending category differs (see Table A1).

An important assumption in the method is that the credit losses in each individual loan category are affected in the same way by changes in macroeconomic variables, regardless of the region. Therefore, we include regional fixed effects in the models to account for differences in the risk level between the regions. The estimated credit losses have varying sensitivity to the macroeconomic variables across lending categories, and each region has different fixed effects adjustments in each lending category.

How large the credit loss ratios are in a lending category in any given scenario thus depends on the region where the exposures are located and how much the category is affected by the macroeconomic variables.

The regions include other countries in addition to Sweden and thus are impacted by more than one scenario. This means that the losses can also vary between banks in any given region. This is because differences in the country exposures within the regions make the scenario for each region different for each bank.

We create a region-specific scenario for each bank and lending category based on the bank's exposures between countries in the lending category in question. For example, the shares of banks' lending to Norwegian firms vary in the loan category *Small and medium-sized enterprises* in the region *Other Nordic countries*. This means that the Norwegian development affects banks' specific

²⁰ Therefore, we only consider models where, for example, GDP is included in the equation with a minus sign.

²¹ It is difficult to identify what is sufficient. Therefore, we allow the variable to be squared instead of using an indicator variable. The difficulty in specifying what is a sufficiently weak macroeconomic development is also one reason that it is beneficial to use data from several countries so the model can rely on more than just the Swedish experience.

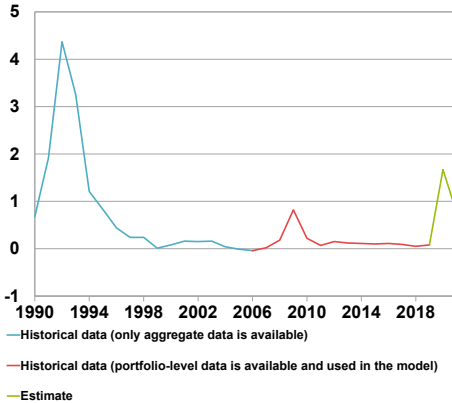
Table 2. Scenario
Per cent

	Sweden				Nordics GDP	Baltics GDP
	GDP	Unemployment	RRE prices	CRE prices		
2020	-7,0	10,2	-7,9	-17,0	-6,3	-8,1
2021	4,8	11,0	-0,2	9,0	4,0	8,1

Source: FI.

Note: GDP, housing prices (RRE prices) and commercial property prices (CRE prices) are stated as annual change in per cent. Unemployment is stated as annual average in per cent.

Diagram 1. Credit losses
Percentage of exposures



Source: The Riksbank and FI.

Note: Annual credit losses as a percentage of total lending to the public (corporates and households). Historical data shows the average for SEB, Swedbank, Handelsbanken and Nordea and is based on data gathered by Sveriges Riksbank. The estimate shows the average for the three major Swedish banks (SEB, Swedbank and Handelsbanken). We use data through Q1 2020, and our estimates begin in Q2 2020.

scenarios differently for *Other Nordic Countries – Small and medium-sized enterprises*.

Our model estimates are based on credit losses that arose under the IAS 39 accounting standard, which applied during our sample period of 2007–2017. Our method therefore does not directly consider the new accounting rules in IFRS 9, since these went into effect on 1 January 2018. As mentioned previously, this has an impact on when the losses occur, but it is less important for the estimate of the size of the total losses in a stressed scenario.²²

How the methodology works

To illustrate how the methodology works, we use the scenario that was used in FI's stability report in the spring of 2020 (see Table 2). It is based on a sharp fall in GDP according to the National Institute of Economic Research's baseline scenario on 29 April 2020 following the spread of COVID-19 and measures to manage the pandemic. We use data with quarterly frequency for the scenario variables and estimate losses on a quarterly basis (see Appendix 1 for more information). However, we show the results aggregated to a yearly frequency. To weight losses at the segment level, we use the figures for exposures that the banks reported for year-end 2019.

Given that crises do not occur frequently and play out differently, the basis on which to determine the correlation during these periods is limited. It is therefore necessary to make assumptions, the validity of which are difficult to assess. The uncertainty in the models is always significant since each crisis is more or less unique. The calculations should therefore be viewed as illustrations of plausible courses of events, but not forecasts.

RESULTS FOR CREDIT LOSSES IN THE SCENARIO

Our estimates show significant credit losses during the scenario period (Diagram 1). We estimate the total credit losses to 2.4 per cent of lending to the public during the years 2020 and 2021.

