SVERIGES RIKSBANK

Staff Memo

A microdata-based approach to stress testing banks’ credit losses from corporate lending

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Staff Memo

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Summary[1]

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The Riksbank is working continuously to further develop and broaden its framework for capital stress tests. In recent years, one focus area has been to develop stress testing methods based on microdata.

In this Staff Memo, we describe a newly developed approach to stress testing banks' credit losses from corporate lending, which is based on detailed microdata on all Swedish non-financial corporations and their loans from Swedish banks. The approach is used to estimate expected credit losses for banks in different macroeconomic scenarios and complements the aggregate stress testing methods currently used by the Riksbank.

Our purpose in this Staff Memo is to describe in detail the microdata-based approach and the models upon which the approach is based. We therefore do not present any stress test outcomes here.

[1] First of all, we would like to thank Tor Jacobson, whose many years of work on providing the Riksbank with high-quality microdata and developing microdata-based analytical methods has been a fundamental prerequisite for our work. Much of the methodological development underlying the microdata-based approach to stress testing that we present in this Staff Memo is based directly or indirectly on Tor's work over the years. We also thank David Forsman, Kristian Jönsson and Olof Sandstedt for valuable comments. The authors are solely responsible for any remaining errors.

1 Introduction

The Riksbank uses various forms of stress tests to assess the resilience of Swedish banks to different scenarios in which economic conditions deteriorate. It is important to know that banks function well even in a downturn, as they are a very important part of the financial system. Firms can use the services of banks to borrow for investment or to save for future investments. Similarly, banks enable households to borrow for housing and save for retirement. Banks are also important participants in the payment system and therefore play a central role in the financial system. If banks encounter problems, this could affect financial stability and real economic development – as this year's Nobel laureates in economic sciences have convincingly demonstrated in their research (see, for example, Bernanke, 1983). But it could also lead to monetary policy having a weaker effect on the economy. For this reason, the Riksbank also continuously analyses the development of the banking system in order to detect threats and vulnerabilities at an early stage and to ensure that the payment system is safe and efficient.

Previously, the Riksbank published a method based on aggregate data to stress test the solvency of the four largest banks (Buncic et al, 2019).[2] However, the Riksbank has continued to develop other methods. This Staff Memo presents one of them that is based on so-called microdata. In this case, it consists of detailed data on the financial statements of Swedish non-financial corporations and data for each individual loan that these firms have.

One advantage of using microdata instead of aggregate data is that it allows us to capture firm-specific characteristics. This means that the results of the stress test are to a large extent influenced by the risks of the individual firms and how these risks evolve over time. Another advantage is that the estimated models are very robust due to the millions of observations in the dataset. On the other hand, the availability of microdata is currently limited, which makes it difficult to capture the risks in banks' total loan portfolios and thus assess their overall resilience. The approach we describe here includes the Swedish banking sector’s exposures to Swedish non-financial corporations, which account for about 20 per cent of banks' total exposures in Sweden and other countries and about 30-35 per cent of their Swedish exposures. In the approach based on aggregate data, the expected losses for the banks’ total exposures are estimated. This means that it is easier to assess banks’ resilience based on the results of the aggregated approach.

[2] The four largest banks are Handelsbanken, Nordea, SEB and Swedbank.

2 How the approach is used step by step

Our microdata-based approach to stress testing banks' credit losses from lending to Swedish non-financial corporations consists of four steps.

In the first step, we use a microdata-based bankruptcy risk model to estimate how a firm's bankruptcy risk is affected by macroeconomic and firm-specific factors. The bankruptcy risk model thus allows us to answer questions such as: By how much does the probability of a firm going bankrupt increase if housing prices fall by 10 per cent, or if interest rates rise by one percentage point, or if the firm's leverage increases?

In the second step, we specify a macroeconomic scenario and use the model to compute the bankruptcy risk for each firm and quarter in the scenario.

In the third step, we compute the expected loss for each individual loan in each bank's corporate loan portfolio by multiplying the size of the loan first by the proportion of the loan that is expected to be lost if the firm goes bankrupt and then by the firm's bankruptcy risk as computed in step two.

