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A top-down loan-level stress test for banks' corporate credit risk: Application to risks from commercial real estate markets

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Non-technical summary

Research Question

The credit risk from lending to non–financial firms is an important driver of banks' profitability and their capital. In this paper, we present a scenario analysis to obtain losses in banks' corporate loan portfolio.

Contribution

First, we define what constitutes a loss for a bank in accordance with international accounting standards (IFRS 9). Our accounting measure of a loss is driven by changes in two well–known risk parameters: Loss Given Default and Probability of Default.

Second, we map the accounting model of credit risk to the AnaCredit dataset in which individual loans are the unit of observation. This dataset has not yet been used for the purpose of conducting a scenario analysis of banks' credit risk in Germany. This step yields novel empirical results regarding Loss Given Default and Probability of Default.

In contrast to many existing studies, in our model Loss Given Default is not a fixed parameter applied to a whole portfolio of loans, but is obtained by analyzing the granular collateral data for each loan in AnaCredit individually. In this way, we take important differences in existing collateral among loans explicitly into account: We incorporate the nominal amount of collateral (if any) of a given loan, the various types of collateral (e.g. commercial real estate properties) that banks can seize in case of default of a borrower and consider whether the bank has recourse to assets in addition to collateral posted for the loan.

Banks that do not use internal risk weight models do not report default probabilities in AnaCredit, but play an important role in supplying bank credit to non–financial firms. We estimate missing default probabilities with several machine learning methods and thus obtain the likelihood of default for each borrower in the data. Using this comprehensive set of default probabilities, we are able to tailor an increase in the Probability of Default to specific borrowers such that defaults become more likely in ex ante riskier segments than in less risky ones in our scenario analysis.

Results

We apply the model to investigate the consequences of a further deterioration in the commercial real estate market. For two ad hoc scenarios that vary in the severity of the downturn, we obtain the losses of German banks and the impact on their regulatory capital.

Nichttechnische Zusammenfassung

Fragestellung

Das Kreditrisiko aus der Kreditvergabe an nichtfinanzielle Unternehmen ist von hoher Bedeutung für die Ertragslage und das Eigenkapital der Banken. In diesem Papier stellen wir eine Szenarioanalyse vor, um Verluste im Unternehmenskreditgeschäft zu ermitteln.

Beitrag

Im ersten Schritt definieren wir, was ein Verlust im Kreditgeschäft gemäß den internationalen Rechnungslegungsstandards (IFRS 9) ist. Das hier untersuchte buchhalterische Maß für einen Verlust im Kreditgeschäft wird durch die Veränderung zweier Risikoparameter bestimmt: der Verlustquote bei Ausfall und der Ausfallwahrscheinlichkeit.

Im zweiten Schritt überführen wir das Bilanzierungsmodell in den AnaCredit-Datensatz, in dem die Beobachtungseinheit ein einzelner Kredit ist. Für eine Szenarioanalyse des Kreditrisikos der Banken in Deutschland wurde dieser Datensatz bisher noch nicht verwendet. Dieser Schritt liefert neue empirische Ergebnisse zur Verlustquote bei Ausfall und zur Ausfallwahrscheinlichkeit.

Im Gegensatz zu vielen bestehenden Studien ist die Verlustquote bei Ausfall in dem vorliegenden Modell kein fester Parameter, der auf ein gesamtes Kreditportfolio angewendet wird, sondern wird für jeden einzelnen Kredit ermittelt. Dabei nutzen wir explizit wichtige Unterschiede bei den vorliegenden Sicherheiten zwischen einzelnen Krediten: Wir beziehen den Nominalbetrag der Sicherheiten (sofern vorhanden) eines Kredits sowie die verschiedenen Arten von Sicherheiten (z. B. Gewerbeimmobilien) ein, die Banken im Falle eines Zahlungsausfalls eines Kreditnehmers verwerten, und berücksichtigen, ob die Bank zusätzlich zu den Sicherheiten auf weitere Vermögenswerte zugreifen kann.

Banken, die keine internen Modelle zur Berechnung der Risikogewichte nutzen, melden in AnaCredit keine Ausfallwahrscheinlichkeiten, spielen aber eine wichtige Rolle bei der Kreditvergabe an nichtfinanzielle Unternehmen. Wir schätzen fehlende Ausfallwahrscheinlichkeiten mit mehreren Methoden des maschinellen Lernens, so dass wir die Ausfallwahrscheinlichkeit für jeden Kreditnehmer ermitteln können. Mit Hilfe dieser erweiterten Menge an Beobachtungen können wir eine Erhöhung der Ausfallwahrscheinlichkeit auf bestimmte Kreditnehmer so zuschneiden, dass beispielsweise Ausfälle in ex–ante riskanteren Segmenten wahrscheinlicher werden als in weniger riskanten Segmenten.

Ergebnisse

Wir untersuchen auf Grundlage dieses Modells die Folgen einer weiteren Verschlechterung des Gewerbeimmobilienmarktes. Für zwei Ad-hoc-Szenarien, die sich in der Schwere des Abschwungs unterscheiden, ermitteln wir die Verluste deutscher Banken und die Auswirkungen auf ihr Kernkapital.

A Top-Down Loan-Level Stress Test for Banks' Corporate Credit Risk: Application to Risks from Commercial Real Estate Markets*

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November 19, 2024

Abstract

We study the credit risk of banks in Germany from lending to non-financial firms. We model changes in Expected Credit Loss, which is derived from the guidelines in the IFRS 9 accounting standard. We map the accounting model to a dataset with individual loans as the unit of observation (AnaCredit). We present new approaches to modeling two well-known credit risk parameters: Loss Given Default (LGD), and Probability of Default (PD), which both affect Expected Credit Loss. First, we obtain an approximation of the Loss Given Default for each individual loan. This step makes use of the detailed collateral data available in AnaCredit and reveals a heterogeneity in LGD that is typically ignored in top–down stress tests. Second, regarding PD, we encounter a missing data problem since only a subset of banks reports default probabilities in AnaCredit. We employ machine learning algorithms to impute missing default probabilities. With the help of these credit risk parameters, we then apply the stress test model to two ad–hoc scenarios in which the downturn in CRE markets worsens to varying degrees and report how this would affect the capital of German banks.

Keywords: Stress test, Credit Risk, Banks, Non-financial Firms, Commercial Real Estate, Germany

JEL Codes: G17, G21, C53

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Contents

1 Introduction

This paper studies the risk that the German banking system takes by extending loans to non-financial firms. We obtain the losses that German banks make on this portfolio in a scenario analysis, with special attention to the risks from commercial real estate (CRE) markets. This scenario analysis is a central component of the broader set of results presented in the Financial Stability Review 2024, see Deutsche Bundesbank (2024a). This technical paper explains the rationale for and implementation of the underlying methodological approach, lays out the main findings, and provides additional sensitivity analyses.

Our scenario analysis combines three elements in novel ways. First, our framework is grounded in International Financial Reporting Standards (IFRS 9) and models changes in Expected Credit Loss (ECL) for the entire German banking system. The increases in ECL constitute losses for banks and drive the dynamics of their capital. Second, we shed new light on two measures of credit risk in the German banking system: Loss Given Default (LGD) and P robability of Default (PD), which both affect ECL. Regarding LGD, by accounting for the nominal amount of collateral (if any), the various types of collateral (e.g. commercial real estate properties) that banks can seize in case of default of a borrower and whether the bank has recourse to assets in addition to collateral posted for the loan, we approximate the LGD explicitly and for each loan individually, rather than relying on a fixed LGD parameter (e.g. 45 percent) for an entire portfolio of loans. These new findings are based on AnaCredit, a dataset comprising detailed information on individual bank loans, and could not have been made with access to data from the German credit register since there is no comparable information about the collateral posted for loans available in this national credit register. Regarding PD, we encounter a problem of missing data because a default probability is only observed in AnaCredit if a bank adopts the an internal ratings–based approach (IRBA). Since most smaller banks do not adopt this approach, but play an important role in supplying bank credit to non–financial firms, we estimate missing PD observations with several machine learning methods and add to this literature by providing an example of PD imputation with loan data from Germany.

Third, the top down stress test presented in this paper is the first analysis of risks from CRE markets in Germany based on loan–by–loan data. Within CRE–related loans, we distinguish between segments that are arguably more vulnerable to a further downturn in CRE markets, such as real estate development, from less risky segments, such as loans to large construction companies. In our ad–hoc scenarios, we tailor a possible increase in default probabilities to borrowers in these segments, such that defaults become more likely in ex ante riskier segments than in less risky ones. By exploiting the relevant borrower characteristics and by considering the default probabilities of individual loans in AnaCredit, we thus allow for more heterogeneity in the credit risk of CRE– related loans than is typical in top–down stress tests, which usually operate at a portfolio level.

The methodology and application in this paper may be of interest to the wider stresstest community. To our knowledge, this paper presents the first top–down stress test based on the loan-level information available in AnaCredit. Our approach may be useful for other European supervisors who carry out top–down stress tests with this dataset or, more generally, for other researchers who examine credit risk with loan-level data. The results shown in this paper may also serve as a comparison to future bottom–up stress test exercises in the European banking system, in which banks themselves conduct a scenario analysis, and supervisory authorities then collect and analyze the results provided by the banks.

We proceed as follows: Section 2 lays out the elements of accounting that are in our view most relevant for top–down stress testing credit risk and presents the formal model of the change in ECL. Section 3 describes the empirical implementation of this framework, including the approximation of LGD and the imputation of PD. Section 4 applies the framework to two scenarios to examine the credit risk emanating from CRE markets. Section 5 points out limitations of this analysis and discusses possible extensions. Section 6 reviews our findings.

2 Expected Credit Loss

The stress test model presented in this paper is firmly grounded in international accounting rules. IFRS 9 accounting rules require banks to recognize allowances for losses on loans by determining the Expected Credit Loss (ECL). Section 2.1 introduces concepts that are the foundation for ECL and establishes the link between ECL and banks' capital, which is typically of interest in supervisory stress tests. Section 2.2 discusses the relationship between IFRS 9 and national accounting rules in Germany. In Section 2.3, we translate the qualitative guidelines in IFRS 9 and national accounting into quantities that can be identified or motivated empirically. Together, the formal model of ECL in Section 2.3 and the empirical implementation in Section 3 allow for the application to specific scenarios in Section 4.

2.1 Conceptual framework and terminology

IFRS 9 accounting gives rise to a three–stage model of credit risk. Qualitatively, ECL is defined as ”The expected credit losses that result from all possible default events over the expected life of a financial instrument".[1] In addition, IFRS 9 defines 12-month ECL as "[the] portion of lifetime expected credit losses that ... result from default events ... within the 12 months after the reporting date".[2] We account for these two different time horizons defined in IFRS 9 by distinguishing between lifetime ECL and 12–month ECL in our analysis.

IFRS 9 also determines when ECL is based on a 12–month or a lifetime perspective: If "the credit risk on [a] financial instrument has increased significantly since initial recognition" in the balance sheet, lifetime ECL applies. Otherwise, 12–month ECL is the relevant measure of credit risk.[3] IFRS 9 does not prescribe criteria for a significant increase in credit risk (sometimes abbreviated as SICR) explicitly, but gives both quantitative and qualitative guidelines in this regard.[4] In addition, if "one or more events .. have a detrimental impact on future cash flows" received from an asset, it becomes "credit–impaired" and ECL is computed from a lifetime perspective.[5] Crucially, the IFRS 9 accounting standard expects a significant increase in credit risk to be recognized "*before* an asset becomes credit–impaired or [a] ... default occurs" (emphasis added).[6] This is probably the biggest conceptual difference to the traditional incurred loss model of credit risk.

Taken together, the 12–month and lifetime perspectives, the SICR assessment and the notion of credit-impaired assets give rise to an assignment of loans to one (and only one) of three stages (commonly referred to as Stage 1, Stage 2, Stage 3). The probability of a default of a given borrower increases in each stage[7] and the stages also differ in the time horizon of ECL (12–month or lifetime).