To adapt the point in time for when during the scenario the losses occur to how the banks should apply the current accounting standard,²³ we have redistributed our estimated total losses for these two years based on a qualitative assessment. In our model, the scenario's sudden and deep economic downturn means that credit losses arise instantaneously. We do not consider this to be realistic; rather, we assume that the majority of the credit losses arise in 2020, but that some losses also arise in 2021. The losses amount to 1.7 per cent during the first scenario year and then fall to 0.8 per cent in 2021. This corresponds to SEK 73 billion on average during the two years. In 2019, i.e., the year before the stressed scenario, the banks' credit losses were just under SEK 5 billion.

When we compare credit losses between the regions, they are the highest for the Baltics (Table 3). The loss levels in the Baltics are in

²² In our macro stress test, we assume that the banks have so-called perfect foresight, which means, for example, that credit losses in 2020 in part will reflect knowledge about macroeconomic outcomes during the period 2020–2021. This is a standard assumption in macro stress tests.

²³ See EBA (2020) and FI (2020a) for guidance on the application.

Table 3. Credit loss ratios
Percentage of exposures

	Sweden	Other Nordics	Baltics	Other countries	Average
Mortgages	0,8	0,7	1,0	0,8	0,8
Consumer credit	4,5	4,3	5,3	4,8	4,6
CRE	2,7	2,5	3,3	2,7	2,7
SME	4,1	3,9	4,8	3,9	4,1
Other corporates	4,5	4,4	5,5	4,4	4,5
Average	2,0	2,9	3,3	3,3	2,4

Source: FI.

Note: Refers to the average for the three major Swedish banks and total losses in 2020–2021.

Table 4. Shares of estimated credit losses (in total over the two years of the scenario)
Per cent of total credit losses

	Sweden	Other Nordics	Baltics	Other countries	Sum
Mortgages	12	1	1	1	15
Consumer credit	6	2	1	0	9
CRE	20	5	1	4	29
SME	4	1	1	1	6
Other corporates	15	10	4	12	40
Sum	56	18	7	18	100

Source: FI.

total 3.3 per cent during 2020–2021. This reflects that the historical losses have been largest in this region during the period for which we have data. The Baltic countries comprise approximately 5 per cent of the banks' total exposures (Table 1) and approximately 7 per cent of the total losses in the scenario (Table 4). The share of the losses that occur in Sweden is lower than the share of exposures. This is because the banks' exposures in Sweden are more concentrated to mortgages, which have lower credit loss ratios than other sectors. The total credit loss ratios for the Swedish exposures are 2 per cent for the period (Table 3), and they comprise 56 per cent of the total losses (Table 4).

Unsecured exposures have the highest estimated credit loss ratios during the two-year period: 4.6 per cent for consumer credit, 4.1 per cent for loans to small and medium-sized enterprises, and 4.5 per cent for other corporates (Table 3). Mortgages have the lowest loss ratio at 0.8 per cent, while loans collateralised by CRE have a loss ratio of 2.7 per cent. In terms of total losses in SEK, lending to other corporates stands for two-fifths of the total losses while loans collateralised by CRE and mortgages stand for just over one-fourth and one-seventh, respectively (Table 4).

For other corporates, both original exposures and loss ratios are relatively high, which explains why the segment has the largest losses. Mortgages and lending collateralised by CRE have lower credit loss ratios but large initial exposures. In total, corporate exposures represent three-fourths of the losses compared to half of the total exposures.

CREDIT LOSSES IN EARLIER CRISIS PERIODS

The results in the stressed scenario can be compared to two historical periods with significant stress in the Swedish banking system: the Swedish crisis in the 1990s and the global financial crisis in 2008–2010.

During the period 1991–1993, Swedish GDP fell by approximately 4 per cent, and real estate prices fell by around 14 per cent. This played a role in the banks experiencing major losses. Many banks were close to bankruptcy and needed to be saved through reconstruction or consolidation.²⁴ When the banking crisis was at its worst in 1992, the annual credit losses were 4.4 per cent of total lending, and in 1992 and 1993 43 per cent of the total credit losses came from exposures to real estate-related activities. Forty per cent of the outstanding exposures in 1990 to this sector were realised losses or classified as non-performing loans in 1993.²⁵

During the entire banking crisis in 1991–1993 (Diagram 1), credit losses were on average 3.2 per cent per year. This is significantly higher than our estimates for the scenario. One explanation for this is that we do not have the possibility of including disaggregated credit

²⁴ See, for example, Wallander (1994).