In the fourth and final step, we compute the banks' total expected credit losses in each quarter of the scenario by summing the expected losses for each individual loan from the calculation in step three. Since expected credit losses are computed on a loan-by-loan basis, the losses in the scenario can also be summed up to other levels to give an idea of how they are distributed across different borrower categories. It is thus easy to compute the proportion of losses that come from, for example, commercial real-estate firms, firms in the Stockholm region or commercial real-estate firms in the Stockholm region.

In the following sections, we describe each of the four steps in more detail. We conclude with a summary and a reflection for the future.

2.1 Step 1: Estimate the bankruptcy risk model

A detailed description of the bankruptcy risk model

The first step in the microdata-based approach is to estimate how a firm's bankruptcy risk is affected by macroeconomic and firm-specific factors. We do this using a bankruptcy risk model based on firm-level data that has been developed using the well-established bankruptcy risk model presented in Jacobson, Lindé and Roszbach (2013).[3] In simple terms, our model estimates how a firm's bankruptcy risk is affected

[3] We modify the model in Jacobson, Lindé and Roszbach (2013) in three ways: (i) we estimate the model as a linear probability model instead of a logit model, (ii) we slightly change the set of explanatory variables, especially on the firm side and (iii) we allow the impact of the macro variables to vary between lowly and highly leveraged firms by including an interaction term between the indicator for high leverage and each of the macro variables. The reason we move away from the logit model in Jacobson, Lindé and Roszbach

by four macroeconomic factors (unemployment, treasury-bill yield, corporate lending rate and housing prices) and three firm-specific factors (size, age and leverage ratio). An important feature of our model is that it allows the macroeconomic factors to have different effects on a firm's bankruptcy risk depending on whether the firm has high or low leverage.

In econometric terms, we estimate the following linear probability model:

$$K_{i,t} = \boldsymbol{M_t'\beta} + \boldsymbol{F_{i,t}'\gamma} + HighLeverage \times \boldsymbol{M_t'\theta} + \alpha^Q + \varepsilon_{i,t},$$

where i identifies firms and t identifies time periods. The outcome variable $K_{i,t}$ is an indicator variable equal to one if firm i goes bankrupt in period t. $\boldsymbol{M_t}$ is a vector consisting of four macroeconomic variables: the change in unemployment between time periods t and $t-1$ measured in percentage points ($\Delta Unemp_t$), the interest rate on six-month treasury bills ($TB6M_t$), the difference between the average bank lending rate to non-financial corporations and the interest rate on a six-month treasury bill ($Spread_t$) and the percentage change in the Statistics Sweden real-estate price index FASTPI between the time periods t and $t-1$ (ΔHPI_t).

$\boldsymbol{F}_{i,t}$ is a vector consisting of three firm-specific variables: size measured as the logarithm of firm i's total assets in time period t ($\ln Assets_{i,t}$), age modelled as an indicator variable equal to one if the firm is between 1 and 9 years old, which is the age range with the highest average bankruptcy risk ($Age_{i,t}$), and leverage modelled as an indicator variable equal to one if firm i's debt-to-assets ratio is 80 percent or higher in time period t ($HighLeverage_{i,t}$). The specific 80-percent threshold for classifying a firm as highly leveraged is somewhat arbitrary, but in practice it is not very important for the model estimation either. What is important is that the variable captures the most highly leveraged firms, but whether the threshold is then set at, say, 75, 80 or 85 per cent does not significantly affect the results.

In addition to the macroeconomic and firm-specific variables, the model includes interaction terms between the indicator of high leverage and each of the macro variables. This implies that the effect of a given macro outcome on a firm's bankruptcy risk may differ between highly and lowly leveraged firms. For example, the effect on the bankruptcy risk of the treasury-bill yield for a lowly leveraged firm is given by β_{SSVX6M}, while for a highly leveraged firm the corresponding effect is $\beta_{SSVX6M} + \theta_{SSVX6M}$.

To control for the seasonal variation in firm bankruptcies, the model also includes a dummy variable per quarter, four in total (α^Q). Finally, we cluster-adjust the standard errors in two dimensions: by firm and by time period. Without this adjustment, we would underestimate the size of the standard errors and thus overestimate the precision of the model.

(2013) is simply that it is easier to interpret and understand the results from a linear probability model. We have verified that an equivalent logit model yields qualitatively similar results.