At initial recognition in the balance sheet, a loan belongs to Stage 1.[8] For loans in Stage 1, banks obtain ECL for a horizon of 12 months. Periodically, banks assess credit risk in their loan portfolio and decide if loans move from a less risky stage to a riskier stage or vice versa. Once a loan moves to Stage 2 or Stage 3, the time horizon for ECL becomes the entire "expected life" of the loan.[9]

Changes in the Expected Credit Loss are the main driver of credit risk in the IFRS 9 accounting framework. Finally, to link ECL to the profit and loss (P&L) statement and regulatory capital, if a bank extends a new loan or when it re–assesses the risk of an existing loan, it increases or decreases the stock of ECL. This *change in the ECL* is at the center of this analysis since the adjustment of ECL is

[1]See IASB (2022), section 5.5 and Appendix A.
[2]See IASB (2022), section 5.5 and Appendix A.
[3]See IASB (2022), 5.5.3 and 5.5.5.
[4]For banks that are operating in the European Union, guidelines about the SICR assessments are issued in EBA (2017a).
[5]IASB (2022), B5.5.33 and Appendix A.
[6]IASB (2022), B5.5.7.
[7]Kund and Rugilo (2023) refer to loans in Stage 1 as performing, loans in Stage 2 as under–performing, and loans in Stage 3 as non–performing loans. Montesi and Papiro (2019) further sub–divide the loans in Stage 3 into "past due" and "unlikely to pay", likely motivated by the terminology in Article 178 of Regulation (EU) 575/2013.
[8]If an asset is credit-impaired at recognition, it is immediately transferred to Stage 3. We do not consider this case in the following analysis. This is in line with Montesi and Papiro (2019).
[9]See IASB (2022), p. A429.

recognized in the P&L statement as an impairment loss or an impairment gain.[10] An increase in ECL, i.e. an impairment loss, lowers net income, all else equal. If other sources of income cannot compensate for an increase in ECL, net income becomes negative and regulatory capital decreases.

2.2 IFRS 9 and national GAAP

National and international accounting rules are often applied side by side in a given banking system. The previous sections deal with loss allowance under IFRS 9 accounting rules. There is, however, another accounting standard that has been adopted by a large number of smaller banks in the German banking system. We refer to this set of rules as national generally accepted accounting principles, or national GAAP (in German: Handelsgesetzbuch, abbreviated as HGB). We explain some of the differences between IFRS 9 and national GAAP that are relevant for our analysis, and discuss features that the two standards have in common.

There are two types of allowances under national GAAP: General and specific allowances. When a bank prepares its annual accounts in form of a balance sheet and profit and loss account, it must evaluate all assets and liabilities individually.[11] As a consequence, if a bank doubts that a given borrower is able to pay interest and repay principal given their current and future cash flow streams, it accounts for this risk of a default on the loan by making a specific loss allowance.

Such a non–performing or defaulted loan can become irrecoverable if the bank does not expect to receive cash flows from the loan anymore, which could be due to the complete inability of a borrower to make payments on the loan (e.g. when a formal insolvency process has been completed) or when the bank cannot seize collateral to limit the foregone payments on the loan (e.g. when the borrower has provided no collateral to begin with). In this case, the loan is written off.

While both specific allowances and write-offs pertain to acute credit risks, general allowances consider latent credit risk in banks' lending business. Due to the uncertainty in business activities, a bank can expect some of the fully performing loans in its portfolio to become non–performing, even if the bank does not have evidence that such a risk has materialized yet at the time of preparing the annual accounts.

There are specific guidelines on allowances for latent credit risk. General allowances used to be obtained as:[12]

$$\text{general allowances} = 0.6 \cdot \text{allowance ratio} \cdot \text{current stock of loans}$$

[10] See IASB (2022), p. A429.
[11] See HGB, paragraph 252 (1), number 3.
[12] See BMF (1994) and IDW (1990).

The numerator of the allowance ratio comprised the average amount of specific allowances and write-offs made during the previous five years, while the average stock of loans during that period entered the denominator. Since the numerator in the allowance ratio was derived from credit risk that had actually materialized, it was suggested to reduce these historical allowances by 40 percent for the purpose of latent credit risk.

This formula produced the stock of general allowances at a given date. If this stock exceeded the one in the previous reporting period, additional allowances were recognized. Otherwise, previously recognized allowances were reversed. Notice that this way of obtaining general allowance was backward–looking in nature in contrast to the foward–looking approach of IFRS 9.

National accounting rules approach IFRS 9 with respect to credit risk. Recently, this methodology has been revised substantially, and the revision comes in effect for annual accounts put together after 31.12.2021.[13]

First, although no specific methodology to derive general allowances is prescribed, the new approach explicitly takes an expected loss over the remaining maturity of the loan as the starting point for general allowances.[14] This terminology and the guideline to obtain it[15] suggests a model which uses the relevant PDs, LGDs and EADs as inputs. Furthermore, the emphasis on the remaining maturity shifts attention to possible credit risk materializing in the future: the revision explicitly requires banks to take current information and expectations about future conditions into account, in addition to historical data that can be used to calibrate risk parameters. Taken together, the principles in IDW (2020), in particular numbers 13–15, are compatible with the goal of obtaining a lifetime expected loss, as is standard practice under IFRS 9 (see above).

Second, it is assumed that, at the time the loan is made, the interest rate agreed between the bank and the borrower comprises a risk premium to cover its expected loss (in addition to other components accounting for the costs of banks' operations, funding costs, and the cost of equity).[16] At the reporting date, these costs of credit risk included in the loan are discounted to that point in time and are compared with the lifetime expected loss estimated at that time. If the lifetime expected loss exceeds the costs of credit risk, a general allowance is made to fill the gap.[17] This gap could be due to a deterioration in the creditworthiness of a group of borrowers, say, such that the amount that was originally meant to reflect the expected loss on the loan is no longer sufficient. Such a comparison is not intended in IFRS 9.

[13] See IDW (2020).
[14] See IDW (2020), number 4 and number 13.
[15] see IDW (2020), number 15.
[16] See IDW (2020), number 23.
[17] See IDW (2020), number 21.

Third, as an alternative to the derivation of general allowances outlined in the previous paragraph, banks can use an expected loss for a period of 12 months for this purpose, without accounting for the costs of credit embedded in the loan.[18] This time horizon is in line with the horizon adopted for loans in Stage 1 under IFRS 9 accounting.

Fourth, banks can also choose the impairments allocated to Stage 1 or Stage 2 in IFRS 9 to obtain general allowances, irrespective of their general accounting model (whether it is national GAAP or IFRS 9). Banks that follow IFRS 9 accounting and prepare annual accounts according to national GAAP for tax reasons or for the purpose of statistical reporting can therefore directly adopt IFRS 9 impairments.

In our view, this overhaul implies a convergence of allowances under national GAAP and IFRS 9. Even if the three–stage model under IFRS 9 is not mentioned explicitly in this new national accounting standard, in our reading of these guidelines, they align national GAAP and IFRS 9 much closer than before.

To put these two accounting frameworks into perspective, note that banks who follow IFRS 9 account for only about 28 percent of the loan volume to non-financial firms as of December 2023. Nevertheless, for the reasons outlined above, in our model described in the next section, we take ECL as defined in IFRS 9 as the common accounting measure for all banks in the German banking system.

2.3 Modelling Expected Credit Loss

IFRS 9 does not prescribe a particular model for ECL. When adapting ECL for a top–down stress test, we adjust the risk parameters that enter the Expected Loss (EL), a widely known concept in credit risk, to account for the novel features of IFRS 9. This approach is adopted by Montesi and Papiro (2019), acknowledged in EBA (2017a), p. 9, and is exemplified in Bellini (2019), p. 8.[19]

2.3.1 Building blocks

We distinguish between the default probability for a single period of time and the complete lifetime of a loan. In our analysis, the exact point in time when a borrower defaults is not observable. Rather, defaults can only be attributed to a discrete time interval such as a quarter or a year. Let $M_{i,t}$ be the expected life (see Section 2.1) of loan i from the perspective of time t. For many loans, $M_{i,t}$ is simply the remaining maturity. The time horizon of a loan is therefore indexed by periods $t, t+1$, …, $t+M_{i,t}$.

[18] See IDW (2020), number 24.

[19] An alternative approach derives ECL in a discrete–time survival model and is more common in the academic literature. It is discussed in Bank and Eder (2021) and Bieg and Waschbusch (2017), and is the starting point of the analyses in Xu (2016), Filusch (2021) and Breed et al. (2023), for example.

Let $\text{PD}_{i,t+m-1}^{t+m}$ be the probability that loan i defaults between periods $t+m-1$ and $t+m$, $m = 1, 2, \ldots, M_{i,t}$. We refer to these probabilities as the Point–in–Time PDs (PiT PDs). These PDs are one of the major inputs into the analysis and could stem from banks' own judgement or could be the predictions from a statistical model chosen by a regulatory authority in a top–down stress test. These default probabilities are obtained from the perspective of time t.[20]

Similar to Bank and Eder (2021), let D_i be a non-negative, discrete random variable indicating the time to default of loan i. The PiT probabilities determine the distribution function of D_i, which is denoted $F_{i,t}$, with $F_{i,t}(t+m) = \Pr(D_i \leqslant t+m), m = 0, 1, \ldots, M_{i,t}$, with $F_{i,t}(t) = 0$ for a loan that is not already in default at time t. In principle, the PiT probabilities could be updated as time passes, and we allow the distribution of D_i to depend on both the loan i and the time index t.

We associate D_i with a repeated Bernoulli trial, which has the PiT probabilities $\text{PD}_{i,t+m-1}^{t+m}$ and $1 - \text{PD}_{i,t+m-1}^{t+m}$ at each node between time $t+m-1$ and $t+m$, $m = 1, 2, \ldots, M_{i,t}$. The PiT probabilities yield the conditional PD, i.e. the probability of default in a given period, conditional on the event that a default has not occurred yet,

$$\begin{aligned}\text{PD}_{i,t+m}^{c} &= \Pr\left[D_i = t+m | D_i \geqslant t+m\right] \\ &= \left(\Pi_{j=1}^{m-1}\left(1 - \text{PD}_{i,t+j-1}^{t+j}\right)\right) \cdot \text{PD}_{t+m-1}^{t+m}\end{aligned}$$

for $m = 2, 3, \ldots, M_{i,t}$ and $\text{PD}_{i,t+1}^{c} = \text{PD}_{i,t}^{t+1}$. The conditional PD is also referred to as the marginal PD. Closely related to the distribution function of D_i is its survival function $S_{i,t} = 1 - F_{i,t}$, and here we have $\text{PD}_{i,t+m}^{c} = S_{i,t}(t+m-1)\,\text{PD}_{i,t+m-1}^{t+m}$.

In this setup, we define the lifetime PD, from the perspective of time t, as

$$\text{PD}_{i,t}^{\ell} = 1 - \Pi_{m=1}^{M_{i,t}}\left(1 - \text{PD}_{i,t+m-1}^{t+m}\right) = 1 - S_{i,t}(M_{i,t}) = F_{i,t}(M_{i,t}) \tag{1}$$

When making a judgement about SICR, "an entity shall use the change in the risk of a default occurring over the expected life of the financial instrument...".[21] We relate this requirement to the lifetime probability of default, and will explain the stage transfer in more detail in the next section.

Once the ECL has been obtained for the suitable horizon, it is discounted to the reporting date. According to IFRS 9, discounting involves the "effective interest rate ... or an approximation thereof".[22]

[20] This perspective is motivated by IFRS 9 5.5.17, which requires ECL to reflect "information that is available ... at the reporting date about past events, current conditions and forecasts of future economic conditions".

[21] IASB (2022), 5.5.9.

[22] See IASB (2022), B5.5.44.

