DEUTSCHE BUNDESBANK
EUROSYSTEM

Technical Paper

Risks in domestic banks' corporate lending business

08/2021

Christoph Memmel
Christoph Roling

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

Non-technical summary

Corporate loans are an important part of banks' balance sheets and they react strongly to macroeconomic developments. In this paper, we present a scenario analysis to obtain losses in banks' corporate loan portfolio. We proceed in two steps: First, we design adverse scenarios for credit losses in different sectors. Second, we apply these adverse scenarios to the German banking system.

We present two methods to design plausible adverse scenarios. First, we study the historical distribution of loss rates in different sectors. Second, we estimate the relationship between the loss rate in a given sector and GDP growth, and then use these estimates to derive losses for an adverse scenario of GDP growth. When applying the loss rates from either approach to the loan portfolio, we use a bank's on-balance exposure to different sectors, and expand this exposure in adverse scenarios by making assumptions on the usage of credit lines. We deduct losses on corporate loans from a bank's equity. In addition, we model the increase in risk weights for those banks that use internal models to determine their regulatory capital requirements. Both loan losses and increasing risk weights lower the capital ratio in adverse scenarios.

In this scenario analysis, the aggregate capital ratio falls by 1.1 to 2.4 percentage points, depending on the severity of the scenario. No bank breaches the minimum capital requirements. When interpreting the results, note that we only consider corporate loans in this analysis. Losses from other loan portfolios or risks from the trading portfolio are not included.

Nichttechnische Zusammenfassung

Unternehmenskredite sind ein wesentlicher Bestandteil in den Bilanzen der Banken und reagieren erheblich auf makroökonomische Entwicklungen. In diesem Papier stellen wir eine Szenario-Analyse vor, aus der wir Verluste des Unternehmenskreditportfolios ableiten. Wir gehen in zwei Schritten vor: Zuerst entwerfen wir Stress-Szenarien für Kreditverluste in einzelnen Branchen. Danach wenden wir diese Stress-Szenarien auf das deutsche Bankensystem an.

Wir zeigen zwei Methoden auf, mit denen plausible Stress-Szenarien entworfen werden können: Zum einen, indem die historische Verteilung der Verlustquoten in den einzelnen Branchen betrachtet wird, und zum anderen, indem ein Zusammenhang zwischen den Verlustquoten und dem Wirtschaftswachstum geschätzt wird und dann ein Stress-Szenario für das Wirtschaftswachstum zugrunde gelegt wird. In beiden Fällen verwenden wir die bilanziellen Forderungen einer Bank und erweitern sie in Stress-Szenarien um einen Teil der Kreditzusagen, indem wir Annahmen zu deren Nutzung treffen. Die Verluste, die in einem Stress-Szenario einer Bank entstehen, ziehen wir von ihrem Eigenkapital ab; bei Banken, die das Kreditrisiko mit internen Verfahren bestimmen, wird zusätzlich modelliert, wie sich die aufsichtlich geforderte Eigenkapitalunterlegung (Risikogewichte) im Stress-Szenario ändert. Sowohl Kreditverluste als auch ein Anstieg der Risikogewichte senken die Eigenkapitalquote in den Stress-Szenarien.

Je nach Schwere des Stress-Szenarios sinkt die Eigenkapitalquote um 1,1 bis 2,4 Prozentpunkte im Aggregat, wobei keine der Banken die Eigenkapitalanforderungen unterschreitet. Bei der Deutung der Ergebnisse muss berücksichtigt werden, dass das Kreditportfolio für Unternehmenskredite isoliert einem Stress unterzogen wurde; Risiken aus dem Handelsportfolio oder anderen Teilen des Kreditportfolios bleiben unberücksichtigt.

Risks in domestic banks' corporate lending business

Christoph Memmel[1] und Christoph Roling[2,3]

March 14, 2022

We introduce an empirical approach to studying credit risk in the corporate loan portfolio. First, historical adverse scenarios for loss rates are identified at sector level. Second, we estimate the empirical association between loan losses and economic growth and then apply it to a scenario of adverse economic growth. We additionally model an increase in risk weights for banks that use an internal ratings-based approach (IRBA) to calculate the capital adequacy requirement for their loan portfolio.

Keywords: Credit Risk, Default Rate, Stress Test

JEL classification: C53, G01, G17, G21.

[1]Deutsche Bundesbank, Wilhelm-Epstein-Str. 14, 60431 Frankfurt am Main, Germany. Phone: +49-69-9566-4421, E-mail: `christoph.memmel@bundesbank.de`

[2]Deutsche Bundesbank, Wilhelm-Epstein-Str. 14, 60431 Frankfurt am Main, Germany. Phone: +49-69-9566-3044, E-mail: `christoph.roling@bundesbank.de`

[3]Disclaimer: The views expressed here do not necessarily reflect the opinion of the Deutsche Bundesbank or the Eurosystem.

1 Rationale and results

We will introduce an empirical approach that lends itself to investigating banks' potential corporate loan losses using a scenario analysis. This approach is a central component of the scenario analyses presented in the Financial Stability Review 2021, see Deutsche Bundesbank (2021b). The technical paper explains the rationale for the underlying methodological approach and corroborates the robustness of the results discussed therein.

The starting point for the analysis is the loss rate in lending business, i.e. the ratio of losses on corporate loans recorded by banks in the past within a year and the volume of outstanding loans. Since borrowers in various sectors (e.g. farming, manufacturing, services) can be affected to varying degrees by an economic slump, the historical distribution of these loss rates is looked at for each sector.

The adverse scenarios derived from these historical loss rates differ in terms of the severity of the assumed economic shock. In the first scenario, the largest historical loss rates for selected sectors hit particularly hard by the COVID-19 pandemic, such as wholesale and retail trade, or parts of the services sector, such as hotel and restaurant services, are applied to the banks' current loan portfolio, whereas the remaining sectors are only mildly stressed.

In the second scenario, this assumption is made more severe by applying the largest historical loss rates to all sectors. Since the pandemic is without precedent in the data, in a third scenario the maximum value of the loss rates is additionally increased by two standard deviations. A one-year horizon is assumed in all scenarios. The three adverse scenarios are compared with a baseline scenario in which loss rates rise by 40%[1] in all sectors.

The analysis looks at banks' exposures to borrowers in various sectors and comprises domestic and foreign lending. A static balance sheet is assumed here, which means that the

[1] See also Deutsche Bundesbank (2020).

stock of loans and the composition of the loan portfolio do not change over the observed one-year horizon.

Table 1 presents corporate loan losses as a percentage of exposures. The loss rates triple in adverse scenario 1 relative to the baseline scenario and rise by roughly a factor of 6 in adverse scenario 3, the most severe scenario. The extent to which banks are affected by the materialisation of credit risk depends, in this analysis, on the size of the exposures to particularly jeopardised sectors.

Common Equity Tier 1 (CET 1) capital can be deemed the banks' key measure of their ability to absorb losses. According to Table 1, losses in the baseline scenario amount to around 1.5% of CET 1 capital. In the most severe scenario, scenario 3, this figure rises to around 10%.

The loan losses calculated here can, furthermore, be used to analyse domestic banks' regulatory capital ratio. To this end, two aspects are added to the analysis.

First, loans' risk weights generally also go up in an economic crisis. In regulatory terms, that results in an increase in risk-weighted assets (RWAs), particularly at banks that use an IRBA to calculate the regulatory capital requirement in their loan portfolio (IRBA banks). A rise in risk weights is simulated in the present analysis, which is based on the probabilities of default (PDs) from the above scenarios. The rise in RWAs reduces these banks' CET 1 ratio (CET 1 as a percentage of RWAs).

Second, banks' other business lines besides corporate lending have to be taken into account. A simplifying assumption is made in this analysis in that the banks' earnings (net interest income, for instance) and expenditure not accruing to value adjustments in corporate lending (such as staff costs) cancel each other out. The losses identified here thus correspond to the profit for the year. The recorded losses thus erode banks' capital.

Figure 1 shows the banking system's capitalisation in the adverse scenarios. On aggregate, the CET 1 ratio (CET 1/RWAs) falls slightly, by 0.4 percentage point, in the baseline scenario, whereas in the adverse scenarios the decline ranges between 1.1 and

2.4 percentage points. No institution fails to meet the capital requirements (Pillar 1 plus binding Pillar 2 Requirements). A comparison of the median value of 1.1 with the weighted mean of 2.4 in Figure 1 (lower right-hand panel) shows that the bigger banks experienced a larger decrease in their capitalisation than smaller banks.

Some of these bigger banks use an internal ratings-based approach (IRBA) to calculate the risk weights in the loan portfolio, though in the adverse scenarios the rise in these risk weights on account of increased PDs is taken into account. Therefore, owing to an increase in RWAs, among other factors, the larger banks' capital ratio declines more steeply than that of smaller institutions which apply predetermined risk weights, such that those banks' RWAs, assuming a static balance sheet, remain unchanged.

The above approach is purely a historical–statistical analysis. The scenarios are derived ad hoc from the historical distribution of loss rates. An alternative starting point is economic growth measured in terms of real gross domestic product (GDP). In an econometric model, the correlation between the change in GDP and corporate loan losses is estimated. This estimated correlation and predefined paths which describe GDP growth up until the end of 2023 in several scenarios can likewise be used to study materialising credit risk. In contrast to the scenario analysis described above, which looks at a one-year horizon, here we look at developments in a medium term of around three years.

We see a statistically significant negative relationship between real GDP growth and loan defaults. However, the size of this negative correlation is subject to uncertainty. If the year 2020 is incorporated into the estimation of the econometric model, the estimated correlation ends up weaker than if the estimation ends in 2019, prior to the beginning of the pandemic. The reason for this discrepancy is that loan losses rose only moderately in 2020, whereas GDP fell sharply at the same time.

In order to incorporate uncertainty about the relationship between real economic growth and materialising credit risk, we conduct the scenario analysis both with the correlation that strips 2020 out of the estimation and with the correlation that we obtain if 2020 is input into the analysis. The results are shown in Figure 14 und Table 7. If we base this on the larger correlation (in absolute value), the aggregate CET 1 ratio falls by roughly 1.7 percentage points. If the smaller correlation is used, the decline amounts to 1.4 percentage points.

The scenario analysis we introduce here is an isolated view of the risk from lending to firms. The analysis can be extended to incorporate the impact of a credit risk from real estate lending or a materialising market risk.

The individual components of the scenario analysis will be expanded upon in the sections below. Section 2 presents the history of loss rates. The loss rate in the individual sectors will be explained using GDP growth in an alternative approach (Section 3). Banks' exposures are the topic of Section 4, and in Section 5 we will calculate the losses that occur in an adverse scenario. In Section 6 we explain how, for those banks that apply an internal ratings-based approach in their loan portfolio for supervisory purposes, the risk weights to be attached to the loans rise. The results of the preceding sections will be summarised in Section 7. We will then classify and contextualise the results in Section 8.

2 Historical loss rates in corporate lending business

Two sources are used to define loss rates: the borrowers statistics and the credit register for loans of EUR 1 million or more. Borrowers statistics cover lending to domestic enterprises and households. The credit register for loans of EUR 1 million or more also captures lending to foreign enterprises, governments and public sector entities, provided they exceed a threshold of EUR 1 million.

2.1 Loss rates based on borrowers statistics

The loss rate in sector b and year t is derived from the sum of value adjustments per year and the average annual stock of loans in the banking system:

$$\text{loss rate}_{b,t}^{\text{domestic}} = 100 \cdot \frac{\sum_{i=1}^{N}\sum_{q=1}^{4} \text{value adjustments}_{i,t,q,b}}{\frac{1}{4}\sum_{i=1}^{N}\sum_{q=1}^{4} \text{loans}_{i,t,q,b}}, \tag{1}$$

in which value $\text{adjustments}_{i,t,q,b}$ refer to value adjustments that bank i made in year t and in quarter q, $q \in 1, 2, 3, 4$, and in sector b, $t = 2002, .., 2020$ and $b = 1, 2, \dots, B$. Value adjustments encompass changes caused by specific value adjustments and any write-downs or write-ups of non-performing debt.[2] In the same way, $\text{loans}_{i,t,q,b}$ refers to the volume of outstanding loans.

Figure 3 presents historical loss rates for various sectors within Germany. The manufacturing and services sectors can be broken down further into sub-sectors, as depicted in Figure 4 and Figure 5.

In most sectors, the maximum loss rates used in the adverse scenarios occur during the recession in 2003 or the financial crisis in 2009. Developments in the loss rate in the transport sector are strongly influenced by lending to the shipping sector.[3] Following the financial crisis, loss rates in most sectors fell. In 2020, however, the COVID-19 pandemic sent loss rates higher again in some sectors, such as manufacturing.

The volume of outstanding loans differs among the sectors observed here, see Section 4.1. Additionally, we therefore also show the loss rates weighted by loans. Let

$$\text{loss rate}_{t}^{\text{domestic}} = \sum_{b=1}^{B} \omega_{b,t} \text{loss rate}_{b,t}^{\text{domestic}} \tag{2}$$

$$\omega_{b,t} = \frac{\sum_{i=1}^{N}\sum_{q=1}^{4} \text{loans}_{i,t,q,b}}{\sum_{\tilde{b}=1}^{B}\sum_{i=1}^{N}\sum_{q=1}^{4} \text{loans}_{i,t,q,\tilde{b}}}$$

[2]See Deutsche Bundesbank (2021a), p. 145.
[3]Siehe Deutsche Bundesbank (2013), S. 27

Figure 6 depicts this aggregate loss rate and the contributions (summands in Equation (2)). At the beginning of the period under observation, the aggregate loss rate is driven by the high contributions of services, which may be attributable to the recession of 2003. In 2020, there was an increase in the aggregate rate, which can be attributed, amongst other things, to contributions from manufacturing and services. In an analogous manner, Figure 7 and Figure 8 show the aggregate loss rates for manufacturing and the services sector.

In adverse scenario 1, selected sectors experience strong stress by assuming the maximum historical loss rate. In the other sectors, the rates per sector rise by one standard deviation versus the figure for 2020. For this, we assume B_1 to be at-risk sectors and B_2 not-at-risk sectors, where $B_1 + B_2 = B$. The sectors shall be sorted such that the at-risk sectors are indexed with $b = 1, 2, \ldots, B_1$. Then

$$\text{loss rate}^{\text{domestic}}_{b,\text{stress-scenario 1}} = \begin{cases} \max\limits_{t=2002,\ldots,2020} \text{loss rate}^{\text{domestic}}_{b,t}, & b = 1, 2, \ldots, B_1 \\ \text{loss rate}^{\text{domestic}}_{b,2020} + 1 \cdot \sigma_b, & b = B_1 + 1, \ldots, B \end{cases} \tag{3}$$

where σ_b refers to the standard deviation of the loss rates in sector b. The selection of these sectors is based on an ongoing observation of developments in sales in various sectors and anecdotal evidence. For details on the selection of at-risk sectors, see Pelzer (2021).

The loss rates in adverse scenarios 2 and 3 are defined as:

$$\text{loss rate}^{\text{domestic}}_{b,\text{stress-scenario 2}} = \max_{t=2002,\ldots,2020} \text{loss rate}^{\text{domestic}}_{b,t} \tag{4}$$

$$\text{loss rate}^{\text{domestic}}_{b,\text{stress-scenario 3}} = \max_{t=2002,\ldots,2020} \text{loss rate}^{\text{domestic}}_{b,t} + 2 \cdot \sigma_b \tag{5}$$

for $b = 1, 2, \ldots, B$.

Table 2 presents the loss rates in the scenarios. Sectors exposed to particularly strong stress in adverse scenario 1 are shown in bold. The figure observed in 2020 is also given by way of comparison. In the adverse scenarios, loss rates are many times higher than the loss rates in 2020 or the baseline scenario.

2.2 Loss rates based on the credit register for loans of EUR 1 million or more

The situation we describe above refers to domestic lending. Major banks with an international focus, in particular, also issue loans to enterprises abroad. A loss rate is therefore constructed that can be applied to these banks' entire loan portfolio. This is done using the credit register for loans of EUR 1 million or more. This data source includes information on the amount of specific value adjustments at creditor and borrower level. If this amount rises from zero to a positive value for a creditor-borrower pair, a credit event is assumed to have occurred. The sum of these credit events per sector is calculated as a percentage of the number of creditor-borrower pairs. This ratio is referred to as the default frequency and may be interpreted as an approximation of the probability of default (PD).