²⁵ See Wallander (1994). For a description of how lending to the real estate sector has changed since the beginning of the 1990s, see Finansinspektionen (2019).

Table 5. Shares of credit losses during the financial crisis, 2008–2010.
Per cent of total credit losses

	Sweden	Other Nordics	Baltics	Other countries	Sum
Mortgages	1	0	10	0	11
Consumer credit	NA	NA	NA	NA	10
CRE	3	0	23	1	26
SME	2	2	25	0	29
Other corporates	6	2	14	2	23
Sum	11	4	72	3	100

Source: FI.

Note: It is not possible to break down consumer credit by region.

losses from this period in the estimation of the models (Diagram 1).²⁶ In terms of change in GDP, the scenario we use is worse than the development during the period 1991–1993. However, the real estate market was hit harder during this period. At the same time, there have been structural changes to the economy since the crisis in the 1990s. For example, Sweden had a fixed exchange rate, which contributed to a situation where interest rates were high despite the Swedish economy being in an economic recession.²⁷ High interest rates make it more difficult for firms and households to make their interest payments. It is also worth noting that the credit losses arose in another credit climate with less detailed regulation on lending and risk management, that together with the deregulation contributed to high credit growth in the 1980s.

Another period of stress arose during the global financial crisis in 2008–2010. During the worst year – 2009 – the four major Swedish banks had a credit loss ratio of on average 0.8 per cent. The losses were 1.2 per cent during the entire period 2008–2010, which is half of the credit losses we estimate in this analysis. During the global financial crisis, Swedish economic development was poor, but the economy recovered quickly. The domestic real estate market also emerged without any major price falls (compare with the scenario in Table 2). This contributed to the Swedish banks not experiencing any major losses on their Swedish exposures during the global financial crisis (Table 5). However, they did have major credit losses in the Baltics, where the downturn lasted longer and real estate prices fell sharply.

Two-thirds of their credit losses were for Baltic loans even though they only represented around 5 per cent of the banks' total lending. In our estimates with the COVID-19 pandemic scenario, the majority (more than 50 per cent) of the losses come instead from Swedish exposures. This largely reflects that the scenario is severe for Sweden and that the banks have the most exposures there (Table 1 and Table 2). The fact that our model approach assumes that the sensitivity to different macroeconomic outcomes is the same in all regions also plays a role but is mitigated by us controlling for fixed differences in the risk level. This also means that Swedish credit losses, given the history of low credit loss ratios, is lower than other regions' credit losses, all else equal.

The distribution of losses by lending categories in the scenario is similar in some respects to the global financial crisis (Table 4 and Table 5). Exposures to corporates represent around three-fourths of the losses in our calculations. This corresponds to losses on exposures to corporates during the global financial crisis. However, our calculations generate larger losses from other corporates and lower losses for small and medium-sized enterprises. Mortgages also differ. They represent 15 per cent of the estimated losses during the period

²⁶ If we had had access to disaggregated data there would not only have been an impact on the general level of estimated credit losses; it would have also impacted the portfolios differently. For example, the difference between the credit loss ratios for corporates and mortgages was higher during the banking crisis than the credit loss ratios from the financial crisis.

²⁷ High rates during an economic recession are less probable with a variable exchange rate.

2020–2021, compared to 11 per cent of the actual losses in 2008–2010. This difference is particularly large for Swedish mortgages. In other words, the difference in losses on Swedish mortgages in the current scenario compared to the global financial crisis is larger than the difference in losses for Swedish corporates. This is because variables that are more important for the credit loss model for mortgages – relative to other models, house prices and unemployment – changed to a relatively small extent during the financial crisis and the model relies more on the Baltic’s credit loss variations during the global financial crisis than the other credit loss models. Mortgages also represent a higher share of the banks’ total lending today compared to ten years ago.

Discussion on the credit loss method

Our estimated credit losses for the scenario are lower than the losses that arose during the crisis in the 1990s. They also fall below the levels that have been observed historically during crises in other advanced economies.²⁸ At the same time, the losses on Swedish exposures are larger than during, for example, the financial crisis.

The differences in losses between periods and scenarios can depend on several factors. One is that the depth and length of the crises vary. In addition, the correlation between macroeconomic variables and credit losses is estimated over a limited historical period that contains specific crisis events. The more the scenario we analyse differs from the historical outcomes and crisis events, the more cautiously the results should be interpreted. How banks’ credit losses ultimately are impacted by an economic downturn is also dependent on significantly more factors than how deep the economic downturn is. For example, they depend on how vulnerable the financial system is at the start of the crisis, which types of corporates and households are hit the hardest, and which measures are introduced to help corporates and households in order to mitigate the downturn. These are also examples of dimensions that are difficult to capture in this approach that are presented here.

