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The common drivers of default risk

Christoph Memmel

Yalin Gündüz

Peter Raupach

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

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Abstract

Using a unique data set on German banks' loans to the German real economy, we investigate banks' credit risk. This data set includes the volume of loans per bank and industry as well as the corresponding write-downs. Our empirical study for the period 2003–2011 yields the following results: (i) Beyond the nationwide credit loss rate, industry composition, and regional factors, the loans' maturity structure is found to drive the bank-wide loss rates in the credit portfolio. (ii) The nationwide loss rate has the most impact, followed by the maturity structure and the industry composition. (iii) For nationwide banks, these common factors explain about 26% of the time variation in the loss rate of credit portfolios; for regional banks, this percentage is less than eight percent.

Keywords

Credit risk, systematic risk, maturity, stress tests

JEL Classification

G21

Non-technical summary

How much default events depend on systematic factors which have an impact on entire borrower groups plays a key role in the default risk of credit portfolios. The stronger the influence of such factors is, the less useful is a diversification across a large number of borrowers and the stronger are the fluctuations in portfolio losses over time. As a bank has to use capital to absorb loss fluctuations, it is crucial for both risk managers and regulators to identify systematic factors and be aware of their relative influence.

A direct probability estimate of common defaults is inappropriate, as it is in the nature of the credit business that defaults - and let alone common defaults - rarely occur. First, asset value models are used in practice, which recognize the loans as a derivative of the (non-observable) firm value of borrowers. The systematic factors of such models are generally not observable. Second, "intensity-based" models are employed. Their systematic factors can be interpreted as an average default rate in a given sector (a branch of industry, e.g.) at a given time. In both types of model, the borrowers have to be assigned to suitable groups, preferably so that the link between the defaults is as large as possible within the group and as small as possible between the groups. Allocation by industrial sector is usual, but neither exhaustive nor obligatory. In principle, other classification criteria can be just as meaningful.

This is the point of departure for our study. We use a Bundesbank dataset, which covers all German on-balance-sheet credit business with the real economy from 2003 to 2011. It contains credit volumes and write-downs for every bank, broken down into borrower categories and maturity bands. In addition, many credit exposures can be assigned to a region. Our empirical model is essentially an intensity-based approach, as we calculate systematic factors as averages of individual write-down rates.

We show that up to 26 percent of the temporal variation of bank-specific write-down rates can be explained by four systematic components. Besides the nationwide loss rate, the portfolio composition with respect to industry and maturity is significant, as well as the borrower's region. There are, however, major differences here, depending on whether the banks are active nationally or only regionally. For nationwide banks, we find the above-mentioned explanatory power of 26 percent. The nationwide loss rate has the greatest impact here, followed by the industry composition and, finally, the maturity. It is not possible to make any statement about regional factors for these banks. For exclusively regionally active banks, the systematic factors overall have far weaker impact of only 8% and the maturity has a stronger influence than industry. The region has the smallest impact, although it is still a significant factor. The strong influence of the maturity is surprising and, to our knowledge, new in the literature.

Besides the results on the relative importance of the factors, the study provides a useful benchmark for risk managers and regulators, as it covers the German credit operations as a whole and thus an information basis which is not accessible for individual banks. We also show how our results can be used in stress tests.

Nicht-technische Zusammenfassung

Für das Ausfallrisiko von Kreditportfolios spielt eine entscheidende Rolle, wie stark die Ausfallereignisse von systematischen Faktoren abhängen, die sich auf ganze Schuldnergruppen auswirken. Je stärker der Einfluss dieser Faktoren, desto weniger nützt eine Diversifikation über viele Schuldner und desto stärker schwanken die Portfolioverluste im Zeitverlauf. Da eine Bank die Verlustschwankungen mit Eigenkapital auffangen muss, ist es sowohl für Risikomanager als auch für Regulierer entscheidend, systematische Faktoren zu identifizieren und ihren relativen Einfluss zu kennen.

Eine direkte Wahrscheinlichkeitsschätzung gemeinsamer Ausfälle verbietet sich, denn es liegt in der Natur des Kreditgeschäfts, dass Ausfälle – und umso mehr gemeinsame Ausfälle – selten auftreten. Man behilft sich in der Praxis zum einen mit sogenannten Firmenwert-Modellen, die Kredite als Derivat des (nicht beobachteten) Firmenwerts von Schuldnern begreifen. In der Regel sind die systematischen Faktoren dieser Modelle nicht beobachtbar. Zum anderen nutzt man sogenannte intensitätsbasierte Modelle. Hier definiert man systematische Faktoren, die als durchschnittliche Ausfallrate in einem Sektor (z. B. einem Industriezweig) zu einem bestimmten Zeitpunkt interpretiert werden können. Bei beiden Modelltypen muss man also die Schuldner in geeignete Gruppen einteilen, und zwar möglichst so, dass die Kopplung der Ausfälle innerhalb der Gruppe groß ist und zwischen den Gruppen klein. Dabei ist eine Einteilung in Industriezweige üblich, aber weder erschöpfend noch zwingend. Grundsätzlich können andere Kriterien der Einteilung ebenso sinnvoll sein.

An dieser Stelle setzt unsere Studie an. Wir nutzen einen Datensatz der Bundesbank, der das gesamte bilanzielle innerdeutsche Kreditgeschäft mit der Realwirtschaft von 2003 bis 2011 umfasst. Er enthält Kreditvolumina und Wertberichtigungen für jede Bank, aufgespalten in Kreditnehmergruppen und Laufzeitbänder. Außerdem können wir viele Kreditexposures einer Region zuordnen. Unser empirisches Modell ist im Grunde ein intensitätsbasierter Ansatz, denn wir berechnen systematische Faktoren als Durchschnitte individueller Abschreibungsraten.

Wir zeigen, dass bis zu 26 Prozent der zeitlichen Variation bankspezifischer Abschreibungsraten durch vier systematische Komponenten erklärt werden kann. Neben dem allgemeinen Kreditzyklus sind die Portfoliozusammensetzung hinsichtlich der Industrie und der Kreditlaufzeit von Bedeutung, ebenso wie die Region des Kreditnehmers. Dabei gibt es aber große Unterschiede abhängig davon, ob die Banken landesweit oder nur regional aktiv sind. Im Fall überregionaler Banken finden wir die erwähnte Erklärungskraft von 26 Prozent. Hier hat der allgemeine Zyklus den stärksten Einfluss, gefolgt von der Industriezusammensetzung und schließlich der Kreditlaufzeit. Eine Aussage über regionale

Faktoren ist für diese Banken nicht möglich. Für ausschließlich regional aktive Banken haben die systematischen Faktoren insgesamt einen viel schwächeren Einfluss von nur acht Prozent, und die Laufzeit hat für diese Banken einen stärkeren Einfluss als die Industrie. Die Region wirkt sich am wenigsten aus, ist aber dennoch ein signifikanter Faktor. Der starke Einfluss der Laufzeit ist überraschend und nach unserem Wissen neu in der Literatur.