The model is estimated with firm-level data from UC

We estimate the bankruptcy risk model using firm-level data from the credit bureau UC AB, which covers all Swedish limited companies (*aktiebolag*) from the early 1990s to the present. Here we describe which information from the UC database is used in the model estimation.

For each firm that goes bankrupt, we observe the date of bankruptcy, which we use to create the outcome variable in the model (the bankruptcy indicator $K_{i,t}$). We also observe the registration date of each firm, which we use to create the age variable ($Age_{i,t}$). In addition, we observe each firm's financial statement data, which we use to create the size variable ($\ln Assets_{i,t}$) and the indicator for high leverage ($HighLeverage_{i,t}$), which is determined by the ratio of total liabilities to assets on the firm's balance sheet.[4]

We regularly update the model estimates as new data comes in. Currently, the model is estimated on more than 33 million observations from the first quarter of 1990 to the fourth quarter of 2020, spread over almost one million unique firms.

Both macroeconomic and firm-specific factors are important in explaining why firms go bankrupt

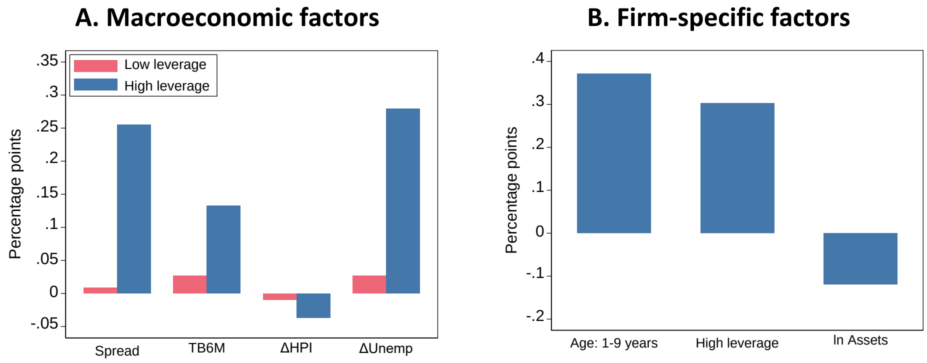
What factors drive firm bankruptcies according to the bankruptcy risk model? To answer this question, we illustrate the results of the model estimation graphically in Figure 1. The different bars in the left panel show how the bankruptcy risk of lowly and highly leveraged firms is affected by the model's macroeconomic factors, while the bars in the right panel show how the bankruptcy risk is affected by the firm-specific factors.

A striking pattern emerges for the macroeconomic factors: a deterioration in the macroeconomic situation has a major impact on the bankruptcy risk for highly leveraged firms (blue bars), but hardly any impact at all for lowly leveraged firms (red bars). Take unemployment as an example: if unemployment rises by one percentage point in a quarter, it increases the quarterly bankruptcy risk for a highly leveraged firm by 0.3 percentage points, but only by 0.03 percentage points for a lowly leveraged firm. The impact of changes in unemployment on the bankruptcy risk is thus ten times higher for highly leveraged firms than for lowly leveraged firms. Similar patterns emerge for the interest-rate factors – a rise in the short-term treasury-bill yield or the corporate interest-rate spread significantly increases the bankruptcy risk for highly leveraged firms, but has only a marginal impact on lowly leveraged firms. In fact, of these three macro variables, only the short-term treasury-bill yield has a statistically significant impact on the bankruptcy risk for lowly leveraged firms. In the case of real-

[4] Since the bankruptcy risk model is estimated with data at quarterly frequency while the financial statement variables are only available at annual frequency, we interpolate quarterly values from the annual values for the financial statement variables. See Jacobson, Lindé and Roszbach (2013) for details on the interpolation procedure.

estate prices, the effect on the bankruptcy risk is statistically insignificant for both lowly and highly leveraged firms. If this sounds surprising, it is important to remember that this is the effect of real-estate prices on the bankruptcy risk when all other variables in the model are held constant. Put differently, it means that real-estate prices do not affect firm bankruptcies once we have taken into account the business cycle and the level of interest rates in the economy.[5,6]

Figure 1. How is bankruptcy risk affected by macroeconomic and firm-specific factors?