Let $l_{i,j,b,\tau}$ be the credit volume between bank i and borrower j in sector b and at time τ. The following shall apply below: $\tau = 1, 2, \ldots, T$, where $\tau = 1$ corresponds to the first quarter of 2008 and T refers to the total number of observed periods (quarters). In addition, we assume $v_{i,j,b,\tau}$ to be the sum of specific value adjustments that bank i has made for the existing credit relationship with borrower j. We then assume for $\tau > 1$

$$D_{b,\tau} = \left\{(i,j) \middle| \left((i,j) \in \mathbb{N}^2\right) \wedge (v_{i,j,b,\tau} > 0) \wedge (v_{i,j,b,\tau-1} = 0)\right\},$$

and

$$L_{b,\tau} = \left\{(i,j) \middle| \left((i,j) \in \mathbb{N}^2\right) \wedge (l_{i,j,b,\tau} > 0) \wedge (v_{i,j,b,r} = 0, \forall r \leq \tau)\right\}.$$

For a finite set Ω, let $\left|\Omega\right|$ be the number of elements in Ω, with $\left|\Omega\right| = 0$ if $\Omega = \emptyset$. The default frequency in sector b and quarter τ is then defined as

$$p_{b,\tau} = 100 \cdot \frac{\left|D_{b,\tau}\right|}{\left|L_{b,\tau}\right| + \left|D_{b,\tau}\right|}, \tag{6}$$

with $b = 1, 2, \ldots, B$, where B, in turn, designates the total number of sectors and $\tau = 2, 3, \ldots, T$. At time $\tau = 1$, $v_{i,j,b,\tau-1}$ is not observable and therefore $p_{b,1}$ is not defined.

The default frequency $p_{b,\tau}$ gives the number of new credit events per sector as defined above as a percentage of the total number of credit relationships (bank-borrower pairs), for which no specific value adjustment has yet been made or for which the specific value adjustments were made for the first time.

This definition can then be used to derive an annual default frequency. To this end, the sum total of new credit events per annum is determined per sector (annual sum of the numerator in Equation (6)) and divided by the average number of credit relationships (annual average of the denominator in Equation (6)).

In order to translate this annual default frequency into a loss rate, information on loss given default (LGD) in the credit register for loans of EUR 1 million or more is additionally used. To this end, the average LGD per sector is calculated based on the entire period under observation (from the first quarter of 2008 onwards). The product of this average LGD and the annual default frequency yields the annual loss rate. This loss rate in sector b and year t is referred to as the loss rate$_{b,t}$ below.

Remark.

1. *In the credit register for loans of EUR 1 million or more, some banks (the IRBA banks) also specify probabilities of default (PD) pursuant to Article 160 or Article 163 of the Capital Requirements Regulation (CRR) for the borrowers. There are two reasons why we decided to calculate a default frequency as described above. One is that all banks, not just the IRBA banks, report the amount of specific value adjustments,*

which is the basis for the definition of the default frequency. Second, the above default frequency is based on actual value adjustments and is consequently comparable with the figures in the borrowers statistics.

2. *The default frequency is based on the number of bank-borrower pairs, which need not be the same as the number of loans between the two parties. The observations of the credit register for loans of EUR 1 million or more relate to bank-borrower pair level, not the individual loan level.*

3. *It should be noted, moreover, that changes to specific value adjustments that occur after the first specific value adjustment is made are not fed into the default frequency according to the above definition. We disregard subsequent changes in specific value adjustments and do not record them as a new credit event as the subsequent specific value adjustments may have many causes that are not connected to a new credit event, for instance a change in the initial assessment of the need for value adjustments or – for non-euro loans – a change in the exchange rate.*

4. *To differentiate between the domestic loss rate and the loss rate*$_{b,t}$*, the following points should be noted: the domestic loss rates are based on the valuation changes in the borrowers statistics; information on amounts of specific value adjustments is not available. In the definition of loss rate*$_{b,t}$*, no distinction is made within sector b between lending in various countries. The loss rate is based on the sum total of credit events as defined above across all countries.*

5. *Note lastly that the sector definitions in the borrowers statistics do not match those used in the credit register for loans of EUR 1 million or more. In the credit register for loans of EUR 1 million or more, sectors are based on the customer classification (NACE Rev. 2) and are called economic activities. This document nonetheless uses the term sector throughout.*

In Figure 9 und Figure 10, we present the loss rate$_{b,t}$ for the years 2008 to 2020. The loss rates are shaped heavily by the financial crisis of 2009, in which most sectors experienced the historically highest figures. There was no major increase in loss rates in 2020.

Like the depiction in Figure 6, Figure 11 shows the aggregate loss rate weighted with the stocks of loans as well as the contributions made by individual sectors. For ease of presentation, the services sectors (NACE Section I to NACE Section S) are shown as a single sector. As the stocks of loans used here are only available from the third quarter of 2014, this disaggregation is only available from 2014. It is seen that key contributions come from services, manufacturing, transport and wholesale and retail trade. Figure 12 shows the aggregate loss rate for services as well as the contributions made by the individual sub-sectors. Real estate activities (NACE Section L) make the largest contribution to this aggregate loss rate.

In the next step, the scenarios are specified as in Equation (3) - Equation (4).

$$\text{loss rate}_{b,\text{stress-scenario 1}} = \begin{cases} \max\limits_{t=2008,\ldots,2020} \text{loss rate}_{b,t}, & b = 1, 2, \ldots, B_1 \\ \text{loss rate}_{b,2020} + 1 \cdot \sigma_b, & b = B_1 + 1, \ldots, B \end{cases} \tag{7}$$

in which σ_b refers to the standard deviation of the loss rates in sector b and

$$\text{loss rate}_{b,\text{stress-scenario 2}} = \max_{t=2008,\ldots,2020} \text{loss rate}_{b,t} \tag{8}$$

$$\text{loss rate}_{b,\text{stress-scenario 3}} = \max_{t=2008,\ldots,2020} \text{loss rate}_{b,t} + 2 \cdot \sigma_b \tag{9}$$

for $b = 1, 2, \ldots, B$.

Table 3 represents the loss rates in the scenarios. Sectors exposed to particularly strong stress in adverse scenario 1 are shown in bold. The figure observed in 2020 is also given by way of comparison. In the adverse scenarios, loss rates are many times higher than the loss rates in 2020 or the baseline scenario.

3 Credit risk and the macroeconomic environment

The results above are based on a statistical analysis of historical loss rates in Germany's banking system. The scenarios are derived from the sample maximum and the sample variance of these loss rates, and they leave open the question of where an increase in loss rates comes from. This section examines how the credit risk of German banks is linked to changes in the macroeconomic environment. In particular, it looks at growth in real gross domestic product (GDP).

To illustrate this, the default frequency for corporate loans in quarter τ across all sectors is constructed based on Equation (6),

$$p_\tau = 100 \cdot \frac{\sum_{b=1}^{B} \left| D_{b,\tau} \right|}{\sum_{b=1}^{B} \left| L_{b,\tau} \right| + \left| D_{b,\tau} \right|}. \tag{10}$$

Figure 13 shows the quarterly change in real GDP and the default frequency for corporate loans according to (10). Two observations can be made. First, in 2009 it appears that a decline in GDP growth precedes a rise in the default frequency. Second, real GDP changes very significantly in 2020, while the default frequency remains largely unchanged. The correlation between the change in GDP and the default frequency for each sector according to Equation (6) is investigated below. In order to illustrate the impact of the strong GDP changes at the end of the sample, the parameters of the linear regression model

$$y_{b,\tau} = \alpha + \beta \cdot \mu_{\tau-1} + \gamma' d_\tau + \varepsilon_{b,\tau}, \quad \tau = 2008\text{Q}2, 2008\text{Q}3, \ldots, T, \tag{11}$$

are estimated in each case for $T = 2015\text{Q}3, 2015\text{Q}4, ..., 2021\text{Q}1$. Where $T = 2015\text{Q}3$, the estimation is based on 30 quarters, where $T = 2021\text{Q}1$, the sample length is 52 quarters. The dependent variable $y_{b,\tau}$ is the annualised default frequency in sector b and quarter τ, $y_{b,\tau} = 4 \cdot p_{b,\tau}$, $b = 1, 2, ..., B$, where $p_{b,\tau}$ is defined in Equation (6). Furthermore, μ_τ refers to the annualised, quarterly change in real gross domestic product (GDP) as a percentage. If X_τ is calendar and seasonally adjusted real GDP, $\mu_\tau = 100\left((X_\tau/X_{\tau-1})^4 - 1\right)$.

Lastly, d_τ represents a vector of quarterly indicator variables that refer to the first, second or fourth quarter.

Figure 14 shows the determination coefficient R2 in the regressions Equation (11). Prior to 2020, the determination coefficient hovers between 0.2 and 0.6 and thus indicates a moderate yet non-negligible correlation between GDP growth and default frequencies. In the third quarter of 2020, however, this correlation decreases enormously across virtually all sectors.

Table 5 shows the results of Equation (11) for $T = 2019Q4$ in detail. Similarly, Table 6 displays the results for $T = 2021Q1$. We see two possible interpretations for these results. First, the pre-pandemic correlation may have been overstated as it was driven primarily by the developments in 2009. Second, 2020 may be viewed as a break in this correlation due, for example, to extraordinary fiscal, monetary policy and regulatory measures; see Deutsche Bundesbank (2020), pp. 63–64. The correlation analysis shown here cannot shed any light on the cause of this potential break, however.

Nevertheless, this analysis does point to a high degree of uncertainty surrounding the relationship between credit risk materialising in the banking system and macroeconomic developments. In order to take account of this uncertainty in a scenario analysis, the following method was chosen.

First, the parameters of a regression model, similar to Equation (11), are estimated. This estimation is carried out on the basis of the entire available sample, with the sample ending in the first quarter of 2021. In addition, another estimation of this model is carried out, but this time, the sample is limited to the pre-pandemic period, i.e. up to and including the end of the fourth quarter of 2019.

Second, the default frequencies are derived for a one-year period using predefined paths for GDP growth. The default frequencies in these scenarios are calculated for each of the two models described above.

Specifically, the model

$$p_{b,\tau} = \alpha + \beta \cdot \mu_{\tau-1} + \varepsilon_{b,\tau}, \quad \tau = 2008\text{Q}2, 2008\text{Q}3, \dots, T, \tag{12}$$

is considered, where the default frequency $p_{b,\tau}$ is in turn given by Equation (6). Furthermore, μ_τ is now the change in real GDP on the preceding quarter expressed as a percentage. It became clear that the indicator variables d_τ do not have any significant explanatory power, which means that they are no longer taken into account. This model's parameters are each estimated for $T = 2019\text{Q}4$ and $T = 2021\text{Q}1$. The evolution of default frequencies in the scenarios is then given by $\widehat{p}_{b,\tau} = \widehat{\alpha} + \widehat{\beta} \cdot \mu_{s,\tau-1}$ where $\widehat{\alpha}$ and $\widehat{\beta}$ refer to the estimates of the parameters in Equation (12), and $\mu_{s,\tau}$ describes the growth in GDP in scenario s, where $s \in \{\text{baseline scenario}, \text{adverse scenario}\}$. This requires that $0 \leq \frac{\widehat{p}_{b,\tau}}{100} \leq 1$ applies in all sectors b and all quarters τ. In reality, this condition is not necessarily met in the linear regression model. If $\widehat{p}_{b,\tau} < 0$, the estimate is replaced by zero.

Instead of imposing the restriction $0 \leq \frac{\widehat{p}_{b,\tau}}{100} \leq 1$, the dependent variable in Equation (12) can also be transformed: if

$$p^*_{b,\tau} = \log\left(\frac{\frac{p_{b,\tau}}{100}}{1 - \frac{p_{b,\tau}}{100}}\right)$$

is the logit transformation of the default frequency $p_{b,\tau}$, (see, inter alia, Jimenez and Mencia (2009)), the above regression can be carried out with $p^*_{b,\tau}$ instead of $p_{b,\tau}$. If the inverse of this transformation is then applied to $\widehat{p}^*_{b,\tau}$, this ensures that the default frequencies considered in the scenarios are not negative. However, the logit transformation is only properly defined for $0 < \frac{p_{b,\tau}}{100} < 1$. Historically, the case $p_{b,\tau} = 0$ occurs in four sectors, even materialising in consecutive quarters in two sectors. To prevent a loss of historical information, we chose not to carry out this transformation.

An alternative method that explicitly allows for the fractional nature of the dependent variable, and thus that is bounded, was put forward by Papke and Wooldridge (1996). This is a maximum likelihood method that permits $p_{b,\tau} = 0$ and ensures that $0 \leq \frac{\widehat{p}_{b,\tau}}{100} \leq 1$ has been met. It is performed to accompany the robustness check for the results derived from the model in Equation (12).

As a final step, the default frequencies are translated into loss rates by multiplying them by an average LGD for each sector. This method is consistent with the approach outlined in Section 2.2.

Figure 15 shows the historical path of real GDP and its growth in a baseline scenario and in an adverse scenario, which are examined below. While the baseline scenario allows for an economic recovery, the adverse scenario envisages a far more subdued pathway for economic activity. We continue our discussion of the banking system losses in these scenarios in Section 5.

4 Exposures in corporate lending business

In order to estimate corporate loan losses, the loss rates described above in the baseline scenario and in the stress scenarios are applied to the loan portfolio available at the end of March 2021. Irrevocable lending commitments are taken into account alongside the stock of on-balance exposures.

4.1 On-balance exposures

In line with the method outlined above, Figure 16 - Figure 18 illustrate exposures to domestic enterprises according to the borrowers statistics. The sample includes 1,464 domestic banks as at the end of March 2021. Figure 16 illustrates that the services sector is of very great importance to banks' loan portfolio, accounting for around 52% of exposures in March 2021. If we look solely at non-financial corporations and disregard the financial intermediation sector (financial enterprises such as insurers), this share increases to 59%. Figure 18 indicates that the loans were mainly granted to the sub-sectors housing enterprises, other real estate activities and other business activities.

Figure 19 und Figure 20 show the stock of loans by NACE section according to the supervisory reporting system (FINREP) based on the entire loan portfolio (domestic and foreign). In March 2021, the sample includes around 300 domestic banks. The volume of exposures to enterprises abroad is indeed significant in some sectors, such as real estate activities, manufacturing, professional and administrative support service activities, or wholesale and retail trade.

4.2 Irrevocable lending commitments

Following the outbreak of the pandemic, credit lines played an important role in its most critical period in March 2020. Enterprises covered part of their liquidity needs by drawing down irrevocable lending commitments. For banks, this transforms off-balance transactions into on-balance business. This is why additional exposure potential that may arise from lending commitments is added to the aforementioned on-balance stock of loans in this stress test as well. The exposures arising from lending commitments are determined in a separate analysis. Drawdowns of these commitments vary across sectors such that they are higher in at-risk sectors than in less-at-risk sectors in stress scenario 1. They differ across scenarios, too: the baseline scenario sees around 3% of the stock of irrevocable lending commitments being transformed into on-balance exposures, while the most severe stress scenario (scenario 3) expects this share to increase to 100% in some sectors.

5 Losses in corporate lending business

The estimated losses can now be calculated as the product of the loss rates and the stocks of loans. First, these losses are shown based on the purely historical and statistical analysis (see Section 2). An alternative approach would be to examine the losses originating from the correlation between historical credit events and the change in gross domestic product (see Section 3).

As in Section 2, let N be the number of banks in the sample, N_1 the number of banks conducting lending business in Germany and abroad and N_2 the number of banks that only grant loans to domestic enterprises, where $N = N_1 + N_2$. Then

$$\text{loss}_{i,s} = \begin{cases} \sum_{b=1}^{B} \frac{\text{loss rate}_{b,s}}{100} \cdot \text{loans}_{i,b,s}, & i = 1, 2, \dots, N_1 \\ \sum_{b=1}^{B} \frac{\text{loss rate}_{b,s}^{\text{domestic}}}{100} \cdot \text{loans}_{i,b,s}^{\text{domestic}}, & i = N_1 + 1, N_1 + 2, \dots, N \end{cases}$$

applies, where $s \in$ baseline scenario, stress scenario 1, stress scenario 2, stress scenario 3 and loss $\text{rate}_{b,s}$ is explained in Section 2.2 and loss $\text{rate}_{b,s}^{\text{domestic}}$ in Equation (3). The stock of loans is taken from two sources. For banks that only grant loans to domestic enterprises, the stock of loans is based on the borrowers statistics. For banks that also grant loans to enterprises abroad, the stock of loans is taken from the supervisory reporting system (FINREP). These loans consist of on-balance exposures and irrevocable lending commitments. Drawdowns of these lending commitments vary across scenarios (see Section 4.2), such that the stock of $\text{loans}_{i,b,s}$ depends on the respective scenario s.