Neben den Ergebnissen zur relativen Wichtigkeit der Faktoren bietet die Studie einen nützlichen Maßstab für Risikomanager und Regulierer, weil sie das gesamte deutsche Kreditgeschäft umfasst und damit eine Informationsbasis, die für einzelne Banken nicht zugänglich ist. Zusätzlich stellen wir dar, wie unsere Ergebnisse in Stresstests verwendet werden können.

Contents

The Common Drivers of Default Risk[1]

1 Introduction

The credit quality of loans is measured in credit portfolio models through systematic (common) and idiosyncratic (purely borrower-specific) factors. Although there is no standard approach for identifying the systematic component, multi-factor Merton-type credit portfolio models typically assume industry- or country-dependent, correlated systematic risk factors (see Gordy (2000), Crouhy, Galai, and Mark (2000), or Bluhm, Overbeck, and Wagner (2003) for an overview). Alternatively, in intensity-based credit portfolio models such as CreditRisk+, systematic factors represent (current) average default rates specific to certain sectors, which may be industries or countries. Conditional on realizations of the systematic factors, independent random loss rates are drawn for each sector such that their (conditional) expectations coincide with the systematic factors.

Neither of these models is easy to calibrate to real credit portfolio risk, i.e., to historic credit losses. The simple reason is that credit events are rare, and so a fortiori are *joint* credit events – what the portfolio aspect of credit risk is all about. Even in large credit portfolios, or in the universe of rated bond issuers, the number of defaults in a year is quite low; but even if one can observe a large cross-section of borrowers, in most cases the time dimension is very limited. When calibrating credit portfolio models to default data, risk managers need both a reasonable number of credit events in a period and some degree of intertemporal independence as well.

By making use of a unique proprietary data set containing all of German banks' credit related write-downs between 2003 and 2011, we are able to report on the common drivers of default risk. We use a linear model to explain write-down rates of all German banks by common factors that are nothing but averages of these rates – conditional averages, though, depending on different characteristics such as industry or maturity. This approach is related to explaining individual stock price movements by those of industrial indices. For many studies in the literature, one crucial point is that the systematic component is a latent variable. In contrast, our interpretation of systematic credit risk drivers is a simple and very direct one. Using – observable – averages as systematic drivers has the advantage that we can exploit standard econometric tools such as panel regressions.

[1]Christoph Memmel: telephone: +49 (0) 69 9566 8531, e-mail: christoph.memmel@bundesbank.de. Yalin Gündüz: telephone: +49 (0) 69 9566 8163, e-mail: yalin.gunduz@bundesbank.de. Peter Raupach: telephone: +49 (0) 69 9566 8536, e-mail: peter.raupach@bundesbank.de. All authors have the same postal address: Deutsche Bundesbank, Wilhelm-Epstein-Strasse 14, D-60431 Frankfurt am Main, Germany. The views expressed in this paper are those of the authors and do not necessarily reflect the opinions of the Deutsche Bundesbank. We thank Klaus Düllmann and participants of the research seminar at Deutsche Bundesbank for valuable discussions.

For a linear model as ours, averages also represent an optimal choice in that they have the highest-possible explanatory power among all systematic factors on the same level of aggregation.[2] While we acknowledge a similarity to intensity based models, to our knowledge no study has yet investigated the magnitude of systematic components by regressing loss rates on their averages.

We show that up to 26 per cent of the time variation in the bank-individual write-down rates can be explained through four common components. Besides the nationwide loss rate, differences in the portfolio composition with respect to the industry and the maturity are significant common drivers, as well as the region a bank operates in. The nationwide loss rate has the most impact, followed by the maturity structure, industry composition and the regional component. Nationwide active banks build the sample for which we find the maximum explanatory power of 26 per cent (i.e. the share of explained variation of a bank's credit portfolio in the time series). The corresponding explanatory power for regionally active banks is less than 8 per cent.

The contributions of this study are three-fold. First, we provide evidence on the magnitude of different systematic components in credit risk portfolios. With the help of a comprehensive data set that covers all lending to the domestic real economy, we explain the loss rate in the portfolios of German banks through common factors and identify the relative impact of these factors. We expect that quantifications of common components in our study would provide a benchmark for the credit portfolio risk literature. Second, we expect to contribute to the stress testing literature in a similar manner. The factors identified in this study can provide a starting point for researchers, practitioners, and regulators in their aim of stressing default probabilities. Third, we identify the maturity structure of the loans as an important driver of the banks' credit risk.

The following section introduces the common factors we analyze by noting down what the recent literature has suggested. Section 3 describes our data set. We derive the research questions in Section 4, test them, and deliver the results in Section 5. In Section 6, we make some remarks concerning the application of the results in stress tests. Section 7 concludes.

[2]When aggregation is undertaken on any certain level, e.g., industries, an alternative industry specific systematic factor would be a random variable that is constant throughout all borrowers within one industry. Regressing loss rates on any such factor cannot result in a higher explanatory power than regressing on the industry specific average loss rate. This is simply because the latter is a conditional expectation of the dependent variable; conditional expectations are well-known to minimize the squared errors among all variables on the same level of aggregation.

2 Drivers of credit risk

With the help of our data set, we can analyze four factors of credit portfolio risk: the time dimension of the credit cycle, which we choose to capture by the nationwide loss rate; the industry composition; the loans' maturity structure; and the regional allocation of the loans. Our analysis will be based on understanding the effects of these systematic factors on loan losses. Among different loss types, we will focus on loan write-downs throughout the study, unless otherwise specified.[3]

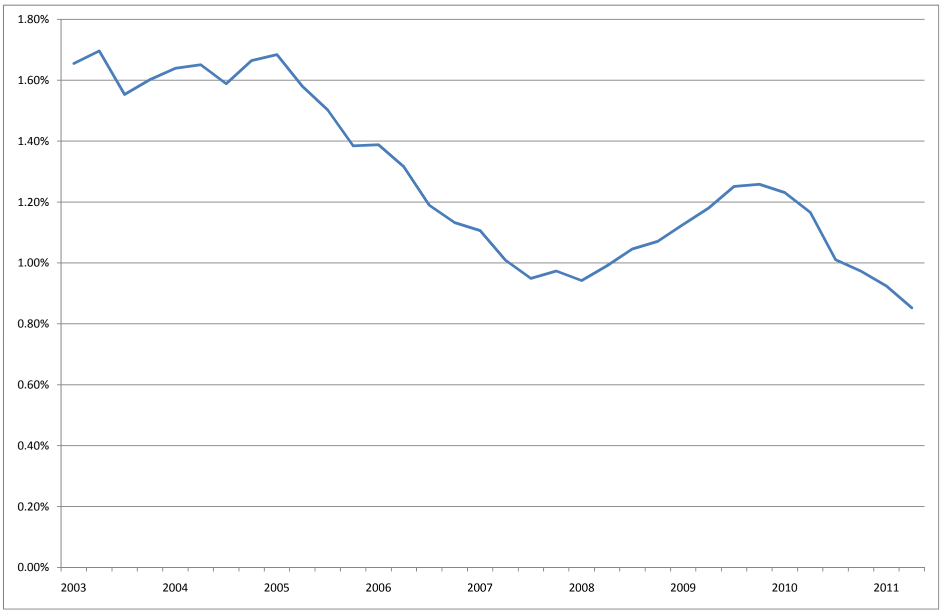
2.1 Credit cycle

The stage of the economy's credit cycle drives the (gross) write-downs in the banks' credit portfolio. Recessions and financial crises lead to peaks in the write-downs, whereas boom phases are characterized by troughs (see Figure 1). By building a macro-econometric model linked to credit portfolio changes, Pesaran, Schuermann, Treutler, and Weiner (2006) show that the interrelationship between credit cycles and firms is the main driver of defaults. Similarly, by analyzing the Italian banking industry, Quagliariello (2007) finds that loan-loss provisions, non-performing loans and return on assets follow credit cycles. Liu and Ryan (1995) document that the ratio of write-downs to outstanding loans may vary widely for commercial loans from period to period due to economic conditions.

