Banks' Credit Losses and Lending Dynamics*

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Abstract

Using detailed data of the credit exposure of German banks to domestic firms, we find that banks which have suffered substantial credit losses in one industry reduce their lending by 1.60 euro for each euro lost, on average. Our method to control for demand is novel, to our knowledge. The sensitivity found is in line with (quite heterogeneous) results of earlier studies but significantly lower than sensitivities under the assumption of constant leverage. Furthermore, thinly capitalized banks grant fewer loans than others but do not seem to react differently to substantial credit losses.

Keywords: Credit losses, Bank lending

JEL classification: G 21

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1 Introduction

Providing the real economy with credit is a core function of the banking sector. An impaired ability or willingness of banks to extend credit may do harm to the real economy as otherwise sensible projects may not be funded.

Using detailed data of German banks' credit portfolios, we estimate how a bank adjusts its corporate lending after an shock in the form of a heavy credit loss. As we want to make the estimates useful particularly for macroprudential considerations, we analyze in detail how the adjustment is altered by the severity of the shock and the bank's capital endowment. We are mainly interested in the identification and quantification of the effect rather than deeper reasons for its existence, as our study is mainly motivated by stress tests for which the investigated effect is an important parameter.

The relationship between a shock to banks and their lending to the real economy is generally considered difficult to establish, mainly for three reasons: (i) the endogeneity of bank capital, (ii) the problems in disentangling credit supply and demand and (iii) the presence of other institutions that might jump in for the affected bank.

To overcome the problem of the endogeneity of bank capital, we select events that could hardly be predicted. The basic idea is that we only look at banks that have suffered a really substantial credit loss in a single industry. We argue that such losses are exogenous for the most part because no bank considers a credit loss of, say, 30% of its loan exposure to an industry as part of the business plan.

To be clear: Every bank knows it will suffer a large loss one day. However, the bank has not much of a clue what the day of its biggest loss will be even if it has chosen a particularly risky (or safe) strategy. Not the possibility of a heavy loss is key to our identification strategy but the event in-itself. The former can well be reflected in loan rates as part of a rational risk attitude; the latter is something a bank never wishes to happen. While that argument would not hold if the heaviest losses did not differ much from normal losses, they actually do because their distribution is fat-tailed; see Section 4.2.

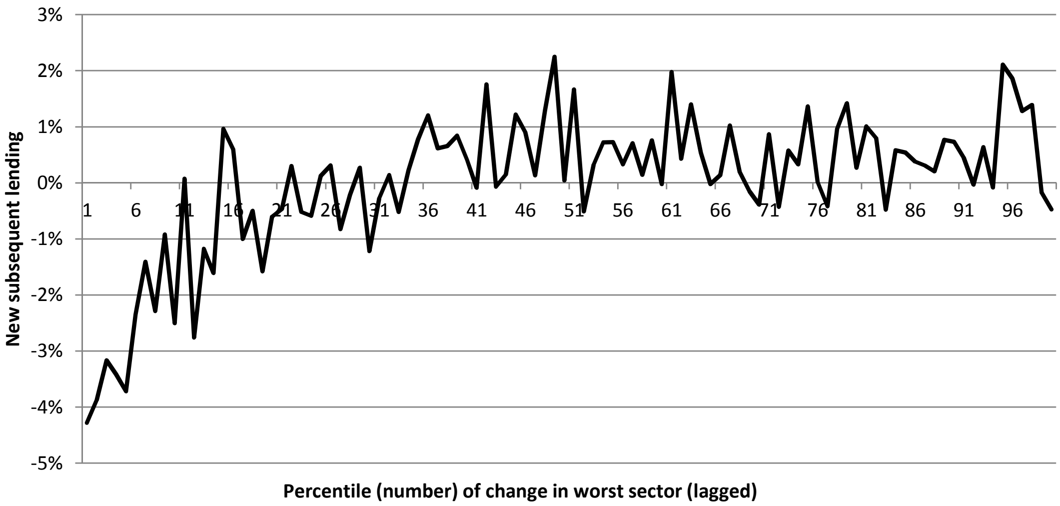
To keep the shock as surprising (or non-predictable) as possible, we define losses over the shortest horizon possible in our data and use a dummy variable for the occurrence of an extreme loss, rather than the losses extent, which dampens the potential influence that banks may have on the size of losses.

In our main analysis, we contrast the severity of a bank's loss in its worst industry (identified as the one with the largest loss) with the new lending in the other industries in the bank's credit portfolio. To give a first impression of the effect, Figure 1 plots new business against loss severity. The x-axis is given by percentile levels of value changes (the negative of losses) in a bank's worst industry in a quarter, starting with the lowest values (largest losses) on the left. The black line displays average[1] new lending (to the remaining industries) over the 4 subsequent quarters. The 20 per cent largest losses (the 20 observations on the left) seem to lead to a reduction in new lending, relative to the 80 percentiles on the right (representing smaller losses), which appear to randomly oscillate around a constant.

We exclude the worst industry from the calculation of new lending mainly for two reasons. First, large further write-downs (but also write-ups) in this industry can be expected, for instance as a result of an intensified scrutiny of problem loans, the revaluation of collateral, or shocks to the liquidation value. We are hesitant to interpret the corresponding changes in the exposure to this industry as actual lending decisions. Second, banks may wish to keep the industry composition of their credit portfolio constant. Large losses in an industry would then be followed

[1] Averages are taken over banks for each quarter, followed by a general de-trending.

Figure 1: New business vs credit losses



For each bank, industry, and quarter we calculate valuation changes relative to the total domestic corporate exposure; negative values are losses. The industry with the lowest value (largest loss) defines the worst loss and industry for each bank × time observation. All negative such values are grouped in percentiles, defining the x-axis (1–99), with worst values (largest losses) on the left. Values on the y-axis are based on the new domestic corporate lending after the 4 subsequent quarters, excluding the worst industry, normalized by the total domestic corporate exposure. Plotted values are averages, taken over the subsamples defined by the loss percentiles, subject to de-trending.

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by increased lending particularly to that industry.

To address the other two problems typical to analyses like ours (no separate observation credit supply and demand, competitors potentially jumping in for banks hit by a severe loss), we construct for each bank a benchmark bank the new lending business of which is included as a control variable. Given any bank in the sample, we assign it a hypothetical competitor constructed from the aggregate lending of all other banks, however a competitor that has distributed its exposures over regions and industries in the same way as the bank under consideration.

If, for instance, a locally active bank has made 1/3 of its lending to farmers (constituting an industry) in the county Vechta and 2/3 to food producers (another industry) in the Cloppenburg county (and nothing else), it is benchmarked by all other banks' loan exposures exactly to those two industries in those counties at the same $(1/3, 2/3)$ proportion. In this context, "all other banks" can actually mean very few banks, depending on who else is lending in Vechta and Cloppenburg to farmers and food producers. If, by contrast, the bank under consideration is active throughout Germany, it is benchmarked by an equally composed and hence nationwide active hypothetical competitor.

Key to our identification strategy is the assumption that control for demand at the level industry × region, constructed from 23 industries and 401 German counties, is sufficient. According to the current state of the art, we would follow Khwaja and Mian (2008) and include fixed effects at industry × region × time or at least region × time level. However, given the structure of our data, this is not appropriate in the context of our paper. Let us emphasize the reasons here.

First, the exposure of the 1774 banks in our sample is very differently concentrated over regions. Only few banks cover all regions whereas most of the banks lend in very few counties only.[2] Imagine the banking system consists of 400 locally active banks, each lending in one county

[2]Local concentration of many banks' lending is partly a consequence of the "regional principle" of German

only, and a single big bank that is active everywhere. If we included region × time fixed effects (ignoring industries for now), we would have to resort to bank × region × time observations, resulting in 400 observations per quarter for the local banks and another 400 for the big bank.

By contrast, we want to analyze decisions on loan portfolios, that is, decisions that are plausible to be made at bank level. Interested in a representative picture of bank behavior, we do not want to duplicate the big bank's decision 400 times even though we acknowledge that this decision is presumably made on a larger credit volume. Weighting observations would be a potential remedy to the problem which, in the end, turns out to be a step towards what we actually do.

Second, our selection of a bank's worst industry is based on random variables such that industries are not a simple dimension that observations are divided into. If we included industry × region × time fixed effects we would typically not find another bank with the same worst industry at the same time for the same region and hence lose the majority of observations. As a compromise we could resort to region × time fixed effects, but only at the cost of precision, as the new business of the banks matching at region × time level would have to include the worst industry. The approach we take does not suffer from this dilemma.

Our data from Bundesbank's borrower statistics (Kreditnehmerstatistik) is not as granular as the ones from the German credit register (Millionenkredit-Register) where observations are available at bank-borrower level. Nevertheless, our data consists of credit portfolios broken down into 23 industries of the German real economy. Moreover, and unlike the German credit register, it carries information on loan terms, as each industry portfolio is further broken down into three bands of maturity (at grant), which turns out to be a significant determinant of new lending.

Furthermore, the credit register has a lower reporting threshold of EUR 1mn. The loans falling under this threshold do not matter much for the biggest banks but a lot for the majority of banks in our sample. Their portfolio compositions would be heavily biased if we restricted the analysis to loans covered by the credit register. We use the credit register only for the construction of benchmark banks.

In our empirical study of German banks' lending to domestic firms from 2002Q4 to 2017Q4, we find that banks that have suffered from substantial credit losses in one industry reduce their new lending on average by 1.60 euro per euro of such a loss. This relationship is non-linear, as can be seen in Figure 1. Concerning bank capitalization, we find that banks with low capital ratios decrease their lending compared to better capitalized banks. However, these banks with low capital ratios do not seem to react differently to a substantial credit loss.

The paper is structured as follows. In Section 2, we give a brief overview of the literature. In Section 3, the empirical model is described, and the data used is explained in Section 4. In Section 5, we present the empirical results. Section 6 concludes.