Losses in the event of predefined evolution of GDP are calculated analogously, although the loss rates described in Section 3 are used.

6 Rise in risk weights for corporate loans

If borrowers' creditworthiness deteriorates, this is reflected not only in higher value adjustments in banks' loan portfolios (and corresponding reductions in their capital), but also in higher risk weights, at least at banks that use an internal ratings-based approach to determine risk weights (IRBA banks).

The idea behind our adjustment of RWAs in the stress test is

- to interlink the rising loss rates in the event of stress with the PDs underlying the risk weights,

- while smoothing these PDs so that the effect of the RWA adjustment does not dominate the result.[4] This is consistent with observations from other stress tests. For example, in the 2018 EBA stress test, the share of the RWA adjustment in the total decline in the capital ratios was less than one-third.[5]

To achieve these sub-targets, the loss rates in the stress scenario are fed into the calculation of PDs for the risk weights, not in their entirety, but as a weighted average of their history (calculation of the mean value over time for each sector) and of the remaining sectors (calculation of the mean value over a cross-section of sectors). Specifically, the adjustment is carried out in three steps:

1. First, sector-specific PDs are calculated by dividing the sector-specific loss rates for one year by that sector's average LGD; see Section 2.2. This is used to calculate the moving average from the current year and the previous four years.

$$\widehat{PD}_{b,t} = \frac{1}{T} \sum_{j=0}^{T-1} \frac{\text{loss rate}_{b,t-j}}{\widetilde{\text{LGD}}_b}$$

   where a period of $T = 5$ years is observed and loss $\text{rate}_{b,t}$ is defined in Section 2.2, and $\widetilde{\text{LGD}}_b$ refers to the mean value of the LGDs weighted with the stocks of loans.

2. From this, we compute an average of the estimated PDs weighted with the stocks of loans, which we call $\widetilde{PD}_t$. Furthermore, a weighted sum is calculated from the sector-specific PDs determined in the first step and from this cross-sector average

[4]Generally, banks appear to use estimates for PDs that are considerably less volatile than the PDs from market data (see also the results in Annex 2; these show that only one-quarter of the PDs reported by banks to the credit register respond to short-term fluctuations in PDs from market data).

[5]In this case, the capital ratio of banks in the stress scenario was 5.2 percentage points lower than in the baseline scenario; the effect caused by the rise in RWAs (the proper term would be risk exposure amounts, or REAs) was 1.6 percentage points, i.e. 31% of the stress effect. This effect turned out to be smaller still in the 2021 EBA stress test (see EBA (2021)).

(Stein (1956)):

$$\widehat{PD}_{\text{Stein},b,t} = \omega \cdot \widehat{PD}_{b,t} + (1-\omega) \cdot \widetilde{PD}_t,$$

where the weight $\omega = 0.5$ is selected. The weighting factor ω and the time T (see step 1) were selected empirically such that the second sub-target formulated above – the non-domination of the rise in RWAs – is achieved.

3. Based on this estimate $\widehat{PD}_{\text{Stein},b,t}$, the risk weight is determined for each sector and each scenario using the Basel formula (see Annex 1). If $\Delta RW_{b,t}$ refers to the change in the risk weight in sector b and $w_{b,t,i}$ to the corresponding share in the loan portfolio of bank i, the change in the average risk weight in the corporate portfolio of bank i can be computed as

$$\Delta RW_{i,t}^{\text{Corporates}} = \alpha_{i,t} \cdot \sum_{b=1}^{B} w_{i,b,t} \cdot \Delta RW_{b,t}$$

assuming a static balance sheet. Here, $\alpha_{i,t}$ stands for the share of the loan portfolio to which bank i applies the IRB approach.

Table 4 shows the average risk weights in the baseline scenario and in the stress scenarios. In the baseline scenario, the risk weights are frequently lower than 100%; only a small number of sectors record a risk weight over 100%, such as manufacturing. Risk weights increase as the scenarios become more severe. On an aggregate average, they rise by 23% in the most severe scenario compared with the baseline scenario. It should be noted that this increase in risk weights relates solely to the sub-portfolio of corporate loans.

7 Impact on Common Equity Tier 1 (CET 1) ratio

As mentioned above, the Common Equity Tier 1 (CET 1) capital ratio of a bank changes due to two effects – a change in the CET 1 capital and a change in the risk-weighted assets

(RWAs):

$$\Delta CET1 = \left(\frac{\Delta CET1}{CET1} - \frac{\Delta RWA}{RWA} \right) \cdot CET1, \tag{13}$$

where, in our stress test, the change in CET 1 capital $\Delta CET1$ is the loss according to Section 5 and the change in risk-weighted assets $\Delta RWA = \Delta RW \cdot \text{Total Assets}$ according to Section 6. The absolute change in the CET 1 capital ratio is a good approximation of the difference between the relative change in CET 1 capital and the relative change in risk-weighted assets, where this difference is multiplied by the CET 1 capital ratio (see Annex 3).

The notation in Equation (13) illustrates that the decline in the CET 1 capital ratio (for given static capital consumption and equity ratios) is sharper for IRBA banks. In order to compare the results of IRBA banks and non-IRBA banks, we ensure that the RWA effect does not dominate (see Section 6).

Figure 1 shows the overall impact from the baseline scenario and the stress effect on the Common Equity Tier 1 (CET 1) ratio calculated not as an approximation based on (Equation (13)) but directly as the difference between the CET 1 ratios. We see that the decline in the CET 1 ratio – in the baseline scenario and in all stress scenarios – is much greater due to capital consumption than due to the rise in risk weights, which is partly due to how the risk weights are modelled (see Section 6). The decrease in the CET 1 ratio (of between 1.1 and 2.4 percentage points depending on the stress scenario) may not seem significant, but we are only looking at the loan portfolio made up of corporate loans; other potential losses arising from the retail loan portfolio or from market risk are not considered here.

The decrease in the CET 1 capital ratio across banks can be broken down further. The more severe the scenario, the more the curve and the percentage of banks shift towards sharper declines. The decline in the system-wide CET 1 capital ratio, which sharpens as the severity of the scenario increases, is accordingly borne by the banking system as a whole and not just by individual banks, even if there are banks with significant declines.

8 Summary

In this paper, we outline the datasets, mechanisms and formation of scenarios that allow us to translate data on corporate loans into declines in banks' capital ratios. Studies should not just stop at the analysis of corporate loans; the empirical approach presented in this paper can be extended to other parts of the loan portfolio, such as real estate loans, whether commercial or intended for households.

References

Cohen, B. H. and M. Scatigna (2016). Banks and capital requirements: Channels of adjustment. *Journal of Banking & Finance 69*, 56–69.

Deutsche Bundesbank (1998, August). Monthly Report. https://www.bundesbank.de/resource/blob/623106/70837baefd6e46f1e4d2c8d0e38e4dc6/mL/1998-08-credit-register-data.pdf.

Deutsche Bundesbank (2013, September). Monthly report. https://www.bundesbank.de/resource/blob/666260/6f26521cd39bb4891014d530803d003a/mL/2013-09-monatsbericht-data.pdf.

Deutsche Bundesbank (2020, October). Financial Stability Review. https://www.bundesbank.de/resource/blob/847248/36cb058e4c06d08de803607eeea46ae5/mL/2020-finanzstabilitaetsbericht-data.pdf.

Deutsche Bundesbank (2021a, January). Borrowers statistics. https://www.bundesbank.de/resource/blob/883170/a08978f7cca5a6c716410d737954c7f8/mL/statso01-04-kreditnehmerstatistik-data.pdf. Special Statistical Publication 1.

Deutsche Bundesbank (2021b, November). Financial Stability Review. https://www.bundesbank.de/resource/blob/880192/f930bd576207991f68c9c659caee21af/mL/2021-finanzstabilitaetsbericht-data.pdf.

EBA (2021). 2021 EU-wide stress test - results. European Banking Authority.

Jimenez, G. and J. Mencia (2009). Modelling the distribution of credit losses with observable and latent factors. *Journal of Empirical Finance 16*(2), 235–253.

Papke, L. E. and J. M. Wooldridge (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates. *Journal of Applied Econometrics 11*(6), 619–632.

Pelzer, M. (2021). Deleveraging potential in the German banking system and effects on financial stability. Bundesbank Technical Paper.

Stein, C. (1956). Inadmissibility of the usual estimator for the mean of a multivariate normal distribution. *Proceedings of the 3rd Berkeley Symposium on Probability and Statistics 1*, 197–206.

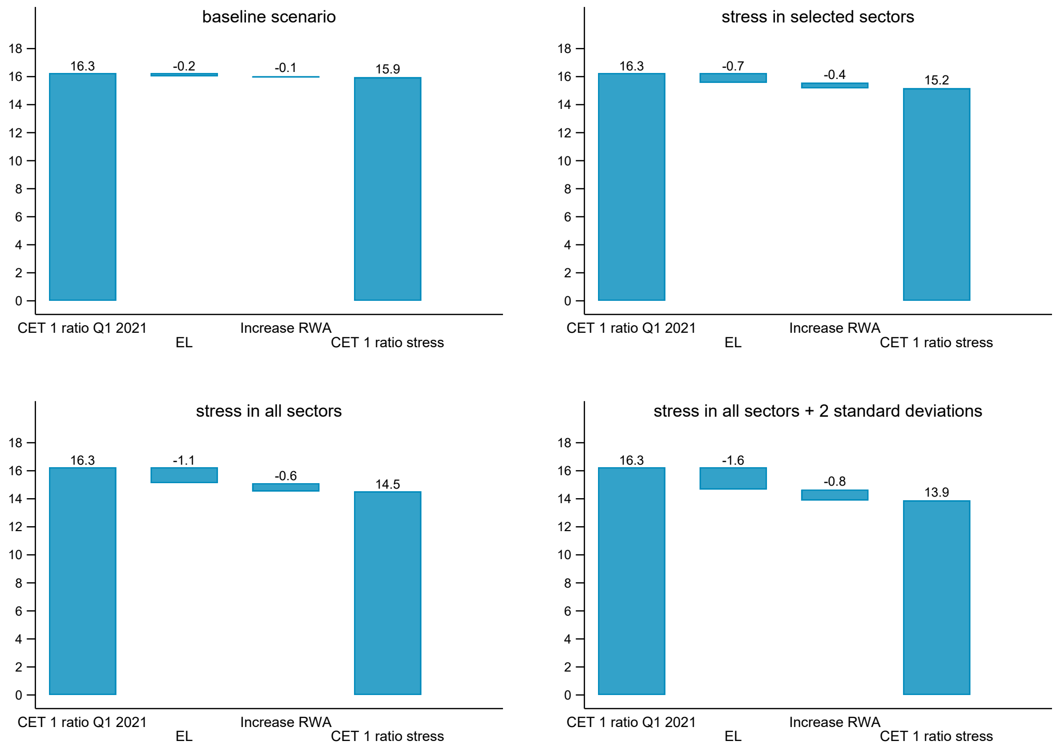

Figure 1:
Decomposition of the CET 1 capital ratio in the baseline and the stress scenarios based on historical loss rates
This figure decomposes the change in the CET 1 capital ratio into the contributions made by the Expected Loss (EL) and the increase in risk weights for corporate loans. These contributions are measured in percentage points. The starting point is the observed aggregate CET 1 capital ratio (CET 1 capital in percent of RWA) in March 2021, see Section 2 and Section 4. The Expected Loss is derived from the loss rates in the scenarios and the loan amounts in March 2021. The increase in risk weights is relevant only for those banks that use the advanced approach ("IRBA banks"), and also only for those credit portfolios, for which the advanced approach is actually taken. The horizon of the scenarios is one year. The decomposition is computed according to the method suggested by Cohen and Scatigna (2016). A deviation of the total effect from the sum of the contributions is due to rounding errors.

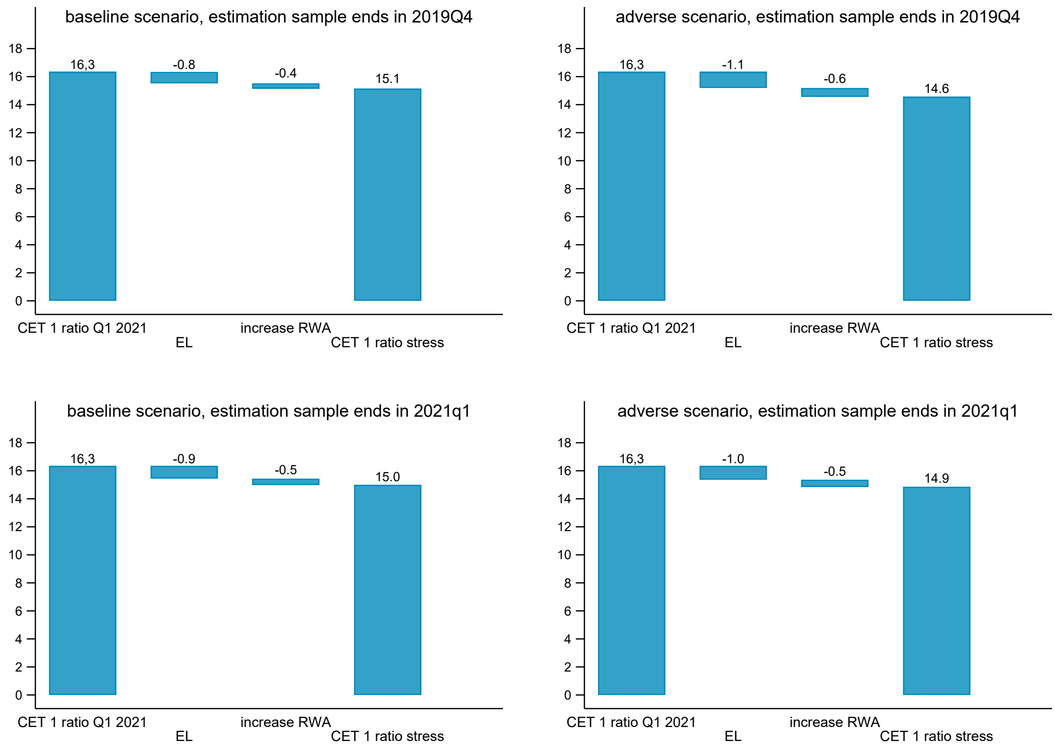

Figure 2:
Decomposition of the CET 1 capital ratio in the baseline and the stress scenarios based on GDP growth

This figure decomposes the change in the CET 1 capital ratio into the contributions made by the Expected Loss (EL) and the increase in risk weights for corporate loans. These contributions are measured in percentage points. The starting point is the observed aggregate CET 1 capital ratio (CET 1 capital in percent of RWA) in March 2021, see Section 3 and Section 4. Specifically, we estimate the model

$$p_{b,\tau} = \alpha + \beta \cdot \mu_{\tau-1} + \varepsilon_{b,\tau}, \quad \tau = 2008Q2, 2008Q3, \ldots, T, \tag{14}$$

in which $p_{b,\tau}$ is defined in Equation (6). The default rate indicates the number of new credit events in a given quarter and a given sector as a percentage of the total number of bank-firm pairs ("loans") in this sector and this quarter. A new credit event takes place if a bank reports an increase in the stock of value adjustments from zero to a positive value for the first time. Furthermore, μ_τ is the quarterly change in real GDP relative to the previous quarter in percent. We estimate the parameters in this model for both $T = 2019Q4$ and $T = 2020Q4$. The default rates in the scenarios are then given by $\widehat{p}_{b,\tau} = \widehat{\alpha} + \widehat{\beta} \cdot \mu_{s,\tau-1}$, where $\widehat{\alpha}$ and $\widehat{\beta}$ are the estimates of the parameters in the associated model above, and $\mu_{s,\tau}$ is the GDP growth in scenario s, in which $s \in \{\text{baseline scenario}, \text{adverse scenario}\}$. If $\widehat{p}_{b,\tau} < 0$, then this estimate is replaced by zero. The increase in risk weights is relevant only for those banks that use the advanced approach ("IRBA banks"), and also only for those credit portfolios, for which the advanced approach is actually taken. The scenario ends in the fourth quarter of 2023, see Figure 15. The decomposition is computed according to the method suggested by Cohen and Scatigna (2016). A deviation of the total effect from the sum of the contributions is due to rounding errors.