Ivashina and Scharfstein (2010) document how the financial crisis of 2008 affected the credit supply to the corporate sector. They show that lending fell across all types of syndicated loans. They suggest that not only the credit supply fell; the recession has likely decreased the credit demand. Our German data set shows an increase in the write-down/credit ratio during the crisis period, compared to earlier years. However, the relative highs of the 2003–2005 period were not attained during the financial crisis. This may be due to the resiliency of the German real economy. In contrast to other European countries, the German real economy recovered rather quickly after the severe recession of 2009, perhaps due to its strong production sector and the strong growth in its main Asian export markets. While the gross credit amount has mostly remained stable, the gross volume of write-downs has only slightly increased. In the end, the write-down/credit

[3]Liu and Ryan (1995) recognize the following distinguishing classification for loan-loss measures: First, loan-loss reserves (when a percentage of loans are judged to be uncollectible, the book value of assets may be reduced by debiting the loan-loss provision expense account and crediting the loan-loss reserve or so-called allowances account, which are counter-assets to loans). Second, loan-loss provisions (as an expense item as described above). Third, non-performing loans (Liu and Ryan suggest that loan defaults are anticipated by changes in non-performing loans two years prior. They could be viewed in three categories: (i) Loans more than 90 days past due, (ii) restructured debt, and (iii) foreclosed real estate). Fourth, loan write-downs (they are accounting adjustments which decrease the asset item outstanding loans and the allowance).

Figure 1: Gross loan write-downs of the German real economy



Note: Period 2003Q3–2011Q4; moving average over four quarters (current and the three preceding quarters); all German borrowers (excluding MFIs and government, long-term mortgage loans only included for private households); per annum, approximated gross write-downs.

ratio levels during the crisis remained lower than between 2003 and 2005, the period when German growth was anemic (see Figure 1).

Among the various ways a credit cycle can be defined, our approach is very direct: we identify it by the nationwide average loss rate in our sample's credit portfolio. When trying to (partly) explain bank-individual loss rates by a national average of the explained variables, we get close to the maximum explanatory power one can achieve by any single nationwide factor, at least within the class of linear models. In this sense, more commonality than the one we capture by our nationwide average is not to be expected from global factors in other specifications.

2.2 Industry composition and regional differences

Credit portfolio models have traditionally had the tendency to model the systematic risk factor through industry dependence, country of the borrower and through correlation matrices (Düllmann and Masschelein (2007)). However, relatively few studies have tried to quantify the effects of industry and regional composition in a *joint* statistical analysis, at least not on the level of sub-national regions. In their recent study, Aretz and Pope (2011) look at how default risk varies across countries and industries. The authors realize that country effects should prevail over global effects on default risk, since it is shown to be highly negatively correlated to equity returns (Griffin and Karolyi (1998)). Aretz and Pope are able to show how global and industrial variables affect changes in default risk. Country effects account for 38% of the systematic variation in changes of the credit risk implied by the structural model. Interestingly, relatively open market economies depend less on country factors and more on global factors. On the other hand, changes in default risk in relatively local industries load more effects on country factors than the relatively more globally open industries do. Our analysis further provides a proportional weight of the borrower's industry and its region within Germany among all observed systematic factors. Instead of analyzing on a country level, we show that a regional breakdown of credit risk within a country should be accounted for.

2.3 Maturity

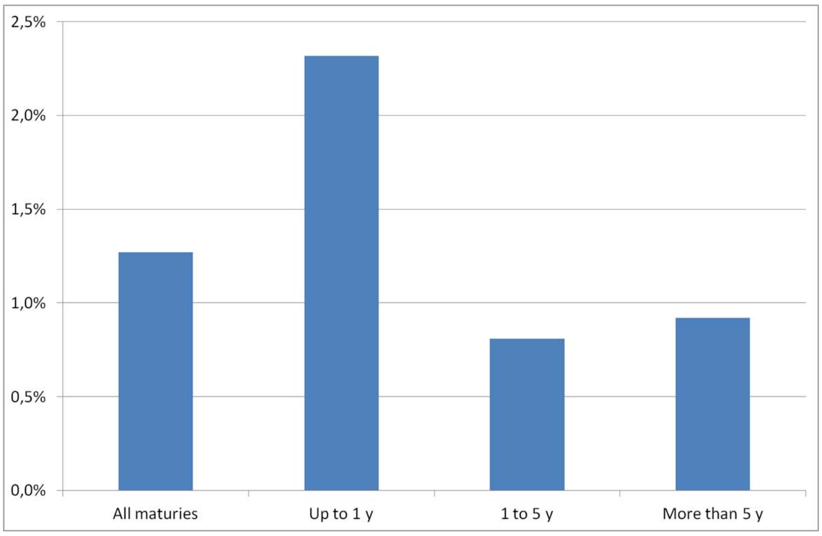
The maturity composition of a firm's debt may reflect its creditworthiness. Flannery (1986) discusses in a theoretical model different settings (especially concerning asymmetric information and transaction costs) and shows that a high-quality firm can use the maturity structure of its debt to signal its high creditworthiness. However, in the model, there is no monotonic relationship between the firm's creditworthiness and the maturity of its debt. Diamond (1991), as well, does not find such a monotonic relationship in his theoretical model. Rey and Stiglitz (1993) develop a model where (albeit in the case of bank funding) short-term contracts are used as a monitoring device (in this case of a bank) by means of the simple threat to withdraw funds if things go bad. Again, there is no simple relationship between risk and optimal maturity.

In our data, however, we see a huge difference regarding the calculated loss rates in the different maturity brackets (see Figure 2): It looks as if short-term debt (debt with an initial maturity of up to one year) is much more likely to default than medium and long-term debt. This pattern is true for all industries. The reasoning behind this can be manifold.