2.3.2 Stage transition

The transition between IFRS 9 stages is crucial to determine Expected Credit Loss. IFRS 9 suggests the following stylized decision rules regarding the transfer of a loan which is currently in Stage 1:

1. If a loan becomes credit–impaired, then it is transferred from Stage 1 to Stage 3.
2. If a loan does not become credit–impaired and there is a significant increase in credit risk, then it is transferred from Stage 1 to Stage 2.
3. If a loan does not become credit–impaired and there is no significant increase in credit risk, then it remains in Stage 1.

The terms ”credit–impaired” and ”significant increase in credit risk” are taken directly from IFRS 9. We link these concepts to observable quantities.

First, we equate credit-impaired loans with non-performing or defaulted loans. Although IFRS 9 does not explicitly define the term default, the definitions of a non-performing loan and a defaulted loan under EU regulation[23] and a credit-impaired loan under IFRS 9 are very close in practice.[24] For these loans, the PiT PD is equal to one, $\mathrm{PD}_{i,t+m-1+j}^{t+m+j} = 1$ for $j = 0, 1, \ldots, M_{i,t} - m$ if loan i defaults between periods $t + m - 1$ and $t + m$. Thus, we assume that once a loan enters Stage 3, it does not go back to Stage 2 or Stage 1. This assumption is the same as in EBA (2024), p. 10, according to which exposures do not ”cure” from a Stage 3 status.

Second, we relate a significant increase in credit risk to an increase in the lifetime PD. IFRS 9 accounting rules give some guidance on this assessment. For example, a loan that is more than 30 days past due could be transferred from Stage 1 to Stage 2. In practice, this decision involves considerable judgement, and banks report both qualitative and quantitative indicators when making the SICR assessment, including an increase in lifetime PD or the application of forbearance measures.[25] In a sample of 47 large European banks, about 60 percent reported an increase in PD as a key metric for this purpose.[26] Moreover, EBA (2017a) recommends that if banks base SICR on changes in PDs, the relative change to PD at initial recognition in the balance sheet should be considered. This relative change could be accompanied by a criterion based on the difference between PD at the reporting date and PD at initial recognition.[27]

[23] See Article 47(a) and Article 178 of Regulation (EU) 575/2013.
[24] See EBA (2021), p. 36.
[25] See EBA (2021), p. 26 and p. 32.
[26] See EBA (2021), p. 37–38.
[27] See EBA (2017a), p. 33.

The transition between IFRS 9 stages depends formally on the Probability of Default and threshold criteria. Against this background, we translate a significant increase in credit risk as

$$\text{significant increase in credit risk for loan } i \text{ in Stage 1 at time } t \; :\Leftrightarrow$$
$$\left(\frac{\mathrm{PD}^{\ell}_{i,t}}{\mathrm{PD}^{\ell}_{i,0}} > \tau^{\ell}_1\right) \text{ and } \left(\Delta_0\mathrm{PD}^{\ell}_{i,t} > \tau^{\ell}_2\right) \tag{2}$$

for $t = 1, 2, \ldots, M_{i,t}$, in which $\mathrm{PD}^{\ell}_{i,0} > 0$ is the lifetime PD at the time of the initial recognition of the loan, $\Delta_0\mathrm{PD}^{\ell}_{i,t} = \mathrm{PD}^{\ell}_{i,t} - \mathrm{PD}^{\ell}_{i,0}$ is the absolute change in the lifetime PD since initial recognition and $\tau^{\ell}_1, \tau^{\ell}_2 \in \overline{\mathbb{R}}$ are threshold parameters. For example, if the relative increase is chosen as the only criterion, we have $\tau^{\ell}_1 > 1$ and $\tau^{\ell}_2 = -\infty$. Conversely, if the only criterion for a stage transfer is the difference between lifetime PDs, we have $\tau^{\ell}_1 = -\infty$ and $\tau^{\ell}_2 \in \mathbb{R}^+$. A combination of these two criteria will typically have $\tau^{\ell}_1 > 1$ and $\tau^{\ell}_2 \in \mathbb{R}^+$. Leading examples include a value of $\tau^{\ell}_1 = 3$, i.e. a threefold increase in the lifetime PD, which is chosen in the EU–wide bottom–up stress test, see EBA (2024), p. 17, and is also studied in EBA (2021), p. 32.

Though IFRS 9 expects the SICR to be based on a ”change in the risk of a default occuring over the expected life” of the loan, the standard admits that ”changes in the risk of default occurring over the next 12 months” can serve as a ”reasonable approximation of changes in lifetime risk of a default”.[28] Due to the Basel framework of regulatory capital requirements, banks have traditionally considered risk parameters over a horizon of one year when determining risk–weighted assets.[29] Hence, we consider the following alternative transition rule:

$$\text{significant increase in credit risk for loan } i \text{ in Stage 1 at time } t \; \approx$$
$$\left(\frac{\mathrm{PD}^{\text{12m}}_{i,t}}{\mathrm{PD}^{\text{12m}}_{i,0}} > \tau^{\text{12m}}_1\right) \text{ and } \left(\Delta_0\mathrm{PD}^{\text{12m}}_{i,t} > \tau^{\text{12m}}_2\right), \tag{3}$$

in which the 12–month PD serves as an approximation of the lifetime PD, and $\tau^{\text{12m}}_1, \tau^{\text{12m}}_2 \in \overline{\mathbb{R}}$ are threshold parameters.

According to EBA (2017a) this approximation is widely used: In their sample of large European banks, 40 percent of the sample use a 12–month PD as an approximation for the lifetime PD in the SICR assessment.[30] Moreover, in the EU–wide bottom up stress test, 12–month PDs are a suitable approximation of lifetime PDs if the latter are not available.[31]

[28] IASB (2022), B5.5.13.
[29] BCBS (2017), p. 92.
[30] EBA (2017a), p. 41.
[31] EBA (2024), p. 17.

Note that IFRS 9 allows banks to assume that credit risk has not significantly increased if the loan is deemed to have "low credit risk" at the reporting date.[32] Low credit risk is associated with loans that have "a low risk of default", and with lending relationships in which "the borrower has a strong capacity to meet its contractual cash flow obligations".[33] As an example, a loan can qualify for the low credit risk exemption if there is an external rating of investment grade for the instrument. External ratings are not required for an exemption, however, and banks can make use of "internal credit risk ratings or other methodologies".[34]

Nevertheless, EBA (2017a) expects the "use of the exemption" to be "limited".[35] EBA (2021) reports that there are relatively few banks that use this exemption for loans to small non-financial firms, though the exemption covers large corporate borrowers in some cases. In our model, the low credit risk exemption means that even if Equation (2) or Equation (3) holds, the loan remains in Stage 1, and 12-month ECL applies.

Finally, for a loan in Stage 2, the decision rule is very similar to the rule specified above: If a loan is credit–impaired (i.e. defaulted), then it is transferred from Stage 2 to Stage 3. If it is not credit–impaired, then it remains in Stage 2. Similar to loans in Stage 3, we do not allow a re–transfer from Stage 2 to Stage 1. This assumption is stricter than the assumptions in Montesi and Papiro (2019) or in the framework described in EBA (2024), which explicitly allow for cures in Stage 2. We leave cures from Stage 2 in our analysis for future work.

2.3.3 ECL as a Stage–dependent Expected Loss

We link Expected Credit Loss in IFRS 9 to regulatory Expected Loss. Based on the Basel framework of regulatory capital requirements, banks have traditionally considered risk parameters over a horizon of one year.[36] Thus, risk parameters already available for this horizon are the natural starting points to derive 12–month ECL.[37] These parameters could also be adjusted to end up with the relevant lifetime figures. Accordingly, we distinguish one-year risk parameters with a superscript "12m" from lifetime risk parameters with a superscript ℓ.

Motivated by the design of bottom–up stress test exercises, we assume all banks assess risks at a given time T over a fixed time horizon indexed by $h = 1, 2, \ldots, H$. In our empirical application, we consider quarterly data with a horizon $H = 4$.[38] Hence T marks the starting point of the scenario analysis

[32] IASB (2022), 5.5.10.
[33] IASB (2022), B5.5.22.
[34] IASB (2022), B5.5.23.
[35] EBA (2017a), p. 37.
[36] BCBS (2017), p. 92.
[37] See also Bellini (2019), p. 32.
[38] The EU–wide bottom up stress tests studies a horizon of three years, see EBA (2024), p. 6.

and all quantities up to time T are known and risk parameters over the scenario horizon are also available. The evolution of risk parameters could be supplied by an auxiliary model or could be chosen in an ad–hoc fashion, as in the application in Section 4.

Changes in Expected Credit Loss are at the center of the analysis. We assume that the stock of impairments at the beginning of the scenario horizon is the Expected Loss according to

$$\mathrm{ECL}_{i,T} = \begin{cases} \mathrm{PD}_{i,T}^{\mathrm{12m}}\mathrm{LGD}_{i,T}^{\mathrm{12m}}\mathrm{EaD}_{i,T}^{\mathrm{12m}} & \text{if loan } i \text{ is in Stage 1} \\ \mathrm{PD}_{i,T}^{\ell}\mathrm{LGD}_{i,T}^{\ell}\mathrm{EaD}_{i,T}^{\ell} & \text{if loan } i \text{ is in Stage 2 or in Stage 3} \end{cases} \tag{4}$$

where PD $\times$ LGD $\times$ EaD is the formula for regulatory Expected Loss.

Here, we assume that $\mathrm{PD}_{i,T}^{\mathrm{12m}}$, $\mathrm{LGD}_{i,T}^{\mathrm{12m}}$ and $\mathrm{EaD}_{i,T}^{\mathrm{12m}}$ are derived from regulatory risk parameters. We have described $\mathrm{PD}_{i,T}^{\ell}$ in Section 2.3.1, and for a loan in Stage 3 we have $\mathrm{PD}_{i,T}^{\ell} = 1$. We describe our calculation of the lifetime loss given default and the exposure at default below. These parameters could, for example, take simple forms: The EaD could be equal to the outstanding amount of the loan at the reporting date, and the LGD could be equal to one minus the ratio of collateral the bank can seize in case of default (if any) and the outstanding amount, and it could be invariant over time.[39]

We consider loans in Stage 1 at time T. For a transfer to Stage 2, we apply the rule in Equation (3) for $t = T+1, T+2, \ldots, T+H$. In our empirical analysis, we set $\tau_1^{\mathrm{12m}} = 3$ and $\tau_2^{\mathrm{12m}} = -\infty$ such that only the relative increase in 12–month PDs matters, see Section 4.

For such a loan, with probability $\mathrm{PD}_{i,T}^{T+1}$, it defaults between T and $T+1$ and transfers to Stage 3 with associated loss $\mathrm{LGD}_{i,T+1}^{\ell}\mathrm{EaD}_{i,T+1}^{\ell}$ since the loan is credit–impaired and the lifetime horizon applies, see Section 2.3.1. If it does not default and it is not transferred to Stage 2, 12–month ECL continues to apply with the relevant 12–month risk parameters prevailing in period $T+1$. Hence

$$\mathbb{E}_T\left[\mathrm{ECL}_{i,T+1}\right] = d_{i,T+1}\left(\mathrm{PD}_{i,T}^{T+1}\mathrm{LGD}_{i,T+1}^{\ell}\mathrm{EaD}_{i,T+1}^{\ell} + \left(1 - \mathrm{PD}_{i,T}^{T+1}\right)\mathrm{PD}_{i,T+1}^{\mathrm{12m}}\mathrm{LGD}_{i,T+1}^{\mathrm{12m}}\mathrm{EaD}_{i,T+1}^{\mathrm{12m}}\right) \tag{5}$$

in which $\mathbb{E}_T$ denotes the expectation from the perspective of time T, i.e. it is an expectation conditional on some information set available up to time T, which can include information about the evolution of the economy going forward. In our framework, the PiT probability $\mathrm{PD}_{i,T}^{T+1}$ and other risk parameters are included in the information set at time T. Furthermore, $d_{i,T+1}$ is a discount factor to reflect the time value

[39] See Bieg and Waschbusch (2017), p. 687-690, for such an example.

of money.[40] The expected change in ECL, which drives the dynamics of the P&L statement and ultimately of regulatory capital, is then $\mathbb{E}_T\left[\text{ECL}_{i,T+1}\right] - \text{ECL}_{i,T}$.