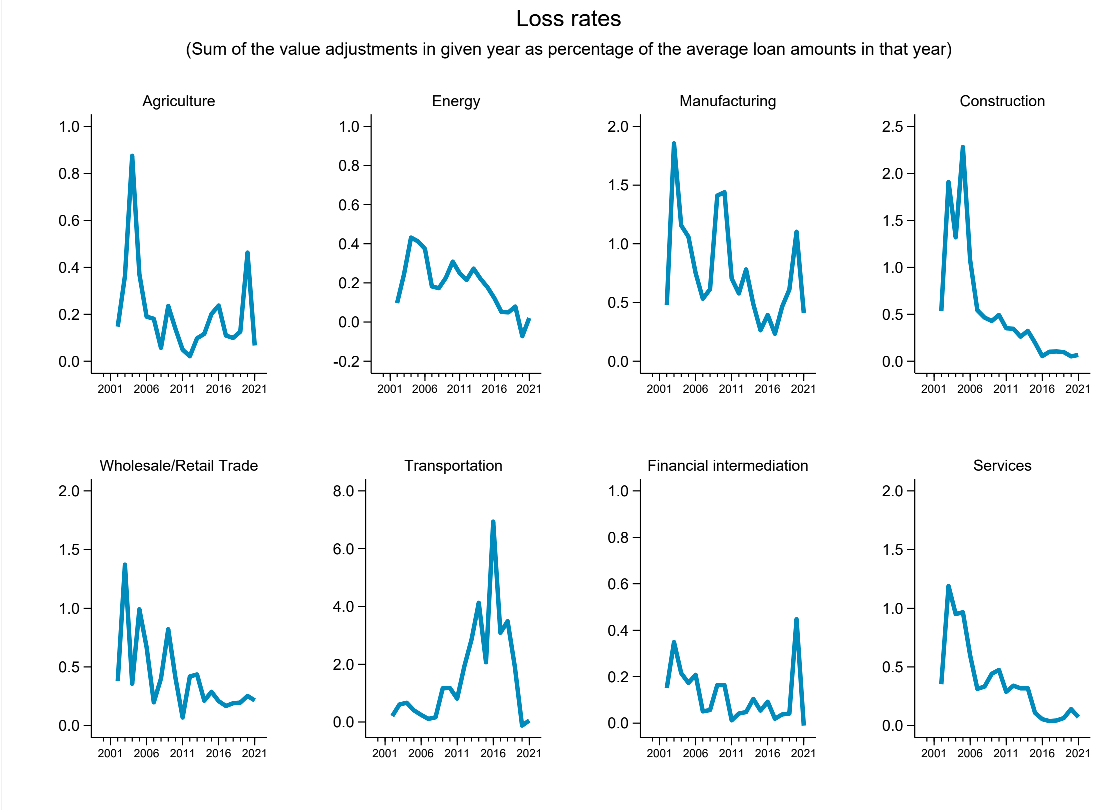

Figure 3:
Annual loss rates for loans made to domestic firms - All sectors
The loss rate in sector b and year t is defined as

$$\text{loss rate}_{b,t}^{\text{domestic}} = 100 \cdot \frac{\sum_{i=1}^{N} \sum_{q=1}^{4} \text{value adjustments}_{i,t,q,b}}{\frac{1}{4} \sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b}}, \tag{15}$$

in which value adjustments$_{i,t,q,b}$ refer to value adjustments that bank i made in year t and in quarter q, $q \in 1, 2, 3, 4$, and in sector b, $t = 2002, .., 2021$ and $b = 1, 2, \ldots, B$. Value adjustments encompass changes caused by specific value adjustments and any write-downs or write-ups of non-performing debt; see Deutsche Bundesbank (2021a), p. 145. In the same way, loans$_{i,t,q,b}$ refers to the volume of outstanding loans. The year 2021 covers the first half of the year only.

Figure 4:
Annual loss rates for loans made to domestic firms - Manufacturing
The loss rate in sector b_k and year t is defined as

$$\text{loss rate}^{\text{domestic}}_{b_k,t} = 100 \cdot \frac{\sum_{i=1}^{N} \sum_{q=1}^{4} \text{value adjustments}_{i,t,q,b_k}}{\frac{1}{4} \sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b_k}}, \tag{16}$$

in which value adjustments$_{i,t,q,b_k}$ refer to value adjustments that bank i made in year t and in quarter q, $q \in 1,2,3,4$, and in sub-sector b_k, $t = 2002,..,2021$ and $k = 1,2,\ldots,K$. Value adjustments encompass changes caused by specific value adjustments and any write-downs or write-ups of non-performing debt; see Deutsche Bundesbank (2021a), p. 145. In the same way, loans$_{i,t,q,b}$ refers to the volume of outstanding loans. The year 2021 covers the first half of the year only.

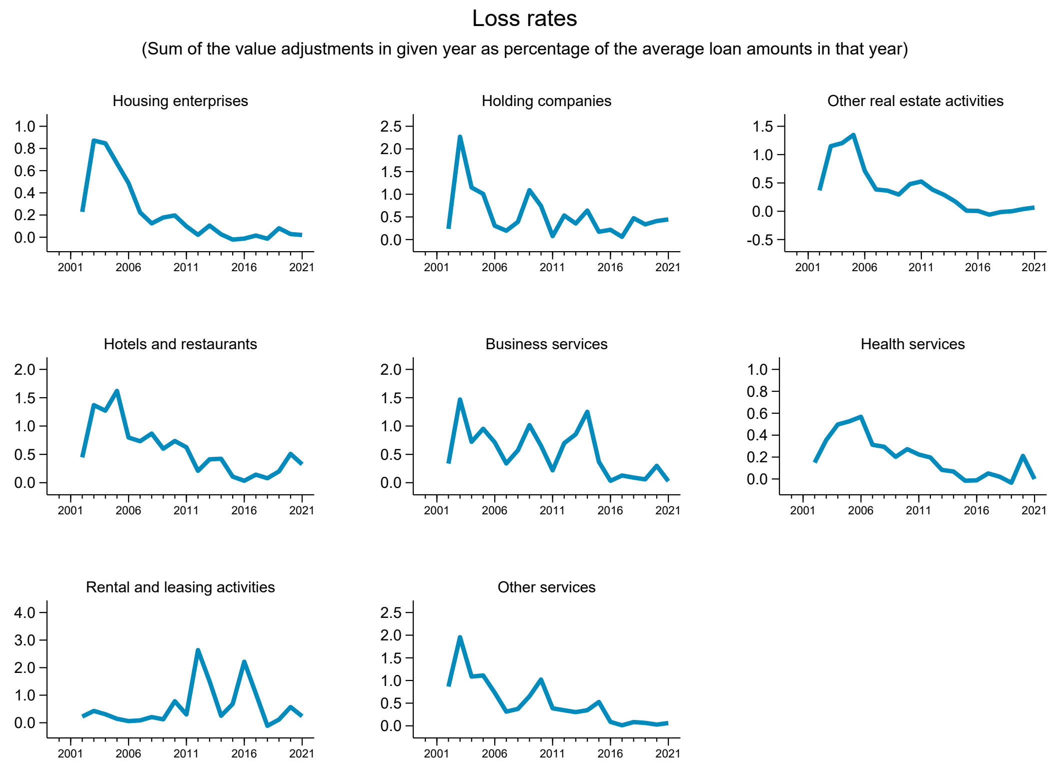

Figure 5:
Annual loss rates for loans made to domestic firms - Services
The loss rate in sector b_k and year t is defined as

$$\text{loss rate}^{\text{domestic}}_{b_k,t} = 100 \cdot \frac{\sum_{i=1}^{N} \sum_{q=1}^{4} \text{value adjustments}_{i,t,q,b_k}}{\frac{1}{4} \sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b_k}}, \tag{17}$$

in which value adjustments$_{i,t,q,b_k}$ refer to value adjustments that bank i made in year t and in quarter q, $q \in 1, 2, 3, 4$, and in sub-sector b_k, $t = 2002, .., 2021$ and $k = 1, 2, \ldots, K$. Value adjustments encompass changes caused by specific value adjustments and any write-downs or write-ups of non-performing debt; see Deutsche Bundesbank (2021a), p. 145. In the same way, loans$_{i,t,q,b_k}$ refers to the volume of outstanding loans. The year 2021 covers the first half of the year only.

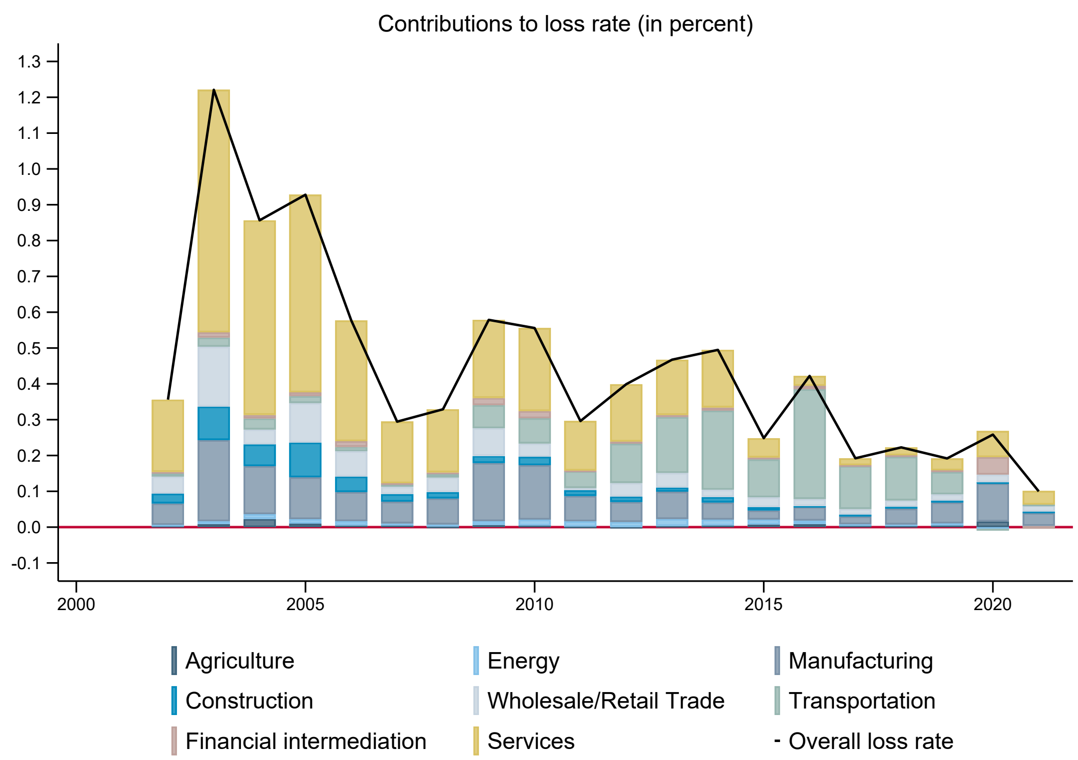

Figure 6:
Decomposition of the loss rates for loans made to domestic firms - All sectors
The aggregate loss rate in year t is defined as

$$\text{loss rate}_t^{\text{domestic}} = \sum_{b=1}^{B} \omega_{b,t} \text{loss rate}_{b,t}^{\text{domestic}}$$

$$\omega_{b,t} = \frac{\sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b}}{\sum_{\tilde{b}=1}^{B} \sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,\tilde{b}}}$$

in which loss $\text{rate}_{b,t}^{\text{domestic}}$ is defined in Equation (1). The loan amounts are taken from the borrower statistics, see Deutsche Bundesbank (2021a). The year 2021 covers the first half of the year only.

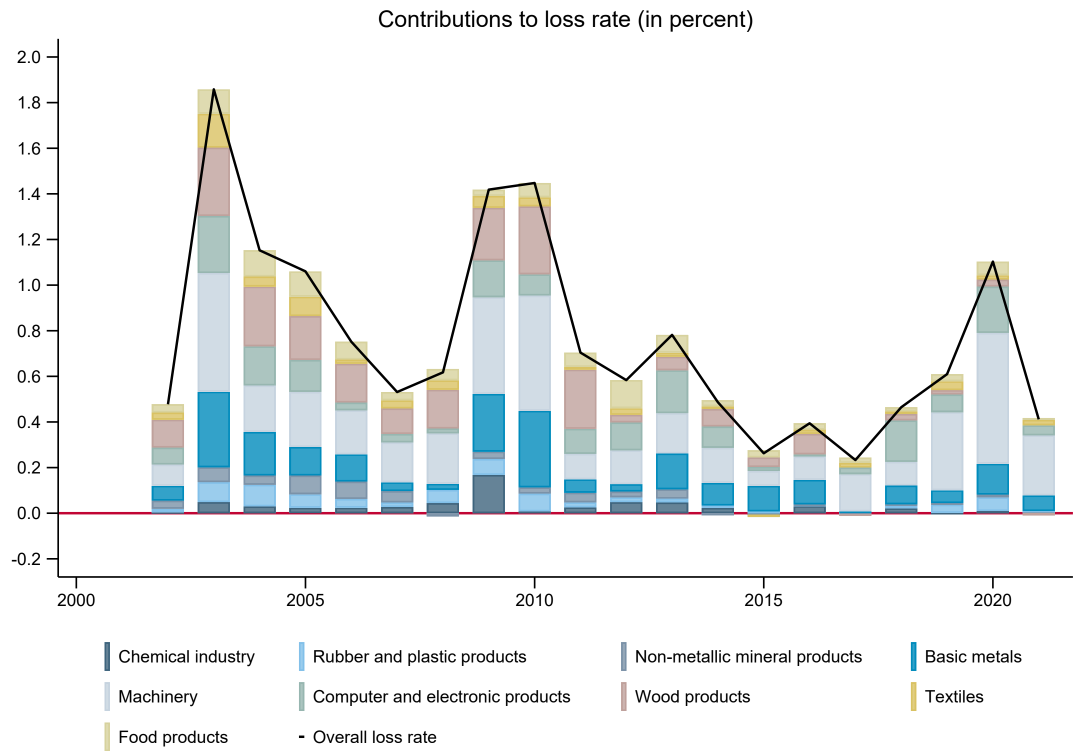

Figure 7:
Decomposition of the loss rates for loans made to domestic firms - Manufacturing
The aggregate loss rate in manufacturing in year t is defined as

$$\text{loss rate}_t^{\text{domestic}} = \sum_{k=1}^{K} \omega_{b_k,t} \text{loss rate}_{b_k,t}^{\text{domestic}}$$

$$\omega_{b_k,t} = \frac{\sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b_k}}{\sum_{\tilde{k}=1}^{K} \sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b_{\tilde{k}}}}$$

in which loss rate$_{b_k,t}^{\text{domestic}}$ is the loss rate in sub-sector b_k within manufacturing, $k = 1, 2, \ldots, K$. The loan amounts are taken from the borrower statistics, see Deutsche Bundesbank (2021a). The year 2021 covers the first half of the year only.

