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**The winner's curse –
evidence on the danger of
aggressive credit growth in banking**

Thomas Kick
Thilo Pausch
Benedikt Ruprecht

Editorial Board:

Daniel Foos
Thomas Kick
Jochen Mankart
Christoph Memmel
Panagiota Tzamourani

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

Tel +49 69 9566-0

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

Internet <http://www.bundesbank.de>

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Non-technical summary

Research Question

Excessive credit growth has been a driver of the recent financial crisis, and has been fueled by deteriorating lending standards during boom periods. As a consequence many banks suffered from large write-offs and some banks even faced serious distress events. Regulation addressed the build-up of credit risk by introducing the countercyclical capital buffer as a new macroprudential instrument. This study addresses the question why banks engage in excessive lending and examines their motives to do so. Furthermore, the methodology we propose allows identifying banks that engage in excessive lending even when no lending boom at the aggregate level occurs. Finally, we analyse whether banks identified as excessive credit suppliers are more likely to default.

Contribution

Our contribution to the literature is threefold. First, we develop a simple theoretical *Winner's Curse* argument based on an overoptimistic view to explain why banks engage in excessive credit growth. Second, we propose a new methodology to measure excess credit growth at the bank level. The method separates banks' real credit growth into its cyclical and its trend component (i.e. we measure deviations from the "organic growth" of a bank). Applied to aggregate data, this method is known to identify lending booms and may be used when deciding to activate the countercyclical capital buffer. Third, we test our theoretical model and the proposed empirical methodology using a unique prudential data set that allows us to determine write-offs not only at a bank level but also at a sectoral credit portfolio level.

Results

Our theoretical model predicts that a limited number of overoptimistic banks may engage in excessive lending whereas the aggregate credit market is still rationing lending. Traditional measures of (excessive) credit growth show that extending credit is beneficial for banks and lowers their loan write-offs. Hence, in general banks seem to monitor their credit engagements well. However, using our proposed measure of excessive credit growth, we do not only find that these excess suppliers suffer disproportionately large write-offs, but are also more likely to rely on capital support from the bankers' associations insurance schemes, or to experience restructuring mergers in subsequent years. Therefore, our approach is suitable to identify banks that engage in too much risk-taking through credit expansion and helps banking supervision to closely monitor these banks with respect to capital shortfalls and deleveraging needs. It helps identifying weak banks as proposed in the Supervisory Review Process of the Basel Accord.

Nichttechnische Zusammenfassung

Forschungsfrage

Exzessives Kreditvergabeverhalten von Banken, angetrieben durch sinkende Kreditvergabe-standards, war einer der Treiber der jüngsten Finanzkrise. Die Folgen waren erhöhte Abschreibungen bis hin zur schweren Schieflage einzelner Banken. Die Bankenregulierung hat mit der Einführung des antizyklischen Kapitalpuffers als ein neues makroprudenzielles Instrument reagiert. Diese Studie untersucht, warum Banken ihr Kreditangebot exzessiv ausweiten und analysiert deren zugrundeliegenden Motive. Darüber hinaus erlaubt es unsere Methodik, Banken mit exzessivem Kreditwachstum zu identifizieren, auch wenn auf aggregierter Ebene kein Kreditboom vorliegt. Schließlich wird untersucht, ob Banken mit exzessivem Kreditwachstum höhere Ausfallwahrscheinlichkeiten aufweisen.

Beitrag

Unsere Studie liefert drei Beiträge zur Literatur. Erstens entwickeln wir ein theoretisch fundiertes “Winner’s Curse” Modell, bei dem Banken aufgrund einer zu optimistischen Risikoeinschätzung ihr Kreditwachstum zu stark ausweiten. Zweitens schlagen wir eine Methodik zur Messung exzessiven Kreditwachstums auf Bankebene vor. Diese trennt die zyklischen Komponenten des realen Kreditwachstums vom Wachstumstrend einer Bank (d.h. wir messen Abweichungen vom “organischen Wachstum” des jeweiligen Instituts). Auf aggregierter Ebene wird diese Methodik zur Identifizierung von Kreditbooms und bei der Aktivierung des antizyklischen Kapitalpuffers herangezogen. Drittens testen wir unser theoretisches Modell sowie die empirische Methodik an einem aufsichtlichen Datensatz mit Kreditausfällen sowohl auf Bankebene als auch auf Ebene sektoraler Kreditportfolien.

Ergebnisse

Unser theoretisches Modell zeigt, dass eine bestimmte Anzahl von Banken durchaus eine exzessive Kreditvergabe verfolgen kann, während sich der gesamte Kreditmarkt immer noch im Bereich einer Kreditrationierung befindet. Herkömmliche Kennzahlen (exzessiven) Kreditwachstums verdeutlichen, dass die Ausweitung des Kreditvolumens für den Großteil der Banken aufgrund sinkender Kreditausfälle positive Effekte nach sich zieht. Im Allgemeinen scheinen Banken über ein gutes Controlling für ihre Kreditvergabe zu verfügen. Kennzahlen, die auf der neuen Methode basieren, zeigen hingegen, dass Banken mit exzessivem Kreditwachstum überproportionale Kreditausfälle erleiden und auch in den Folgejahren mit höherer Wahrscheinlichkeit Kapitalhilfen von den Sicherungseinrichtungen der Bankenverbände benötigen bzw. eine Sanierungsfusion notwendig wird. Somit ist unser Ansatz zur Identifikation jener Banken geeignet, welche durch exzessive Kreditvergabe überhöhte Risiken eingehen. Dies kann der Bankenaufsicht helfen, diese Institute verstärkt zu überwachen und ggf. zusätzliches Kapital bzw. einen Abbau von Risikopositionen einzufordern, und ist kompatibel zu den Vorschlägen des Baseler Akkords zur Identifizierung schwacher Banken.