Iterating forward, the expected ECL for loans in Stage 1 in the subsequent periods is given by

$$\mathbb{E}_T\left[\text{ECL}_{i,T+h}\right] = \sum_{j=1}^{h} d_{i,T+j}\text{PD}^{c}_{i,T+j}\text{LGD}^{\ell}_{i,T+j}\text{EaD}^{\ell}_{i,T+j} + d_{i,T+h}S_{i,T}\left(T+h\right)\text{PD}^{12\text{m}}_{i,T+h}\text{LGD}^{12\text{m}}_{i,T+h}\text{EaD}^{12\text{m}}_{i,T+h} \tag{6}$$

for $h = 2, 3, \ldots, H$, in which the conditional PD $\text{PD}^{c}_{i,T+h}$ and the survival function $S_{i,T}$ were defined in Section 2.3.1. The expected one-period change in ECL, i.e. the expected impairment gain or loss, is obtained stepwise as $\mathbb{E}_T\left[\text{ECL}_{i,T+h}\right] - \mathbb{E}_T\left[\text{ECL}_{i,T+h-1}\right]$.

For loans in Stage 2 at time T, the analysis proceeds analogous to Equation (5) and Equation (6) with the relevant lifetime risk parameters. For example,

$$\mathbb{E}_T\left[\text{ECL}_{i,T+1}\right] = d_{i,T+1}\left(\text{PD}^{T+1}_{i,T}\text{LGD}^{\ell}_{i,T+1}\text{EaD}^{\ell}_{i,T+1} + \left(1-\text{PD}^{T+1}_{i,T}\right)\text{PD}^{\ell}_{i,T+1}\text{LGD}^{\ell}_{i,T+1}\text{EaD}^{\ell}_{i,T+1}\right) \tag{7}$$

Loans in Stage 3 already have a PD equal to one, and changes can only occur if the lifetime LGD or EaD change over time.

Thus, in the following analysis, we adopt IFRS 9 accounting rules for all banks in the German banking system. Specifically, in analogy to Equation (4), we have

$$\text{ECL}_{i,T} = \begin{cases} \text{PD}^{12\text{m}}_{i,T}\text{LGD}^{12\text{m}}_{i,T}\text{EaD}^{12\text{m}}_{i,T} & \text{if an impairment for loan } i \text{ is made as general allowance} \\ \text{PD}^{\ell}_{i,T}\text{LGD}^{\ell}_{i,T}\text{EaD}^{\ell}_{i,T} & \text{if an impairment for loan } i \text{ is made as a specific allowance} \end{cases}$$

Similarly for a loan with a general allowance, we check the transition rule in Equation (3). If the condition is not fulfilled, we treat it as a loan in Stage 1 such that Equation (5) applies at time $T+1$. In contrast, if the condition is met, we adopt a lifetime perspective for the loan, and Equation (7) is used. The iteration for subsequent periods according to Equation (6) works analogously.

[40] See IASB (2022), 5.5.17.

3 Empirical implementation for the German banking system

3.1 Sample construction

3.1.1 Sample of loans

We study loan data provided by banks located in Germany. We examine data in the European Credit Data Statistics, referred to as AnaCredit, as of March 2023. The dataset comprises loans with a total commitment of the debtor of at least 25,000 Euros granted by credit institutions resident in Germany as well as by branches that are resident in Germany but that belong to credit institutions resident abroad.[41] Against this background, we make the following adjustments to obtain the final sample analyzed in this paper:

1. We restrict the sample to loans in which the debtor is a non–financial firm. Hence, the interbank lending market or retail lending by banks to households are not included in this analysis.[42]

2. We restrict attention to the following loan instruments: Credit card debt, overdrafts, revolving credit other than overdrafts and credit card debt, credit lines other than revolving credit, and all other loans. This last category includes loans in which the total loan amount is paid out in one instalment.[43] In particular, deposits, reverse repos, trade receivables and financial leases are excluded from the sample of loans.

3. We only consider loans for which the remaining maturity is observable and positive.

4. We only consider loans for which the outstanding amount is reported and positive.

5. We only consider loans for which the IFRS 9 stage designation (Stage 1, Stage 2, Stage 3) is reported or for which the national GAAP impairment type (general allowance, specific allowance) is reported.

6. If the reported PD of a loan is less then 0.03 percent, which is the minimum PD according to Article 325bp(5)(a) of the European Capital Requirements Regulation (CRR), we set it to missing. For these loans and for loans for which default probabilities are not reported to begin with, the PD is imputed as explained in Section 3.3.

[41] See Deutsche Bundesbank (2024b), p. 5.
[42] Barasinska et al. (2019) describe a stress test of residential real estate loans.
[43] See Deutsche Bundesbank (2024b), p. 78.

3.1.2 Sample of banks

Our sample includes 729 banks and bank holding companies, which together account for 87 percent of the risk-weighted assets within the German banking system. To construct our sample of banks, we initially start a broader sample of all 1241 banks and bank holding companies for which supervisory data on capital is available. In the following, the term "bank" will be used to refer to either a bank or a bank holding company, the latter of which may encompass multiple subsidiaries. To each bank, we match all loans in the AnaCredit dataset that are issued by the bank itself or any of its German subsidiaries.[44] We are not able to attribute loans to every bank, however. In particular, we cannot match loans to banks that do not issue NFC loans and to small banks, which are partly exempt from reporting requirements in AnaCredit.[45] Overall, the final sample consists of 729 banks, which represent the 87 percent of risk-weighted assets of the original group of 1241 banks.

3.2 LGD approximation

We approximate the Loss Given Default by analyzing collateral data for each loan. If a borrower defaults on a loan, the bank may be able to cover some of its losses. We assume that the proceeds from seizing assets satisfy

$$\text{proceeds}_{i,t} = \text{collateral}_{i,t} + \eta_{i,t} \cdot \max\left(\text{EaD}_{i,t} - \text{collateral}_{i,t}, 0\right) \cdot \mathbb{1}_{i,\text{recourse}} \tag{8}$$

in which $\text{collateral}_{i,t}$ is the (non-negative) value of existing collateral of loan i at time t, $\text{EaD}_{i,t}$ is the corresponding exposure at default, $\mathbb{1}_{i,\text{recourse}}$ is an indicator equal to one if loan i is a recourse loan and equal to zero otherwise, and $\eta_{i,t} \in [0, 1]$ is a parameter.

We distinguish between K different types of collateral,

$$\text{collateral}_{i,t} = \sum_{k=1}^{K} \text{collateral}_{i,t,k}$$

in which $\text{collateral}_{i,t,k}$ denotes the nominal amount of the collateral of type k. In the empirical analysis, we sort collateral into seven types: Commercial real estate collateral, offices and commercial premises, residential real estate, other physical collateral, government guarantees, and other collateral.[46] Government guarantees comprise financial guarantees by central, state and local governments, social security

[44] It is important to note, however, that our data does not extend to loans from foreign subsidiaries of German bank holding companies.

[45] See also Deutsche Bundesbank (2024b), p. 9.

[46] For the distinction between residential and commercial real estate collateral as well as offices and commercial premises, see ECB (2019), p. 218.

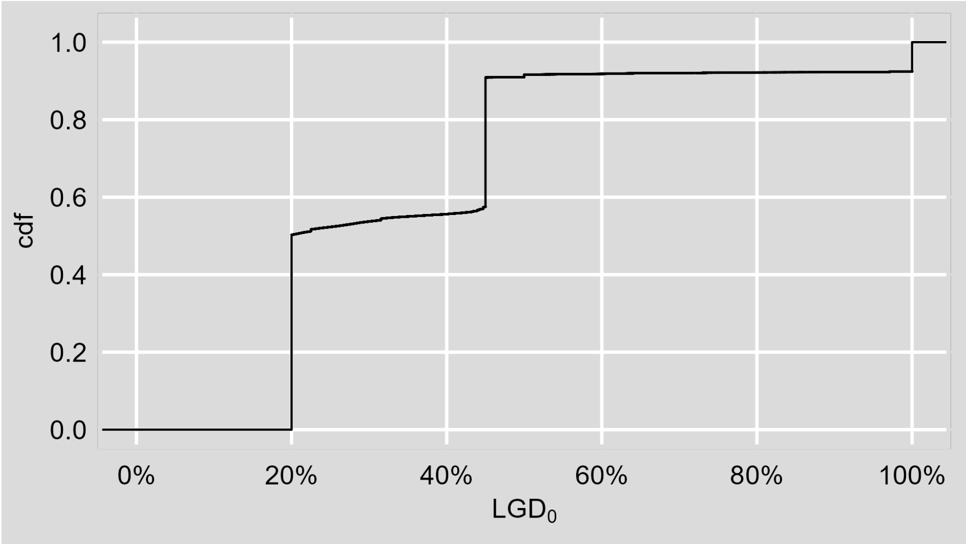

Figure 1: **Distribution of LGDs across loans**

Note: For all loans in our sample, this figure shows a CDF for the LGD at $h = 0$.

funds, and guarantees provided by the Kreditanstalt fuer Wiederaufbau (KfW), a federal agency with an explicit guarantee by the German central government. Other collateral includes securities, gold, currency and deposits, loans, trade receivables, equity and investment fund shares, life insurance policies, credit derivatives, and financial guarantees other than the ones mentioned above.

First, in a default event, the bank first realizes existing collateral, which we set to zero if it is not available in the data. Second, if the loan is a recourse loan ($\mathbb{1}_{i,\text{recourse}_i} = 1$), the bank can then seize additional assets to cover its loss. In fact, for some loans, the collateral value exceeds the exposure, and we limit the realization of these additional assets to be non–negative. The parameter $\eta_{i,t}$ controls the share of the remaining exposure that can be recovered. Third, if the loan is a non-recourse loan ($\mathbb{1}_{i,\text{recourse}} = 0$), however, the bank cannot seize other assets.

The recovery rate and the loss rate are then given by

$$\text{recovery rate}_{i,t} = \frac{\text{proceeds}_{i,t}}{\text{EaD}_{i,t}}$$
$$\text{LGD}_{i,t} = \max\left(1 - \text{recovery rate}_{i,t}, \text{LGD}_{\text{min}}\right) \tag{9}$$

in which $\text{LGD}_{\text{min}} \in [0, 1]$ is a parameter. Note that recovery rate$_{i,t}$ is not bounded from above by one since the total proceeds can exceed the exposure of a bank. In our implementation, we bound the LGD from above by one and we also set a conservative lower bound for it such that $\text{LGD}_{i,t} \in [\text{LGD}_{\text{min}}, 1]$.

Figure 1 shows the distribution of the LGD in our sample. There is significant bunching at the three values LGD$_{\text{min}}$, $1-\eta_{i,t}$, and one. This bunching is particularly pronounced for loans in Stage 1 and Stage 2. For most of these loans one of the following three cases applies: (1) The collateral is either close to the loan exposure (LGD$_{i,t}$ = LGD$_{\text{min}}$), or (2) the loan is not collateralized, but the bank has recourse to other assets (LGD$_{i,t} = 1-\eta_{i,t}$), or (3) the loan is neither collateralized nor is it a recourse loan (LGD$_{i,t} = 1$).