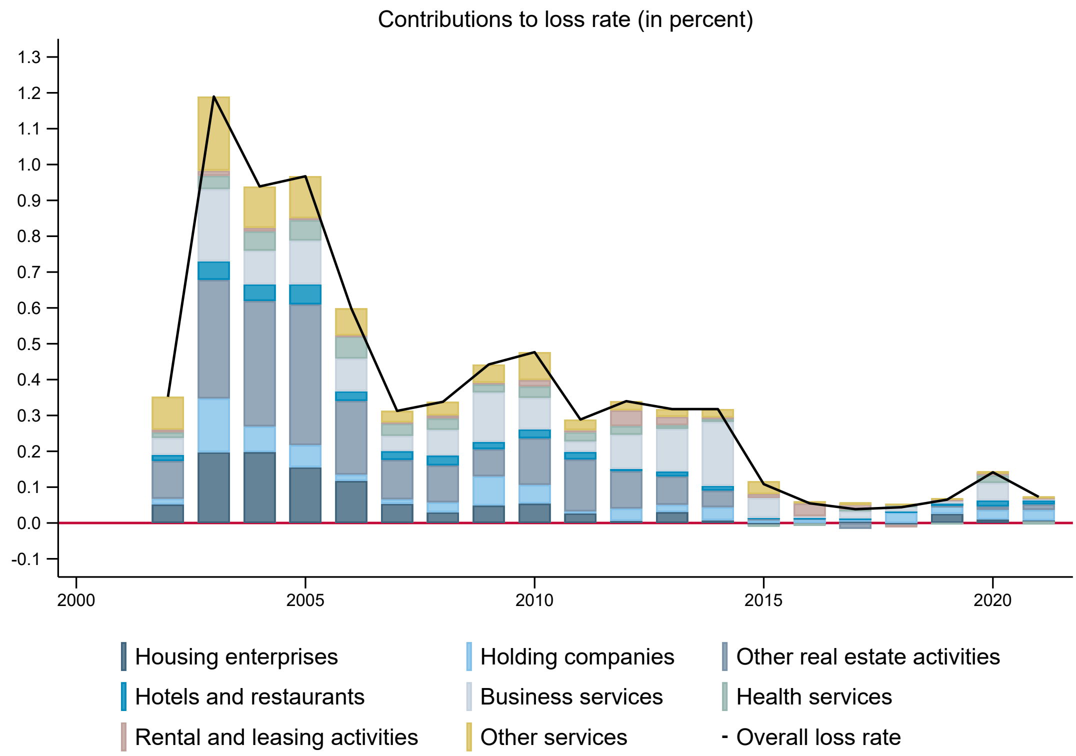

Figure 8:
Decomposition of the loss rates for loans made to domestic firms - Services
The aggregate loss rate in the service sector in year t is defined as

$$\text{loss rate}_t^{\text{domestic}} = \sum_{j=1}^{J} \omega_{b_j,t} \text{loss rate}_{b_j,t}^{\text{domestic}}$$

$$\omega_{b_j,t} = \frac{\sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b_j}}{\sum_{\tilde{j}=1}^{J} \sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b_{\tilde{j}}}}$$

in which loss rate$_{b_j,t}^{\text{domestic}}$ is the loss rate in sub-sector b_j within the service sector, $j = 1, 2, \dots, J$. The loan amounts are taken from the borrower statistics, see Deutsche Bundesbank (2021a). The year 2021 covers the first half of the year only.

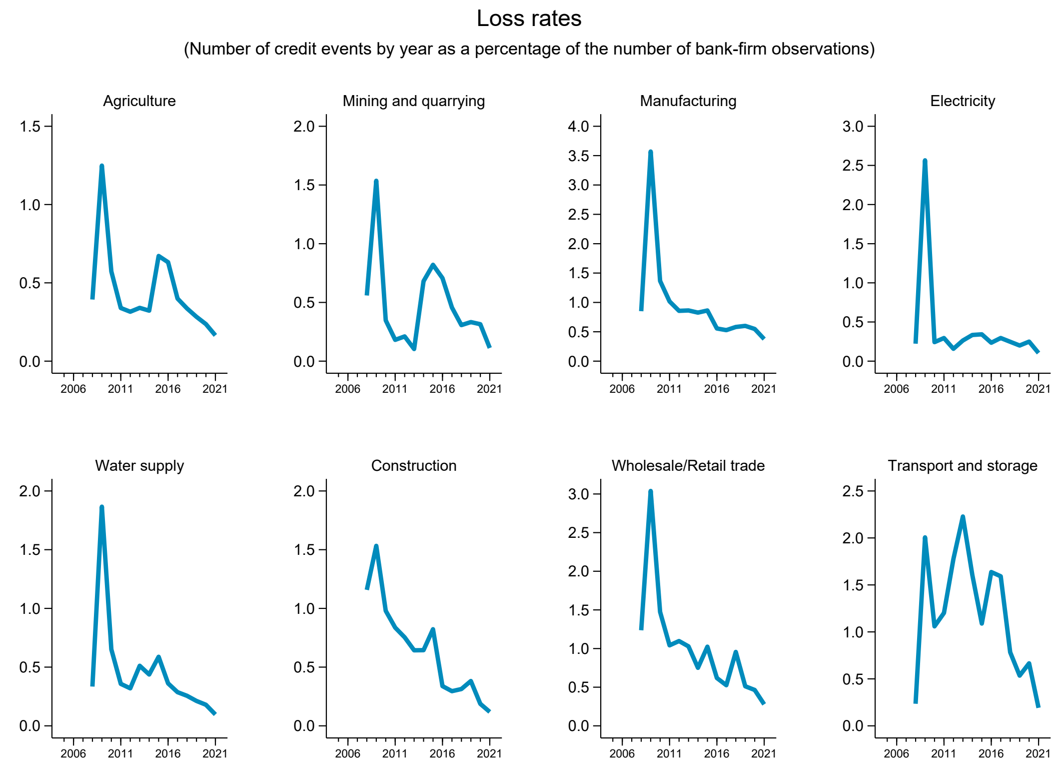

Figure 9:
Annual loss rates for loans made to firms - NACE sector A to sector H

This figure shows loss rate$_{b,t}$ in NACE sector b and year t. Let $l_{i,j,b,\tau}$ be the credit volume between bank i and borrower j in sector b and at time τ. The following shall apply below: $\tau = 1, 2, \ldots, T$, where $\tau = 1$ corresponds to the first quarter of 2008 and T refers to the total number of observed periods (quarters). In addition, $v_{i,j,b,\tau}$ is the sum of specific value adjustments that bank i has made for the existing credit relationship with borrower j. Then, for $\tau > 1$, let

$$D_{b,\tau} = \left\{(i,j)\middle|\left((i,j) \in \mathbb{N}^2\right) \wedge (v_{i,j,b,\tau} > 0) \wedge (v_{i,j,b,\tau-1} = 0)\right\},$$

and

$$L_{b,\tau} = \left\{(i,j)\middle|\left((i,j) \in \mathbb{N}^2\right) \wedge (l_{i,j,b,\tau} > 0) \wedge (v_{i,j,b,r} = 0, \forall r \leq \tau)\right\}.$$

For a finite set Ω, let $\left|\Omega\right|$ be the number of elements in Ω, with $\left|\Omega\right| = 0$ if $\Omega = \emptyset$. The default frequency in sector b and quarter τ is then defined as

$$p_{b,\tau} = 100 \cdot \frac{\left|D_{b,\tau}\right|}{\left|L_{b,\tau}\right| + \left|D_{b,\tau}\right|}, \tag{18}$$

with $b = 1, 2, \ldots, B$, where B, in turn, designates the total number of sectors and $\tau = 2, 3, \ldots, T$. At time $\tau = 1$, $v_{i,j,b,\tau-1}$ is not observable and therefore $p_{b,1}$ is not defined. To derive an annual loss rate, the sum total of new credit events per annum is determined per sector (annual sum of the numerator in Equation (19)) and divided by the average number of credit relationships (annual average of the denominator in Equation (19)). In order to translate this annual default frequency into a loss rate, the average LGD by sector is multiplied by the annual default rate. These loss rates are based on the credit register for loans of EUR 1 million or more, see siehe Deutsche Bundesbank (1998). The loss rates and the loan amounts comprise domestic and foreign lending. The year 2021 includes the first quarter only.

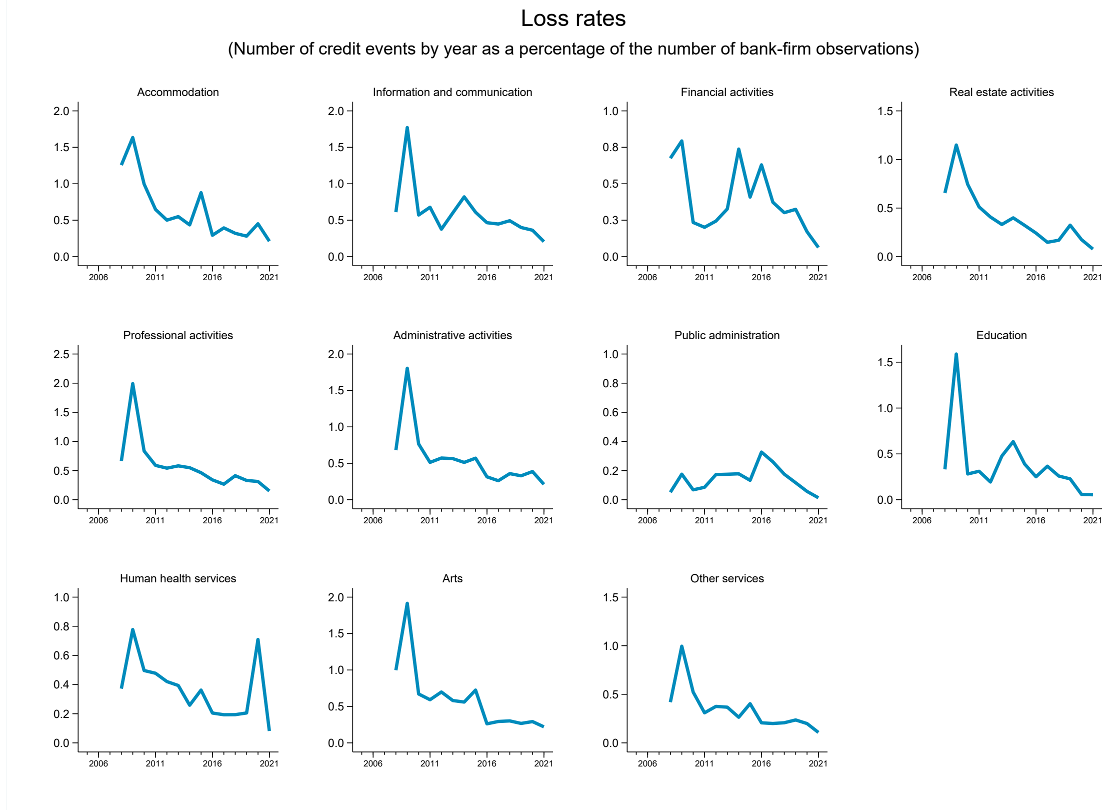

Figure 10:
Annual loss rates for loans made to firms - NACE sector I to sector S

This figure shows loss $\text{rate}_{b,t}$ in NACE sector b and year t. Let $l_{i,j,b,\tau}$ be the credit volume between bank i and borrower j in sector b and at time τ. The following shall apply below: $\tau = 1, 2, \ldots, T$, where $\tau = 1$ corresponds to the first quarter of 2008 and T refers to the total number of observed periods (quarters). In addition, $v_{i,j,b,\tau}$ is the sum of specific value adjustments that bank i has made for the existing credit relationship with borrower j. Then, for $\tau > 1$, let

$$D_{b,\tau} = \left\{(i,j) \middle| \left((i,j) \in \mathbb{N}^2\right) \wedge (v_{i,j,b,\tau} > 0) \wedge (v_{i,j,b,\tau-1} = 0)\right\},$$

and

$$L_{b,\tau} = \left\{(i,j) \middle| \left((i,j) \in \mathbb{N}^2\right) \wedge (l_{i,j,b,\tau} > 0) \wedge (v_{i,j,b,r} = 0, \forall r \leq \tau)\right\}.$$

For a finite set Ω, let $|\Omega|$ be the number of elements in Ω, with $|\Omega| = 0$ if $\Omega = \emptyset$. The default frequency in sector b and quarter τ is then defined as

$$p_{b,\tau} = 100 \cdot \frac{|D_{b,\tau}|}{|L_{b,\tau}| + |D_{b,\tau}|}, \tag{19}$$

with $b = 1, 2, \ldots, B$, where B, in turn, designates the total number of sectors and $\tau = 2, 3, \ldots, T$. At time $\tau = 1$, $v_{i,j,b,\tau-1}$ is not observable and therefore $p_{b,1}$ is not defined. To derive an annual loss rate, the sum total of new credit events per annum is determined per sector (annual sum of the numerator in Equation (19)) and divided by the average number of credit relationships (annual average of the denominator in Equation (19)). In order to translate this annual default frequency into a loss rate, the average LGD by sector is multiplied by the annual default rate. These loss rates are based on the credit register for loans of EUR 1 million or more, see siehe Deutsche Bundesbank (1998). The loss rates and the loan amounts comprise domestic and foreign lending. The year 2021 includes the first quarter only.

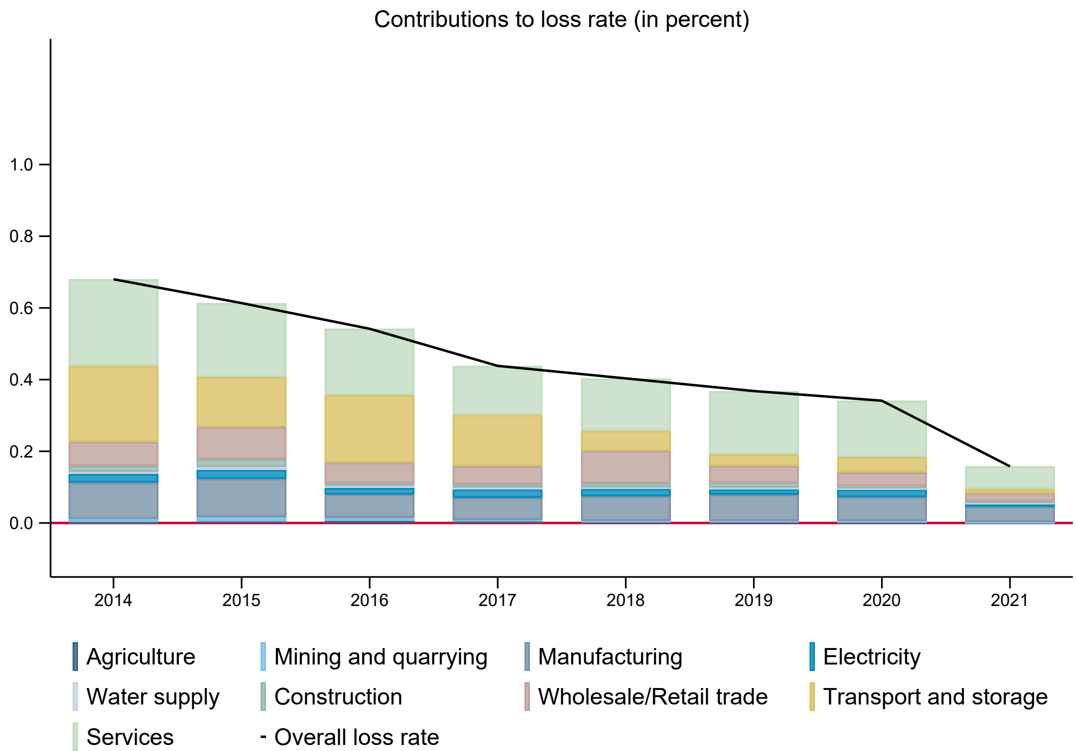

Figure 11:
Decomposition of the loss rates for loans made to domestic and foreign firms - All sectors

The aggregate loss rate in year t is defined as

$$\text{loss rate}_t = \sum_{b=1}^{B} \omega_{b,t} \text{loss rate}_{b,t}$$

$$\omega_{b,t} = \frac{\sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b}}{\sum_{\tilde{b}=1}^{B} \sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,\tilde{b}}}$$

in which loss $\text{rate}_{b,t}$ is explained in Section 2.2. The sectors I to S in the NACE are aggregated to one sector, which is referred to as Services in the figure. The loan amounts are taken from supervisory data (FINREP) and are available since the third quarter of 2014. The loss rates and the loan amounts comprise domestic and foreign lending. The year 2021 includes only the first quarter.