2 Literature

The question of bank capital and lending is often investigated; see for instance Kim and Sohn (2017) for an overview. There is much empirical evidence that banks experiencing binding capital constraints reduce their lending (see, for instance, Acharya, Eisert, Eufinger, and Hirsch (2018), Gropp, Mosk, Ongena, and Wix (2018), Tölö and Miettinen (2018) and Popov and Van Horen (2014)). Often it is found that this relationship is non-linear and depends on bank characteristics: Brei, Gambacorta, and Von Peter (2013) and Carlson, Shan, and Warusawitharana (2013) find

savings and loans banks and cooperative banks. Each cooperative bank is bound to a certain region (which can but does not have to coincide with counties) and must not "poach" in other cooperative banks' regions. Exceptions do exist but represent a small amount of lending only. A similar principle holds for savings and loans banks.

that a bank's capital endowment is crucial for the strength of the relationship between capital and lending; Kim and Sohn (2017) and Ivashina and Scharfstein (2010) stress the impact of the banks' liquidity. We as well find that the lending relationship is highly non-linear, however not with respect to the capital endowment, but with the size of losses that affect the capital endowment.

Many researchers study cross-border lending, for instance Peek and Rosengren (1997), Aiyar, Calomiris, Hooley, Korniyenko, and Wieladek (2014) and De Haas and Van Horen (2013). Apart from documenting international spill-overs, this approach helps to separate credit supply and demand. We also look at spill-overs, however across industries rather than countries.

While an effect between capital endowment and lending is generally evident, the size of the effect is less clear. But size matters especially in the context of stress tests, as the lending reduction after a credit shock is a central link between the financial sector and the real economy and hence key to the modeling of feedback effects between them. Table 1 documents that estimates of the lending reduction caused by a capital gap (measured in euros reduced per euro of the gap) varies a lot across empirical studies. These estimates provide the context for our results.

The capital cushion of a bank, that is the capital in excess of the regulatory minimum, is exposed to different kinds of shocks, which correspond to different measures used by researchers to quantify these shocks. Relevant measures are: (i) a bank's capital ratio, (ii) the deviation of the capital ratio from a target level, (iii) a bank's capital requirements, and (iv) losses that have an impact on bank capital.

All four measures are used in the literature: while Hancock and Wilcox (1994) directly make use of the capital ratio, Berrospide and Edge (2010) look at the deviation of the actual capital ratio from the estimated target ratio. Changes in capital requirements have the methodological advantage of an exogenous event (see for instance Gropp et al. (2018)); in addition, these studies are not affected by the problem of a possible substitution of credit supply (as all banks are similarly concerned by changes in capital requirements). However, there is little variation in the cross section of banks, with few exceptions such as Aiyar et al. (2014), Aiyar, Calomiris, and Wieladek (2016) and Imbierowicz, Kragh, and Rangvid (2018) who make use of the time variation in minimum capital requirements in the UK and Denmark where bank supervisors actively use their discretion to prescribe bank individual capital surcharges. Furthermore, there is often a wedge between announcements of regulatory reforms (or details thereof) and their implementation.

In this paper, we deal with losses in the credit portfolio rather than capital gaps. However, our findings are comparable to results relating to capital, provided that a one-euro credit loss reduces bank capital by one euro and that the bank's capital ratio has been at its target level prior to the credit event.

Other authors focus on the separation of credit demand and supply. One approach is comparing the loan granting of banks affected by a shock with the outcome of non-affected banks (Peek and Rosengren, 1997), which is also our approach. Another approach is the separate observation of loan demand (for instance by loan applications) and realized loans (Jiménez, Ongena, Peydró, and Saurina, 2012; Puri, Rocholl, and Steffen, 2011; Jiménez, Ongena, and Peydró, 2014). This approach is highly preferable but mostly lacks the data necessary, as in our case.

The substitution of credit supply does not need to be confined to the banking sector; it is possible that also non-bank institution step in (see, for instance, (Peek and Rosengren, 2016)).

Altogether, there is substantiated empirical evidence that a gap in a bank's capital endowment, a significant loss, or capital ratios below the target lead to a reduction in new lending.

Table 1: Effect of a Capital Gap of 1 Euro

Study / Assumption	Lending red.	For banks with ...	Sample
Constant leverage	10.00 euro	—	—
Hancock and Wilcox (1994)	4.63 euro	Low capital ratio	US banks, 1991
Berrospide and Edge (2010)	1.86 euro	—	US banks, 1992–2008
Hancock and Wilcox (1993)	1.37 euro	Large loan losses	US banks, 1990
Gambacorta and Shin (2018)	0.36 euro	—	Int. banks, 1995–2012

This table shows the reduction in a bank's lending ("Lending red."; horizon: one year) as a consequence of a capital gap of 1 euro. "Constant leverage": a target capital ratio of 10% is assumed. Concerning the study Gambacorta and Shin (2018): own calculations under the assumption of a loan-to-asset ratio of 60%.

However, the estimated size of this effect is very heterogeneous in the literature, reaching from a reduction of less than half a euro to ten euros for every euro of capital gap.

3 Empirical Modeling

Our data allow us to identify credit losses incurred by an individual bank in a single industry. As explained above, we assume that the heaviest of such credit losses are exogenous events. We estimate by how much a bank that has suffered such a substantial loss in a certain industry expands or contracts its credit exposure to the *other* industries afterwards.

We exclude the industry with the substantial loss for two further reasons not mentioned in the introduction. First, the bank may see a general problem in the prospects of the concerned industry and hence tend to reassess related exposures. Second, the split between the problematic industry and the rest of the portfolio tempers the effect of systematic credit risk factors, as inter-sector spillover effects are typically lower than intra-sector effects (Chernih, Henrard, and Vanduffel, 2010).

Throughout this paper, t stands for a quarter (2002Q4–2017Q4), index i for a bank (1774 in our data), j for an industry (23), and k for a maturity bracket (3). Our data contains the loan exposures $ex^k_{t,i,j}$ to each bank $\times$ industry $\times$ maturity cell and corresponding value changes $c^k_{t,i,j}$, which are changes in the valuation of the exposure between $t-1$ and t, based on the positions in $t-1$. A write-down is reflected in negative values of $c^k_{t,i,j}$ (or negative contributions to it, if multiple revaluations overlay).

We make use of the maturity information only in the calculation of a control variable, the amount of maturing (or expiring) loans (see Section 3.2); the key variables $ex_{t,i,j} \equiv \sum_k ex^k_{t,i,j}$ and $c_{t,i,j} \equiv \sum_k c^k_{t,i,j}$ are at bank $\times$ industry level.

Net new lending business $n_{t,T,i,j}$ over T quarters is of key interest in our analysis. In the base-case it is defined as the simple exposure difference

$$n_{t,T,i,j} \quad \equiv \quad ex_{t+T,i,j} - ex_{t,i,j}. \tag{1}$$

This measure of new business includes value changes, which could alternatively be subtracted from the exposure difference:

$$n^{\text{alt}}_{t,T,i,j} \equiv ex_{t+T,i,j} - ex_{t,i,j} - \sum_{k=1}^{T} c_{t+k,i,j}. \tag{1-alt}$$

Preferences for either definition are linked to the question of whether planned new business should be understood as the expansion of business *after* correction for expected losses (consistent with (1)) or whether the pure loan contracting minus expiring loans is relevant (consistent with (1-alt)). We opt for version (1) because it is the micro counterpart to the ultimate loan growth in the whole economy; definition (1-alt) is subject to a robustness test in Section 5.2.

Losses in an industry and, among them, the severe ones, are identified as follows. For each bank and quarter, we select the industry with the worst value change:

$$\text{bad}\,(t,i) \quad \equiv \quad \text{argmin}_j\,(c_{t,i,j}) \quad \text{if } \min_j\,(c_{t,i,j}) < 0.$$

Observations with $\min_j\,(c_{t,i,j}) \geq 0$ are excluded because almost all of them contain multiple industries with zeros. Each of the industries would be a candidate "worst" industry such that we could not sensibly define the remaining industries. Our focus is on the most negative values (that is, the biggest losses) anyway.

In the estimates we investigate the relationship between the worst value change:

$$c_{t,i}^{\text{bad}} \quad \equiv \quad c_{t,i,\text{bad}(t,i)} \tag{2}$$

and subsequent new business in the remaining portfolio:

$$n_{t,T,i}^{\neg \text{b}} \quad \equiv \quad n_{t,T,i,[-\text{bad}(t,i)]} \equiv \sum_{j \neq \text{bad}(t,i)} n_{t,T,i,j}. \tag{3}$$

Note the brackets $[\ldots]$ as a symbol for aggregation: $[j]$ means aggregation over all possible values of j, whereas $[-j]$ means that a certain index value, such as $\text{bad}\,(t,i)$, is excluded from aggregation. In the base case, T equals 4 quarters. Of course, $c_{t,i}^{\text{bad}}$ and $n_{t,T,i}^{\neg \text{b}}$ are bound to the existence of $\text{bad}\,(t,i)$.

3.1 Controlling for demand

Following the common sense in the literature, an analysis like ours crucially depends on a proper control for credit demand and systematic credit risk factors. This view will turn out to apply to our data as well, but our approach is not standard and, to our knowledge, novel. We construct a bespoke hypothetical competitor of each individual bank from all other banks in such a way that its exposures are distributed over Germany's around 400 counties almost exactly as the bank under consideration.[3] That is, we control for demand at industry $\times$ county level in a way that reflects portfolio weights and corrects for bank size. This would not be possible if we just used time $\times$ county fixed effects.

To understand the concept it is sufficient to start with $ex_{t,i,j,r}$, the exposure of bank i to industry j in region r (a county) at time t. How we construct this figure is described in Section 4.4. First, we define exposure weights of bank i

$$w_{t,i,j,r} \equiv \frac{ex_{t,i,j,r}}{ex_{t,i,[j],[r]}}$$

of industry $\times$ region cells.[4] The task is to rescale the exposures of the bank's competitors such that the resulting weights replicate those of bank i. Prior to rescaling, industry $\times$ region weights

[3]To some extent, our approach is similar to the one of (Abadie, Diamond, and Hainmueller, 2010) where they apply it to cigarette consumption.