First, when the creditworthiness of a firm deteriorates, the firm is likely to draw on its credit lines. This increases the firm's short-term debt. In the event that the firm later actually gets into distress, the additional short-term debt needs to be written down by the respective bank (in addition to the original debt). We do not have data on credit lines; therefore this hypothesis cannot be analyzed with our data.[4] However, a result of Norden and Weber (2010) backs this hypothesis. Using data from an internationally active

[4]Credit lines constitute a substantial part of corporate debt. Sufi (2008) mentions that U.S. public firms maintain over 80% of their bank financing through credit lines, and Kashyap, Rajan, and Stein (2002) indicate credit lines to account for 70% of bank borrowing for U.S. small firms. In contrast, Jimenez, Lopez, and Saurina (2009) report them to constitute only 42% of bank financing for Spanish firms.

Figure 2: Gross loan write-downs of the German real economy, broken down by maturities



Note: Period 2003Q3–2011Q4; all German borrowers (excluding MFIs and government, long-term mortgage loans only included for private households); initial maturities; per annum, approximated gross write-downs.

German bank, they find that institutional and retail borrowers who later default gradually increase the usage of their credit lines. Similarly, Jimenez et al. (2009) show that in the year of default, the average credit line usage of defaulting Spanish firms is 75% larger than of non-defaulting firms. In the appendix, we formalize this argument and show that, indeed, the calculated loss rate for short-term debt may be higher than the one for long-term debt even if both types of debt are equally risky in terms of default probability and loss-given-default. In order to check whether the effect described in the model could have the same magnitude as the observed effect at all, we perform an estimate of undrawn credit lines based on supervisory data, which we cannot report due to confidentiality reasons. The outcome suggests that a full use of credit lines before default would be consistent with loss rates of short-term credit being three times larger than the other loss rates, under the assumption that default risk and loss-given-default are the same for all maturities. Although the observed magnitude indicates an increase by factor three, it is unlikely that *all* firms draw on *all* credit lines before default. We conclude that drawing credit lines can make up a substantial part of the differences in the loss rates, while acknowledging that other sources are present as well.

Second, while in the theoretical papers cited above the debt contracts are negotiated in a competitive market with many participants, and especially with bond investors or lenders that cannot easily coordinate, the SME-dominated corporate loan market in Germany may look a bit different. It is more plausible that the power to design the characteristics of loan contracts is often in the hands of the banks. For them, the option to withdraw funds at an intermediate step of a debt-financed project is an option that is worth more if uncertainty about the project's outcome is higher. Uncertainty does not only concern the pure default event but also the value of the borrower's assets, or collateral, which may have changed more as more time has gone by. In this case, we would expect that banks primarily grant short-term loans for risky projects.

Third, an argument brought forward by bank practitioners why they require interest payments at all, as opposed to zero-coupon loans, is that the obligation to pay interest is a simple test whether the borrower is able to pay back anything at all. Two subsequent short-term contracts can be seen as just a more radical variant of this. According to anecdotal evidence, bank practitioners follow a rule of thumb that long-term loans are given only to either secure borrowers or if secure collateral is pledged. This rule is confirmed by Kirschenmann (2010) who compares loan applications with loan grants. She finds restricting loan maturity to be complementary to restricting loan size and both to be used more frequently as information asymmetry between borrower and lender increases. If information asymmetry is associated with credit risk, we should observe short-term loans to default more often than on average.

Fourth, it is also possible that we observe a difference between recovery rates of long-term vs. short-term loans rather than a difference in default rates. A possible explanation is the presence of trade credit in the short-term bucket. While the bank may hold a blanket assignment on its borrower's stock of merchandize as a collateral against the credit line, that claim is actually junior to that of the borrower's suppliers, which renders collateral of that kind worth less than, for instance, real estate or similar goods being pledged in project finance, which tends to be long-term.

While we find the highest loss rates for short-term loans, there is mixed evidence in the literature about the relationship between maturity and credit risk. On the one hand, Dennis, Nandy, and Sharpe (2000) find that the maturity of revolving loans is the shorter the less secured the loan is, the lower the borrower's Z-score, the higher its earnings variance or its leverage, and the smaller the firm. All such changes are associated with rising credit risk, and so our finding confirms that of Dennis et al. (2000). In contrast, Kirschenmann and Norden (2012) find the opposite effect for a set of loans to German SMEs, i.e., the worse the internal rating is, the longer is the maturity. A one-step rating difference on a five-step scale causes a relative maturity difference of 10 to 80 percent, on average.

To account for the significantly higher loss rate of short-term debt, we make use of the maturity breakdown in our data set when we explain the actual loss rate of a bank's loan portfolio.

2.4 Other factors

Naturally, qualitative factors such as corporate governance could also come into picture when discussing asset quality. Berger and DeYoung (1997) relate higher levels of non-performing loans to reductions in cost efficiency through Granger causality tests. In the opposite direction, low levels of cost efficiency Granger-cause higher non-performing loans, indicating bad management of banks. Besides, the concentration in the credit portfolio seems to impact the bank's write-downs in its credit portfolio (See Behr, Kamp, Memmel, and Pfingsten (2007), Böve, Düllmann, and Pfingsten (2010)). The reasoning behind this is that concentrated banks build industry-specific knowledge and that this knowledge outweighs foregone benefits from diversification, i.e., that banks with a concentrated credit portfolio exhibit lower loss rates. Another determinant seems to be the credit growth in the past. Foos, Norden, and Weber (2010) show that banks having exhibited an excessive credit growth in the past suffer from higher loss rates in the present. This effect may be owing to lowered credit standards that often go hand in hand with excessive credit growth.

We refrain from including these factors in our analysis, and aim to capture them through bank-specific fixed effects. To do so is only justified under the assumption that these factors do not change much in the course of time.

3 Data

Every bank in Germany has to report its credit exposure to the German real economy. Each quarter, the Bundesbank's borrowers statistics collect this data, broken down into different brackets of initial maturity, different industries, and groups of retail borrowers. Since the fourth quarter of 2002, these statistics have also included the valuation changes of these positions, i.e. the (net) write-downs.[5] In Table 1, we name the industries and sectors into which the lending is broken down. Loans to enterprises, which account for 70.3% of lending to German borrowers, are divided into 23 industries. Lending to private households (29.0%) consists of three types, one of which is housing loans. Additionally, there are loans to non-profit organizations (0.7% of lending). In addition, exposure and write-downs (for each industry) are broken down into three maturity brackets according to the initial maturity. The brackets are: up to one year, over one year and up to five years, and more than five years. All in all, there are $81 = (23 + 3 + 1) \times 3$ subportfolios.

Savings banks and cooperative banks operate in the region around their location. The

[5] According to Deutsche Bundesbank (2009, p. 148), we understand write-downs and write-ups as "valuation [...] changes caused by individual value adjustments and any write-downs/write-ups of non-performing debt".

Table 1: Break-down of the banks' lending into German borrowers (excluding MFIs and government, long-term mortgage loans only included for private households). Average share and average approximated gross write-downs (per annum) for the period 2003–2011.