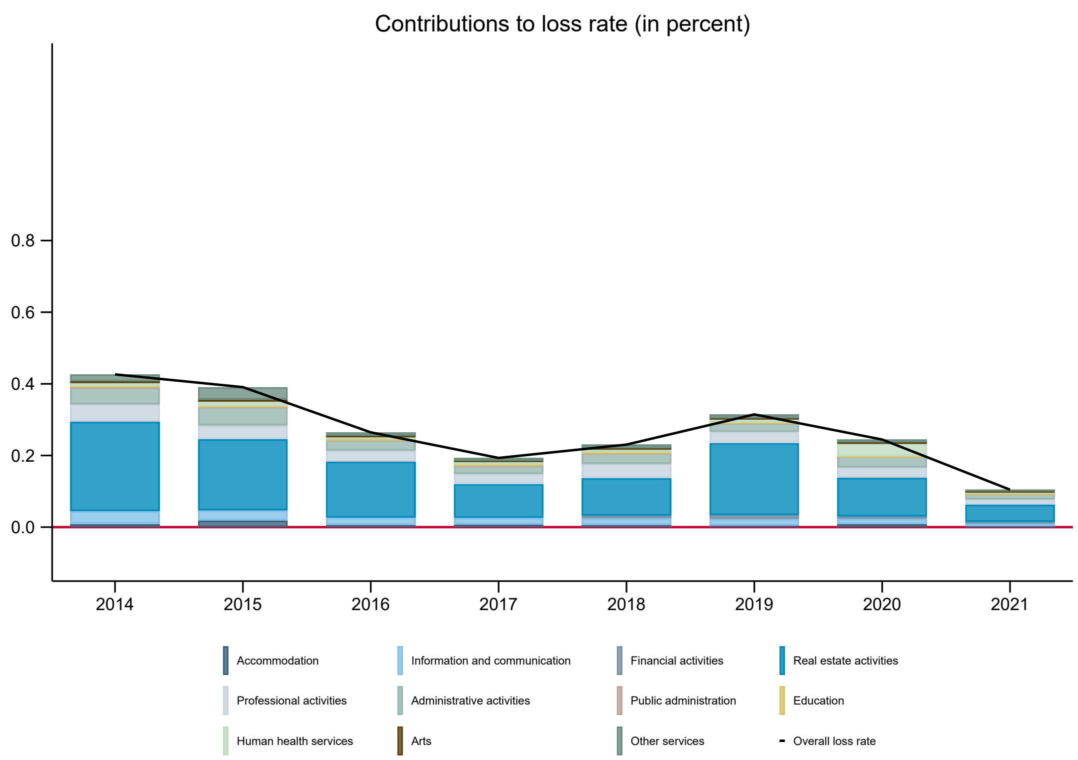

Figure 12:
Decomposition of the loss rates for loans made to domestic and foreign firms - Services

The aggregate loss rate in the service sector in year t is defined as

$$\text{loss rate}_t = \sum_{j=1}^{J} \omega_{b_j,t} \text{loss rate}_{b_j,t}$$

$$\omega_{b_j,t} = \frac{\sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b_j}}{\sum_{\tilde{j}=1}^{J} \sum_{i=1}^{N} \sum_{q=1}^{4} \text{loans}_{i,t,q,b_{\tilde{j}}}}$$

in which loss $\text{rate}_{b_j,t}$ is the loss rate in sub-sector b_j within the service sector, $j = 1, 2, \ldots, J$ and is based on the definition in Section 2.2. The loan amounts are taken from supervisory data (FINREP) and are available since the third quarter of 2014. The loss rates and the loan amounts comprise domestic and foreign lending. The year 2021 includes only the first quarter.

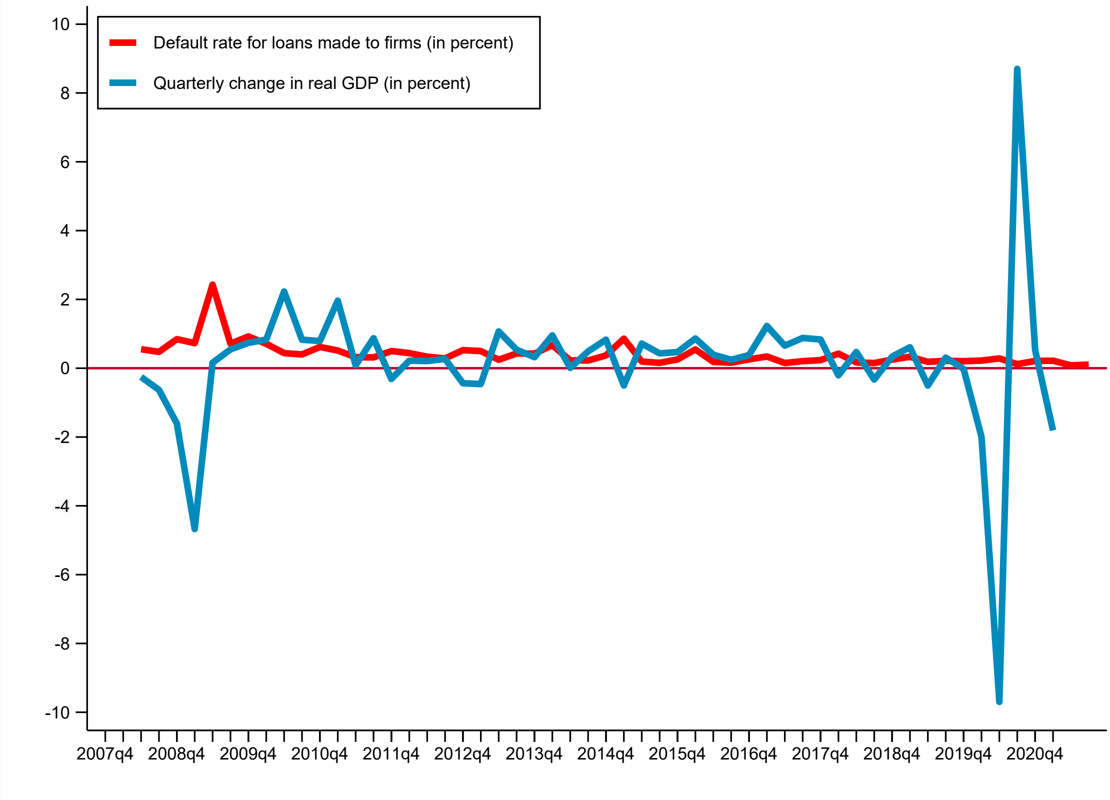

Figure 13:
Default rate for loans made to firms and change in real GDP
Based on the definition in Equation (6), the default rates for loans made to firms is given by

$$p_\tau = 100 \cdot \frac{\sum_{b=1}^{B} |D_{b,\tau}|}{\sum_{b=1}^{B} |L_{b,\tau}| + |D_{b,\tau}|}$$

in which $\tau = 2, 3, \ldots, T$, and $\tau = 2$ corresponds to the second quarter in 2008 and $\tau = T$ corresponds to the first quarter in 2021. The seasonally adjusted real GDP is taken from the time series database of Deutsche Bundesbank, see https://www.bundesbank.de/dynamic/action/en/statistics/time-series-databases/time-series-databases/759784/759784?listId=www_s311_b4_vgr_bip.

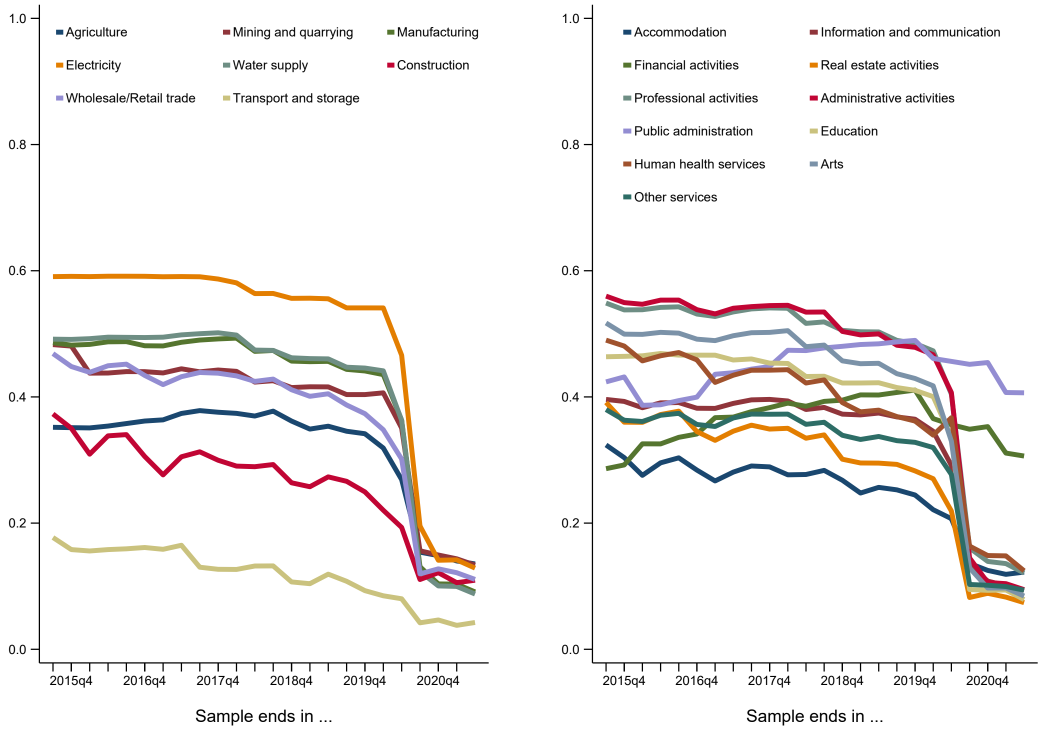

Figure 14:
Coefficient of determination (R^2) as a function of the sample size
This shows the R^2 for each of the following linear regressions:

$$y_{b,\tau} = \alpha + \beta \cdot \mu_{\tau-1} + \gamma' d_\tau + \varepsilon_{b,\tau}, \quad \tau = 2008Q2, 2008Q3, \ldots, T,$$

in which $T = 2015Q3, 2015Q4, \ldots, 2021Q2$. If $T = 2015Q3$, the sample size is 30 quarters, if $T = 2021Q2$, the sample size is 52 quarters. The dependent variable $y_{b,\tau}$ is the annualized default rate in sector b and quarter τ, $y_{b,\tau} = 4 \cdot p_{b,\tau}$, $b = 1, 2, \ldots, B$, in which $p_{b,\tau}$ is defined in Equation (6). The default rate indicates the number of new credit events in a given quarter and a given sector as a percentage of the total number of bank-firm pairs ("loans") in this sector and this quarter. A new credit event takes place if a bank reports an increase in the stock of value adjustments from zero to a positive value for the first time. These default rates are based on the credit register for loans of EUR 1 million or more, see Deutsche Bundesbank (1998). In addition, μ_τ is the annualized, quarterly percentage change in real GDP so that if X_τ is the seasonally adjusted real GDP, then $\mu_\tau = 100\left((X_\tau/X_{\tau-1})^4 - 1\right)$. Finally, d_τ is a vector of quarterly indicator variables for the first, second and fourth quarter.

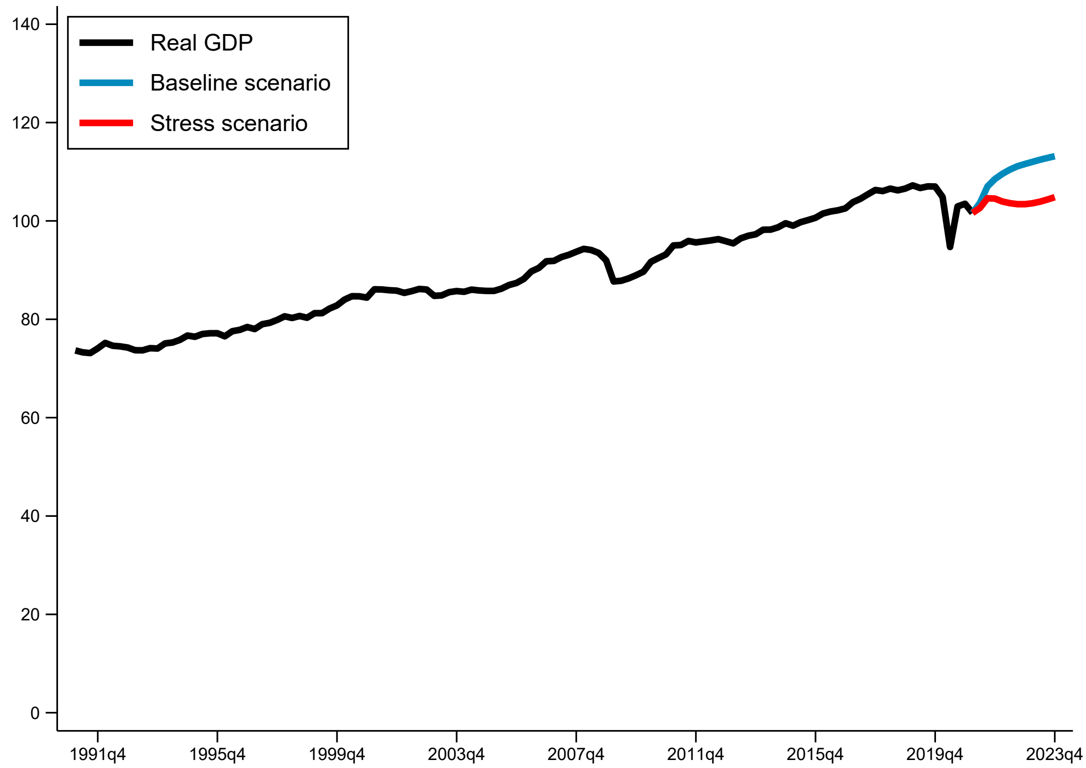

Figure 15:
Real GDP in the baseline and stress scenario
This figure shows historical GDP and the paths in the baseline and stress scenario.

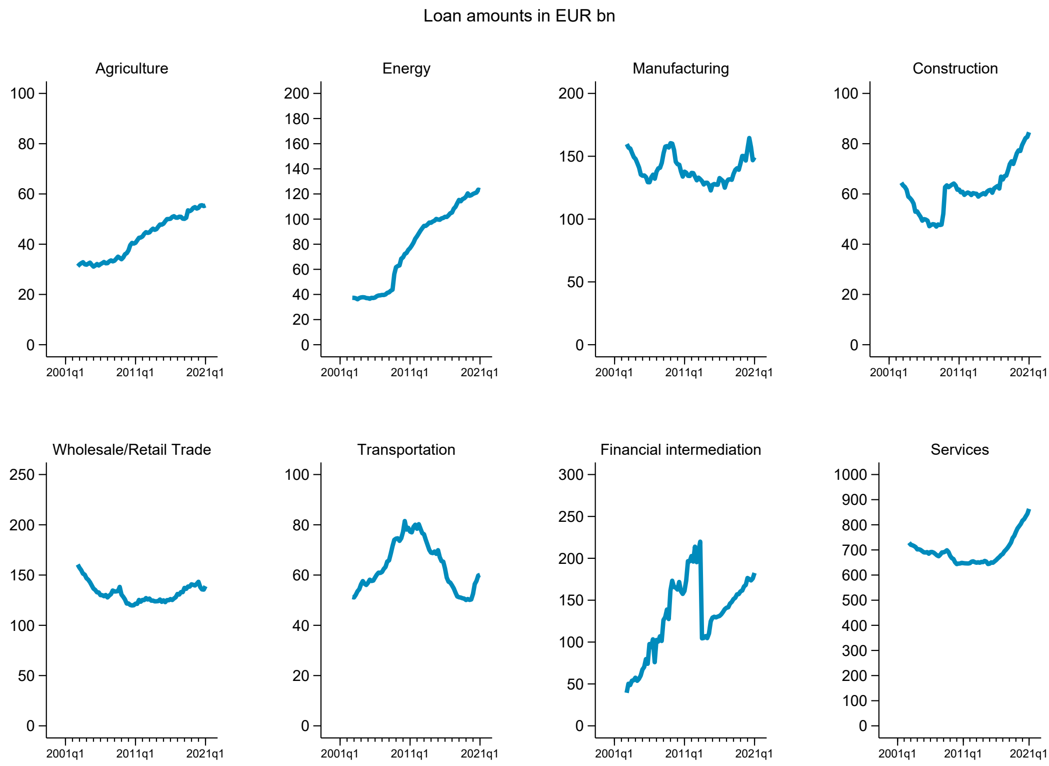

Figure 16:
Loans to domestic firms - All sectors
This figure shows the loans to domestic firms by sector in EUR bn. These loan amounts are taken from the borrowers statistic, see Deutsche Bundesbank (2021a). The sample comprises 1,464 banks as of March 2021.