Note. The bars show the parameter estimates for the firm-specific factors ($\hat{\boldsymbol{\beta}}$) and for the macroeconomic factors for lowly ($\hat{\boldsymbol{\gamma}}$) and for highly leveraged firms ($\hat{\boldsymbol{\gamma}} + \hat{\boldsymbol{\theta}}$).

Highly leveraged firms are not only more sensitive to the macroeconomic situation, but also have a 0.3 percentage point higher bankruptcy risk regardless of the economic situation. In other words, after computing the impact of macroeconomic factors on the bankruptcy risk of highly and lowly leveraged firms in a given quarter, there is an additional 0.3 percentage-point bankruptcy risk for the highly leveraged firms. The bankruptcy risk is also higher for young firms: a firm in the age range 1-9 years has a 0.4 percentage-point higher bankruptcy risk in a given quarter than start-ups and firms older than 10 years. Small firms also have a higher bankruptcy risk. The bar representing the size effect in the right panel shows that a firm that is 100 log points larger than another in terms of total assets has a 0.12 percentage-point lower bankruptcy risk per quarter. An example makes the magnitude of this effect easier to grasp: firms with 10 and 100 million SEK in assets, respectively, have a 0.55 and 0.27

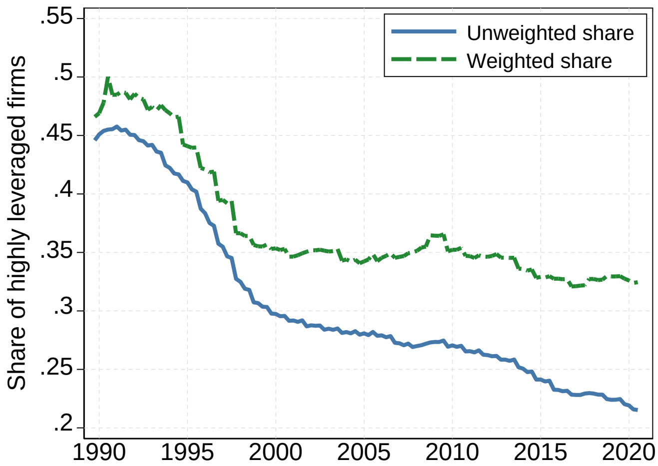
[5] If we instead re-estimate the bankruptcy risk model with the change in real-estate prices as the only macro variable, its effect is statistically significant for both lowly and highly leveraged firms. This is because real-estate prices in such a specification act as a barometer of the economic situation in general.

[6] However, the fact that real-estate prices do not help to explain firm bankruptcies does not necessarily mean that they are irrelevant for banks' loan losses. Real-estate prices affect the value of assets pledged as collateral for loans and can therefore affect the Loss Given Default (LGD) in the event of bankruptcy. Our approach does not currently capture such effects, as we do not model LGDs empirically but assume the same LGD for all borrowers regardless of the scenario.

percentage-point higher bankruptcy risk per quarter than a firm with one billion SEK in assets.[7]

The large difference between the impact of the macroeconomic situation on the bankruptcy risk of lowly and highly leveraged firms means that the same macro scenario will have a different impact on firm bankruptcies – and thus on banks' credit losses – depending on how leveraged the corporate sector is. So how has corporate sector leverage evolved over time? Figure 2 shows the proportion of highly leveraged firms according to our definition, i.e. with a debt-to-asset ratio of 80 per cent or higher. The figure shows that the size-weighted share of highly leveraged firms fell sharply during the 1990s crisis, from just under 50 per cent to around 35 per cent, and has remained broadly constant since.[8]

Figure 2. Share of highly leveraged firms in the corporate sector, 1990-2020



Note. The figure shows how the share of Swedish non-financial corporations that are highly leveraged according to our definition (debt-to-asset ratio of 80 per cent or more) has evolved over time. The size-weighted share is computed using total assets as weight.

Thus, the corporate sector is financially more robust today than in the early 1990s, which means that a macro scenario similar to the 1990s crisis today would result in lower credit losses for banks than those actually observed during the 1990s crisis. However, the situation could change in the future, for example if asset prices in the economy fall persistently. This is because firms' assets then decrease in value, resulting in the erosion of equity and a subsequent increase in the leverage ratio. In

[7] Note that all interpretations of effect sizes in this section are "all else equal" interpretations. This means that they represent the effect of a change in a particular factor when all other factors in the model are held constant.

