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The common drivers of default risk☆

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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 contains the volume of loans, and write-downs on loans, per bank and industry. Our empirical study for the period 2003–2011 yields the following results: (i) alongside the average nationwide credit loss rate, industry composition, regional factors, and the state of the global economy, the loans' maturity structure is identified as an additional driver of the bank-wide loss rates in the credit portfolio. (ii) The nationwide loss rate has the largest 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 figure is less than 8%.

1. Introduction

The credit quality of loans is measured in credit portfolio models by 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 et al., 2000, or Bluhm et al., 2003 for an overview). Alternatively, in default-rate 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. The model introduced by Wilson (1997, 1997), which is the basis of the commercial product CreditPortfolioView (CPV), is also based on default rates, as it regards the model part by which the commonality of credit risks in a portfolio is steered. As in CreditRisk+, a default rate is assigned to each sector; these rates are either commonly driven by observable macroeconomic variables in a vector autoregressive setup (CPV Macro) or by latent gamma-distributed factors (CPV Direct).[1] Jokivuolle and Virén (2013) use an approach similar to the "macro" version of CPV for stress testing.

None of these models is easy to calibrate to historic credit losses, for the simple reason 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 where it is possible to observe a large cross-section of borrowers, the time dimension is very limited in most cases. When calibrating credit portfolio models to default data, risk managers need both enough credit events in a given period and a reasonable number of intertemporally independent observations.

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.

☆ This article is a revised version of Memmel et al. (2012). The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Deutsche Bundesbank or its staff.

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[1] The default rates do not enter the modeling of credit losses directly; instead, a sector's default rate is a random variable on which a dynamic rating migration matrix is conditioned. All commonality of credit migrations, however, comes from the modeling of default rates. Conditional on these rates, all individual changes of credit risk are independent.

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We use a linear model to explain write-down rates of all German banks by common factors that are merely averages of these rates – albeit conditional averages depending on different characteristics such as industry or maturity. This approach is related to explaining individual stock price movements by the movements of industrial indices or to the Capital Market Line of the CAPM (see, for instance, Roll, 1977) where stock returns are explained by weighted averages of stock returns, i.e. the return of the market portfolio. For many studies in the literature on credit risk, one crucial point is that the systematic component is a latent variable. By contrast, our interpretation of systematic credit risk drivers is simple and very direct. The advantage of using – observable – averages as systematic drivers is that we can exploit standard econometric tools such as panel regressions. Using such averages limits the usefulness of additional control variables. For instance, employing a nationwide average loss rate as the regressor obviates, by construction, the need for any other nationwide factor (such as GDP). This does not necessarily render GDP economically irrelevant; it is only not directly related to our research question of how different loan categorizations affect the maximum commonality of credit risk within the resulting categories, and how large these commonalities are for different types of banks. We are therefore not seeking causality in our regressions.

While we acknowledge a methodological similarity to default-rate based credit portfolio models, to our knowledge no academic study has used regressions of loss rates on their averages to investigate the magnitude of systematic components. There are a few related papers on portfolio risk modeling that suggest (but do not carry out) estimations similar to ours. For instance, Giese (2004) extends the CreditRisk+ model by linking sector-specific default rates through a doubly stochastic mechanism. To calibrate it to data, he suggests regressions of sector specific default data of loans or bonds, which is in the same spirit as ours. However, estimations are not carried out in his study. Similarly, Fischer and Dietz (2011), who build on the work of Bürgisser et al. (2001), assume conditional means of sector default rates to be linear combinations of independent gamma-distributed systematic factors. This can be interpreted as our linear setup under additional distributional assumptions. The authors suggest standard correlation estimates to which their restricted correlation matrix is calibrated. In Section 4.2 we give a more detailed discussion of the approaches in the context of linearity.

Many authors estimate the commonality of credit losses using nonlinear models; an overview is found in Berg et al. (2011, Exhibit C2). All these estimations require single-name default (or migration) information. As this is not included in our data, a direct comparison with nonlinear models is impossible. Although we have bank-specific loss information for a fairly large number of subportfolios, we do not know how many loans are behind them and also do not know the number of defaults. The degree of diversification in each subportfolio can be very different, which is the main reason why we rely on nationwide (but industry- and maturity-specific) averages and perform bank-level estimates. This makes the assumption of homogeneous noise less critical.

As data determines the range of available estimation methods, the lack of comparable estimations in the literature can also be explained by the atypical structure of our data. It lies between the following two extremes. One is given by the typical case of a commercial bank which should exactly know what loans have defaulted and how large the losses are. But this precise knowledge is often limited to the portfolio of a single bank.[2] The other extreme is given by public data sets such as national default statistics. They are highly aggregated, containing no bank-level information, but cover the whole domestic economy. Our data set is an intermediate case. It has the same scope as national statistics but is, with bank-specific information in over 80 reporting units, by far more detailed. Since it contains no direct information on default events, it is less granular than the data typically available to a commercial bank.

Models with latent systematic factors, which dominate the measurement of credit portfolio risk, usually imply a nonlinear relationship between loss rates of different sectors, which is often established by a linear superposition of latent factors which then translate into a loss rate by a nonlinear relationship. In the context of these models, the linear relationship between loss rates in our model deserves justification. We argue in the model section that, first, nonlinearities are observationally far from obvious even within the nonlinear models, and, second, that linear measures have been suggested for the calibration of nonlinear models.

We show that up to 26% of the time variation in individual write-down rates can be explained through five common components. Besides the nationwide loss rate, differences in the portfolio composition with respect to the industry, the maturity, and the region in which a bank operates, as well as its lending exposure to export-oriented industries (by which we seek to capture effects of the state of the global economy) are significant common drivers. The nationwide common loss rate has the largest impact, followed by the maturity structure, industry composition, regional component and the state of the global economy. Nationally active banks form the sample for which we find the maximum explanatory power of 26% (i.e. the percentage 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%. Although the high number of regional (savings and cooperative) banks is very specific to the German context, we nonetheless expect our results with the German-lender-specific data set to be applicable to a wide range of studies with other banking market structures and time periods. Fewer regional banks and a higher ratio of nationwide operating banks would translate into a higher share of systematic risk. Moreover, the time horizon we investigate captures both crisis and non-crisis periods, which enables us to obtain insights across the full economic cycle.

The contributions of this study are threefold.

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. This effort jointly contributes to the risk management and banking literature on loss rates: We extend the previous works which look at determinants of loss rates (Sinkey and Greenawalt, 1991), determinants of problem loans (Salas and Saurina, 2002), determinants of credit contract terms (Dennis et al., 2000), the systematic nature of default risk across industries and regions (Aretz and Pope, 2013), and credit line usage (Sufi, 2008; Jimenez et al., 2009; Norden and Weber, 2010).

Second, the relative impact of the factors contains information on which type of loan classification makes sense in the quantification of credit portfolio risk. We identify the maturity structure of loans to be a major driver.

Third, we expect that the quantifications of common components in our study will provide a benchmark for the credit portfolio risk literature. The regression results can directly be fed into a simulation engine for portfolio loss rates. We expect to contribute to the stress testing literature in a similar manner (Vazquez et al., 2012). The factors identified in this study can provide a starting point for

2 The joint credit data pool of all German savings banks is a notable exception.