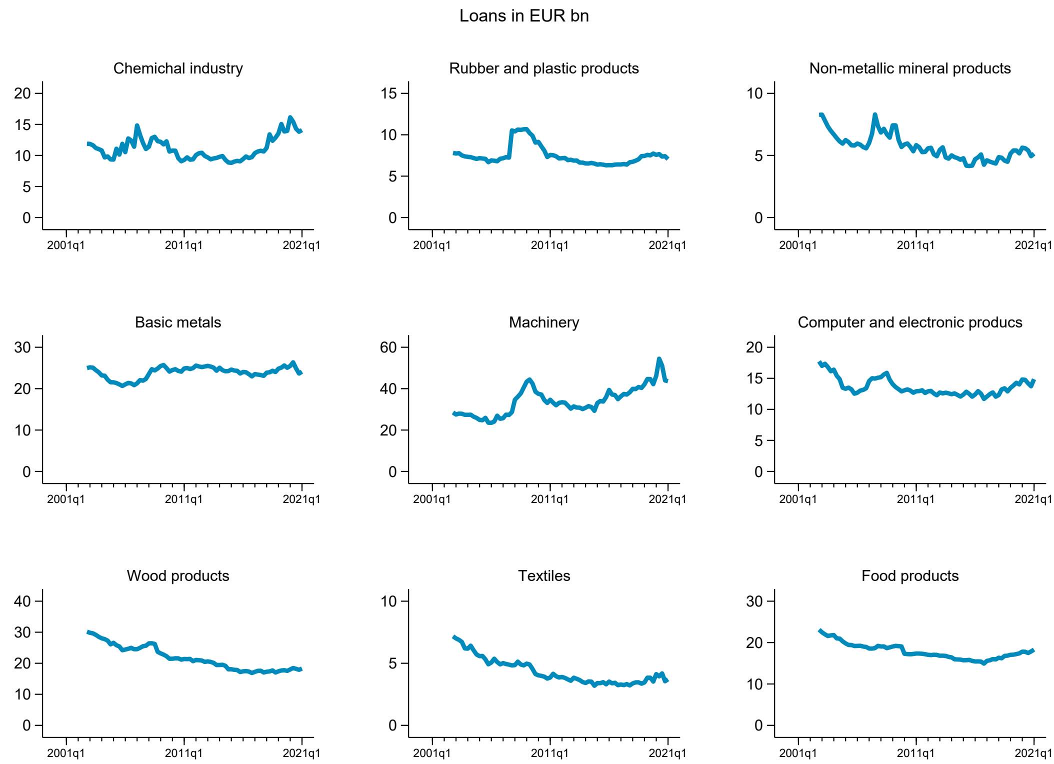

Figure 17:
Loans to domestic firms - Manufacturing
This figure shows the loans to domestic firms in the sub-sector of the manufacturing sector in EUR bn. These loan amounts are taken from the borrowers statistic, see Deutsche Bundesbank (2021a). The sample comprises 1,464 banks as of March 2021.

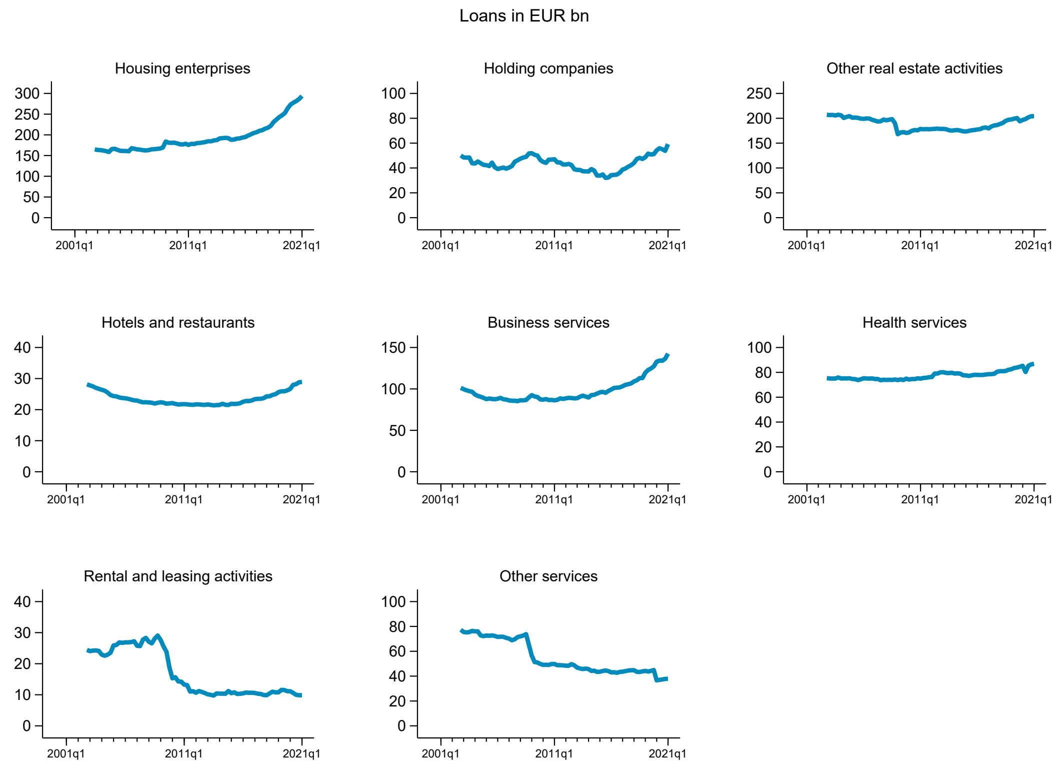

Figure 18:
Loans to domestic firms - Services
This figure shows the loans to domestic firms in the sub-sectors of the service sector in EUR bn. These loan amounts are taken from the borrowers statistic, see Deutsche Bundesbank (2021a). The sample comprises 1,464 banks as of March 2021.

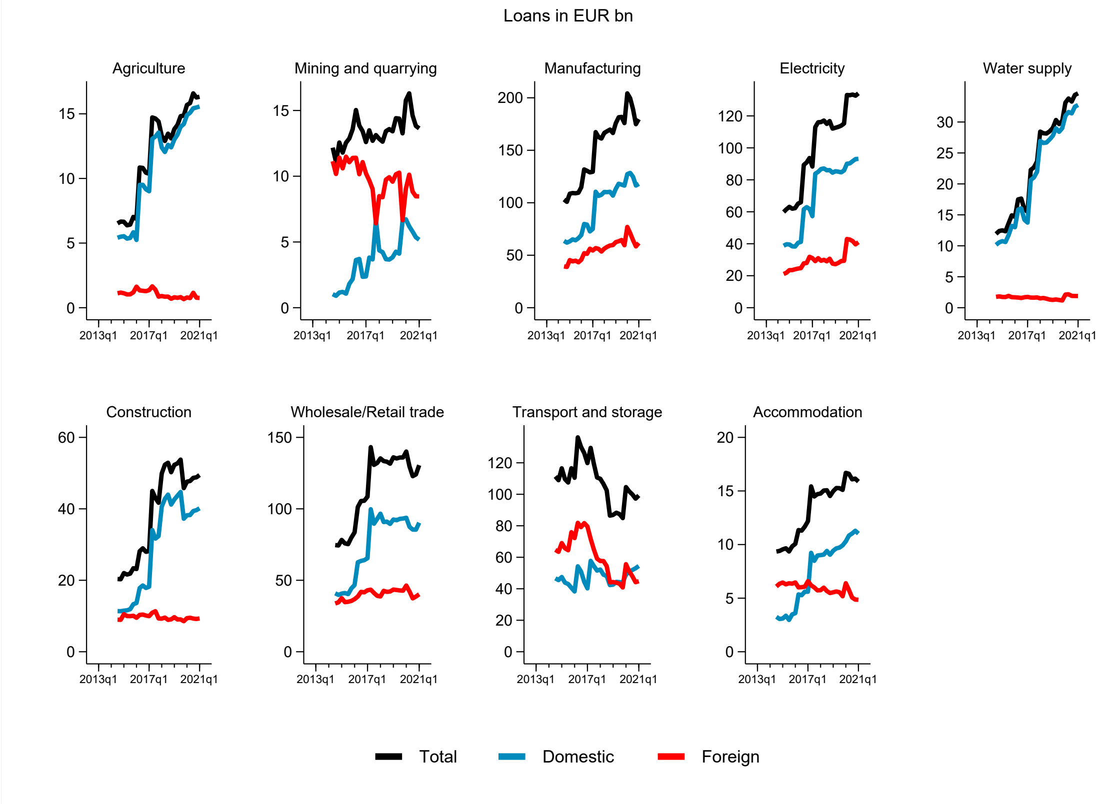

Figure 19:
Loans to domestic and foreign firms - NACE sector A to NACE sector I
This figure shows the loans according to the NACE classification in EUR bn. These loan amounts are taken from supervisory data (FINREP) and include lending to domestic and foreign firms. The sample comprises 305 banks as of March 2021.

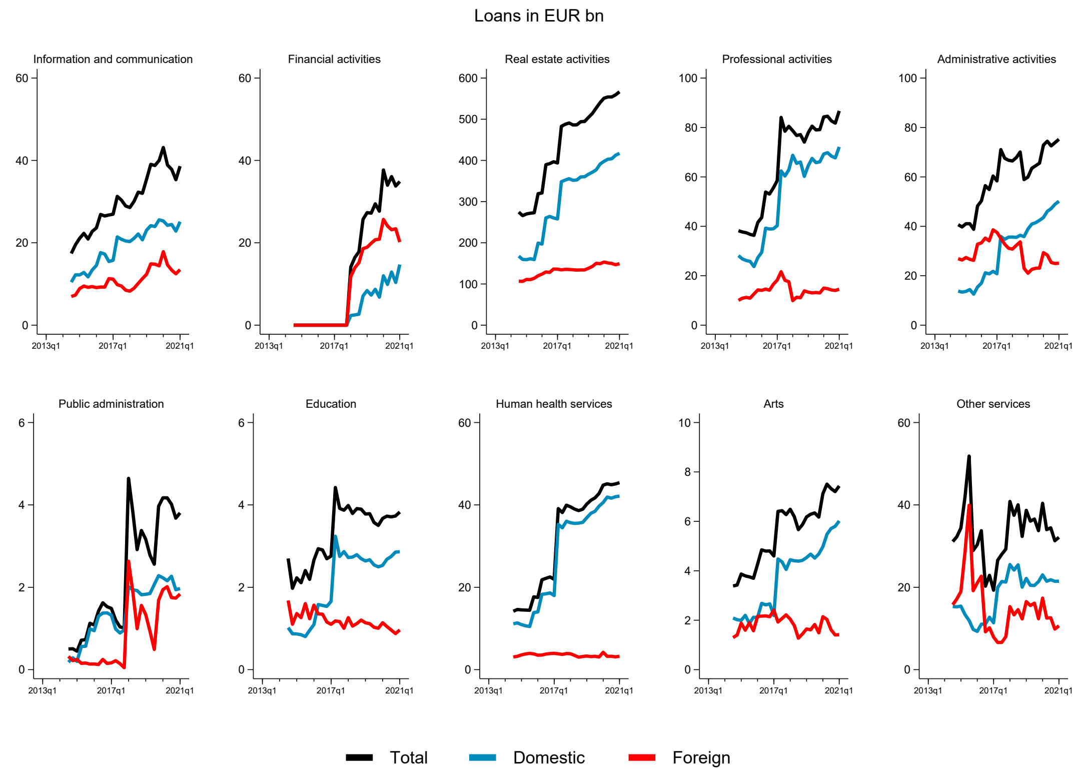

Figure 20:
Loans to domestic and foreign firms - NACE sector J to NACE sector S
This figure shows the loans according to the NACE classification in EUR bn. These loan amounts are taken from supervisory data (FINREP) and inclucde lending to domestic and foreign firms. Data for the sector Financial activities is available since the first quarter of 2018. The sample comprises 305 banks as of March 2021.

	baseline scenario	stress scenario 1	stress scenario 2	stress scenario 3
Expected Loss as a percentage of loan amounts	0.4	1.2	1.9	2.6
Expected Loss as a percentage of CET 1 capital	1.5	4.3	7.1	10.0

Table 1
Expected Loss by scenario

This table shows the Expected Loss from lending to firms. Let N be the number of banks in the sample, N_1 the number of banks that lend to both foreign and domestic firms, and let N_2 be the number of banks that only lend to domestic firms, so that $N = N_1 + N_2$. Then

$$\text{Expected Loss}_{i,s} = \begin{cases} \sum_{b=1}^{B} \frac{\text{loss rate}_{b,s}}{100} \cdot \text{loans}_{i,b,s}, & i = 1, 2, \ldots, N_1, \\ \sum_{b=1}^{B} \frac{\text{loss rate}_{b,s}^{\text{domestic}}}{100} \cdot \text{loans}_{i,b,s}^{\text{domestic}}, & i = N_1 + 1, N_1 + 2, \ldots, N, \end{cases}$$

where $\text{loss rate}_{b,s}$ is the loss rate in sector b and scenario s, $b = 1, \ldots, B$ (see Section 2.2 and Figure 9 and Figure 10) and $s \in \{\text{baseline scenario}, \text{stress scenario 1}, \text{stress scenario 2}, \text{stress scenario 3}\}$. Analogous definitions apply to $\text{loss rate}_{b,s}^{\text{domestic}}$ (see Section 2.1 and Figure 3 - Figure 5) and the loan amounts. Loan amounts depend on the scenario because the level of credit lines that are used change with the scenario. In stress scenario 1, the historical maximum of the loss rates is applied to selected sectors, while in the remaining sectors there is only a moderate increase in loss rates. In stress scenario 2, the historical maximum of the loss rates is applied to each sector, while in stress scenario 3, the maximum loss rate is further increased by two standard deviations in each sector. In the baseline scenario, loss rates increase by about 40% in all sectors. The number of banks is 1,386.

Table 2

Branche	**actual value in 2020**	**baseline scenario**	**stress scenario 1**	**stress scenario 2**	**stress scenario 3**
Agriculture	0.46	0.65	0.88	0.88	1.27
Energy	-0.07	0.00	0.06	0.43	0.69
Chemical sector	0.10	0.14	0.60	2.22	3.22
Rubber and plastic products	1.26	1.77	1.83	1.87	3.01
Non-metallic mineral products	0.33	0.46	0.96	1.82	3.08
Basic metals	0.84	1.19	1.42	2.07	3.23
Machinery	1.83	2.58	2.89	2.89	4.23
Computer and electronic products	2.21	3.11	2.29	2.29	3.76
Wood products	0.26	0.37	1.94	1.94	3.09
Textiles	0.77	1.08	3.40	3.40	4.97
Food products	0.52	0.73	0.77	0.97	1.46

Continued on next page

Table 2 – *Continuing from previous page*

sector	**actual value in 2020**	**baseline scenario**	**stress scenario 1**	**stress scenario 2**	**stress scenario 3**
Construction	0.05	0.07	0.68	2.28	3.55
Wholesale/Retail trade	0.25	0.36	0.58	1.37	2.03
Transportation	-0.12	0.00	6.94	6.94	10.53
Financial intermediation	0.45	0.63	0.56	0.56	0.68
Housing enterprises	0.03	0.04	0.31	0.87	1.44
Holding companies	0.41	0.58	0.92	2.27	3.31
Other real estate activities	0.04	0.06	0.47	1.35	2.20
Hotels and restaurants	0.51	0.72	1.62	1.62	2.53
Business services	0.30	0.42	1.47	1.47	2.30
Health services	0.21	0.30	0.40	0.57	0.94
Rental and leasing activities	0.57	0.80	2.64	2.64	4.14
Other services	0.03	0.04	1.96	1.96	2.95

Table 2
Loss rates for loans to domestic firms in 2020 and in the scenarios
The loss rate in sector b and year 2020 is defined as

$$\text{loss rate}^{\text{domestic}}_{b,2020} = 100 \cdot \frac{\sum_{i=1}^{N}\sum_{q=1}^{4} \text{value adjustments}_{i,2020,q,b}}{\frac{1}{4}\sum_{i=1}^{N}\sum_{q=1}^{4} \text{loans}_{i,2020,q,b}},$$

in which value adjustments$_{i,2020,q,b}$ are the value adjustments that are made by bank i in year 2020 and quarter q, $q \in \{1,2,3,4\}$, and sector b, $b = 1,2,\ldots,B$. Value adjustments encompass changes caused by specific value adjustments and any write-downs or write-ups of non-performing debt; see Deutsche Bundesbank (2021a), p. 145. In the same way, loans$_{i,t,q,b}$ refers to the volume of outstanding loans. The loss rates in the scenarios are described in Section 2.1. In stress scenario 1, the historical maximum of the loss rates is applied to selected sectors, while in the remaining sectors there is only a moderate increase in loss rates. In stress scenario 2, the historical maximum of the loss rates is applied to each sector, while in stress scenario 3, the maximum loss rate is further increased by two standard deviations in each sector. In the baseline scenario, loss rates increase by about 40% in all sectors.

sector	acutal value in 2020	baseline scenario	stress scenario 1	stress scenario 2	stress scenario 3
Agriculture	0.24	0.33	1.24	1.24	1.78
Mining and quarrying	0.31	0.44	0.68	1.51	2.26
Manufacturing	0.55	0.77	3.58	3.58	5.19
Electricity	0.25	0.35	0.88	2.53	3.80
Water supply	0.17	0.25	0.61	1.84	2.71
Construction	0.18	0.26	0.57	1.53	2.30
Retail/Wholesale trade	0.46	0.65	1.12	3.02	4.35
Transport and storage	0.64	0.91	2.15	2.15	3.32
Accommodation	0.45	0.63	1.62	1.62	2.44
Information and communication	0.36	0.51	1.78	1.78	2.52
Financial activities	0.17	0.24	0.39	0.80	1.23
Real estate activities	0.18	0.25	0.46	1.15	1.71
Professional activities	0.31	0.44	1.99	1.99	2.88
Administrative activities	0.38	0.54	1.78	1.78	2.57
Public administration	0.06	0.08	0.14	0.32	0.48
Education	0.06	0.08	1.57	1.57	2.33
Human health services	0.70	0.99	0.89	0.89	1.15
Arts	0.28	0.40	1.86	1.86	2.74
Other services	0.20	0.28	1.00	1.00	1.44

Table 3
Loss rates for loans to firms in 2020 and in the scenarios
The definition of the loss rates in 2020 and in the scenario is explained in Section 2.2. These loss rates are based on the credit register for loans of EUR 1 million or more, see siehe Deutsche Bundesbank (1998). The loss rates in the scenarios are described in Section 2.2. In stress scenario 1, the historical maximum of the loss rates is applied to selected sectors, while in the remaining sectors there is only a moderate increase in loss rates. In stress scenario 2, the historical maximum of the loss rates is applied to each sector, while in stress scenario 3, the maximum loss rate is further increased by two standard deviations in each sector. In the baseline scenario, loss rates increase by about 40% in all sectors.