[4]Recall that a bracket stands for summation over the respective index.

after aggregation over all banks except bank i are

$$w_{t,[-i],j,r} = \frac{ex_{t,[-i],j,r}}{ex_{t,[-i],[j],[r]}} = \frac{\sum_{k\neq i} ex_{t,k,j,r}}{\sum_{k\neq i}\sum_{j,r} ex_{t,k,j,r}}.$$

Hence, the rescaling factor should be

$$\frac{w_{t,i,j,r}}{w_{t,[-i],j,r}}, \tag{4}$$

which can also be interpreted as the Radon-Nikodym derivative of the exposure distribution $(w_{t,i,j,r})$ relative to $\left(w_{t,[-i],j,r}\right)$.

Below we rescale the new lending business of the aggregate bank (excluding bank i) in order to calculate the new lending of the benchmark bank. As new business is a function of two periods, t and $t+T$, we would occasionally generate extreme outliers if we directly used (4) of period t only. To avoid such outliers we make a pragmatic adjustment in that we mix the weights (or distributions) of the two periods before we get the rescaling factor. That is, we actually use

$$\nu_{t,T,i,j,r} \equiv \frac{w_{t,i,j,r} + w_{t+T,i,j,r}}{w_{t,[-i],j,r} + w_{t+T,[-i],j,r}} \tag{5}$$

rather than the quotient in (4). This smoothing approach is not perfectly clean as the numerator includes a little component of the new lending of bank i, which will be the main dependent variable. We can show, however, that the component is of second order and way too small to explain the effects found.[5]

Rescaling by $\nu_{t,T,i,j,r}$ cannot work perfectly if the denominator in (5) is zero, which indicates that neither in period t nor $t+T$ a competitor is found for this industry $\times$ county cell. Luckily, the problem applies to 1.5% of all cells with positive numerators only, which we consider tolerable for the purpose of controlling for demand. We just leave the weights in the benchmark portfolio zero where the denominator is zero. To correct for the exposure "lost" in this way we lift all other rescaling factors proportionally to make them add up to 1 again:

$$\nu^{*}_{t,T,i,j,r} \equiv \left(\sum_{k,l} w_{t,T,i,k,l}\mathrm{I}\left(w_{t,T,[-i],k,l} > 0\right)\right)^{-1} \mathrm{I}\left(w_{t,T,[-i],j,r} > 0\right) \times \nu_{t,T,i,j,r}\,,$$

where $\mathrm{I}(\ldots)$ is an indicator function and

$$w_{t,T,i,k,l} \equiv \frac{1}{2}\left(w_{t,i,k,l} + w_{t+T,i,k,l}\right).$$

This adjustment is equivalent to assigning average values to missing cells. It turns out that the actual composition error in the benchmark portfolio is much lower than 1.5%, on average.[6] The final benchmark exposure is given by:

$$ex^{\mathrm{bm}}_{t,T,i,j,r} \equiv \nu^{*}_{t,T,i,j,r}\frac{1}{2}\left(ex_{t,[-i],j,r} + ex_{t+T,[-i],j,r}\right).$$

[5] Information on this estimate is available on request.

[6] Each portfolio in our main estimate covers 22 of 23 industries and 401 regions. Of these 22×401 cells, only 1.5% cannot be matched properly. To measure the deviation, we choose (for a single quarter) all cells with a positive original weight $w_{t,4,i,k,l}$ and define bank specific samples of the deviations $\nu^{*}_{t,4,i,j,r}w_{t,4,[-i],k,l} - w_{t,4,i,k,l}$, of which we calculate standard deviations as a bank specific error measure. These 1774 standard deviations have a maximum of 5% and a mean of 0.03%.

To calculate the new lending business of the benchmark bank, we determine the region specific new business (1) for the aggregate bank, that is,

$$n_{t,T,[-i],j,r} \quad \equiv \quad ex_{t+T,[-i],j,r} - ex_{t,[-i],j,r} \, , \tag{6}$$

and rescale it to bring it in line with the portfolio weights of bank i:

$$n^{\mathrm{bm}}_{t,T,i,j,r} \quad \equiv \quad \nu^*_{t,T,i,j,r} \times n_{t,T,[-i],j,r} .$$

Region specific figures are no longer needed. We aggregate new business over regions and also over all industries, except the "bad" industry of bank i (symbolized by superscript ¬b):

$$n^{\mathrm{bm},\neg\mathrm{b}}_{t,T,i} \quad \equiv \quad n^{\mathrm{bm}}_{t,T,i,[-\mathrm{bad}(t,i)],[r]} . \tag{7}$$

This is the new lending business of the benchmark bank. Still denominated in euros, it can be huge (if bank i is nationwide active) or small and thus requires normalization, as well as the new business of bank i and corresponding value changes (we apologize for the sloppy notation):

$$c^{\mathrm{bad}}_{t,i} := \frac{c^{\mathrm{bad}}_{t,i}}{ex_{t,i,[j],[r]}} \qquad \text{and} \qquad n^{\neg\mathrm{b}}_{t,T,i} := \frac{n^{\neg\mathrm{b}}_{t,T,i}}{ex_{t,T,i,[j],[r]}} \qquad \text{and} \qquad n^{\mathrm{bm},\neg\mathrm{b}}_{t,T,i} := \frac{n^{\mathrm{bm},\neg\mathrm{b}}_{t,T,i}}{ex^{\mathrm{bm}}_{t,T,i,[j],[r]}} . \tag{8}$$

Unlike with the numerators, we do not exclude the "bad" industry from the normalizing exposure in the denominator. Taking the whole portfolio there does not only help to interpret the results more easily but also stabilizes the results, as $ex_{t,i,[-j],[r]}$ can vary substantially with j especially if small banks are invested in a few industries only.

To get a feeling for the usefulness of this whole machinery, we repeat the exercise of Figure 1 for the benchmark banks. If demand and/or systematic credit risk factors matter, $n^{\mathrm{bm},\neg\mathrm{b}}_{t,T,i}$ should be sensitive to the severity of $c^{\mathrm{bad}}_{t,i}$. To benchmark the benchmark, we also construct a much simpler variable which aggregates the new lending business of all banks (except i) *without* rescaling:

$$n^{\mathrm{agg},\neg\mathrm{b}}_{t,T,i} \equiv \frac{ex_{t+T,[-i],[-\mathrm{bad}(t,i)]} - ex_{t,[-i],[-\mathrm{bad}(t,i)]}}{0.5 \times \left(ex_{t+T,[-i],[-\mathrm{bad}(t,i)]} + ex_{t,[-i],[-\mathrm{bad}(t,i)]}\right)} . \tag{9}$$

This alternative benchmark variable is invariant to the exposure distribution over regions. If taking account for the regional dimension in the form of a bespoke benchmark bank is useful, $n^{\mathrm{bm},\neg\mathrm{b}}_{t,T,i}$ should be more sensitive to $c^{\mathrm{bad}}_{t,i}$ than $n^{\mathrm{agg},\neg\mathrm{b}}_{t,T,i}$ from (9).

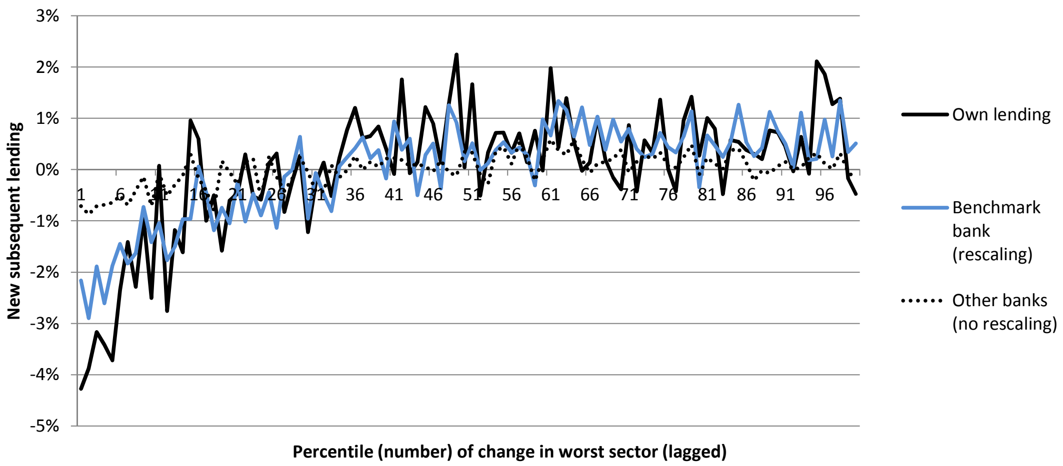
Figure 2 displays $n^{\neg\mathrm{b}}_{t,T,i}$ from Figure 1 and the two benchmarks. The quite impressive similarity of $n^{\mathrm{bm},\neg\mathrm{b}}_{t,T,i}$ (blue solid line) and $n^{\neg\mathrm{b}}_{t,T,i}$ (black solid line) indicates that demand matters; not controlling for it would give a wrong impression of the supply side of lending. The weaker sensitivity of $n^{\mathrm{agg},\neg\mathrm{b}}_{t,T,i}$ (dotted line) suggests that the rescaling mechanism, targeted at a good fit of local bank business, captures a significant dimension of demand.

3.2 Other control variables

Each industry portfolio in the Borrower Statistics is broken down into three bands of maturity (at grant), which allows us to estimate the amount of loans that have matured within a certain period. This number is potentially relevant as a bank can rather easily downsize its portfolio by just letting loans expire. By contrast, getting rid of loans before maturity requires action, such as loan sales, and involves transaction and administrative costs.