3.3 Imputation of default probabilities

For 27% of the loan volume in our stress test, no bank reports a PD of the debtor. We horse-race different parametric and non-parametric machine learning methods to find the best method to impute missing PDs. Based on various evaluation criteria, we decide to use a random forest algorithm for imputation. If banks estimate a probability of default for a debtor based on the internal-ratings based (IRB) approach, they report this PD.[47] This applies to 53% of the loan volume in our analysis. If banks do not follow the IRB approach, this PD is not available.[48] Since most banks in the German banking system adopt the standardized approach (SA) to credit risk, PDs are not observed for firms borrowing from these banks. We impute the missing PDs with the following methods. For 19%, while the bank does not report a PD for the borrower, at least one other bank does. In this case, we use the median across all banks that report a PD for this borrower to impute the missing PD.[49] About 1% of loan volume is in default and we assign a PD of one. This leaves us with 27% of the loan volume for which we still need to impute the PD since no bank in our sample reports a PD for these borrowers. There are multiple ways in which we could impute these missing PDs. The idea behind all approaches is to use borrower characteristics that we do observe, such as industry, location, etc., to impute the PD that we do not observe based on relationships between borrower characteristics and PDs estimated from observations for which we do observe the PD. To decide for one specific algorithm, we evaluate the performance of different approaches in the sample of borrowers for which we observe the PD.

3.3.1 Different Imputation Algorithms

We horse race the following parametric and non-parametric imputation algorithms:

- Unconditional mean: As benchmark, we use the unconditional mean PD of all observations.

[47] For more information about the IRB approach, see EBA (2017b) and ECB (2024).
[48] ECB (2019), p. 251/252.
[49] In future work, one could also exploit PDs reported in the European AnaCredit dataset.

- Unconditional median: As further benchmark, we use the unconditional median PD of all observations.
- Similar borrowers: In the spirit of Degryse et al. (2019), we construct groups of similar borrowers, i.e. borrowers in the same industry (2 digit NACE code) , location (country and 2 digit postal code) and size (micro, small, medium, large) and use the median PD of these similar borrowers as imputation. If no similar borrower is available for a given borrower, we relax the similarity conditions in a stepwise procedure and use similar borrowers e.g. from the 1 digit NACE code.
- Random forest: We use a random forest algorithm (for details, see Morgan (2020)). We use the following variables: Legal form of the borrower (which most of the time includes the country), size (micro, small, medium, large), industry (letter NACE code), industry (2 digit NACE code). For the legal form and the 2 digit NACE code, we use only the ten most frequent observations in the sample and code the other observations as 'other' to avoid too many categories of this categorical variable.
- k-nearest neighbors: k-nearest neighbors imputation is based on the idea that similar data points should have similar values. Imputation is done by first calculating the Euclidean distance between each missing value and all other points, then choosing the k nearest points based on this distance metric. Finally, the missing value is imputed using the mean of the values from these k nearest neighbors (see Kowarik and Templ (2016)). We use the following variables: Industry (2 digit NACE code), size (micro, small, medium, large), bank leverage (defined as outstanding loan volume / total assets), legal form of the borrower, location (country and 1 digit postal code).
  - In the evaluation exercise, we used $k = \sqrt{N}/2$. However, it turns out that in the actual stress test data, this is computationally too demanding. Therefore, we decrease k to $k' = k/2 = \sqrt{N}/4$.

To benchmark our results, we also calculate these measures for an hypothetical imputation in which we calculate the mean of PDs reported for the same borrower by other banks. This gives us an idea of the upper bound of that an imputation method can probably achieve.

3.3.2 Evaluation of Imputation Algorithms

Methodology To evaluate the quality of different imputation algorithms, we use the sample of borrowers from AnaCredit for which we have PDs available. We create ten samples and randomly assign 20% of missing PDs in each of these ten samples. Then we run all the imputation algorithms described above on the ten samples separately. They use information from the 80% of remaining observations to predict the 20% that are missing. Finally, we compare the imputed PDs with the observed PDs.

Evaluation Criteria We can calculate various measures to compare the performance of the imputation algorithms. We use the root mean squared error (RMSE) and the correlation between the imputed and the observed PDs as our most important criteria. In addition, we also analyse the mean absolute error (MAE). Finally, we compare the run time of each of the algorithms as a we have to trade-off an increase in performance against computational efficiency.

Results Figure 2 shows the results of the evaluation exercise. Each panel plots a different evaluation criterion, the y-axis depicts values for different samples, the x-axis the value of the evaluation criterion and the colored shapes the different imputation methods.

The RMSE is our most important evaluation criterion. Compared to the pink star as our benchmark, both non-linear methods, i.e. the random forest and the k-nearest neighbors, perform well and outperform unconditional measures. As a large sample makes k-nearest neighbours computationally much more intensive, we opt for the random forest approach.

3.4 Intra-year and lifetime default probabilities

We translate annual default probabilities to the corresponding intra–year figures, assuming equal likelihood of default in sub–periods. We model the evolution of impairments according to the expected changes in ECL as explained in Section 2.3.3, with a quarterly time index t. If banks adopt an internal ratings based approach for a given borrower, we observe a regulatory 12–month PD. We assume that the probability of a default is constant over sub-periods, which implies the following relationship between the 'survival probability' for the next 12 months and the corresponding intra–year probabilities:

$$1 - \text{PD}_{i,t}^{12m} = \left(1 - \text{PD}_{i,t}^{t+1}\right)^4,$$

or

$$\text{PD}_{i,t}^{t+1} = 1 - \left(1 - \text{PD}_{i,t}^{\text{12m}}\right)^{\frac{1}{4}}. \tag{10}$$

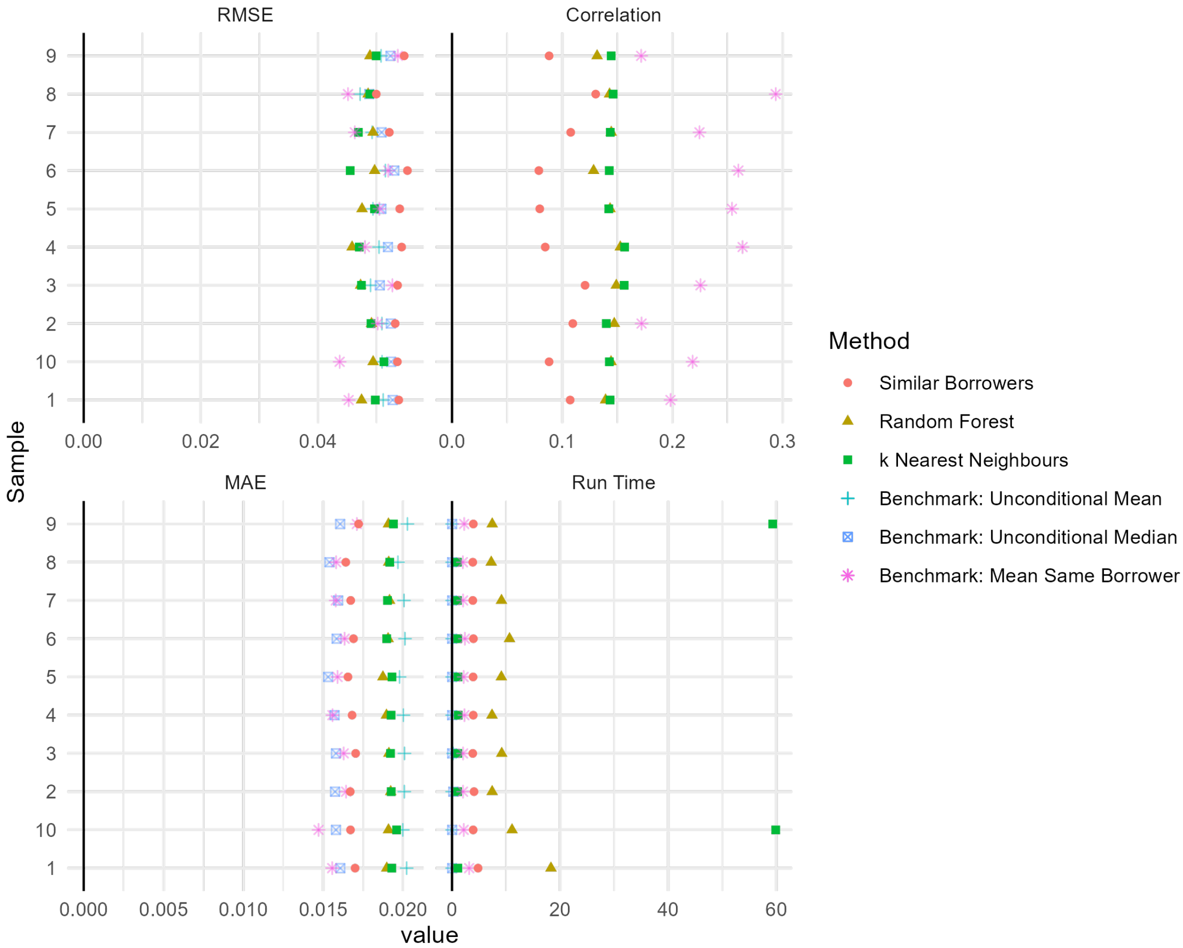

Figure 2: **Evaluation of different imputation algorithms**

Note: For ten different random samples depicted on the y-axis, this figure shows for the six different imputation algorithms marked by the color and shape how the perform according to four different evaluation criteria whose values are depicted on the x-axis.

Notice that $\mathrm{PD}_{i,t}^{12\mathrm{m}}$ is compatible with regulatory requirements and thus adopts a through–the–cycle (TTC) perspective. It is typically derived as a long–run average of 12–month default rates, with an observation period of at least five years.[50] In the scenario analysis in Section 4, the 12–month regulatory PDs at the end of the sample period are the starting point of the analysis. This can be viewed as an inconsistency to the terminology in Section 2.3.1, which ties ECL to Point–in–Time default probabilities that are forward–looking in nature. In practice, however, the differences between TTC and PiT probabilities are not as clear–cut, see EBA (2021), footnote 89. We leave an examination of TTC and PiT probabilities and a possible calibration exercise between the two for future work.

Finally, we observe the remaining maturity $M_{i,t}$ of each loan in years and obtain the lifetime PD as

$$\mathrm{PD}_{i,t}^{\ell} = 1 - \left(1 - \mathrm{PD}_{i,t}^{12\mathrm{m}}\right)^{M_{i,t}} \tag{11}$$

3.5 Scaling the expected impairment loss

We take differences in the observed loan exposures across data sources into account. In our empirical analysis, we analyze loan–level statistical data. At the level of a single bank, by aggregating the individual loan exposures, we obtain the total NFC exposure of this particular lender at a given point in time.

In addition, in a separate dataset, we can make use of supervisory information at the bank level. Supervisory data comprises regulatory capital, risk–weighted assets and loan exposures for various portfolios, such as central governments, institutions, households or non–financial corporations. Thus, we can compare the size of the NFC loan portfolio at the bank level between the two datasets.

We find non–negligible differences. This discrepancy could be due to the fact that the terms ”loan” or ”exposure” are defined differently in the two datasets. We leave resolving this issue for future work.

In fact, for most banks, the size of the NFC portfolio according to supervisory data exceeds the aggregate exposure according to loan–level data. To make sure that our empirical analysis, which is based on loan–level data, does not underestimate the NFC exposure, we re–scale impairments losses at the bank level:

$$\text{scaled impairment loss} = \frac{\text{NFC exposure supervisory data (FINREP)}}{\text{NFC exposure statistical data (AnaCredit)}} \times \text{expected impairment loss} \tag{12}$$

[50] See EBA (2021), p. 67.