[8] Of course, the unchanged proportion of highly leveraged firms since the second half of the 1990s does not mean that corporate debt has remained unchanged since then in absolute terms – on the contrary, it has increased substantially – but that debt has grown at roughly the same rate as assets.

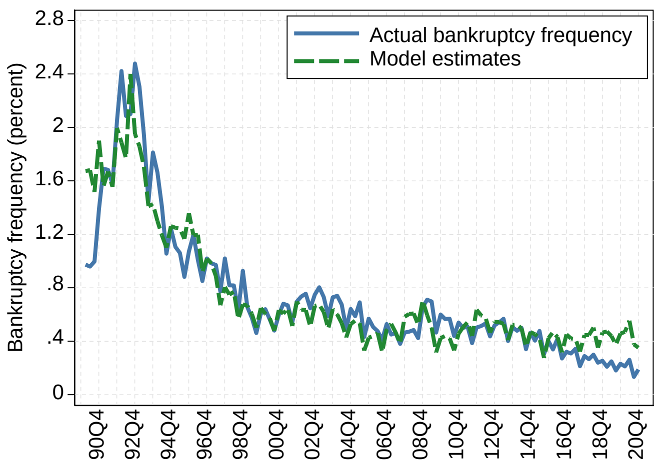
such a situation, the corporate sector would become significantly more sensitive to macroeconomic shocks.

The model can explain the bankruptcy trend in the corporate sector over time

The bankruptcy risk model is at the core of the microdata-based approach. Therefore, a necessary condition for the approach to work is that the model can explain the bankruptcy trend in the corporate sector over time. One way to assess this is to examine the in-sample fit of the model, i.e. to compute the bankruptcy risk for each firm and quarter in the data set based on the actual historical macro and firm outcomes and then compare the average model-estimated bankruptcy risk with the actual historical bankruptcy rate in each quarter.

We illustrate the results of this exercise in Figure 3, which shows how the model-estimated average bankruptcy rate and how the actual bankruptcy rate have evolved over time.

Figure 3. The model explains the bankruptcy trend in the corporate sector well



Note. The solid blue line shows the quarterly bankruptcy rate (firms going bankrupt as a proportion of the total number of firms) for Swedish non-financial corporations. The dashed green line shows the average bankruptcy probability computed by our model when fitted with actual historical macroeconomic and firm-specific outcomes as input.

As can be seen, the two lines follow each other closely, indicating that the model is good at describing the bankruptcy trend in the corporate sector over time. This means that if we give the model an accurate forecast of macroeconomic developments, we receive back an accurate forecast of the bankruptcy trend in the corporate sector.[9]

[9] A more precise way to describe the model's in-sample fit is to compute what Jacobson, Lindé and Roszbach (2011) refer to as aggregate R^2, which is R^2 from a time series regression where the outcome

2.2 Step 2: Compute the bankruptcy risk for each firm and quarter

The second step in the approach is to specify a macroeconomic scenario and then compute the bankruptcy risk for each firm and quarter in that scenario based on the model estimation in the first step. We compute the bankruptcy risk for a firm as the predicted value from equation 1 ($\widehat{K}_{i,t}$) when the macro variables assume the values specified in the scenario and the firm variables assume the values from the latest available financial statements. Note that the bankruptcy risks we compute with the model are on a quarterly basis – the bankruptcy risk in a year is thus obtained approximately by multiplying $\widehat{K}_{i,t}$ by four.[10]

An implicit assumption in this calculation is that firms' leverage does not change over the course of the scenario. In many cases this is a rather reasonable assumption, but in scenarios where asset prices fall rapidly it may become unreasonable, as firms' leverage is then rapidly pushed up as the value of their assets falls and their equity consequently is eroded. Therefore, when we conduct stress tests involving substantial falls in asset prices, we also conduct sensitivity analyses to show how the results are affected by different assumptions about how firms' leverage evolves over the course of the scenario.