To calculate the *share of maturing loans* we assign an average maturity to each maturity

Figure 2: New business vs credit losses; controlling for demand



Values on the x-axis are the same as in Figure 1, representing percentile levels of $c_{t,i}^{\text{bad}}$. "Own lending" (black solid line) is $n_{t,T,i}^{\neg\text{b}}$ from (3), the new business of bank i, exclusive of the "bad" industry where the biggest loss has been made. "Benchmark bank" (blue solid line) is $n_{t,T,i}^{\text{bm},\neg\text{b}}$, the corresponding new business of the benchmark bank obtained from rescaling. "Other banks" (dotted line) is $n_{t,T,i}^{\text{agg},\neg\text{b}}$ from (9), the benchmark new business without rescaling. All variables are normalized by the corresponding total-bank corporate exposure and de-trended.

band, that is, 2 quarters to the 0–1y band, 6 quarters to the 1–5y band, and 28 quarters to the >5y band. As this is all maturity at grant (such that loans remain in their band throughout), and for lack of better information, we assume all loans in a band to have the same average maturity and to mature in a constant stream. Hence, the band specific maturing rates are 1/2, 1/6, and 1/28 per quarter. Taking $\left(ex_{t,i,j}^{(k)}\right)_{k=1,2,3}$ to be the maturity specific exposures in an industry, we calculate the quarterly euro amount of maturing loans,

$$ml_{t,i,j} \quad \equiv \quad \frac{1}{2}ex_{t,i,j}^{(1)} + \frac{1}{6}ex_{t,i,j}^{(2)} + \frac{1}{28}ex_{t,i,j}^{(3)},$$

which is then aggregated over T periods and sectors, consistently with the construction of new business, and normalized by the same exposure as the latter:

$$sml_{t,T,i}^{\neg\text{b}} \quad \equiv \quad \min\left(1, \frac{\sum_{s=0}^{T-1} ml_{t+s,i,[-\text{bad}(t,i)]}}{ex_{t,T,i,[j]}}\right). \tag{10}$$

The minimum operator is necessary because the amount of maturing loans can actually exceed the average exposure: if, for instance, all loans were belonging to the first maturity band, they would be completely replaced twice a year.

3.3 Estimation

We estimate how a bank's new lending reacts to heavy credit losses and capital. The following variables are of key interest:

$$bigL_{t,i} \equiv \text{I}\left(c_{t,i}^{\text{bad}} < \text{Qtl}_{10\%}\left(c_{\cdot,\cdot}^{\text{bad}}\right)\right)$$

is the dummy for 10% largest losses of all $c_{t,i}^{\text{bad}}$ in the sample (dots stand for sampled indices, in this case time and banks). The dummy $lowC_{t,i}$ is its counterpart for *low capital*, defined as

$$lowC_{t,i} \equiv \mathrm{I}\left(CapT1_{t,i} < \mathrm{Qtl}_{10\%}\left(CapT1_{t,\cdot}\right)\right),$$

where $CapT1$ is the Tier-1 capital ratio. Importantly, this dummy is determined quarter by quarter, unlike $bigL_{t,i}$. As $CapT1$ strictly goes up in the period under investigation, we prefer to look at a bank's capitalization relative to its peers. Our notion of a low capital endowment is therefore specific to a quarter. We lag $lowC$ by one quarter to avoid the mechanical effect of a severe loss on capital. The dummy variable $interact_{t,i}$ is the logical AND of $lowC_{t-1,i}$ and $bigL_{t,i}$.

In the base case we estimate new business over 4 quarters:

$$\begin{aligned} n_{t+1,4,i}^{\neg \text{b}} &= \alpha_i + \beta_1 \cdot bigL_{t,i} + \beta_2 \cdot lowC_{t-1,i} + \beta_3 \cdot interact_{t,i} \\ &\quad + \beta_4 \cdot n_{t-3,4,i}^{\neg \text{b}} + \beta_5 \cdot sml_{t+1,4,i}^{\neg \text{b}} + \beta_6 \cdot n_{t+1,4,i}^{\text{bm},\neg \text{b}} + \beta_7 \cdot n_{t-3,4,i}^{\text{bm},\neg \text{b}} + \varepsilon_{t,i}, \end{aligned} \tag{11}$$

in which we include bank fixed effects, lagged (own) new business, the share of maturing loans, and contemporaneous and lagged new business of the benchmark bank as control variables.

4 Data

4.1 General aspects

We take a bank's domestic corporate credit portfolio and the corresponding losses from Bundesbank's Borrowers Statistics; Memmel, Gündüz, and Raupach (2015) and the documentation (Deutsche Bundesbank, 2009) describe the data set in detail. It gives – at bank level and at quarterly frequency – the domestic corporate credit portfolio, broken down into 23 industries (Table 9), and three brackets of maturity at grant (0–1y, 1–5y, >5y), yielding $69 = 23 \times 3$ subportfolios.

What is more, not only the credit exposure is given, but also the change in value due to changes in a borrower's credit worthiness – in the same breakdown. In the study, we use quarterly data from this statistics starting in 2002Q4, the first time when valuation changes were reported. Our data currently end in 2017Q4 but will be extended.

Unfortunately, capital figures for the whole year 2007 are not at our disposal, which precludes a thorough analysis of the effects of the Global Financial Crisis. The data gap is not caused by the crisis but by inconsistencies involved with the transition from Basel I to II.

As most related studies (for instance Hancock and Wilcox (1993), Berrospide and Edge (2010) and Gambacorta and Shin (2018)), we define new lending as simple changes in the stock of outstanding loans from one period to the next. We also calculate new lending under the alternative definition (1-alt), which corrects for exposure changes due to revaluations. While the possibility to do this is a nice feature of our data, it turns out not to matter much.

A mild outlier treatment is applied: we remove the first and 99th percentile of the new-business variable $n_{t+1,4,i}^{\neg \text{b}}$. Furthermore, we remove banks with a total exposure of less than 10 mn euro. In 0.07% of the observations we limit losses (at the most disaggregate level) to the exposure reported for the previous quarter. Although not necessarily being data errors, these cases would make trouble in the form of more-than total losses or losses arising from zero exposures.

4.2 Credit losses

We restrict ourselves to domestic corporate loans, leaving out the three private household sectors included in the Borrower Statistics, and the sector of non-profit organizations. We do so in order to strengthen the exogeneity of events. It is more a surprise to a bank if one corporate loan has to be written off, compared to the case that ten retail loans perish; that is, the loss distribution of a few large loans tends to be more extreme in the tail than the loss distribution of a more granular portfolio of retail loans. Restricting ourselves to corporate loans, we can reason as follows that most of the nonzero losses observed in the corporate sectors originate from single defaults:

In our sample, 75% of the valuation changes in an industry are zero, on average, which allows us to estimate for how many of the actual losses only a single default is responsible. Under the simplifying assumption that all loans default independently at a uniform constant intensity, the number of defaults in a portfolio is Poisson distributed[7], and this distribution is determined by the 75% zeros. Then, the 25% nonzero losses consist by 86% of single-default events.[8]

In a granular retail portfolio, by contrast, losses at portfolio level are much more frequent and stable in size, and hence less surprising to a bank. As the surprise aspect is essential to our identification strategy, we leave retail portfolios out.

We could not assume banks were surprised by credit events if the largest losses in the sample did not really differ from normal losses. Two arguments support that they do differ. First, Table 2 documents the value change $c_{t,i}^{\text{bad}}$ (the negative of a loss rate) as defined in (2) to be extremely leptokurtic. Second, we standardize $c_{t,i}^{\text{bad}}$ (i.e. so that its mean is 0 and its standard deviation equals 1) and estimate the mean in its lower 10% tail (where $bigL = 1$), which gives us a more robust tail measure similar to the expected shortfall. The result, -2.33 (corresponding to a credit loss in the affected industry of 1.4% per quarter relative to the whole domestic corporate loans), is the same as for (the negative of) a chi-square random variable with 1.6 degrees of freedom. What is more, we look at extreme credit events in the next quarter, not in a longer period. For instance, it is quite likely (probability of 64%) that a will bank suffer from at least one 5%-event (at an horizon of one quarter) in a period of 5 years.

4.3 Summary statistics

In Table 9 in Appendix D, we report the composition of the aggregate credit portfolio and corresponding losses. Descriptive statistics of variables directly or indirectly used in the regression (11) are presented in Table 2.

4.4 Regional distribution of exposures

The Borrower Statistics (BS, "Kreditnehmerstatistik") do not bear information on the regions (in our case, counties) lent to. In order to be able to control for demand at a granular level of regions, we complement the BS by the German credit register (CR, "Millionenkredit-Register").

The CR is much more detailed than the BS, on the one hand, as it contains detailed information on individual corporate borrowers, including their sectors and, more importantly, the regions of their seats, which we make use of. On the other hand, the CR is incomplete due to a

[7]The assumption of independence is not as far-fetched as it may seem: Memmel et al. (2015) find that more than 90% of the variation in a bank's loss rate is bank-specific and less than 10% is due to systematic factors. The distribution is *exactly* Poisson only if a loan can default multiply within a quarter, which does not make a difference for the low default probabilities relevant in corporate lending.

[8]Taking N, the number of loan defaults in a portfolio, to be Poisson distributed, the given probability $\Pr(N = 0) = 0.75$ implies $\Pr(N = 1) = 0.216$ and this, in turn $\Pr(N = 1|N > 1) = 0.216/0.25 = 0.862$.

Table 2: Descriptive statistics of key variables

	$c^{\text{bad}}_{t,i}$	$n^{\neg\text{b}}_{t,4,i}$	$n^{\text{bm},\neg\text{b}}_{t,4,i}$	$sml^{\neg\text{b}}_{t+1,4,i}$
Mean	–0.27%	2.67%	1.01%	56.2%
Std	0.46%	10.19%	8.39%	20.3%
Q25	–0.33%	–2.54%	–2.98%	41.7%
median	–0.11%	2.47%	1.24%	53.0%
Q75	–0.022%	7.70%	5.23%	68.5%
Skewness	–5.0	0.06	–0.90	0.44
Kurtosis	48.5	6.4	21.3	2.8
N	30018	30019	30019	30019

All variables are normalized according to (8) by total credit exposure as covered by the Borrower Statistics. Estimates are based on the sample used in the base case estimate of Table 3, column 1. The first and 99th percentile of $n^{\neg\text{b}}_{t,4,i}$ have been removed prior to the estimate.

reporting threshold of EUR 1mn, which does not matter much for the biggest banks but a lot for the majority of banks in our sample. Their portfolio compositions would be biased heavily if we resorted to CR data exclusively. That's why we only use it to construct the control variable for demand.

Details of how we calculate the region specific exposures $ex_{t,i,j,r}$ used in Section 3.1 are found in Appendix A.