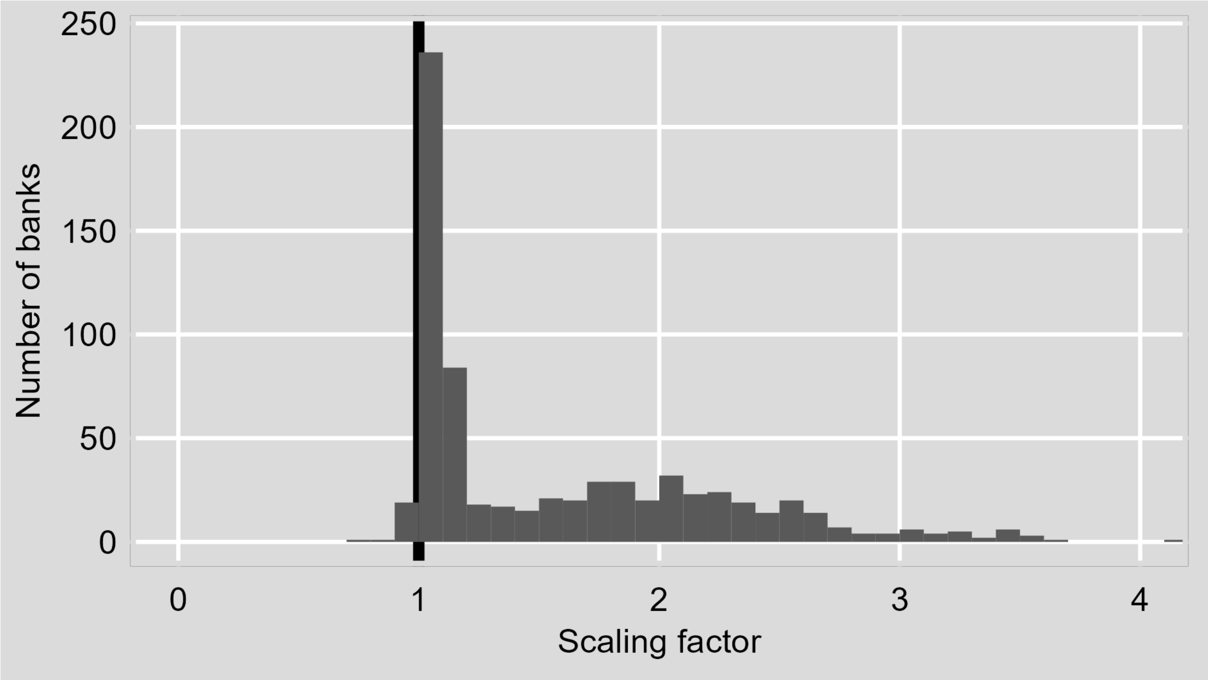

Figure 3: **Distribution of the scaling factor across banks**

Note: This figure shows a histogram for all banks in our sample where banks are sorted according to the scaling factor used in Equation (12). The scaling factor is defined as $\frac{\text{NFC exposure supervisory data (FINREP)}}{\text{NFC exposure statistical data (AnaCredit)}}$. The vertical line is at 1. 31 banks with larger scaling factor are not shown in the figure.

in which the expected impairment loss is the total change in ECL at the bank level over the course of a given scenario, see Section 4. The assumption underlying this approach is that the loss ratio for the part of the NFC portfolio that is reported in supervisory data but not covered in the loan–level data is the same as for the observed portion of the portfolio.

Figure 3 shows the distribution of the scaling factor across the 729 banks in our analysis. For many banks, the scaling factor is close to 1. However, there are some banks with a significantly larger scaling factor.

4 Application: Risks from commercial real estate markets

In the analysis published in the Financial Stability Review 2024 (see Deutsche Bundesbank (2024a)), we apply our model to obtain losses from credit risks related to commercial real estate (CRE) markets. Since the last Financial Stability Review, the downturn in the CRE market has continued (see Deutsche Bundesbank (2023), p. 62/63). The impairments for commercial real estate loans are substantial. The downturn in commercial real estate markets continued over the course of 2024, albeit at a slower pace.

As a result, banks that are particularly active in these markets had to form large write-downs in some cases. The non-performing loans (NPLs) ratio of commercial real estate secured loans has doubled since the end of 2022, albeit from a low level. In the second quarter of this year, the aggregate rate is 4.2%. NPL ratios for significant institutions (SIs) are above average, at 5.1% in the second quarter of 2024.[51] One reason for this is that these banks have an above-average exposure to the particularly affected US market. The NPL ratio of SIs for the corresponding US exposures is 12.6%, while the NPL ratio for German exposures is only 3.3%. Less significant institutions (LSIs), on the other hand, have a significantly lower NPL ratio for commercial real estate loans, at 3.4%, owing to their focus on the domestic commercial real estate market.[52]

An assessment of possible future states of the banking system hinges critically on the assumptions that are put into such an analysis. Against the background of Section 2 and Section 3, Appendix A makes all assumptions and parameter choices explicit. Next, we present the scenarios that we model and the results of the scenario analysis. We conclude with some additional sensitivity analyses.

4.1 Scenarios

We present two scenarios.

In the "Limited CRE Downturn" scenario, we assume collateral values to decline and default risk to increase, in particular for risky CRE borrowers. We assume a strong downturn in both domestic and non–domestic CRE markets. In the ad–hoc scenario, the value of commercial real estate collateral falls by 25%. This assumption reflects changes in market prices and the fact that many banks saw their collateral appreciating for a long time and have not revalued large parts of the collateral associated with their loans during the downturn. The decline of 25% is based on the estimation of the fifth percentile from a commercial real estate prices-at-risk model (Herbst, Plaasch, and Stammwitz (2024)). In the ad–hoc scenario, the value of residential real estate collateral[53] falls by 10.6%. Such a decline in two consecutive years would align prices with the level that socio–demographic and economic fundamentals suggest is appropriate (Deutsche Bundesbank (2024c), p. 48).

[51] Significant institutions are all banks that are directly supervised by the ECB.

[52] LSIs are all banks that are subject to national supervision and are therefore not directly supervised by the ECB.

[53] When defining commercial real estate collateral, we follow the ESRB definition, according to which commercial real estate also includes rental housing, i.e. real estate for residential purposes that is not owned by natural persons (ESRB (2019b)). The AnaCredit classification differs from the fact that residential real estate, which is deposited as collateral for corporate loans, is referred to as residential real estate. This allows us to analyse various developments for the collateral values of residential real estate and "classic commercial real estate" in the analysis.

When choosing changes in the probability of default of borrowing firms, we take into account that the risk in the commercial real estate market is heterogeneous. The European System Risk Board provides a broad definition of commercial real estate for the purpose of assessing financial stability (ESRB (2019b)). We would like to allow for borrowers who are covered by this broader definition to be affected differently by a given shock to CRE markets. Unfortunately, the AnaCredit data do not allow to identify particularly vulnerable commercial real estate and real estate development borrowers. Therefore, we combine borrower characteristics in AnaCredit with additional research about the business models of the relevant borrowers and match this information by name to approximate a borrower's vulnerability.

Against this background, we assume that real estate development becomes more risky with a 3.6–fold increase in the initial PDs for these borrowers. The average, volume–weighted PD rises from 4.2% to 15% in this sub–portfolio. For less risky commercial real estate borrowers such as construction firms, we assume that the PD will increase by a factor of 2.4, implying that the average, volume–weighted PD will rise from 2.1% to 5% for these borrowers.

In this scenario, we also pay special attention to the US CRE market, which has seen a downturn in late 2023. In our analysis, this downturn intensifies. The US CRE market is particularly important, as German banks are exposed significantly to this market and losses in this portfolio may potentially be more pronounced due to specific conditions in these loans, including bullet, non-recourse loans. The value of US real estate, which id pledged as collateral, is assumed to fall by 25%. This corresponds roughly to the decline in US office real estate prices in 2023.[54] Uncertainty about the US commercial real estate market is high and adjustment processes are not yet complete, as the US office market seems to be hit particularly hard by the structural shock from the shift to remote work.

We assume that the initial PDs of all US commercial real estate borrowers[55] will increase by a factor of 4.4. Accordingly, the average, volume-weighted PD, which is already at an elevated level, rises from 9.7% to 43%. With an LGD of 35%, which can be derived from banks' Stage 3 coverage ratios, we obtain a loss rate of 14.7%. This number corresponds to the loss rate for US commercial mortgage backed securities in 2008 (International Monetary Fund (2021), Figure 3.3.).

[54] German banks are predominantly active financing offices in the US CRE market.
[55] Identified via NACE codes 41, 43 and 68.

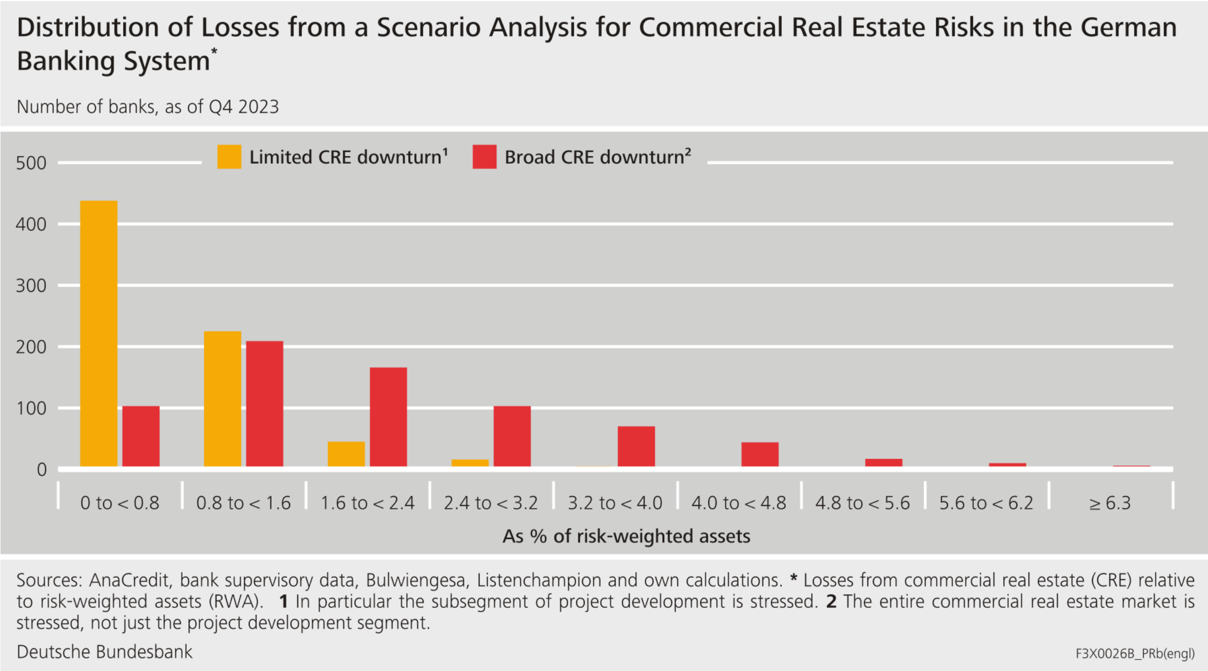

Figure 4: **Distribution of simulated losses across banks**

Note: For the two stress test scenarios described in Section 4.1, this figure sorts banks by their losses relative to risk-weighted assets.

In the "Broad CRE Downturn" scenario, we assume additionally that less risky commercial real estate borrowers' default risk increases significantly. In the broader CRE downturn scenario, we assume a particularly strong increase in PDs among borrowers in real estate development. We now assume that other CRE borrowers, such as real estate companies and construction firms, as well as borrowers in real estate development become more likely to default on their loans. We assume a 4.8-fold increase in initial PDs for risky CRE borrowers. The average, volume–weighted PD rises from 4.2% to 20%. For less risky commercial real estate borrowers, we assume a 3.8-fold increase in PDs, meaning that the average volume–weighted PD increases from 2.1% to 8%. The evolution of the value of collateral is the same is in the first scenario.

4.2 Results

The banking system is likely able to cope with defaults of CRE loans increasing more strongly than expected. We now analyze the risks from commercial real estate.[56] In the first "Limited CRE Downturn" scenario, the particularly affected sub-segment of real estate development was stressed.[57]

[56] The stressed loans also include loans to non-financial companies secured with real estate for residential purposes, e.g. apartment buildings, as defined in ESRB Recommendation 2016/14 in conjunction with 2019/03.

[57] Real estate developers, such as the now insolvent Signa Group, plan and implement both new construction projects and refurbishment of existing buildings. Their aim is a higher resale value or higher rental income.