We can illustrate how to compute bankruptcy risks with an example. The model estimation of β_{TB6M} is 0.028, which means that if the interest rate on a six-month treasury bill increases by one percentage point, the bankruptcy risk of a lowly leveraged firm increases by 0.028 percentage points. In other words, this means that if we multiply β_{TB6M} by the interest rate on a six-month treasury bill in the scenario, we obtain the "contribution" from this specific risk factor to the firm's bankruptcy risk in the scenario. For the sake of the example, let us assume that we have set the interest rate at 2.5 percentage points in the first quarter of the scenario. The interest-rate factor will then contribute $0{,}028 \cdot 2{,}5 = 0{,}07$ percentage points to the overall bankruptcy risk of a lowly leveraged firm. By doing the same for all the factors included in the model and then summing them up, we obtain the firm's bankruptcy risk in the first quarter of the scenario.

variable is the actual bankruptcy rate in the corporate sector and the explanatory variable is the average model-estimated bankruptcy probability. Our model generates an aggregate R^2 of just over 0.85 for the period 1990Q1-2020Q4, implying that the series of model-estimated bankruptcy probabilities explains 85 per cent of the variation in the bankruptcy rate in the corporate sector over time.

[10] A disadvantage of linear probability models is that, unlike logit and probit models, they can generate predicted values outside the range 0-100 per cent. In cases where we obtain predicted values of less than zero or greater than 100 per cent, we adjust these by setting them to zero and 100 per cent, respectively.

2.3 Step 3: Compute expected loss per loan in the scenario

Formula to compute expected loss

The third step is to compute the expected loss for each individual loan in the banks' corporate loan portfolios in the scenario. We start from the bankruptcy risks computed in step two. In simple terms, we compute the expected loss for a given loan by starting with the size of the loan and then multiplying it first by the proportion of the loan that is expected to be lost if the firm goes bankrupt and then by the firm's bankruptcy risk.

We thus use the following formula to compute the expected loss on loan j to firm i in time period t:

$$Expected\ Loss_{i,j,t} = EAD_{j,t} \cdot LGD_{j,t} \cdot PD_{i,t}.$$

$EAD_{j,t}$ stands for exposure at default and denotes the size of the loan j in SEK in time period t, adjusted for off-balance sheet exposures. The adjustment is made by adding 75 per cent of any off-balance sheet loan amount to the on-balance sheet loan amount.[11] $LGD_{j,t}$ stands for loss given default and denotes the proportion of loan j in time period t that is expected to be lost if the firm goes bankrupt. We normally set $LGD_{j,t}$ to 45 per cent in the estimations. Finally, we have $PD_{i,t}$ which stands for probability of default and denotes the bankruptcy risk for firm i in time period t. The value of $PD_{i,t}$ is therefore what we computed in the first and second steps of the approach ($PD_{i,t} = \widehat{K}_{i,t}$).[12]

We have chosen these values for CCF and LGD based on the Basel framework's foundation IRB approach, but they do not always correspond exactly to what they

[11] The factor multiplied by the off-balance sheet total is referred to in the Basel framework as the credit conversion factor, or CCF. The most common type of loan for which this adjustment is important is lines of credit. A line of credit is a loan where the bank sets a limit for the borrower, who can then utilise as much of the loan as they need as long as it is within the limit. For example, if a bank has given a firm a line of credit with a limit of SEK 1 million and the firm has utilised SEK 600,000 of this at a certain point in time, the exposure at default for the loan would be SEK 900,000 given a CCF of 75 per cent ($EAD = 600\ 000 + 400\ 000 \cdot 0{,}75 = 900\ 000$).

[12] The attentive reader will note that here we use the terms default and bankruptcy synonymously. This is strictly speaking not correct. According to the Basel framework, default means either that a borrower is more than 90 days past due with payments to the lender (the 90 days past due criterion) or that the lender considers it unlikely on some other basis that the borrower will repay the loan (the unlikeliness to pay criterion). Bankruptcy, on the other hand, is a legal process for winding up a firm and its debts, which is activated when the firm's inability to pay its debts is deemed to be permanent. In other words, default is a broader concept which in principle also includes bankruptcy. However, confirmed loan losses for banks are always associated with the bankruptcy of borrowers; by contrast, loan loss reserves for firms that have defaulted but then avoid bankruptcy are reversed (enter as profit-increasing items in the profit and loss account), resulting in net losses for these firms over time being zero. In this respect, the only potential difference between assuming default and bankruptcy in forward-looking loan loss estimates is how losses on individual borrowers are distributed over time. This justifies our somewhat careless use of the terms default and bankruptcy as synonyms here.