5 Results

5.1 Baseline results

In the introduction we name three challenges that need to be dealt with, namely (i) the endogeneity of bank capital, (ii) the separation of credit supply and demand, and (iii) the possible substitution of credit supply by other institutions. Our study design addresses these challenges: First, the restriction to heavy losses allows us to assume that these losses are unexpected and exogenous. Second, we benchmark the new lending of banks by the lending of their competitors at high precision in that we correct for the differences in the – regional and sectorial – portfolio compositions of individual banks and competitors.

In Table 3, we report the result of Equation (11) and of some alternative specifications. We draw the following conclusions:

First, substantial credit losses, that is, the 10% worst credit losses, lead to a significant reduction in new lending: one euro of substantial credit losses leads to 1.60 euro of reduction in new lending. This figure does not directly derive from Table 3, as $bigL$ is a dummy variable. However, Equation (19) in Appendix C allows us to transform the dummy coefficient into a euro amount.[9]

Second, controlling for credit demand is crucial. The corresponding variable is highly significant; its inclusion reduces the coefficients for the credit losses, as can be seen by comparing the second and third column in Table 3.

Third, a substitution effect for credit supply through other institutions is dominated by the demand effect, provided it exists. Otherwise, $n^{\text{bm},\neg\text{b}}_{t+1,4,i}$ should have a negative coefficient. Also a refined estimation presented in Section 5.2 does not suggest any substitution effect.

[9] In addition, we scale the coefficient obtained from (19) up by the factor 1/0.894 to account for fact that we estimate new business not for the whole portfolio but the portfolio without the industry where the large loss occurred.

Table 3: Impact of substantial losses on new business

Dependent variable: New lending $n^{\neg b}_{t+1,4,i}$ (4 quarters, %)	(1) Base case	(2)	(3)	(4)
$bigL_{t,i}$ dummy (10% worst losses)	-0.949***		-0.939***	-1.112***
	(0.241)		(0.236)	(0.236)
$lowC_{t-1,i}$ dummy (10% lowest capital)	-1.017**	-1.004**		
	(0.420)	(0.411)		
$interact_{t,i}$ big loss & low capital	0.0248			
	(0.890)			
$n^{\neg b}_{t-3,4,i}$ lag-4 new lending (%)	0.0328***	0.0345***	0.0326***	0.0434***
	(0.0116)	(0.0117)	(0.0116)	(0.0116)
$sml^{\neg b}_{t+1,4,i}$ maturing loans (%)	-0.0916***	-0.0929***	-0.0923***	-0.106***
	(0.0111)	(0.0111)	(0.0111)	(0.0113)
$n^{bm,\neg b}_{t+1,4,i}$ new lend. benchm. (%)	0.0846***	0.0857***	0.0845***	
	(0.0133)	(0.0133)	(0.0134)	
$n^{bm,\neg b}_{t-3,4,i}$ —, lag 4	0.0639***	0.0654***	0.0639***	
	(0.00966)	(0.00964)	(0.00966)	
Constant	7.837***	7.812***	7.782***	8.615***
	(0.628)	(0.631)	(0.630)	(0.638)
Bank FEs	yes	yes	yes	yes
Observations	30019	30019	30019	30019
R–squared (within)	0.032	0.031	0.031	0.023
Adjusted R–squared (within)	0.032	0.031	0.031	0.023

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the change in new lending due to substantial credit losses in one industry (see Equation 11). Period: 2002Q4–2017Q4. The share $\alpha = 10\%$ of the largest credit losses (normalized by a bank's total loan volume to domestic firms) is marked by the dummy variable $bigL$. The dummy $lowC$ takes value 1 if a bank's capital ratio is in the first decile of the banks' Tier-1 capital ratios in the respective quarter (lag 1). The dummy $interact$ is $bigL$ AND lagged $lowC$. Benchmark new business $n^{bm,\neg b}_{t+1,4,i}$ is defined in (7) and (8). The share of maturing loans $sml^{\neg b}_{t+1,4,i}$ is defined in (10). Standard errors in parentheses. *, ** and *** denote significance at the 10%, 5% and 1% level.

Fourth, bank capital matters. We see that banks with low capital provide significantly less credit than banks with a higher capital ratio.[10] However, as the interaction term of $lowC$ and $bigL$ is insignificant, we do not see a difference to banks for which low capital has combined with a substantial loss. Which is surprising because, according to common wisdom, thinly capitalized banks should react especially strongly to a heavy loss. We consider this point still to be open.

To offer a preliminary explanation, capital shortfalls (or the perception of it) might be dealt with mainly on the liability side, by corporate action such as retaining earnings, issuing new capital, or debt-equity swaps. This argument is supported by Memmel and Raupach (2010) who find around 80% of the adjustment of capital ratios to be done on the liability side. Similarly, Kok and Schepens (2013) find that banks whose current capital ratios are below a target level rather try to increase their capital than changing the asset composition.

To offer another explanation, even the biggest losses in our data might be just too small for a triggering event that makes a bank start to worry about its capital ratio. Indeed, the average direct mechanical effect of the 10% largest losses (for which $bigL = 1$) on the capital ratio is 23 basis points only.

Fifth, comparing column (1) and (2) in Table 3, an inclusion of the dummy $bigL$ for extreme losses increases the R^2 by only 0.079 percentage points, which is a small gain in explanatory power, at first glance. But a driver of seemingly low power at bank level can have greater aggregate effects:

In Appendix B, we present a simplified model in which low explanatory power of an estimate at bank level corresponds to high power of the same estimate executed on aggregate variables. In this model, the 0.079 percentage point gain in R^2 at bank level would lead to an R^2 gain of 5.7% if estimated at national level (which we cannot do in practice, as it conflicts with our identification approach). Our observation is in line with Berrospide and Edge (2010), who find modest effects of bank capital on lending when analyzed at bank level, and larger effects on the corresponding national aggregates.

The issue may become relevant when microprudential results as ours are transferred to macroprudential considerations, especially in stress tests. Then, a common shock hits the banking system, and an effect that otherwise appears to get lost in idiosyncratic variation may have considerable aggregate consequences.

5.2 Robustness and extensions

We first test alternative ways of constructing a benchmark bank. If corporate borrowing were a purely local process, our choice to assign a locally active bank a benchmark bank with equally local business would be perfect. It is clearly imperfect for different reasons. First, the bigger a borrower or the more wide-spread its business, the easier it is to approach another bank situated elsewhere if the current lender suddenly stops lending. Second, credit demand can be driven by systematic factors that affect larger regions commonly. Third, the business of a bank's local competitors is driven by idiosyncratic factors to a larger extent than that of a higher aggregate of competitors, which may impair the statistical power of $n^{\mathrm{bm},\neg\mathrm{b}}_{t+1,4,i}$, the locally adapted benchmark new business.

We construct four types of benchmark banks that differ in the size of regions across which a benchmark bank must have the same industry × region portfolio composition as the bank under consideration (the industry breakdown is unchanged). The most disaggregate benchmark bank has been constructed in Section 3.1; its portfolio composition fits at county level. The next type fits at the level of 38 administrative districts ("Regierungsbezirke"), a political sub-structure of

[10] Recall that $lowC$ is determined quarter by quarter; see Section 3.3.

the 16 German states ("Bundesländer"), which define the next-higher aggregation level. Finally, we also construct a nationwide benchmark bank the portfolio composition of which only fits with regard to industries, whereas any regional information is ignored. If two individual banks have the same industry weights, they are assigned the same nationwide benchmark bank.

In calculations we just need to give the region index r in the formulas of Section 3.1 a different meaning; r either runs through 401 counties, 38 administrative districts, 16 states, or takes the single value 1 for the nationwide benchmark.

Table 4 shows the results. In column 1, which contains the new business of all four types of benchmark banks, we see that only the county and the nationwide level generate benchmark new business with significant explanatory power.[11] The significance of the nationwide variable suggests a considerable influence of systematic factors on demand. But local factors seem to matter as well, as the variable on county level remains significant. Note, however, that these local factors are not idiosyncratic to banks but systematic in that they concern, by construction, *different* banks in the same region.

If only one of the four types of benchmark new lending is included (columns 2–5), we see that the coefficients get larger with rising level of aggregation, as well as the within-R^2, which increases from 3.2% to 4.6%. This effect is consistent with a variation in the presence (or even prevalence) of idiosyncratic drivers in local lending. The higher the level of aggregation in benchmark new lending, the smaller are the disturbances that bias the estimation coefficients downwards.[12] Note, however, that adjusting the portfolio composition at the most disaggregate level adds more than just noise to the model; otherwise, it would not be significant in the full specification of column 1.

Turning to the variable of our main interest, *bigL*, its estimated influence on new lending is smaller for a richer control set falling in the regional aggregation level of benchmark new business. Taking into account the standard deviations of estimators we consider the results to be qualitatively the same. Results for low capital are very stable, whereas the interaction term remains insignificant.

The next test concerns the horizon h (in quarters) over which new business and the share of maturing loans are calculated. Table 5 shows results for 1, 4, and 8 quarters, with local and nationwide benchmark new business as demand controls. One quarter seems to be too short as a time to react to a severe loss. If the horizon is extended from 4 to 8 quarters, the quantitative lending effect of *bigL* roughly doubles, which documents that reactions are not completed after one year. The impact of low capital shows the same pattern, while the interaction term remains insignificant, as in all preceding estimates.

Next, we have a deeper look into the potential substitution of credit supply by a bank's competitors after it has suffered a severe loss. From the positive coefficients of benchmark new business in the base case regression we have concluded that substitution, if present, does not dominate the effect of demand, as this would imply a negative or at least insignificant coefficient of $n^{\text{bm},\neg\text{b}}_{t+1,4,i}$. We refine this observation in Table 6 by an additional term marked in gray, which interacts *bigL*, the indicator of large losses, with benchmark new business. If there is substitution, competitors lend more (relative to what they would lend as a pure reaction to

[11] The similarly constructed variables for new business could be highly correlated and thus harm the reliability of regression results. According to Table 10 in Appendix D, there is a couple of correlations up to 0.8, however only with variables that have turned out to be insignificant in the full model of column 1. The correlation between the county and the nationwide variables is 0.28 and 0.39 between their lags and hence moderate.