Average risk weight (in percent)	**baseline scenario**	**stress scenario 1**	**stress scenario 2**	**stress scenario 3**
Agriculture	92	107	110	117
Mining and quarrying	91	100	108	115
Manufacturing	103	122	125	133
Electricity	87	99	111	120
Water supply	86	96	107	115
Construction	83	93	101	108
Wholesale/Retail trade	99	107	117	123
Transport and storage	92	97	99	104
Accommodation	71	82	84	89
Information and communication	98	114	118	125
Financial activities	89	91	98	104
Real estate activities	72	82	90	96
Professional activities	87	104	107	113
Administrative activities	81	94	97	103
Public administration	81	89	96	103
Education	82	101	104	112
Human health services	86	92	96	101
Arts	75	90	92	98
Other services	72	87	90	96
RWA Corporates (EUR bn)	659	725	766	811

Table 4
Average risk weights for corporate loans in the baseline scenario and the stress scenarios (in percent)
The risk weights for corporate loans in the scenarios are defined in Section 6. In addition to the risk weights, the aggregate risk weighted assets (RWA) for corporate loans are presented in EUR bn. These risk weighted assets are derived from the existing loan amounts and the average risk weights. The average risk weights and the aggregate RWA for corporate loans are based on a sample of 28 banks that use an internal ratings-based approach (IRBA). In stress scenario 1, the historical maximum of the loss rates is applied to selected sectors, while in the remaining sectors there is only a moderate increase in loss rates. In stress scenario 2, the historical maximum of the loss rates is applied to each sector, while in stress scenario 3, the maximum loss rate is further increased by two standard deviations in each sector. In the baseline scenario, loss rates increase by about 40% in all sectors.

Table 5

Dependent variable: default rate (in percent)	Agriculture	Mining and quarrying	Manufacturing	Electricity	Water supply	Construction	Trade
GDP growth $(\tau - 1)$ in percent	-0.11	-0.26	-0.47	-0.58	-0.31	-0.13	-0.30
	(0.029)	(0.053)	(0.083)	(0.085)	(0.054)	(0.045)	(0.067)
p-value $H_0: \beta \geq 0$	0.000	0.000	0.000	0.000	0.000	0.003	0.000
Constant	0.95	1.24	2.64	1.65	1.48	1.82	2.60
	(0.221)	(0.405)	(0.637)	(0.653)	(0.415)	(0.342)	(0.510)
p-value $H_0: \alpha = 0$	0.000	0.004	0.000	0.015	0.001	0.000	0.000
Number of observations	47	47	47	47	47	47	47
R^2	0.34	0.40	0.44	0.54	0.45	0.25	0.37

Continued on next page

Table 5 – *Continuing from previous page*

Dependent variable: default rate (in percent)	Transport and storage	Accomodation	Information and communication	Financial activities	Real estate activities	Professional activities
GDP growth $(\tau - 1)$ in percent	-0.16	-0.19	-0.21	-0.05	-0.14	-0.29
	(0.100)	(0.072)	(0.048)	(0.038)	(0.037)	(0.048)
p-value $H_0 \colon \beta \geq 0$	0.063	0.005	0.000	0.079	0.000	0.000
Constant	3.81	1.94	1.50	0.50	1.23	1.60
	(0.764)	(0.369)	(0.293)	(0.281)	(0.368)	(0.352)
p-value $H_0 \colon \alpha = 0$	0.000	0.001	0.000	0.092	0.000	0.000
Number of observations	47	47	47	47	47	47
R^2	0.10	0.24	0.36	0.41	0.28	0.48

Continued on next page

Table 5 – *Continuing from previous page*

Dependent variable: default rate (in percent)	Administrative activities	Public administration	Education	Human health services	Arts	Other services
GDP growth ($\tau - 1$) in percent	-0.28	-0.02	-0.24	-0.10	-0.33	-0.13
	(0.046)	(0.018)	(0.046)	(0.023)	(0.061)	(0.032)
p-value $H_0 : \beta \geq 0$	0.000	0.113	0.000	0.000	0.000	0.000
Constant	1.77	0.12	1.36	0.89	1.85	1.11
	(0.352)	(0.138)	(0.350)	(0.173)	(0.466)	(0.244)
p-value $H_0 : \alpha = 0$	0.000	0.407	0.000	0.000	0.000	0.000
Number of observations	47	47	47	47	47	47
R^2	0.48	0.49	0.41	0.36	0.43	0.33

Table 5
Default rates and GDP growth, Q2 2008 - Q4 2019

The table presents the point estimates and standard errors of the parameters in the following linear regression model:

$$y_{b,\tau} = \alpha + \beta \cdot \mu_{\tau-1} + \gamma' d_\tau + \varepsilon_{b,\tau},$$

in which $y_{b,\tau}$ is the annualized default rate in sector b and quarter τ, $y_{b,\tau} = 4 \cdot p_{b,\tau}$, $b = 1, 2, \ldots, B$, $\tau = 2, 3, \ldots, T$, and $p_{b,\tau}$ is defined in Equation (6). The sample starts in the second quarter of 2008 and ends in the fourth quarter of 2019. The default rate indicates the number of new credit events in a given quarter and a given sector as a percentage of the total number of bank-firm pairs ("loans") in this sector and this quarter. A new credit event takes place if a bank reports an increase in the stock of value adjustments from zero to a positive value for the first time. In addition, μ_τ is the annualized, quarterly percentage change in real GDP so that if X_τ is the seasonally adjusted real GDP, then $\mu_\tau = 100\left((X_\tau/X_{\tau-1})^4 - 1\right)$. Finally, d_τ is a vector of quarterly indicator variables for the first, second and fourth quarter. For brevity, the OLS estimates of the parameter γ are not shown. OLS standard errors are shown in parenthesis. Finally, the p–values for tests of the null hypotheses $\beta \geq 0$ and $\alpha = 0$ are presented.

Table 6

Dependent variable: default rate (in percent)	Agriculture	Mining and quarrying	Manufacturing	Electricity	Water supply	Construction	Trade
GDP growth $(\tau-1)$ in percent	-0.02	-0.06	-0.09	-0.12	-0.06	-0.03	-0.07
	(0.015)	(0.028)	(0.046)	(0.050)	(0.030)	(0.022)	(0.035)
p-value $H_0: \beta \geq 0$	0.068	0.019	0.023	0.012	0.021	0.098	0.029
Constant	0.70	0.68	1.65	0.48	0.82	1.46	1.90
	(0.229)	(0.435)	(0.720)	(0.792)	(0.473)	(0.350)	(0.550)
p-value $H_0: \alpha = 0$	0.004	0.127	0.027	0.544	0.089	0.000	0.001
Number of observations	52	52	52	52	52	52	52
R^2	0.14	0.14	0.10	0.14	0.10	0.11	0.12

Continued on next page

Table 6 – *Continued from previous page*

Dependent variable: default rate (in percent)	Transport and storage	Accomodation	Information and communication	Financial activities	Real estate activities	Professional activities
GDP growth ($\tau - 1$) in percent	-0.04	-0.03	-0.04	-0.01	-0.03	-0.06
	(0.046)	(0.034)	(0.025)	(0.018)	(0.018)	(0.027)
p-value $H_0\colon \beta \geq 0$	0.219	0.182	0.057	0.238	0.062	0.013
Konstante	3.30	1.51	1.05	0.39	0.90	0.99
	(0.721)	(0.537)	(0.393)	(0.284)	(0.290)	(0.427)
p-value $H_0\colon \alpha = 0$	0.000	0.007	0.010	0.175	0.003	0.025
Number of observations	52	52	52	52	52	52
R^2	0.04	0.12	0.10	0.31	0.08	0.14

Continued on next page

Table 6 – *Continued from previous page*

Dependent variable: default rate (in percent)	Administrative activities	Public administration	Education	Human health services	ARts	Other services
GDP growth $(\tau - 1)$ in percent	-0.05	-0.00	-0.05	-0.04	-0.06	-0.03
	(0.026)	(0.008)	(0.025)	(0.017)	(0.033)	(0.016)
p-value $H_0: \beta \geq 0$	0.027	0.300	0.024	0.019	0.045	0.046
Constant	1.18	0.07	0.81	0.66	1.16	0.79
	(0.412)	(0.133)	(0.391)	(0.271)	(0.527)	(0.254)
p-value $H_0: \alpha = 0$	0.006	0.613	0.044	0.019	0.032	0.003
Number of observations	52	52	52	52	52	52
R^2	0.10	0.41	0.09	0.15	0.10	0.10

Table 6
Default rates and GDP growth, Q2 2008 - Q1 2021
For further details, see the notes in Table 5. The only difference to Table 5 is the sample size: The results in this table are based on the full sample from the second quarter 2008 to the fourth quarter in 2020. In Table 5, the sample ends in the fourth quarter of 2019.

Panel A: linear regression

Sample	Expected Loss in percent of loans		Expected Loss in percent of CET 1	
	baseline scenario (1)	stress scenario (2)	baselines scenario (3)	stress scenario (4)
Pre-COVID-19: sample ends in Q4 2019	1.5	1.9	5.1	7.2
Post-COVID-19: sample ends in Q1 2021	1.6	1.6	5.6	6.1
Panel B: Maximum Likelihood (Fractional Regression Model)				
Pre-COVID-19: sample ends in Q4 2019	1.6	1.7	5.3	6.5
Post-COVID-19: sample ends in Q1 2021	1.6	1.6	5.6	6.1

Table 7
Credit risk and the economy: Expected Loss in the baseline and stress scenario

The table shows the Expected Loss in the baseline and stress scenario in percent of loans to firms and in percent of Common Equity Tier 1 capital (CET 1) as of Q1 2021. The scenarios are depicted in in Figure 15. The numerator of each of the ratios in the table comprises the sum of the Expected Loss for the entire scenario horizon until the end of 2023. The Expected Loss is derived from the following linear regression model:

$$p_{b,\tau} = \alpha + \beta \cdot \mu_{\tau-1} + \varepsilon_{b,\tau}, \quad \tau = 2008Q2, 2008Q3, \dots, T,$$

in which $p_{b,\tau}$ is the default rate in sector b and quarter τ, see Equation (6), and $b = 1, 2, \dots, B$. The default rate indicates the number of new credit events in a given quarter and a given sector as a percentage of the total number of bank-firm pairs ("loans") in this sector and this quarter. A new credit event takes place if a bank reports an increase in the stock of value adjustments from zero to a positive value for the first time. In addition, μ_τ is the quarterly percentage change in real GDP. This model is estimated for $T = 2019Q4$ (Pre-COVID-19) and $T = 2021Q1$ (Post-COVID-19). Using the estimated parameters $\widehat{\alpha}$, $\widehat{\beta}$ and the path of GDP growth according to the scenarios, the scenario forecasts of the default rates, $\widehat{p}_{b,\tau}$, are produced, in which $0 \leq \frac{\widehat{p}_{b,\tau}}{100} \leq 1$. If $\widehat{p}_{b,\tau} < 0$ in a given sector b and a given quarter τ, then this scenario forecast is replaced by zero. These default rates are then multiplied by an average LGD, which is obtained for each sector, to produce the loss rates. Finally, for each bank and each sector, the Expected Loss is the product of the loan amounts and these loss rates. The loan amounts are the balance sheet exposures according to supervisory data (FINREP) plus irrevocable credit lines according to the credit register for loans of EUR 1 million or more. These results are shown in Panel A. In Panel B, we show analogous results obtained from the estimation procedure by Papke and Wooldridge (1996), which ensures that $\frac{\widehat{p}_{b,\tau}}{100} \in [0, 1]$ by design. There are 1.368 banks in this sample.

Appendix 1: Basel risk weight function

$$RW = 1.06 \cdot 12.5 \cdot MA \cdot LGD \cdot UL$$

$$MA = (1 + (\overline{M} - 2.5) \cdot b)/(1 - 1.5 \cdot b)$$

$$b = (0,11852 - 0.05478 \cdot \log(PD))^2$$

$$UL = \Phi\left(\frac{\Phi^{-1}(PD) + \sqrt{\rho} \cdot \Phi^{-1}(0.999)}{\sqrt{1-\rho}}\right) - PD$$

$$\rho = 0.24 - 0.12 \cdot (1 - \exp(-50 \cdot PD))$$

We set the maturity to $\overline{M} = 3$ years and the LGD to 45%. The PD is larger or equal to 0.03%.

Appendix 2: IRBA PDs and corporate bond spreads

We examine the empirical relationship between PDs that are reported by IRBA banks in the credit register for loans of EUR 1 million or more in each quarter, and daily corporate bond spreads with the following model:

$$PD_{t,b} = \alpha + \beta \cdot spread_{t,b} + \varepsilon_{t,b},$$

in which t is the end of the quarter (2008Q4-2019Q4), and b is the economic sector (10 sectors in total). On each trading day h (and for each sector b), we then have

$$\widehat{PD}_{t+h,b} = \hat{\alpha} + \hat{\beta} \cdot spread_{t+h,b}$$

and

$$\widehat{PD}_{t+h,b} = PD_{t,b} + \hat{\beta}\,(spread_{t+h,b} - spread_{t,b})$$

After applying a logarithmic transformation to the PDs and the spreads, we obtain a parameter estimate of β equal to 0.3, see Table 8:

$$\log(PD_{t,b}) = \alpha + \beta \cdot \log(spread_{t,b}) + \varepsilon_{t,b}$$

Future PDs are estimated as:

$$\widehat{PD}_{t+h,b} = \exp\left(\log(PD_{t,b}) + 0.2562 \cdot (\log(spread_{t+h,b}) - \log(spread_{t,b}))\right)$$

	coefficient	standard error
α	0.1821***	0.0280
β	0.2562**	0.0904
R^2 (within)	13.3%	
Number of observations/sectors	450	10

Table 8
Quarterly data from 2008Q4 to 2019Q4; ** and *** indicate statistial significance at the 5% and 1% level.

Appendix 3: Change in capital ratios

From $KKQ = KK/RWA$ (in which KK: CET 1 and RWA: risk weighted assets), we have

$$\Delta KKQ = \frac{\partial KKQ}{\partial KK} \cdot \Delta KK + \frac{\partial KKQ}{\partial RWA} \cdot \Delta RWA$$

Equation (13) follows from rearranging the derivatives.