Item	Borrower	Share of lending	Gross write-downs (p.a.)
Enterprises (excluding long-term mortgage loans)		70.3%	1.35%
1	Agriculture, forestry, fishing and aquaculture	1.7%	0.73%
2	Electricity, gas and water supply; refuse disposal, mining and quarrying	4.4%	0.38%
—	Manufacturing	10.2%	2.00%
3	Chemical industry, manufacture of coke and refined petroleum products	0.9%	0.97%
4	Manufacture of rubber and plastic products	0.6%	1.98%
5	Manufacture of other non-metallic mineral products	0.4%	2.16%
6	Manufacture of basic metals and fabricated metal products	1.7%	1.92%
7	Manufacture of machinery, equipment, and transport equipment; repair and installation of machinery and equipment	2.4%	2.20%
8	Manufacture of computer, electronic and optical products	1.0%	2.08%
9	Manufacture of wood, wood products, pulp, paper and paper products, printing; manufacture of furniture...	1.6%	2.57%
10	Textiles, apparel and leather goods	0.3%	3.01%
11	Manufacture of food products and beverages; manufacture of tobacco products	1.3%	1.38%
12	Construction	2.7%	2.59%
13	Wholesale and retail trade; repair of motor vehicles and motorcycles	8.3%	1.60%
14	Transportation and storage; post and telecommunications	4.3%	0.94%
15	Financial intermediation (excluding MFIs) and insurance companies	8.5%	0.21%
—	Services (including self-employment)	30.4%	1.46%
16	Housing enterprises	4.8%	1.57%
17	Holding companies	3.4%	1.38%
18	Other real estate activities	7.6%	1.60%
19	Hotels and restaurants	1.0%	2.76%
20	Information and communication; research and development; membership organizations; publishing activities; other business activities	4.3%	1.60%
21	Health and social work (enterprises and self-employment)	3.8%	0.85%
22	Rental and leasing activities	1.9%	0.56%
23	Other service activities	3.6%	1.65%
Private households		29.0%	1.09%
24	Instalment loans (excluding housing loans)	11.8%	1.07%
25	Other loans (excluding housing loans)	5.4%	2.30%
26	Housing loans	11.8%	0.62%
Non-profit institutions (excluding long-term mortgage loans)		0.7%	0.38%
27	Non-profit institutions	0.7%	0.38%
All German borrowers (without MFIs and government)		100%	1.27%

same is mainly true for the regional private commercial banks. For these banks, which we summarize in the group *regional banks*, we take into account the bank's postcode area. Germany is divided into 10 postcode areas, each of which contains around one-tenth of the German population. These areas are much more similar in population numbers than, for instance, the 16 states *(Bundesländer)* of Germany. The rest of the banks are assumed to operate nationwide, especially the big banks and the central institutes of the savings banks and cooperative banks, but also mortgage banks and building societies.

We moderately correct for outliers by removing observations below the 1st percentile of the bank-wide loss rate. Table 2 shows the distribution of the bank-wide yearly loss rate, broken down into nationwide, regional banks and subsamples of five different classes of portfolio size. Looking at different sizes, we do not see a monotonic relationship between size and loss rate. The banks in the middle out of five classes, i.e. the regional banks with medium portfolio size, have the highest loss rates. Even when we look at the tails (1st and 5th percentile), the banks with the smallest portfolio (and thus with the least possibility of risk diversification) do not show the highest risk.
Note that the changes of valuation in our data set are given as net write-downs. To obtain the corresponding gross write-downs, we perform the following approximation: If the change in value for a given bank, quarter, industry, and maturity bracket is negative (gross write-downs exceed write-ups), we take this value; otherwise – i.e., if the write-ups exceed the write-downs – we set the value to zero. Note that a value different from zero is likely to stem from only a small number of loans.[6]

4 Empirical model

In principle, we compare bank i's actual loss rate $q_{t,i}$ of its credit portfolio in period t with the corresponding loss rate $hq_{q,i}$ of what we call an *index portfolio.* The portfolio has the same industry (ind) and maturity (mat) composition as the actual portfolio of bank i, but the loss rates for the different industries and maturities are averages over the whole German economy. The portfolio behaves as if it consisted of credit indices, which are maturity- and industry specific; we therefore call it the *IM-index portfolio.* In all, there are $81 = 27 \times 3$ subportfolios, each of which has a weight $w_{t,i,j,k}$ relative to the whole credit portfolio of bank i (see the appendix for further information). The loss rate

[6] The firm credit portfolio is broken down into 23 industries, each of which is divided into three maturity brackets. Observing write-downs quarterly, we have 276 (= 23 x 3 x 4) reporting items per bank and year. Assume that the bank holds 27,600 uniform loans that are spread equally over the 69 subportfolios, and assume that one out of 100 loans becomes distressed in a year, then we would expect only one distressed loan per reporting item.

Table 2: Bank-wide loss rate (per annum, approximated gross write-downs) of the credit portfolio to German borrowers (excluding MFIs and government, long-term mortgage loans only included for private households), period 2003–2011.

Banks	Nobs	Percentile			
		1st	5th	10th	Median
Nationwide	432	–4.64%	–2.82%	–1.87%	–0.36%
Regional	9,936	–5.11%	–3.42%	–2.65%	–1.04%
1st size quintile	1989	–5.04%	–3.51%	–2.70%	–0.94%
2nd	1,989	–5.08%	–3.46%	–2.70%	–1.03%
3rd	1,989	–5.35%	–3.75%	–2.89%	–1.09%
4th	1,989	–4.67%	–3.15%	–2.55%	–1.04%
5th	1,980	–5.28%	–3.20%	–2.43%	–1.06%
All banks	10,368	–5.11%	–3.41%	–2.63%	–1.01%

$hq_{t,i}^{ind\times mat}$ of bank i's IM-index portfolio at time t calculates as

$$hq_{t,i}^{ind\times mat} = \sum_{j=1}^{27}\sum_{k=1}^{3} w_{t,i,j,k} \cdot Q_{t,j,k}^{ind\times mat} \tag{1}$$

where $Q_{t,j,k}^{ind\times mat}$ is the nationwide loss rate with respect to time t, industry j and maturity bracket k. By definition, we can decompose the loss rate of the IM-index portfolio into three factors:

$$hq_{t,i}^{ind\times mat} = Q_t + \Delta hq_{t,i}^{ind} + \Delta hq_{t,i}^{mat} \tag{2}$$

where Q_t is the nationwide loss rate of the entire credit portfolio in time t,

$$\Delta hq_{t,i}^{ind} \equiv hq_{t,i}^{ind} - Q_t \tag{3}$$

and

$$\Delta hq_{t,i}^{mat} \equiv hq_{t,i}^{ind\times mat} - hq_{t,i}^{ind}. \tag{4}$$

The first summand Q_t in Equation (2) is our measure of the stage in the nationwide credit cycle. In (3), $hq_{t,i}^{ind}$ is the loss rate of an *I-index portfolio* where loss rates are industry-specific (but not maturity-specific) nationwide averages.[7] The variable $\Delta hq_{t,i}^{ind}$ gives the differences in the loss rate of the IM-index portfolio that are due to bank i's deviations in the industry composition while $\Delta hq_{t,i}^{mat}$ does the same for the maturity structure.