[12] For simplicity, think of a model $Y_i = \alpha + \beta X_i + \varepsilon_i$ with an explanatory variable that suffers independent shocks which cannot be split off from the observed variable: $X_i = Z_i + \eta_i$. Here, η stands for the idiosyncratic factors that drive individual local lending. The higher the variance of η, the lower becomes the asymptotic regression coefficient $\beta = \text{cov}(Y, X) / \text{var}(X) = \text{cov}(Y, Z) / (\text{var}(Z) + \text{var}(\eta))$.

Table 4: Different benchmark banks

Dependent variable: New lending $n^{\neg b}_{t+1,4,i}$ (%)	Regions	(1)	(2) Base case	(3)	(4)	(5)
$bigL_{t,i}$ dummy		–0.653***	–0.949***	–0.852***	–0.806***	–0.690***
		(0.243)	(0.241)	(0.241)	(0.242)	(0.243)
$lowC_{t-1,i}$ dummy		–1.024**	–1.017**	–1.002**	–1.028**	–1.020**
		(0.419)	(0.420)	(0.423)	(0.423)	(0.417)
$interact_{t,i}$		–0.198	0.0248	0.0353	0.0176	–0.236
		(0.877)	(0.890)	(0.883)	(0.874)	(0.881)
$n^{\neg b}_{t-3,4,i}$ lag-4 new l. (%)		0.0184	0.0328***	0.0265**	0.0251**	0.0213*
		(0.0115)	(0.0116)	(0.0118)	(0.0119)	(0.0115)
$sml^{\neg b}_{t+1,4,i}$ maturing (%)		–0.0692***	–0.0916***	–0.0817***	–0.0795***	–0.0732***
		(0.0106)	(0.0111)	(0.0108)	(0.0104)	(0.0106)
$n^{bm,\neg b}_{t+1,4,i}$, county (%)	401	0.0368***	0.0846***			
		(0.0127)	(0.0133)			
—, lag 4		0.0243**	0.0639***			
		(0.0100)	(0.00966)			
$n^{bm,\neg b}_{t+1,4,i}$, adm. distr. (%)	38	0.0418		0.221***		
		(0.0374)		(0.0235)		
—, lag 4		0.0212		0.108***		
		(0.0268)		(0.0182)		
$n^{bm,\neg b}_{t+1,4,i}$, state (%)	16	0.0319			0.284***	
		(0.0490)			(0.0290)	
—, lag 4		–0.0160			0.115***	
		(0.0379)			(0.0203)	
$n^{bm,\neg b}_{t+1,4,i}$, DE (%)	1	0.324***				0.413***
		(0.0489)				(0.0356)
—, lag 4		0.133***				0.164***
		(0.0376)				(0.0220)
Constant		6.633***	7.837***	7.285***	7.252***	6.932***
		(0.601)	(0.628)	(0.609)	(0.584)	(0.595)
Bank FEs		yes	yes	yes	yes	yes
Observations		30019	30019	30019	30019	30019
R-squared (within)		0.048	0.032	0.037	0.040	0.046
Adj. R-squared (within)		0.048	0.032	0.037	0.040	0.046

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All variables as in Table 3. Benchmark banks differ in the aggregation level (or size) of regions at which they are fit to individual banks. That is, the benchmark bank has the same portfolio weight in each industry × region cell as the individual (benchmarked) bank. A region can be: a county, an administrative district (adm. distr.), a state, or Germany (DE). Column 2 coincides with column 1 of Table 3.

Table 5: Different time horizons for new lending business

Dependent: $n^{\neg b}_{t+1,h,i}$ (%)	(1)	(2)	(3)	(4)	(5)	(6)
Benchmark bank:		County			DE	
Horizon h in quarters:	1	4	8	1	4	8
$bigL_{t,i}$ dummy	0.0146	–0.949***	–1.664***	–0.0361	–0.690***	–1.586***
	(0.118)	(0.241)	(0.405)	(0.117)	(0.243)	(0.408)
$lowC_{t-1,i}$ dummy	–0.109	–1.017**	–1.638**	–0.0888	–1.020**	–1.718**
	(0.122)	(0.420)	(0.804)	(0.121)	(0.417)	(0.767)
$interact_{t,i}$	–0.163	0.0248	0.600	–0.174	–0.236	0.773
	(0.311)	(0.890)	(1.385)	(0.308)	(0.881)	(1.343)
$n^{\neg b}_{t-h+1,h,i}$ lag-h n. l. (%)	–0.0133	0.0328***	–0.0524***	–0.0206**	0.0213*	–0.0626***
	(0.00959)	(0.0116)	(0.0133)	(0.00980)	(0.0115)	(0.0135)
$sml^{\neg b}_{t+1,h,i}$ maturing (%)	–0.221***	–0.0916***	–0.0708***	–0.201***	–0.0732***	–0.0813***
	(0.0145)	(0.0111)	(0.0217)	(0.0138)	(0.0106)	(0.0213)
$n^{bm,\neg b}_{t+1,h,i}$, county (%)	0.0517***	0.0846***	0.143***			
	(0.00848)	(0.0133)	(0.0196)			
—, lag h	0.0163**	0.0639***	0.0752***			
	(0.00682)	(0.00966)	(0.0140)			
$n^{bm,\neg b}_{t+1,h,i}$, DE (%)				0.309***	0.413***	0.531***
				(0.0216)	(0.0356)	(0.0445)
—, lag h				0.101***	0.164***	0.288***
				(0.0166)	(0.0220)	(0.0295)
Constant	3.793***	7.837***	13.45***	3.515***	6.932***	14.12***
	(0.211)	(0.628)	(1.971)	(0.202)	(0.595)	(1.922)
Bank FEs	yes	yes	yes	yes	yes	yes
Observations	31851	30019	23325	31851	30019	23325
R-squared (within)	0.044	0.032	0.020	0.056	0.046	0.038
Adj. R-squared (within)	0.044	0.032	0.020	0.055	0.046	0.038

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All variables as in Table 4. Benchmark banks differ in the aggregation level (or size) of regions at which they are fit to individual banks. A region can be a county (most granular unit, column 1–3) or Germany (DE, column 4–6). Column 2 coincides with column 1 of Table 3.

credit demand) as a response to the lending cut of the bank that has been hit by the severe loss. The effect is insignificant for the local benchmark bank (column 2) whereas it should be positive in presence of a substitution effect. With the nationwide benchmark bank (column 4) it is even positive, which is potentially due to a tail dependence between $n^{\neg b}_{t+1,4,i}$ and the nationwide variant of $n^{\text{bm},\neg b}_{t+1,4,i}$. Altogether, we find no evidence of a substitution effect.

Next, we replace the definition of new business, (1), by (1-alt), which subtracts value changes from the change in exposure. Table 11 in Appendix D shows that the main regressions are quite insensitive to this modification: *bigL* has a slightly stronger effect under the alternative definition, while the R^2 is a bit lower.

Size is a standard control in the banking literature. Log total assets, our measure of size, should not have much explanatory power in the presence of bank fixed effects, as only 3.5% of the variation in log total assets comes from the time dimension in our data. While column 2 in Table 7 shows that the effects of large losses and capital basically remain unchanged, size has a surprisingly strong and significant effect. As our time dimension is not negligible (our sample encompasses 60 quarters), we may encounter spurious regression results in fixed-effect estimation in the sense of Entorf (1997). Replacing size by its stationary time difference leads to insignificant coefficients and leaves the base case results unchanged (column 3 and 4).

To test the sensitivity to the definition of large losses, we vary the probability of the loss tail. The lower it is, the bigger are the losses and hence the potential effect, of course at the cost of the number of events included. In Table 8, we find the results to be robust against a variation in the loss tail probability between 6% and 40%. That the coefficient of *bigL* reaches its maximum at 10% roughly corresponds with the shape of $n^{\neg b}_{t+1,4,i}$ in Figure 1. Similar to the preceding tests, neither zooming into the tail (columns 1–4) or out of it (columns 6–9) has an effect on the interaction term. It remains insignificant.

Table 6: Is decreased lending substituted by competitors?

Dependent variable: New lending $n^{\neg b}_{t+1,4,i}$ (%)	(1) Base case	(2)	(3)	(4)
$bigL_{t,i}$ dummy (10% worst losses)	–0.949***	–0.948***	–0.690***	–0.567**
	(0.241)	(0.240)	(0.243)	(0.248)
$lowC_{t-1,i}$ dummy (10% lowest cap.)	–1.017**	–1.017**	–1.020**	–1.020**
	(0.420)	(0.420)	(0.417)	(0.417)
$interact_{t,i}$ big loss & low capital	0.0248	0.0210	–0.236	–0.319
	(0.890)	(0.889)	(0.881)	(0.878)
$n^{\neg b}_{t-3,4,i}$ lag-4 new lending (%)	0.0328***	0.0327***	0.0213*	0.0210*
	(0.0116)	(0.0116)	(0.0115)	(0.0115)
$sml^{\neg b}_{t+1,4,i}$ maturing loans (%)	–0.0916***	–0.0915***	–0.0732***	–0.0729***
	(0.0111)	(0.0111)	(0.0106)	(0.0106)
$n^{bm,\neg b}_{t+1,4,i}$, county (%)	0.0846***	0.0818***		
	(0.0133)	(0.0139)		
—, lag 4	0.0639***	0.0638***		
	(0.00966)	(0.00968)		
$bigL_{t,i} \times n^{bm,\neg b}_{t+1,h,i}$, county (%)		0.0289		
		(0.0297)		
$n^{bm,\neg b}_{t+1,4,i}$, DE (%)			0.413***	0.399***
			(0.0356)	(0.0371)
—, lag 4			0.164***	0.163***
			(0.0220)	(0.0221)
$bigL_{t,i} \times n^{bm,\neg b}_{t+1,h,i}$, DE (%)				0.185**
				(0.0868)
Constant	7.837***	7.836***	6.932***	6.917***
	(0.628)	(0.629)	(0.595)	(0.596)
Bank FEs	yes	yes	yes	yes
Observations	30019	30019	30019	30019
R-squared (within)	0.032	0.032	0.046	0.046
Adj. R-squared (within)	0.032	0.032	0.046	0.046

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All variables as in Table 4, except $bigL_{t,i} \times n^{bm,\neg b}_{t+1,h,i}$ where the indicator of large losses is interacted with two types of benchmark new business. Benchmark banks differ in the aggregation level (or size) of regions at which they are fit to individual banks. Column 1 is the base case of Table 3; column 3 is identical with column 5 of Table 4.