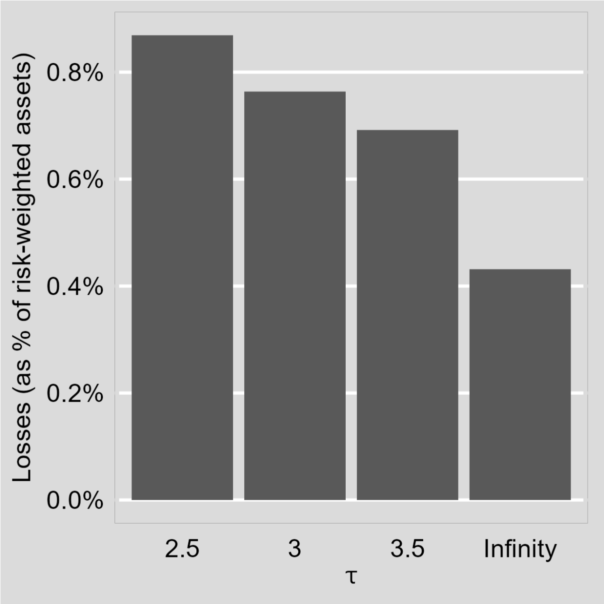

Figure 5: **Sensitivity of results to choice of parameter τ in the "Limited CRE Downturn" scenario**

Note: For the "Limited CRE Downturn" scenario, this figure shows aggregate losses relative to risk-weighted assets for different values of the SICR trigger τ.

The aggregate CET1 ratio of German banks would decline by 0.8 percentage points over the course of a year. However, losses are not evenly distributed, but are concentrated in part of the banking system (Figure 4). The most affected banks would suffer significant losses. These are very few and rather smaller to medium-sized institutions.

By contrast, a broad downturn in CRE would affect the banking system across the board. If a sharp downturn were to affect not only real estate developments but the entire CRE market, the average CET1 ratio would fall more sharply by up to 1.6 percentage points owing to losses from credit risk.[58] A significant proportion of banks would record losses of more than 2.4% of risk-weighted assets (Figure 4). Risks could be exacerbated by contagion of further banks. Our calculations show that a number of smaller and medium-sized banks are likely to no longer be able to meet their aggregate buffer requirements. These banks could then try to meet their buffer requirements again via deleveraging.[59] However, the banking system would still have the potential to provide sufficient loans on aggregate. However, it is not always possible for firms to switch to a new bank smoothly.

4.2.1 Sensitivity analyses

A lower "Significant Increase in Credit Risk (SICR) Trigger" leads to higher losses. As described above, our model requires us to pick values for certain model parameters. A crucial parameter is the SICR trigger which we set to $\tau = 3$ in our baseline analyses. We study how results differ once we choose other values. Figure 5 shows the results for different values of τ in the "Limited CRE Downturn" scenario. Intuitively, a lower SICR trigger leads to higher losses as more loans are transferred to stage 2. In contrast, higher values of the SICR trigger lead to lower losses. The last column with $\tau = \infty$ models a scenario in which no transfer to stage 2 takes place and losses result only from defaults (corresponding to transfers to stage 3) or incremental adjustments of impairments without a change in the stage.

Allowing for heterogeneity in the LGD of various loans captures significant differences across banks. A novel feature of our modeling approach is to allow for heterogeneity in the LGD. Most existing stresstest tools, in contrast, assume a constant LGD of 45%. We test the sensitivity of our results to the modelling approach for the LGD. We compare our main result described above to (i) a similar scenario where we assume that all collateral values would remain constant throughout the scenario and (ii) a model which assumes a LGD of 45% for all loans independent of collateral and recourse. Figure 6 shows the aggregate results. The decrease in collateral values assume in the main result is only responsible for a small part of the total losses which is likely due to the bunching discussed in Section 3.2. Compared to a model which assumes a 45% LGD for all loans, our main result yields significantly lower losses.

The difference between the different modeling approaches does vary across banks. Figure 7 shows this variation across banks. For the two alternative ways to model the LGD, the figure shows for each bank in our sample the losses relative to the losses in the main result and shows the CDF across banks. Assuming a constant LGD of 45% increases losses for most, but not all banks. For some banks, losses more than double. These results underline the value of leveraging granular micro data to get a detailed understanding of the risk in the financial system.

[58] In addition to real estate development borrowers, risks would also increase for other commercial real estate borrowers in such a scenario. For example, construction companies or real estate companies with a focus on renting out apartments.

[59] Deleveraging describes a reduction in the balance sheet with the aim of reducing the share of debt.

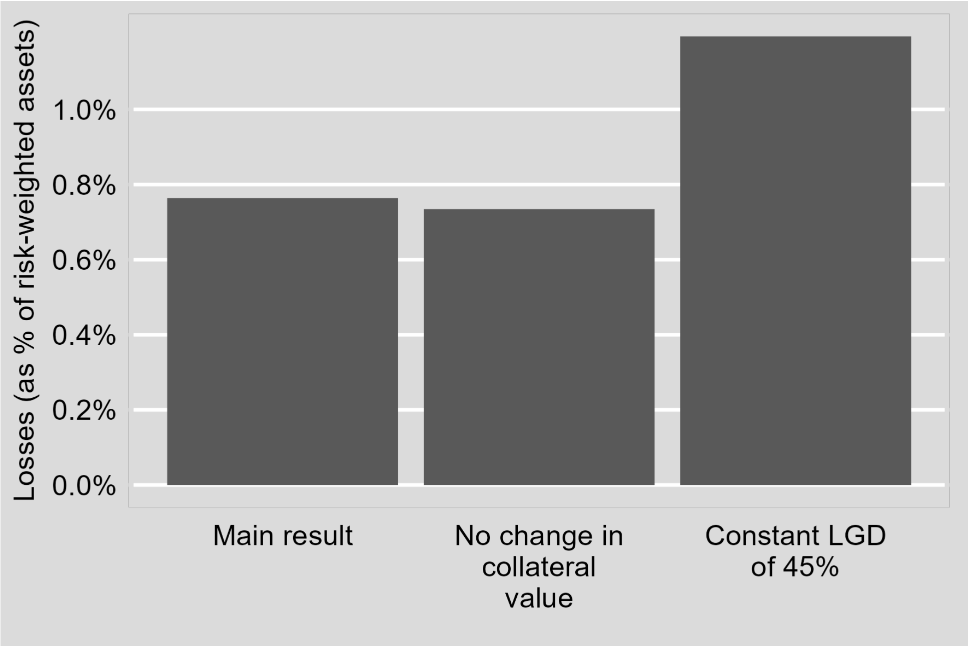

Figure 6: **Sensitivity of results to choice of LGD modelling in the "Limited CRE Downturn" scenario**

Note: For the "Limited CRE Downturn" scenario, this figure shows aggregate losses depending on how the LGD is modeled.

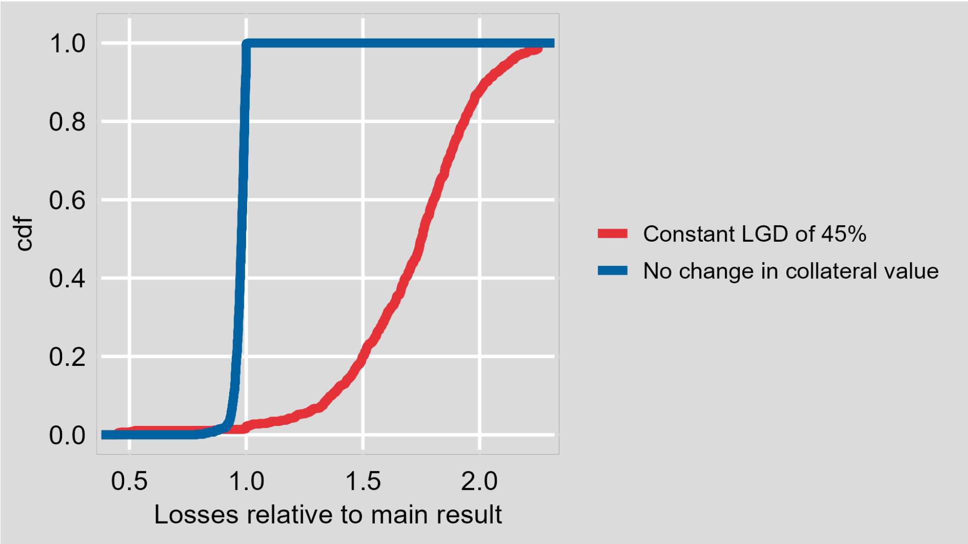

Figure 7: **Sensitivity of results to choice of LGD modelling in the "Limited CRE Downturn" scenario**

Note: For the "Limited CRE Downturn" scenario, this figure compares for each bank in our sample the losses for two alternative ways to model the LGD relative to losses in the main result and plots the CDF.

5 Limitations and extensions

The methodology and the empirical results presented in Section 2 - Section 4 shed new light on stress testing with loan–by–loan data and on risks from CRE markets. Nevertheless, it is important to keep possible limitations of this analysis in mind. We also add further refinements of the framework presented here which we leave for future work.

5.1 Limitations

The scenario analysis described in this paper has several important limitations, including a limited scope, model–free scenarios, and missing information. First, the stress test only considers credit risk from lending to non–financial firms in isolation. Other risks that could materialize simultaneously, such as credit risk from residential mortgages, market risk, or liquidity and funding risks, are not taken into account. These factors can pose additional threats to the stability of the banking system and can interact with credit risk in the corporate loan portfolio in mutually reinforcing ways. Similarly, solvency is not only affected by a decrease in regulatory capital as highlighted in this analysis, but also by an increase in risk weights. Though this additional effect on the denominator of the capital ratio is relevant mainly for banks that follow the internal ratings–based approach (IRBA), these are mostly large, systemically important institutions. Hence, in the scenarios examined in Section 4, capitalization could decrease beyond the effects reported here for some banks in the system.[60] Unlike other supervisory stress tests, we also consider a horizon of one year as opposed to, say, three years.[61]

Second, the scenarios examined in Section 4 are chosen in a purely ad–hoc fashion. This approach has two advantages. First, it enables us to target specific tail–risks freely. In the application in this paper, we focus on the risk from commercial real estate lending, but other scenarios could be of interest, too. For example, we could study risks from specific industries such as the energy or manufacturing sector or we could take a look at country–specific risks. Second, when looking at these scenarios in a stand–alone fashion, they are relatively easy to interpret and to communicate to policy makers or the broader public. The disadvantage of this approach is that the scenarios are not derived in a theoretical economic or a macro–econometric model. The scenarios are not linked to economic fundamentals such as GDP

[60] As a rough estimate of the magnitude of these effects, note that EBA (2023) breaks down the change in capital ratio in the EU–wide bottom up stress test: On aggregate, the materialization of credit risk lowers the capital ratio by 4.05 percentage points in the adverse scenario. This effect is mostly driven by corporate exposures. In addition, the increase in the risk exposure amounts (REA), which stems mostly from an increase in credit risk according to the internal ratings–based approach, yields a reduction of the capital ratio of 1.43 percentage points. The ratio of the effect of an increase in risk weights to the losses from credit risk is hence about 0.35, meaning that the effect on the denominator of the capital ratio is roughly a third of the effect of the numerator on the capital ratio.

[61] See EBA (2023) or IMF (2022).

growth, a wide range of asset prices, or to monetary policy. The results in this paper can therefore not be associated with a specific combination of economic variables of interest or a specific path of monetary policy.

If linking this framework to a macroeconomic model is considered to be desirable, however, such a link can be established, provided that additional modeling steps are taken to feed the outcome of macroeconomic projections into this model. The results presented in this paper thus reflect the current state of this exercise and can be extended going forward, see below.

Third, our modeling choices are guided and constrained by the available information in the AnaCredit dataset. Specifically, banks are only required to report a PD if they follow the internal ratings–based approach (IRBA).[62] Consequently, for a subset of debtors, we face a missing data issue regarding an important risk parameter in this analysis. We resort to approximations and well–known imputation methods to tackle this problem, see Section 3.3. These imputations, however, introduce model uncertainty and an approximation error which is hard to quantify. Moreover, a PD reported in AnaCredit is a through–the–cycle PD in accordance with EU regulation, while the accounting framework described in Section 2 relies on a point–in–time PD, creating an inconsistency or measurement error. As a result, the changes in default probabilities assumed in the scenarios reflect both a change in a point–in–time PD and the associated adjustment when going from a through–the–cycle to a point–in–time perspective.