should be according to the Basel framework. This is partly because there are a number of exceptions in the foundation approach that we do not take into account, and partly because in some cases banks may determine capital adequacy parameters using internal models. However, it is important to keep in mind that the Basel framework methodology for estimating capital adequacy parameters is not a "silver bullet" in itself, but one possible method among several to empirically estimate unknown parameter values. Since there is fundamental uncertainty about what the true values of $LGD_{j,t}$ are – i.e. exactly what proportion of loan j in time period t that will be lost if the borrower goes bankrupt – we treat LGD as an explicit uncertainty factor in the microdata-based approach. Therefore, when applying the approach in practice, we perform sensitivity analyses in which we test how the expected credit losses in the scenarios are affected by alternative LGD assumptions.

Expected credit losses are computed using KRITA data

We compute expected credit losses based on the loans in the KRITA database. KRITA is the Riksbank's credit register and contains detailed monthly data on each individual loan issued by the largest monetary financial institutions in Sweden, with the exception of loans to households. For the sake of simplicity, we will refer to the monetary financial institutions as banks, although they also include, for example, mortgage institutions and financial companies. The number of reporting banks varies slightly over time. As of 31 December 2021, the number of banks was 18. Lending by banks reporting to KRITA covers about 95 per cent of total banking sector lending to all sectors except the household sector, which means that KRITA provides an almost comprehensive picture of banks' corporate lending. On the borrower side, the stress tests include all Swedish non-financial firms except tenant-owner housing associations (*bostadsrättsföreningar*).

2.4 Step 4: Compute total credit losses

Total credit losses are computed by summing the expected losses for each individual loan

The fourth and final step of the approach is to compute the total expected credit losses of the banking sector in the scenario by summing up the expected losses on the individual loans in the loan portfolios. Since expected credit losses are computed on a loan-by-loan basis, the banking sector's losses in the scenario can also be summed up to other levels, thus providing a picture of their distribution across different borrower categories, such as the borrower's industry, age or geographical domicile.

When computing expected credit losses in a scenario, we start from the corporate loan portfolios at the beginning of the scenario and then assume that they remain unchanged over the course of the scenario. We do this because we cannot predict how the portfolios will evolve over the course of the scenario. This means that, for example, if a scenario starts in the first quarter of 2022, we compute expected credit losses for each of the quarters of the scenario based on the loans in each bank's corporate loan portfolio as of 31 December 2021. The assumption that loan portfolios are unchanged over the course of a scenario is common in stress testing and is commonly referred to as the static balance sheet assumption (see, for example, EBA, 2020).

We can thus express the total expected credit losses of the banking sector in time period t as $Expected\ Loss_t = \sum_j Expected\ Loss_{j,t}$.[13] To obtain the expected losses for a specific category of borrower k, for example commercial real-estate firms, we instead sum only the loans in that borrower category: $Expected\ Loss_{k,t} = \sum_{j \in k} Expected\ Loss_{j,t}$, where k denotes the proportion of banks' loan portfolios at the beginning of the scenario that consists of loans to borrower category k. We can then compute the proportion of the banks' total expected credit losses coming from that borrower category using the following formula: $Expected\ Loss_{k,t}/Expected\ Loss_t$.

The ability of the approach to explain historical credit losses cannot be evaluated at this stage due to a lack of data

We showed in section 2.1 above that the bankruptcy risk model is very good at explaining the bankruptcy trend in the corporate sector over time. Ultimately, however, it is not corporate bankruptcies but banks' *credit losses* that our microdata-based approach aims to capture. It would therefore be desirable to evaluate how well the approach is able to explain the evolution of historical credit losses over time in the same way as we did with the bankruptcy risk model in section 2.1 above. Unfortunately, this is not possible, as our microdata on corporate loans does not cover a sufficiently long time period. Indeed, the KRITA database is only available from 2019, which is still too short a period for us to make a meaningful evaluation of the approach’s in-sample fit for credit losses in the same way as we do for bankruptcies.