Somewhat simplified, the credit losses that arise can be viewed as the sum of two parts: a structural part and a part that reflects the state of the economy. To estimate the latter, we use to some extent the experiences in the Baltics during the crisis, but the estimate is hampered by the absence of a drawn-out recession or falling real estate prices in Sweden in our data. The estimates of the structural part are limited in that we only use loss data for four banks during the years 2007–2017. Even if this period covers the global financial crisis that resulted in extensive problems for the Swedish banking system, the problems were primarily related to the banks’ funding and did not result to any major increase in credit losses in Sweden.

Interest rates have also been historically low during the period we are analysing, with no significant increases, which complicates the estimate of the correlation between interest rates and credit losses under normal conditions. As a result, we probably underestimate the structural part and thereby also the credit losses that would arise

²⁸ See, for example, Hardy and Schneider (2013).

following a stress, particularly for credit losses in the real estate sector.

In conjunction with the low interest rates and rapidly rising lending of the past decade, development in the real estate sector has been strong, particularly in Sweden. This sector has historically been sensitive to economic fluctuations in both Sweden and other countries, and it has experienced large credit losses during financial crises with sharply falling real estate prices. In its stability report in the spring of 2020 (FI, 2020b), FI uses the same scenario as the one here to estimate credit losses under stress using micro data.²⁹ The estimates show lower losses for the commercial real estate sector than those we report in this analysis, but in other scenarios where the shock includes higher interest rates the losses for the sector are instead higher than through the approach here.³⁰

An important aim of these estimates is to be able to analyse in which parts of the banks' portfolios the estimated losses will occur. We have therefore chosen to use disaggregated loss data, but we only have access to this type of data over a limited period of time. For example, we do not have disaggregated loss data from the crisis in the 1990s. This does not mean that we consider the experiences from that crisis to be irrelevant for estimating losses today. A long time series that has different types of outcomes of credit losses and macroeconomic variables increases the precision in the estimates. However, a long time series also increases the probability that the historical credit losses are less representative of today's financial and economic conditions. For example, the losses during the banking crisis arose against a background of a fixed exchange rate regime and a different credit climate. Since then, the risk management of banks has developed; for example, the banks have improved their rules on lending to corporates.

There are a number of different potential development areas for the approach that are presented here. It is important to use experiences from periods of significant stress for banks. This applies in particular when credit losses tend to be low during long periods of time and then increase sharply under stress (Diagram 1). In order for the estimates of when such a situation arises to be representative, it is therefore desirable to use several experiences to reduce the risk of relying solely on a single historical outcome. One area for development, therefore, can be to increase the dataset that served as the basis for the estimates, for example with data on credit losses from other countries and from the economic downturn that followed the COVID-19 pandemic. The dataset could also be increased by developing methods to use credit losses that arose in the 1990s and at the same time controlling for the changes in the credit climate and monetary policy since then. Gathering and using better quality data and more detailed micro data for more regions and segments can also be a way to improve the estimates.

The data we have used here is for credit losses relative to the exposure, i.e. the product of PD and LGD. With more detailed data, we could have estimated PD and LGD individually. Some of the factors influencing PD and LGD differ, which means that estimates of

29 See the subsection *Corona pandemic can hit real estate firms hard*. See also Aranki et al. (2020) for a more detailed description of the method that uses micro data at the loan level.

30 See Finansinspektionen (2019), *Den kommersiella fastighetsmarknaden och finansiell stabilitet*. An English translation is available at www.fi.se.

these products could have lower precision. For a mortgage, for example, housing prices are more linked to LGD while unemployment has a more direct link to households' payment capacity and therefore the probability of default (PD). The development of models for both PD and LGD would therefore be able to provide better precision in the estimates. This also facilitates an estimate of the effects from the IFRS 9 accounting standard since it is closely linked to these parameters, unlike the previous accounting standard. The handling of IFRS 9 is important in order to also be able to estimate when in time the losses – and thus any solvency issues – arose during stressed periods (see *IFRS 9*).