The three determinants on the right-hand side of (2) are included in our empirical model. In addition, we include the variable $\Delta Q_{t,R(i)}^{reg}$ which is the difference between the

[7] see (22) in the Appendix for a detailed description

loss rates in the postcode area $R(i)$ where bank i is located, and the nationwide loss rate. This difference is set to zero for banks that operate nationwide.

$$q_{t,i} = \beta_0 + \beta_1 Q_t + \beta_2 \Delta hq_{t,i}^{ind} + \beta_3 \Delta hq_{t,i}^{mat} + \beta_4 \Delta Q_{t,R(i)}^{reg} + \varepsilon_{t,i} \tag{5}$$

In principle, the coefficients β_1 to β_3 should be equal to one, because the nationwide loss rates for the index portfolios are the weighted average of the loss rates of the individual banks. However, there are three arguments for coefficients being different from one: First, the regression is unweighted, whereas the nationwide loss rates are weighted averages; the banks with the largest portfolio have a market share of up to six percent, whereas the median market share is 0.01%, while each bank gets the same weight in the regressions, irrespective of the size of its credit portfolio. Second, we investigate subsamples, and banks in different subsamples may behave differently from the whole sample. Third, in the regressions we choose only those banks that remain in the sample for the whole period from 2003 to 2011, whereas the nationwide loss rates are calculated using all banks that were active in a given year.

The error term $\varepsilon_{t,i}$ deserves to be investigated. It can be broken down into two components: a time-invariant fixed effect and an idiosyncratic shock. The bank-specific fixed effect may be due to unobserved time-invariant effects, such as the efficiency of internal processes or the ability of the staff or management. The time-varying unexplained rest is therefore the component normally referred to as the idiosyncratic risk, meaning idiosyncratic to the bank, not to its loans. Standard econometric tools make it possible to state the relative importance of these two components.

5 Results

5.1 Determinants of the loss rate

We estimate Equation (5) for the whole sample and for the subsamples of nationwide and regional banks. The results are displayed in Table 3. The nationwide factor, the industry composition, the maturity structure and the regional factor are all positive and are all highly significant, for the whole sample as well as for the subsamples of the nationwide and regional banks. Given the econometric setting, these results are not surprising. The four determinants explain about 8% of the serial variation and about 13% of the cross-sectional variation of the bank-wide loss rate of the portfolio of the loans to the German real economy. For the subsample of the nationwide banks the share of explained variation is considerably higher: 26% and 31%, respectively. But note that even for these banks 74% of the time-series variation and 69% of the cross-sectional variation of the loss rate remains unexplained and seems to be due to idiosyncratic effects. By looking at the rather low

Table 3: Bank-wide loss rate as the dependent variable. Robust standard errors. *** denotes significance at the 1% level; period 2003–2011, yearly data; Q is the nationwide credit loss rate, *dhqind* is deviation due to the industry composition (bank-specific), *dhqmat* is the corresponding deviation from the maturity structure (bank-specific) and *dQreg* is the deviation of the loss rate in a bank's postcode area (only for regional banks).

Variable	Bank-wide loss rate $q_{t,i}$		
	All banks	Nationwide banks	Regional banks
Q	0.738***	1.195***	0.716***
	(0.041)	(0.203)	(0.042)
dhqind	0.648***	0.978***	0.606***
	(0.085)	(0.218)	(0.091)
dhqmat	0.810***	0.998***	0.827***
	(0.129)	(0.483)	(0.134)
dQreg	0.157***		0.156***
	(0.049)		(0.049)
constant	–0.002***	0.005***	–0.003***
	(0.001)	(0.002)	(0.001)
R-sq (w)	7.9%	26.4%	7.5%
R-sq (b)	12.6%	31.3%	9.6%
R-sq (o)	9.7%	28.9%	8.2%
Nobs	10,368	432	9,936
Nobanks	1,152	48	1,104

impact of systematic factors, it could have been concluded that banks smooth their write-downs through time, in order to make their earnings appear less volatile. However, Section 340f of the German Commercial Code provides them with a simpler and more efficient tool to achieve this (Bornemann, Kick, Memmel, and Pfingsten (2012)). Therefore, we do not believe that German banks manipulate write-downs for earnings management on a large scale.

For the nationwide banks, the coefficients are not statistically different from one: i.e. an increase of 1 bp in the nationwide loss rate translates into an increase of about 1 bp in the bank's credit portfolio loss rate. The same is true for the variables regarding the industry composition and maturity structure. By contrast, for the regional banks, the coefficients are significantly smaller than one, indicating that these banks are less exposed to nationwide developments; this interpretation is also backed by the smaller coefficients of determination.

In Table 4, we show the regression results broken down into size quintiles. The size of the estimated coefficients and the coefficients of determination are partly monotonic. This is especially true for the nationwide factor Q and the within R-squared. This monotonicity

Table 4: Bank-wide loss rate as the dependent variable. Robust standard errors in brackets; ***, **, * denote significance at the 1%, 5%, 10% level; period 2003–2011, yearly data; Q is the nationwide credit loss rate, *dhqind* is deviation due to the industry composition (bank-specific), *dhqmat* is the corresponding deviation from the maturity structure (bank-specific) and *dQreg* is the deviation of the loss rate in a bank's postcode area (only for regional banks).

Variable	All regional banks	Size quintile				
		1st	2nd	3rd	4th	5th
Q	0.716***	0.572***	0.635***	0.728***	0.806***	0.891***
	(0.042)	(0.094)	(0.101)	(0.101)	(0.085)	(0.085)
dhqind	0.606***	0.224	0.371*	0.759***	1.020***	0.962***
	(0.091)	(0.191)	(0.198)	(0.222)	(0.194)	(0.215)
dhqmat	0.827***	0.596**	0.725***	1.260***	0.815***	1.151***
	(0.134)	(0.283)	(0.278)	(0.355)	(0.270)	(0.288)
dQreg	0.156***	0.036	0.244***	0.220*	0.039	0.378***
	(0.049)	(0.102)	(0.098)	(0.125)	(0.108)	(0.100)
constant	-0.003***	-0.004***	-0.004***	-0.003***	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R-sq (w)	7.5%	4.0%	6.1%	9.1%	10.2%	12.8%
R-sq (b)	9.6%	6.2%	15.6%	12.1%	4.1%	10.6%
Nobs	9,936	1,989	1,989	1,989	1,989	1,980
Nobanks	1,104	221	221	221	221	220

with respect to the five size quintiles gives much stronger evidence than, for instance, the significance of a variable for portfolio size. For the 20 percent of the regional banks with the smallest credit portfolio, the sensitivity to the nationwide factor is 0.572 increasing monotonously to 0.891 for the 20 percent of the regional banks with the largest credit portfolio, i.e. the sensitivity for the largest regional banks is more than 50 percent higher than the one for the smallest regional banks.