5.2 Extensions

This analysis could be extended in at least three ways. First, the transfer from Stage 1 to Stage 2 in our IFRS 9 accounting model depends on a relative increase in PD. While this approach is a natural starting point given the implementation of IFRS 9 in practice, this criterion could be accompanied by a constraint on the difference in default probabilities. A SICR assessment based on two–parameter threshold constraints could give a clearer picture of what constitutes an economically meaningful increase in credit risk. For example, some of the reported default probabilities are very close to zero such that even a threefold increase in a PD results in a level of credit risk that is essentially unchanged. Conversely, if the PD is high to begin with (e.g. 4 percent), a difference of one percentage point, say, could be viewed as a severe increment in risk, but would go unnoticed by an assessment that is based on a threefold increase of the PD alone. Second, while we provide an approximation of LGD and an imputation of missing default probabilities to get a more comprehensive view on PD, we have not explored historical correlations between these risk parameters and economic or industry–specific variables. This is partly

[62] See ECB (2019), p. 253.

due to the short time series in AnaCredit, but could be circumvented by making use of related national datasets with a longer time series horizon, see Memmel and Roling (2021), for example.

Third, the imputation of missing default probabilities (Section 3.3) can be extended and refined. For example, we have not exploited the panel structure of the AnaCredit dataset for the purpose of imputing missing default probabilities. Doing so requires changing the methodological approach in a substantial way, however. Furthermore, hyper-parameters in the Random forest could be fine-tuned using standard grid search or related methods.

6 Conclusion

In this paper, we study banks' credit risk from lending to non-financial firms. We model changes in Expected Credit Loss based on IFRS 9 accounting rules. We map the accounting model to the AnaCredit dataset with individual loans as the unit of observation. We present a novel approximation of the LGD in the German banking system, taking important differences in existing collateral among loans explicitly into account. We also employ machine learning algorithms to impute missing default probabilities. With this comprehensive set of default probabilities, we are able to tailor an increase in the Probability of Default to specific borrowers such that defaults become more likely in ex ante riskier segments than in less risky ones in our scenario analysis. We then apply this model to two ad hoc scenarios in which the downturn in CRE markets worsen. The results of this analysis are presented in the Financial Stability Review, see Deutsche Bundesbank (2024a).

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A Appendix: Summary of all assumptions

Accounting framework and bank behaviour

(A1) The IFRS 9 accounting standard applies to all banks in the sample, see Section 2.2.

(A2) For each loan in the sample assigned to Stage 1 according to the IFRS 9 standard, banks assess a transfer to Stage 2 using Equation (3). The threshold parameters $\tau_1^{\text{12m}}, \tau_2^{\text{12m}}$ are specified in Appendix A.

(A3) There is no loan in the sample that qualifies for the low–credit risk exemption, see Section 2.3.2. This assumption is more conservative than the framework in EBA (2024), which allows for the exemption to be used but requires documentation from banks on how it was implemented.

(A4) There are no cures or write-offs for loans in Stage 3. This assumption is in line with EBA (2024).

(A5) There are no cures for loans in Stage 2. This assumption is stricter than the framework described in EBA (2024). We leave cures from Stage 2 for future extensions of our model.

(A6) The expected change in Expected Credit Loss (ECL) evolves according to formulas presented in Section 2.3.3. Since we do not allow for cures, impairment gains are ruled out, and this expected change is equal to the expected impairment loss.

(A7) We impose a static balance sheet assumption such that if a loan redeems over the scenario horizon, it is replaced by a loan with the same risk characteristics. The overall exposure of a bank remains unchanged over the scenario horizon. We leave an extension of this model to allow for dynamic balance sheets for future work.

Risk parameters: Starting values

The final period in our sample is the fourth quarter of 2023 and is the starting point of the scenario analysis, corresponding to $t = T$ in Section 2.

Regarding the risk parameters described in Section 2.3.3, we make the following assumptions and use the following methods:

(SV PD) The starting values of the risk parameter PD are the reported PDs by the banks that follow the IRB approach. Missing PDs are imputed with random forest regression as described in Section 3.3.

(SV LGD) The starting value of the LGD is given by Equation (9) with $t = T$.

(SV EaD) The risk parameter EaD is equal to the outstanding amount at the end of the sample period.

Risk parameters: Scenarios

The scenario horizon spans four quarters, so in the notation of Section 2, we have $H = 4$. Regarding the evolution of risk parameters over the scenario horizon:

(S–PD) Let $\text{PD}_{i,T}^{\text{12m}}$ be the PD of loan i at time T, which is the end of the sample period. This PD is either observed in the data or imputed as described in Section 3.3. PDs are assumed to grow at a gross annual rate of $1 + \rho$. We translate the annual rate into a quarterly rate, assuming constant quarterly growth,

$$\text{PD}_{i,T+h} = (1 + \rho)^{\frac{h}{4}}\, \text{PD}_{i,T}^{\text{12m}}$$

for h = 1,2, …, H. To tailor the increase in default probabilities to borrowers related to the CRE market, we follow the recommendation by the European Systemic Risk Board to define the CRE sector.[63] In terms of the NACE classification, our definition comprises the Real Estate Activites (sector L) and two sub-sectors within Construction (sector F): Construction of buildings, Specialized construction activities.

Furthermore, we sub–divide the CRE sector into a risky and less risky segment. The risky CRE segment comprises firms engaged in real estate development, while the less risky segment involves construction firms and real estate holding companies. We denote these growth rates as $\rho_{\text{risky CRE}}$ and $\rho_{\text{less risky CRE}}$.

Moreover, borrowers from the US CRE market (whether they are deemed as risky or less risky) are assigned a growth rate of $\rho_{\text{US CRE}}$. Finally, for all other non–financial firms, we specify the growth rate ρ_{other}.

Table A.1 shows the parameter choices for the PD.

[63] See ESRB (2019a), p. 24/25.

Parameter	Limited CRE downturn scenario	Broad CRE downturn scenario
$\rho_{\text{risky CRE}}$	2.6	3.8
$\rho_{\text{less risky CRE}}$	1.4	2.8
$\rho_{\text{US CRE}}$	3.4	3.4
ρ_{other}	0.05	0.05

Table A.1: **PD parameters in the scenario analysis**
The table presents the PD parameter choices in the scenario analysis. PDs are assumed to evolve according to $\text{PD}_{i,T+h} = (1+\rho)^{\frac{h}{4}}\,\text{PD}^{\text{12m}}_{i,T}$. We sub–divide the CRE sector (based on the definition by ESRB (2019a)) into a risky and less risky segment. The risky CRE segment comprises firms engaged in real estate development, while the less risky segment involves construction firms and real estate holding companies. We denote these growth rates as $\rho_{\text{risky CRE}}$ and $\rho_{\text{less risky CRE}}$. Borrowers from the US CRE market (whether they are deemed as risky or less risky) are assigned a growth rate of $\rho_{\text{US CRE}}$. For all other non–financial firms, we specify the growth rate ρ_{other}. All growth rates are decimals. CRE is shorthand for Commercial Real Estate. See Section 4 and Section 3.3 for further information.

Finally, we ensure all PDs do not exceed one and are at least as large as the regulatory minimum for corporate exposures, such that $\text{PD}_{i,t+h} \in [0.03, 1]$ for $h \in 1, 2, \ldots, H$ and all scenarios considered here.[64]

To compute expected changes in Expected Credit Loss as explained in Section 2, we transform the 12–month PDs in the scenarios into intra–year (quarterly) PDs using Equation (10) where necessary. Similarly, we obtain the lifetime PD in each period over the course of the scenario according to Equation (11).

(S–LGD) The LGD is driven by the evolution of the proceeds when a bank seizes assets according to Equation (8). Specifically, in both scenarios, commercial and residential real estate prices and other collateral are assumed to evolve at a gross annual rate of $1 + p_{\text{cre}}$, $1 + p_{\text{rre}}$ and $1 + p_{\text{other physical collateral}}$. We transform the annual growth rate into a quarterly rate, assuming constant quarterly growth, yielding

$$\text{collateral}_{i,T+h,\text{cre}} = (1 + p_{\text{cre}})^{\frac{h}{4}}\,\text{collateral}_{i,T,\text{cre}} \tag{13}$$

for h = 1,2, …, H, in which $\text{collateral}_{i,T,\text{cre}}$ denotes the nominal vale of the collateral of the type commercial real estate at time T, which is the last period before the scenario horizon starts.

The same approach is taken for the collateral type offices and commercial premises. An analogous formula applies to residential real estate collateral and other physical collateral with $1 + p_{\text{rre}}$ and $1 + p_{\text{other physical collateral}}$ instead of $1 + p_{\text{cre}}$ in Equation (13). Moreover, as explained in Section 4, we

[64] See CRR (2024), Article 160, Number 1.

distinguish between US and non–US real estate collateral and specify a gross annual growth rate for each sub–type, see Table A.2.

The value of the remaining collateral types (financial guarantees provided by the KfW, financial guarantees provided by governments, and remaining collateral) does not change.

The remaining parameters $\eta_{i,t}$ and LGD_{min} are specified in Table A.3. We require an LGD of at least 20 percent and assume that for recourse loans, the LGD on additional assets is 45 percent, which is a default choice in the Basel capital requirements.

In terms of the notation of Section 2.3.3, we set $\text{LGD}^{\text{12m}}_{i,t+h} = \text{LGD}^{\ell}_{i,t+h} = \text{LGD}_{i,t+h}$ for $h = 1, 2, \ldots, H$, where $\text{LGD}_{i,t+h}$ is given in Equation (9) with the relevant recovery rate in the respective scenario.

Table A.2 shows the parameter choices for the LGD.

Parameter	Value
$p_{\text{cre,us}}$	-0.25
$p_{\text{cre,non–us}}$	-0.25
$p_{\text{rre,us}}$	-0.25
$p_{\text{rre,non–us}}$	-0.106
$p_{\text{other physical collateral}}$	0.004

Table A.2: **LGD parameters in both scenarios**
The table presents the LGD parameter choices for both scenarios, see Section 4. All growth rates are decimals. CRE is shorthand for Commercial Real Estate, while Residential Real Estate is abbreviated as RRE. Remaining collateral includes securities, gold, currency and deposits, loans, trade receivables, equity and investment fund shares, life insurance policies, credit derivatives, and financial guarantees other than government guarantees and guarantees provided by the Kreditanstalt fuer Wiederaufbau (KfW), whose value does not change over the course of the horizon. See Section 3.2 for further information.

(S–EaD) The exposure at default is equal to the starting value throughout the scenario horizon. Thus, in terms of the notation of Section 2.3.3, we have $\text{EaD}^{\ell}_{i,t+h} = \text{EaD}^{\text{12m}}_{i,t+h} = \text{EaD}_{i,T}$ for $h = 1, 2, \ldots, H$. We leave incorporating credit lines and related optional exposures into EaD for future work.

Table A.3 presents all remaining hardwired parameters in this analysis.

Auxiliary parameters

Table A.3 presents all remaining hardwired parameters in this analysis.

Parameter	Description	Value	Further information
$d_{i,t}$	IFRS 9 discount factor, $\forall i, t$	1	Section 2.3.3
τ_1^{12m}	IFRS 9 Stage transition: Relative increase of PD	3	Section 2.3.2
τ_2^{12m}	IFRS 9 Stage transition: Difference between PDs	$-\infty$	Section 2.3.2
$\eta_{i,t}$	Recourse loans: Share of additional assets that can be realized, $\forall i, t$	0.55	Section 3.2
LGD_{min}	Minimum LGD for all loans (decimal)	0.20	Section 3.2

Table A.3: **Parameter choices in the scenario analysis**
The table presents all parameter choices in the scenario analysis. See Section 2 - Section 3 for details.