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Appendix 1: More information about credit losses

We estimate an equation for each lending category (loans collateralised by CRE, small and medium-sized enterprises, large companies, mortgages, consumption):

$$CL_{rt} = \alpha_r + \beta_1 \cdot GDP_{rt} + \beta_2 \cdot GDP_{rt} \times GDP_{rt} + \beta' X_{rt} + \varepsilon_{rt}, (1)$$

where r denotes region and t denotes time. All models are estimated using quarterly data, and all variables follow the same period of time as the dependent variable. All models contain region fixed effects, four quarters of GDP growth rate, and its squared term. α_r represents region fixed effects. In the estimate, β' represents the elasticity for each macroeconomic variable.

Other variables, represented by X_{rt} in Equation 1, vary for each lending category model. All models, with the exception of mortgages, include the change in unemployment over four quarters measured in percentage points. The mortgage model instead includes unemployment measures in percent. All models for loans to corporates include the ten-year treasury bond measured in per cent. The models for loans to households include the three-year change in households' credit gap measured in percentage points. The models for small and medium-sized enterprises and mortgages include residential real estate prices measured as four-quarter growth in per cent, while the model for loans collateralised by CRE includes the change in prices for commercial real estate, measured as four-quarter growth in per cent.

The macroeconomic variables for the different countries are weighted by the major banks' aggregate exposures to each country in the region 2014–2017 for that category. For example, GDP is calculated for *Small and medium-sized enterprises – Other Nordic countries* as:

$$GDP_{Nordics,t,SME} = \alpha_{DK,SME} \cdot GDP_{DK,t} + \alpha_{FI,SME} \cdot GDP_{FI,t} + \alpha_{NO,SME} \cdot GDP_{NO,t} (2)$$

where $\alpha_{country,category} = \frac{Exp_{country,category}}{Exp_{region,category}}$.

In equation 2, $\alpha_{country,category}$ represents the banking sector's weighted exposure to each country as a share of the total exposures for the region within that category.

Table A1 shows the estimated coefficients for the five models.

Table A1: Regression results

Variables	CRE	SME	Other corporates	Mortgages	Consumer credit
	Credit losses, yearly, per cent of exposure				
GDP, YoY growth (%)	-0.024 (0.023)	-0.013 (0.034)	-0.062* (0.033)	-0.019** (0.009)	-0.044 (0.045)
GDP (%) x GDP (%)	0.011*** (0.002)	0.015*** (0.003)	0.014*** (0.003)	0.003*** (0.001)	0.007** (0.003)
Unemployment, yearly change (p.p.)	0.165*** (0.035)	0.283*** (0.046)	0.446*** (0.054)		0.585*** (0.141)
Unemployment (%)				0.062*** (0.009)	
10-year government bond yield (%)	0.040 (0.030)	0.057 (0.039)	0.076* (0.045)		
Real estate price index, YoY (%)	-0.017*** (0.004)	-0.031*** (0.006)		-0.006*** (0.002)	
3-year change in credit gap, households (p.p.)				0.017*** (0.002)	0.020* (0.011)
<i>Fixed effects</i>					
Constant (Baltics)	0.305*** (0.100)	0.365*** (0.116)	0.459*** (0.132)	-0.383*** (0.091)	0.867*** (0.210)
Other countries	-0.352*** (0.082)	-0.441*** (0.097)	-0.591*** (0.122)	0.052 (0.041)	-0.110 (0.227)
Other Nordics	-0.220*** (0.076)	-0.153* (0.087)	-0.446*** (0.085)	-0.020 (0.045)	-0.555** (0.239)
Sweden	-0.333*** (0.077)	-0.348*** (0.100)	-0.608*** (0.105)	-0.151*** (0.041)	-0.694*** (0.228)
Observations	176	176	176	176	176
R-squared	0.879	0.887	0.877	0.823	0.730

Source: FI.

Note: Each column represents the model for each lending category. **, * and *** denote statistical significance at the 10, 5 and 1 per cent significance level, respectively. Standard errors are in parentheses.

To calculate stressed credit losses, we use the estimated coefficients from **Table A1** together with a macroeconomic scenario. For the results in this analysis, it is the scenario from Finansinspektionen (2020b). We estimate credit losses at the bank, region and category level. Even if we have an equation for each combination of region and category, we use each bank's exposure to various countries within each region for each category to create bank-specific macroeconomic variables. This then results in bank-specific calculations of credit losses for each combination of region and category. Given that all variables in the estimations are specified in the form of annual change, the estimated credit losses should be interpreted as rolling credit losses on an annual basis. Depending on the situation in which the stress test is used, it can be necessary to convert the rolling annual losses to quarterly losses.