We analyze the relative impact of the different determinants by calculating the effect of a one-standard-deviation change in the exogenous variables, i.e. the standard deviation of the exogenous variable in the (sub)sample is calculated and then multiplied by the respective estimated coefficient. In Table 5, we present these results. Looking at the whole sample, we see that the nationwide loss rate is the determinant with the greatest impact, followed by the maturity structure, the industry composition and the regional factor. When we investigate the subsample of nationwide banks, we find two main differences compared with the whole sample, which is heavily dominated by the regional banks. First, the impacts of the single determinants are much higher for the nationwide banks than for the regional banks. This finding is in line with the higher estimated coefficients

Table 5: Impact of the different explanatory variables on the loss rate of the credit portfolios (estimated coefficient multiplied by standard deviation of explanatory variable in the (sub)sample [in percent]); period 2003–2011, yearly data; Q is the nationwide credit loss rate, *dhqind* is deviation due to the industry composition (bank-specific), *dhqmat* is the corresponding deviation from the maturity structure (bank-specific) and *dQreg* is the deviation of the loss rate in a bank's postcode area.

Variable	Impact on loss rate		
	All banks	Nationwide banks	Regional banks
Q	0.215	0.348	0.208
dhqind	0.127	0.349	0.107
dhqmat	0.140	0.237	0.139
dQreg	0.069		0.070

(as shown in Table 3). Second, for the nationwide banks, the industry composition is the most important determinant, even slightly more important than the nationwide loss rate. A complementary analysis where we selectively remove single explanatory variables and compare the within R-squared of the reduced equations gives the same ranking of importance.

The unobserved time-invariant bank-specific effects (fixed effects) account for a bit more than one-third of the variance of the banks' loss rate (nationwide banks: 35.6%, regional banks: 36.4%).

5.2 Robustness checks

Table 2 shows that the distribution of the bank-wide loss rate is far from a normal distribution. As the least squares method is best suited for this distribution, the relatively low R-squared may be explained by the non-normal distribution of the dependent variable. To further investigate this issue, we transform this variable into a uniform variable using the empirical cumulative density function and apply the inverse of the normal cumulative density function, which yields a normally distributed variable. If we use this variable as the dependent variable, the R-squared remains qualitatively the same (a bit lower within R-squared and a bit higher between R-squared).

In our study, we use an approximation for the gross write-downs. Instead, when we turn to the net write-downs, the results remain qualitatively the same; however, the R-squares, especially the *within* R-squared, go down. This finding may be an indication that the gross write-downs are carried out in a timely manner, whereas the write-ups take place with less timely connection.

In Section 4, we break down the loss rate of the *IM-Index portfolio* into the nationwide loss rate Q_t and the industry- and maturity-specific components (see Equations (2) to (4)), i.e. the industry breakdown comes before the breakdown for maturities. Here, we find that, for the whole sample, the maturity has a greater impact than the industry factor. When we switch the order of the breakdowns (first, as before, the nationwide loss rate, then, the maturity breakdown, and finally the industry breakdown), the impact of the maturity factor becomes even stronger. For the nationwide banks, we even find that the industry factor is now less important than the maturity factor. Taking these results together, we can say that the maturity composition has a greater impact on the loss rate than the industry composition.

In a further check, we replace the variable for the regional differences by one of several macro-economic variables on district level (Landkreise), which exhibit time-series and cross-sectional variation. These macro-economic variables include – among others – the GDP, the GDP per capita and the GDP growth rate.[8] Only one of these alternative variables (about 20) has turned out to be significant, but even in this case the share of explained variation is lower than in the case with the original variable.

Finally, we estimate the relationship between the actual and the hypothetical loss rate separately for each year. The estimated nine coefficients fluctuate around one, as theory predicts. There does not seem to be a time tendency, and we do not observe especially low or high coefficients in times of crises.

6 Application to stress testing

To perform top-down stress tests, three components are needed: (i) suitable banking data, (ii) a path for the dynamics of the (stressed) risk factors and (iii) a model that links the banking data with the risk factors (satellite models). Creating a meaningful stress scenario (as mentioned in (ii)) is beyond the scope of this paper. Instead, we make some remarks concerning the linkage of risk factors to the banking data. Usually, the risk factors are macro variables such as interest rates, GDP growth and unemployment rate. What we need is a mapping of such macro variables to industry-specific loss rates:

$$Q_{t,j} = \alpha_j + \beta_j' F_t + \varepsilon_{t,j}, \tag{6}$$

where $Q_{t,j}$ is the (nationwide) loss rate of industry j, F_t is the vector of risk factors and β_j is the vector with the corresponding elasticities. Equation (6) is estimated for each of the 27 industries, using quarterly instead of yearly observations (2003Q3–2012Q1). Due to the limited number of observations (even if we use quarterly data, there are only 35

[8] The variables were only available up to the year 2010; to make the results comparable, we skipped the year 2011 in the original sample.

Table 6: Coefficients of determination (R-squared) for different methods to explain the bank-wide loss rate. The *Benchmark* method consists in using an index composed of the actual nationwide industry specific loss rates and the bank-specific portfolio weights. The second method *(Estimated default rates)* corresponds to the *Benchmark* method, the difference being that the nationwide industry-specific loss rates are replaced by their estimates from two macro factors, and the third method *(Cross-sectionally constant loss rates)* is to apply the two macro factors directly.

Banks	R-squared	Benchmark	Estimated default rates	Cross-sectionally constant loss rates
All	within	6.8%	6.0%	5.1%
	between	9.5%	9.9%	0.0%
Nationwide	within	22.7%	23.0%	15.4%
	between	34.6%	33.6%	0.0%
Regional	within	6.3%	5.6%	4.8%
	between	6.1%	6.5%	0.0%

observations), we restrict ourselves to two macro variables: the industrial production in Germany and the unemployment rate. We choose the combinations of lags (zero to four) for these two variables that minimize the sum of the squared residuals, under the condition that the estimated sensitivities have the economically sensible sign (otherwise, they are set to zero).

We compare three different methods to explain the bank-individual loss rates. The first one consists in applying the actual observed values $Q_{t,j}$. This is our benchmark case and has been used in the previous parts of this paper (here we abstain from the additional breakdown in maturities). The second method is to replace the actual loss rates by the estimated coefficients of Equation (6), and the third method consists of using the same α and β coefficients for each industry in Equation (6), so that the regressors $Q_{t,j}$ have no cross-sectional variation. In Table 6, we give the coefficients of determination (R-squares) for the three different methods. Note that the R-squares of the benchmark method are not equal to those reported in Table 3 because here we neglect the maturity breakdown and the regional factor.

When we compare the benchmark method with the method of the estimated default rates, we see that there is a loss in the explanatory power, but that this loss, however, is limited. Therefore, we are able to link the macro variables to the loss rates in the credit portfolio.

7 Conclusion

We make use of a detailed data set on the credit risk of the German real economy. Investigating the common factors, we find that nationwide credit loss rate, industry composition, maturity structure and regional factors have a significant impact on the banks' loss rate in the credit portfolio. Interestingly, the maturity structure turns out to be an important driver of credit risk, especially for regional banks. Between nationwide and regional banks, there is a huge difference in the explanatory power of the common factors. Whereas more than a quarter of the time variation in the loss rate of nationwide banks is explained by common factors, they only account for less than eight percent of this variation for regional banks. Breaking down the regional banks into size quintiles, we see a monotonic increase in the sensitivity to common factors. However, even for the largest 20 percent of the regional banks, the common factors explain less than 13 percent of the time variation, i.e. this is less than half of the explanatory power of the common factors for nationwide banks.