Table 7: Impact of bank size

Dependent variable: New lending $n^{\neg b}_{t+1,4,i}$ (4 quarters, %)	(1) Base case	(2)	(3)	(4)
$bigL_{t,i}$ dummy (10% worst losses)	–0.949***	–1.139***	–0.779**	–0.952***
	(0.241)	(0.239)	(0.302)	(0.241)
$lowC_{t-1,i}$ dummy (10% lowest capital)	–1.017**	–0.919**	–0.859*	–1.023**
	(0.420)	(0.410)	(0.467)	(0.419)
$interact_{t,i}$ big loss & low capital	0.0248	0.212	0.0388	0.0300
	(0.890)	(0.884)	(0.933)	(0.888)
$n^{\neg b}_{t-3,4,i}$ lag-4 new lending (%)	0.0328***	0.0396***	0.0129	0.0278**
	(0.0116)	(0.0118)	(0.0139)	(0.0121)
$sml^{\neg b}_{t+1,4,i}$ maturing loans (%)	–0.0916***	–0.108***	–0.0853***	–0.0923***
	(0.0111)	(0.0117)	(0.0134)	(0.0112)
$n^{bm,\neg b}_{t+1,4,i}$ new lend. benchm. (%)	0.0846***	0.0923***	0.0915***	0.0846***
	(0.0133)	(0.0136)	(0.0166)	(0.0133)
$n^{bm,\neg b}_{t-3,4,i}$ —, lag 4	0.0639***	0.0726***	0.0696***	0.0649***
	(0.00966)	(0.00968)	(0.0111)	(0.00966)
Log total assets		–8.038***		
		(1.629)		
—, 1-quarter difference			4.842	
			(4.070)	
—, 4-quarters difference				4.704
				(3.389)
Constant	7.837***	57.57***	7.366***	7.829***
	(0.628)	(10.09)	(0.757)	(0.630)
Bank FEs	yes	yes	yes	yes
Observations	30019	30019	23190	30019
R–squared (within)	0.032	0.036	0.029	0.032
Adjusted R–squared (within)	0.032	0.036	0.028	0.032

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All variables as in Table 3; furthermore, log total assets (time t), its quarterly difference (t and $t-1$), and its 1-year difference (t and $t-4$). Column 1 coincides with column 1 of Table 3.

Table 8: Varying loss tail probability

Dep.: New lending $n^{\neg b}_{t+1,4,i}$ (%)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Loss tail probability (%):	2	4	6	8	10	15	20	30	40
$bigL_{t,i}$ (dummy)	–0.688	–0.560	–0.823**	–0.904***	–0.988***	–0.577***	–0.513***	–0.419***	–0.356***
	(0.618)	(0.409)	(0.321)	(0.269)	(0.241)	(0.207)	(0.177)	(0.148)	(0.130)
$lowC_{t-1,i}$ (dummy)	–1.021**	–1.041**	–0.999**	–1.008**	–1.020**	–0.998**	–1.104**	–1.127**	–1.188***
	(0.412)	(0.415)	(0.417)	(0.421)	(0.420)	(0.427)	(0.433)	(0.440)	(0.458)
$interact_{t,i}$ big loss & low c.	1.028	1.197	–0.333	–0.0596	0.0481	–0.109	0.532	0.417	0.465
	(2.314)	(1.771)	(1.296)	(1.073)	(0.897)	(0.695)	(0.582)	(0.447)	(0.399)
$n^{\neg b}_{t-3,4,i}$ lag-4 new lending (%)	0.0340***	0.0339***	0.0334***	0.0331***	0.0328***	0.0334***	0.0334***	0.0337***	0.0339***
	(0.0116)	(0.0117)	(0.0117)	(0.0116)	(0.0116)	(0.0116)	(0.0116)	(0.0116)	(0.0116)
$sml^{\neg b}_{t+1,4,i}$ maturing loans (%)	–0.0927***	–0.0926***	–0.0922***	–0.0919***	–0.0916***	–0.0917***	–0.0917***	–0.0917***	–0.0919***
	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.0111)	(0.0111)
$n^{bm,\neg b}_{t+1,4,i}$ new l. benchm. (%)	0.0856***	0.0854***	0.0851***	0.0848***	0.0846***	0.0848***	0.0849***	0.0851***	0.0852***
	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
$n^{bm,\neg b}_{t-3,4,i}$ —, lag 4	0.0652***	0.0650***	0.0645***	0.0642***	0.0639***	0.0642***	0.0645***	0.0646***	0.0647***
	(0.00963)	(0.00964)	(0.00965)	(0.00965)	(0.00966)	(0.00967)	(0.00965)	(0.00965)	(0.00964)
Constant	7.814***	7.818***	7.820***	7.827***	7.836***	7.834***	7.846***	7.873***	7.901***
	(0.631)	(0.631)	(0.630)	(0.629)	(0.628)	(0.629)	(0.628)	(0.626)	(0.625)
Bank FEs	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	30019	30019	30019	30019	30019	30019	30019	30019	30019
R–squared (within)	0.031	0.031	0.032	0.032	0.032	0.032	0.032	0.031	0.031
Adjusted R-squared (within)	0.031	0.031	0.031	0.031	0.032	0.031	0.031	0.031	0.031

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All variables as in Table 3, except $bigL_{t,i}$, which is based on a varying probability of the loss tail (row 2, in %). Column 5 is identical with the base case in Table 3, column 1.

6 Conclusion

Using a data set that is well suited for the analysis of the relationship between a bank's lending and its credit losses, we find a significant reduction in lending if a bank suffers from a surprising substantial credit loss. What is more, we estimate lending to be reduced by 1.60 euro per euro of credit loss. This reduction in lending is, however, smaller than the one under a constant-leverage assumption: If banks were using the loan volume as the only means to keep their capital ratios strictly constant at, say, 10%, they would reduce lending by 10 euros for every lost euro. Compared to the results from the literature as shown in Table 1, we find a moderate effect. Provided that the reader accepts four empirical studies as a sample, it is the median.

At bank level, the explanatory power of our measure of losses is quite small. Under some reasonable assumptions made in Appendix B, the explanatory power of an aggregate estimation at national level may be much higher.

We further notice that a bank's capital position plays a role but seems to have little impact in case of a substantial credit loss: the new lending of a thinly capitalized bank is significantly lower, whereas the reduction due to a surprising credit loss does not seem to differ from that of better capitalized banks.

Appendix

A Regional distribution of exposures

This appendix supplements Section 4.4 by details of how we calculate the regional exposures $ex_{t,i,j,r}$ used in Section 3.1.

Denote by $ex^{\mathrm{BS}}_{t,i,j}$ the exposure of bank i to industry j at time t as reported in the BS. This is an aggregate over the three maturity bands. Furthermore, denote by $ex^{\mathrm{CR}}_{t,i,j,r}$ the domestic part of the exposure of bank i to industry[13] j in region r (a county) at time t, obtained from the CR. This number is an aggregate over individual borrowers grouped into the same industry × region cell.

Summing CR exposures over regions, the typical relationship between CR and BS exposures especially for small banks and banks more active in retail and SME lending is:

$$\sum_r ex^{\mathrm{CR}}_{t,i,j,r} \quad < \quad ex^{\mathrm{BS}}_{t,i,j}. \tag{12}$$

The converse can happen as well because the definition of credit is more general in the credit register.[14] As we want to keep the figures as close to the BS as possible (because we get loss data from there), we use credit register data only to approximate the regional distribution of credit. To this end, we first downsize CR exposures, if necessary, to the amount explained by BS data:

$$ex^{\mathrm{CR}*}_{t,i,j,r} \quad \equiv \quad \min\left(1, \frac{ex^{\mathrm{BS}}_{t,i,j}}{\sum_r ex^{\mathrm{CR}}_{t,i,j,r}}\right) \cdot ex^{\mathrm{CR}}_{t,i,j,r}. \tag{13}$$

[13]Sectors in the BS are an aggregation of the credit register's sectors. We work with the former throughout of the paper.

[14]For instance, the CR counts bonds held by a bank as credit to the bond issuer; similar for CDS protection sold. Neither of the two is reflected in the BS, which is strictly held consistent with banks' balance sheets (bonds are a separate balance sheet position; CDSs are off balance sheet). CR exposures can also exceed BS exposures if a bank reports the sector affiliation of a borrower inconsistently in the BS and CR.

This modification has no effect under the typical condition (12). What is left from subtraction of credit register exposures is called "pure BS" exposure:

$$ex_{t,i,j}^{\text{BS,pure}} \quad \equiv \quad ex_{t,i,j}^{\text{BS}} - \sum_r ex_{t,i,j,r}^{\text{CR}*}.$$

This is the part of the exposure on which we have no regional information. We assume these loans to be completely made in the region of the bank's head office (given by the function seat (i)), which makes the more sense the smaller the bank is.

The final exposure of bank i in industry j in region r at time t used in Section 3.1 is consequently:

$$ex_{t,i,j,r} \quad \equiv \quad ex_{t,i,j,r}^{\text{CR}*} + \mathrm{I}\left(r = \text{seat}\,(i)\right) ex_{t,i,j}^{\text{BS,pure}}, \tag{14}$$

where $\mathrm{I}\left(\ldots\right)$ is an indicator function. The breakdown guarantees that the initial BS exposure is preserved: $\sum_r ex_{t,i,j,r} = ex_{t,i,j}^{\text{BS}}$.