However, there are good reasons to believe that the approach is also valid for loan losses, as the bankruptcy trend is the main driver of banks' loan losses. This is reflected in particular in the close correlation over time between the bankruptcy rate in the corporate sector and credit losses of banks. In other words, accuracy regarding

[13] We do not have financial statement data for some firms and therefore cannot compute bankruptcy risks for them and not therefore expected losses in the scenarios either. Missing financial statement data is usually due to the fact that the firm in question is either not an *aktiebolag* and therefore does not report financial statement data to the UC database or is a start-up and therefore has not yet issued its first financial statement. We adjust for this on the assumption that the expected loan losses are, in percentage terms, the same in those parts of the loan portfolios where we cannot compute the bankruptcy probability of the borrower as in the rest of the portfolios. The adjustment is made at the bank-sector level. Thus, we scale up bank A’s expected loan losses from firms in sector B by dividing the estimated losses by the proportion of the loan portfolio for which we can actually compute expected losses. We can illustrate the adjustment with a hypothetical example: if we find that a bank's expected losses on lending to commercial real-estate are SEK 1 billion but we can only compute bankruptcy probabilities for 95 per cent of the bank's lending volume to commercial real-estate firms, then we adjust the expected losses to SEK 1.05 billion by dividing 1 by 0.95.

bankruptcies should also mean accuracy regarding credit losses. That said, we will evaluate the ability of the approach to explain credit losses historically once we have a sufficiently long time dimension in the KRITA database to do so in a meaningful way.

3 Summary and reflections for the future

The microdata-based approach to stress testing banks’ credit losses that we have described in this Staff Memo is complete in the sense that it already has everything needed to be used for stress testing in practice. However, this does not mean that we consider the approach to be fully developed – on the contrary, we see considerable potential to improve and further develop it by building on what has been presented in this Staff Memo.

More specifically, we see at least five areas where the microdata-based approach to stress testing banks’ credit losses can be developed and improved.

1. **Develop a microdata-based approach for stress testing banks' credit losses from household lending.**

Lending to Swedish non-financial corporations accounts for about 20-25 per cent of the total lending volume of the Swedish bank groups. The remainder consists of lending to Swedish households and to foreign firms and households. Our microdata-based approach thus covers a relatively small proportion of banks' loan portfolios and it is therefore important to incorporate household lending into it in the future. At present, this is not possible due to the lack of microdata on household assets and liabilities. Should such data become available in the future, a priority is to develop a microdata-based approach for stress testing household lending.

2. **Incorporate foreign corporate lending into the microdata approach.**

In order to cover an even larger proportion of banks' loan portfolios, it would be desirable to also incorporate the loans that banks issue to foreign firms. This would require access to firm-level microdata for the other countries in which Swedish banks operate. Such data exists but is not currently available to us. It would also be desirable to be able to include lending to foreign households, but this is impossible in practice as relevant household microdata exists for only a few countries and access to such data is always tightly restricted.

3. **Develop a separate bankruptcy risk model for the real-estate sector.**

Loans to real-estate firms account for about half of the volume of lending to Swedish non-financial corporations and are thus by far the single most important borrower category for Swedish banks. It would therefore be desirable to develop a specific bankruptcy risk model tailored for real-estate firms that better captures the specific risks faced by these firms.

4. **Develop our own empirically based LGD estimates.**

A weakness of the current design of the microdata approach is that the values for loss given default, i.e. the proportion of a loan that is expected to be lost if the borrower goes bankrupt, are not empirically based, but set at 45 per cent for all firms. As described above, we address this weakness by explicitly considering the LGD values as an element of uncertainty and performing sensitivity analyses in the stress tests, testing how expected credit losses are affected by alternative LGD assumptions. A potentially better approach would be to develop our own empirically based LGD estimates, which would be time-consuming but in principle feasible thanks to the various banking datasets available at the Riksbank.

5. **Use group-level data instead of firm-level data in the microdata approach.**

The bankruptcy risk model is currently estimated with data at the firm level, where a firm is defined by a specific organisation number. However, many Swedish firms are organised in groups and for many groups it is more relevant to consider the firms within them as a single enterprise, rather than as a number of separate firms. A potential improvement to the approach would therefore be to use groups as the unit of analysis – i.e. to estimate the bankruptcy risk model and compute expected credit losses for groups rather than individual firms. This is particularly relevant for the real-estate sector, where a group may consist of hundreds of different subsidiaries which nevertheless constitute one and the same firm in an economic sense. Moving to a group-based bankruptcy risk model requires financial statement data at the group level, which we do not currently have access to.

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