Our results are also important for stress tests of banks' credit portfolios. However, to be able to properly use the results for this purpose, the common factors have to be linked to factors common in macro stress tests, such as GDP growth, interest rates, or unemployment. Our analysis shows that the link can be established without losing too much explanatory power.

Appendix I: Impact of credit lines on the short-term loss rate

This model is to show that the calculated short-term loss rate can be higher than the long-term loss rate, on average, although we assume that short-term debt is not riskier than long-term debt. The higher loss rate for short-term debt is owing to credit lines that are drawn in the event that the firm's creditworthiness deteriorates.

To analyze this seemingly paradox result, we investigate a simple two-period model. In period 1, the firm either draws its credit line (volume c, probability p_c) or not. In period 2, the firm either defaults or not. The default probabilities are PD_c in case credit lines have been drawn or PD_{nc} in case they have remained undrawn. The volume of short-term debt (before credit lines are drawn) is s, for long-term debt it is l.

When we investigate a large number of borrowers (and, for the sake of simplicity, assuming independence among the borrowers and homogeneity concerning their borrowing and probability of default), the exposure and the write-downs (per bank) converge in probability to the respective expectations. The expected volume of short-term debt (after the decision about the drawing of the credit lines) is:

$$ev_s = s + p_c \cdot c \tag{7}$$

The corresponding expected write-downs are (assuming a loss-given-default of 100%, without loss of generality):

$$wd_s = p_c \cdot PD_c \cdot (s + c) + (1 - p_c) \cdot PD_{nc} \cdot s \tag{8}$$

In this paper, we calculate the loss rate as the quotient of write-downs and the exposure, i.e.

$$Q_s = \frac{wd_s}{ev_s} \tag{9}$$

The corresponding terms for the loss rate of long-term debt are:

$$Q_l = \frac{wd_l}{ev_l} \tag{10}$$

with

$$ev_l = l \tag{11}$$

and

$$wd_l = p_c \cdot PD_c \cdot l + (1 - p_c) \cdot PD_{nc} \cdot l \tag{12}$$

Rearranging the terms for Q_s and Q_l, we see that the statement $Q_s > Q_l$ is equivalent to the statement $PD_c > PD_{nc}$, meaning that borrowers who have drawn their credit lines are more likely to default than borrowers who have not drawn their credit lines. This is exactly what Norden and Weber (2010) found in their empirical study. In other words, given equal riskiness of short- and long-term debt: if we assume that borrowers with deteriorating creditworthiness are more likely to draw on their credit lines, then we expect the loss rate of short-term debt in our data to be higher than for long-term debt.

Note: We acknowledge that the assumption "borrowers who have drawn their credit lines are more likely to default" does not have exactly the same meaning as "borrowers with deteriorating creditworthiness are more likely to draw on their credit lines". However, we can show that the model presented here is equivalent to a three-period model where the probability of default either rises or falls in the first period, after which borrowers, if the PD is high, draw their credit lines with higher probability than if the PD is low; in the third period, default occurs at the probability set in the first period. This – equivalent – model is more cumbersome to present and therefore skipped.

Appendix II: Notation

Exposure: $x_{t,i,j,k}$ is the accounting value (in euro) of loans of bank i to industry j in maturity bracket k in time t.

Bank-wide exposure:

$$x_{t,i} := \sum_{j=1}^{27} \sum_{k=1}^{3} x_{t,i,j,k} \tag{13}$$

Industry-wide exposure of maturity bracket k:

$$X_{t,j,k} := \sum_{i=1}^{N} x_{t,i,j,k} \tag{14}$$

Industry-wide exposure:

$$X_{t,j} := \sum_{k=1}^{3} X_{t,j,k} \tag{15}$$

Weight: $w_{t,i,j,k}$ is the portion of loans to industry j in maturity bracket k made by bank i, in relation to the whole loan exposure of bank i; weighted average of the average exposure in the quarters $t-3$, $t-2$, $t-1$ and t:

$$w_{t,i,j,k} = \frac{0.5\ x_{t,i,j,k} + x_{t-1,i,j,k} + x_{t-2,i,j,k} + x_{t-3,i,j,k} + 0.5\ x_{t-4,i,j,k}}{0.5\ x_{t,i} + x_{t-1,i} + x_{t-2,i} + x_{t-3,i} + 0.5\ x_{t-4,i}} \tag{16}$$

Change in value: $c_{t,i,j,k}$ is the change in value (in euro) from time $t-1$ to t of the loans to industry j in maturity bracket k

Industry-wide, maturity specific change in value:

$$C_{t,j,k} := \sum_{i=1}^{N} c_{t,i,j,k}$$

Industry-wide change in value: $C_{t,j}$

$$C_{t,j} := \sum_{k=1}^{3} C_{t,j,k} \tag{17}$$

Bank-wide yearly loss rate: $q_{t,i}$

$$q_{t,i} := \frac{4 \cdot \sum_{k=0}^{3} c_{t-k,i}}{0.5\ x_{t,i} + x_{t-1,i} + x_{t-2,i} + x_{t-3,i} + 0.5\ x_{t-4,i}} \tag{18}$$

with

$$c_{t,i} := \sum_{j=1}^{27} \sum_{k=1}^{3} c_{t,i,j,k} \tag{19}$$

(bank-wide change in value)

Industry-wide, maturity-specific yearly loss rate: $Q_{t,j,k}^{ind \times mat}$

$$Q_{t,j,k}^{ind \times mat} := \frac{4 \cdot \sum_{l=0}^{3} C_{t-l,j,k}}{0.5\ X_{t,j,k} + X_{t-1,j,k} + X_{t-2,j,k} + X_{t-3,j,k} + 0.5\ X_{t-4,j,k}} \tag{20}$$

Industry-wide yearly loss rate: $Q_{t,j}^{ind}$

$$Q_{t,j}^{ind} := \frac{4 \cdot \sum_{l=0}^{3} C_{t-l,j}}{0.5\ X_{t,j} + X_{t-1,j} + X_{t-2,j} + X_{t-3,j} + 0.5\ X_{t-4,j}} \tag{21}$$

Region-specific loss rate: The 10 regions are indexed by R. The mapping $R\left(i\right)$ assigns bank i its region.

$$Q_{t,R}^{reg} := \frac{\sum_{\text{bank } i \text{ is in region } R} c_{t,i}}{\sum_{\text{bank } i \text{ is in region } R} x_{t,i}}$$

Loss rate of the I-index portfolio: Loss rates in this portfolio are industry-, but not maturity-specific nationwide averages.

$$hq_{t,i}^{ind} = \sum_{j=1}^{27} Q_{t,j}^{ind} \left(\sum_{k=1}^{3} w_{t,i,j,k} \right) \tag{22}$$

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