B Explanatory power

A simplified version of Equation (11) is:

$$n_i = \gamma + \beta \cdot \mathrm{I}\left(c_i < \delta\right) + \varepsilon_i \tag{15}$$

with $\text{var}(\varepsilon_i) = \sigma_{\text{bl}}^2$ ("bl" for *bank level*) and $\mathrm{I}\left(c_i < \delta\right) = bigL_i$ with $\Pr(c_i < \delta) = \alpha$. In the baseline regression we set $\alpha = 10\%$. At bank level, the coefficient of determination R_{bl}^2 is

$$R_{\text{bl}}^2 = \frac{\beta^2 \text{var}\left(\mathrm{I}\left(c_i < \delta\right)\right)}{\beta^2 \text{var}\left(\mathrm{I}\left(c_i < \delta\right)\right) + \sigma_{\text{bl}}^2}.$$

Aggregating the new lending of all banks and assuming the c_i to be perfectly correlated leads to the following relationship (variables without the index i):

$$n = \gamma + \beta \cdot \mathrm{I}\left(c < \delta\right) + \varepsilon \tag{16}$$

with

$$\varepsilon = \sum_{i=1}^{N} m_i \varepsilon_i,$$

where $m_i \equiv ex_i/ex$ is the market share of bank i concerning the credit volume. This holds because we can rewrite (15) as follows:

$$\begin{aligned} n \quad &= \quad \sum_{i=1}^{N} \frac{ex_i}{ex} \cdot n_i = \sum_{i=1}^{N} \frac{ex_i}{ex} \cdot \left(\gamma + \beta \cdot \mathrm{I}\left(c_i < \delta\right) + \varepsilon_i\right) \\ &= \quad \gamma + \beta \cdot \mathrm{I}\left(c < \delta\right) + \sum_{i=1}^{N} m_i \varepsilon_i \end{aligned}$$

Under the assumption that c_i is perfectly correlated in the cross section of banks, we obtain:

$$\text{var}\left(\mathrm{I}\left(c < \delta\right)\right) = \text{var}\left(\mathrm{I}\left(c_i < \delta\right)\right).$$

By contrast, we assume the bank-individual effect ε_i to be uncorrelated in the cross section and obtain:

$$\text{var}(\varepsilon) = \mathit{HHI} \cdot \sigma^2_{\text{bl}}$$

where $\mathit{HHI} = \sum_{i=1}^{N} m_i^2$ is the Hirschman-Herfindahl index of the banks' market shares. Accordingly, the R^2 of Equation (16) would be

$$R^2 = \frac{R^2_{\text{bl}}}{R^2_{\text{bl}} + \mathit{HHI} \cdot \left(1 - R^2_{\text{bl}}\right)}. \tag{17}$$

Hence, the smaller HHI becomes, that is, the less concentrated the banking system is, the closer R^2 gets to 1.

C Dummy variable and losses in euro

The following equation can be seen as a simplified version of our baseline regression (11):

$$n_i = \gamma + \beta \cdot \text{I}\left(c_i < \delta\right) + \eta_i. \tag{18}$$

with $\Pr(c_i < \delta) = \alpha$; the latter is set to 10% as in the baseline regression. The coefficient β in (18) can be seen as the (additional) change in new lending in case $c_i < \delta$, where the average losses (below the threshold δ) are in this case $E\left[c_i - \delta | c_i < \delta\right] = E\left[c_i | c_i < \delta\right] - \delta$. This makes the following definition of $\widetilde{\beta}$ sensible:

$$\widetilde{\beta} := \frac{\beta}{E\left(c_i | c_i < \delta\right) - \delta} \tag{19}$$

where $\widetilde{\beta}$ can be seen as the euro-amount of the (additional) change in new lending at a loss corresponding to the average extreme losses (above the threshold δ).

D Supplementary tables

Table 9: Lending and losses by industry

No.	Industry, code	Lending	Losses p.a.
1	Agriculture, forestry, fishing and aquaculture (110)	2.79	0.59
2	Electricity, gas and water supply; refuse disposal, mining and quarrying (120)	7.99	0.34
3	Chemical industry, manufacture of coke and refined petroleum products (131)	4.13	1.76
4	Manufacture of rubber and plastic products (132)	11.55	1.18
5	Manufacture of other non-metallic mineral products (133)	5.83	1.84
6	Manufacture of basic metals and fabricated metal products (134)	12.62	0.19
7	Manufacture of machinery and equipment; manufacture of transport (135)	1.17	0.85
8	Manufacture of computer, electronic and optical products (136)	0.80	1.51
9	Manufacture of wood and wood products; manufacture of pulp, paper and paper products, printing; manufacture of furniture;... (137)	0.58	1.68
10	Textiles, apparel and leather goods (138)	2.40	1.60
11	Manufacture of food products and beverages; manufacture of tobacco products (139)	3.43	1.72
12	Construction (140)	1.37	1.84
13	Wholesale and retail trade; repair of motor vehicles and motorcycles (150)	2.12	1.99
14	Transportation and storage; post and telecommunications (160)	0.44	2.53
15	Financial intermediation (excluding MFIs) and insurance companies (170)	1.71	1.18
16	Housing enterprises (181)	6.83	1.04
17	Holding companies (182)	4.39	1.04
18	Other real estate activities (183)	10.16	1.14
19	Hotels and restaurants (184)	1.43	2.05
20	Information and communication; research and development; membership (185)	6.33	1.46
21	Health and social work (enterprises and self-employment) (186)	5.53	0.61
22	Rental and leasing activities (187)	2.11	1.10
23	Other service activities (188)	4.30	1.46

All figures in percent. Column "Lending" shows the composition of the aggregate domestic corporate credit portfolio of all German banks as reflected by Bundesbank's Borrower Statistics; Column "Losses p.a." shows annual loss rates for each sector. Industry sectors and codes are defined in Bundesbank's Borrower Statistics (Deutsche Bundesbank, 2009).

Table 10: Correlations of key variables

Variable	Aggregation level	$n^{\neg b}_{t,4,i}$	~, lag 4	$n^{bm,\neg b}_{t,4,i}$ County	~, lag 4	$n^{bm,\neg b}_{t,4,i}$ Admin. di.	~, lag 4	$n^{bm,\neg b}_{t,4,i}$ State	~, lag 4	$n^{bm,\neg b}_{t,4,i}$ Germany	~, lag 4	$sml^{\neg b}_{t+1,4,i}$
$n^{\neg b}_{t,4,i}$		1.000										
~, lag 4		0.198	1.000									
$n^{bm,\neg b}_{t,4,i}$	county	0.101	0.103	1.000								
~, lag 4		0.102	0.153	0.093	1.000							
$n^{bm,\neg b}_{t,4,i}$	admin. di.	0.144	0.136	0.438	0.203	1.000						
~, lag 4		0.123	0.215	0.151	0.522	0.269	1.000					
$n^{bm,\neg b}_{t,4,i}$	state	0.158	0.137	0.357	0.198	0.752	0.267	1.000				
~, lag 4		0.122	0.232	0.148	0.453	0.266	0.792	0.285	1.000			
$n^{bm,\neg b}_{t,4,i}$	Germany	0.177	0.136	0.281	0.200	0.548	0.257	0.719	0.258	1.000		
~, lag 4		0.133	0.253	0.120	0.394	0.228	0.634	0.240	0.773	0.232	1.000	
$sml^{\neg b}_{t+1,4,i}$		–0.113	–0.148	–0.090	–0.126	–0.136	–0.163	–0.143	–0.170	–0.163	–0.184	1.000

Correlation of variables as used in Table 4, column 1.

Table 11: Alternative definition of new lending business

Dependent: New lending $n^{\neg b}_{t+1,4,i}$ or $n^{alt,\neg b}_{t+1,4,i}$ (%)	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Base case		No *bigL*		DE benchmark	
Definition of new business:	(1)	(1-alt)	(1)	(1-alt)	(1)	(1-alt)
$bigL_{t,i}$ (dummy)	–0.949***	–0.992***			–0.690***	–0.725***
	(0.241)	(0.253)			(0.243)	(0.253)
$lowC_{t-1,i}$ (dummy)	–1.017**	–0.979**	–1.004**	–0.990**	–1.020**	–0.986**
	(0.420)	(0.411)	(0.411)	(0.403)	(0.417)	(0.409)
$interact_{t,i}$ big loss & low capital	0.0248	–0.264			–0.236	–0.512
	(0.890)	(0.916)			(0.881)	(0.909)
$n^{(alt),\neg b}_{t-3,4,i}$ lag-4 new lending (%)	0.0328***	0.0315***	0.0345***	0.0324***	0.0213*	0.0204*
	(0.0116)	(0.0111)	(0.0117)	(0.0112)	(0.0115)	(0.0109)
$sml^{\neg b}_{t+1,4,i}$ maturing loans (%)	–0.0916***	–0.0828***	–0.0929***	–0.0842***	–0.0732***	–0.0653***
	(0.0111)	(0.0108)	(0.0111)	(0.0108)	(0.0106)	(0.0103)
$n^{(alt),bm,\neg b}_{t+1,4,i}$, county (%)	0.0846***	0.0769***	0.0857***	0.0781***		
	(0.0133)	(0.0128)	(0.0133)	(0.0129)		
—, lag 4	0.0639***	0.0606***	0.0654***	0.0623***		
	(0.00966)	(0.00956)	(0.00964)	(0.00953)		
$n^{(alt),bm,\neg b}_{t+1,4,i}$, DE (%)					0.413***	0.378***
					(0.0356)	(0.0354)
—, lag 4					0.164***	0.167***
					(0.0220)	(0.0220)
Constant	7.837***	7.841***	7.812***	7.822***	6.932***	6.978***
	(0.628)	(0.610)	(0.631)	(0.613)	(0.595)	(0.584)
Bank FEs	yes	yes	yes	yes	yes	yes
Observations	30019	30016	30019	30016	30019	30016
R–squared (within)	0.032	0.027	0.031	0.026	0.046	0.040
Adjusted R-squared (within)	0.032	0.027	0.031	0.026	0.046	0.040

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

All variables as in Table 4, however new business (and so for benchmark banks) is either based on definition (1) (column 1,3,5) or (1-alt) (column 2,4,6) consistently for the dependent variable and controls. Columns 1 and 3 are identical with columns 1 and 2 of Table 3; column 5 is identical with column 6 of Table 4

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