The Winner's Curse -^{*}
Evidence on the Danger of
Aggressive Credit Growth in Banking

Thomas Kick Thilo Pausch Benedikt Ruprecht

Abstract

Excessive credit creation by banks was at the root of the recent financial crisis. Nevertheless, micro-prudential regulation lacks a clear methodology to identify these banks. Combining arguments from banking and auction theory, we show that overoptimism causes excessive lending, subsequently yielding abnormal loan write-offs. We propose a new measure of excessive credit growth known from macroeconomics to identify credit booms and test our model for German bank and bank-portfolio level data. Unlike traditional measures of (excessive) loan growth, our new measure identifies banks that are affected by abnormal loan write-offs, need capital support, or default in subsequent years.

Keywords: Excessive credit growth, Winner's Curse, Loan-to-GDP gap, Micro-prudential regulation, Identifying weak banks

JEL classification: C23, G21, G32.

^{*}Contact address: Deutsche Bundesbank, P.O. Box 10 06 02, 60006 Frankfurt, Germany. Phone: +49 69 9566 8194. E-Mail: thomas.kick@bundesbank.de, thilo.pausch@bundesbank.de, benedikt.ruprecht@bundesbank.de. The authors thank Hans Degryse, Klaus Düllmann, Rainer Haselmann, Christoph Memmel, Klaus Schaeck, Weidong Tian, as well as participants at the 2013 EEA-ESEM Conference (Gothenburg), the 2014 MFA Meetings (Orlando), the 2014 SUERF Colloquium and BAFFI Finlawmetrics Conference (Bocconi), the 2014 Swiss Society for Financial Market Research Conference (Zurich), the 2015 WEAI/IBEFA meeting (Honolulu) and participants at the Bundesbank Seminar on Banking and Finance for their valuable input. This discussion paper represents the authors' personal opinions and does not necessarily reflect the views of the Deutsche Bundesbank or its staff.

1 Introduction

Excessive credit and asset growth has been a major driver of the recent financial crisis (e.g., [Mian and Sufi, 2009](#)). When too many banks follow the same common strategy — for example due to competition (e.g., [Gorton and He, 2008](#); [Aikman et al., 2015](#)) — lending standards are lowered in order to attract more borrowers and a credit boom arises. But how can loan growth be characterized as excessive in advance before a bank fails? Regulators tried to restrict excessive credit growth in the new Basel III capital framework by introducing countercyclical buffers as a macro-prudential tool to prevent the build-up of systemic risk ([BCBS, 2011](#))¹ or by demanding countercyclical loan loss provisioning ([Jiménez and Saurina, 2006](#); [Jiménez et al., 2014b](#)). These approaches increase banks' minimum capital requirements and simultaneously lower banks' excess capital which might be used to fund additional loans. [BCBS \(2010\)](#) offers guidance when credit growth at a national level increases too much and the countercyclical capital buffer should be activated. However, at a micro-prudential level supervisors lack measures to gauge when an individual bank has become vulnerable due to excessive lending.

Therefore, we focus on identifying weak banks with excessive credit growth as motivated by ([BCBS, 2015](#)). Our paper makes *three contributions* to the nexus between excess credit growth and subsequent losses through loan charge-offs and potential bank default. *First*, we offer a new simple theoretical argument for why some banks engage in excessive credit growth as a consequence of a Winner's Curse situation even though credit rationing in the sense of [Stiglitz and Weiss \(1981\)](#) and [Williamson \(1987\)](#) is still present in the aggregate credit market. *Second*, we propose a new methodology to measure excessive credit growth at the bank level. Our approach is based on methods of estimating aggregate credit gaps at the national level (e.g., [Mendoza and Terrones, 2008, 2012](#)) and consistent with the method proposed by [BCBS \(2010\)](#).² Specifically, we estimate excess credit growth as the difference between real loan growth and its long term trend, where the trend is derived from the Hodrick-Prescott (HP) filter. *Third*, we use a unique regulatory data set that allows us to identify write-offs (following credit growth) not only at the bank level, but also at the portfolio level to test the results of our model. We find that banks identified as excessive credit suppliers — either with respect to total credit or their major sectoral portfolios — will incur disproportionately large write-offs in subsequent years. Furthermore, excessive credit suppliers are more likely to default and to receive capital support in later years. Therefore, our method is a useful tool for micro-prudential supervisors to identify endangered institutions and can be used to justify capital charges in excess of the minimum requirements of Basel III under the Supervisory Review Process of Pillar 2.

To develop our simple theoretical model, we combine arguments from the literature on banking and auction theory to explain why some banks excessively expand credit. We argue that there exists a kind of Winner's Curse in credit markets. At the time when

¹The Accord states: *As witnessed during the financial crisis, losses incurred in the banking sector during a downturn preceded by a period of excess credit growth can be extremely large. Such losses can destabilize the banking sector [...].* ([BCBS, 2011](#), paragraph 29). National authorities can demand a Common Equity Tier 1 ratio of up to 2.5% of risk-weighted assets.

²National authorities consider the macroeconomic credit-to-GDP gap when deciding about the level of the countercyclical buffer. The gap is determined as the difference between actual credit-to-GDP ratio and its long-term trend, which is calculated using the Hodrick-Prescott filter ([BCBS, 2010](#)).

banks make lending decisions, they need to evaluate the general level of credit risk in the aggregate lending market. Being too optimistic encourages the bank to extend more new loans than would be optimal. That is, banks may find themselves in a situation where lending and credit risk turn out to be excessive ex post, causing extremely high rates of loan default. Interestingly, the intention to ration credit does not protect banks against excessive future loan losses.

We test the predictions of our model by analyzing the relationship between past measures of (excess) loan growth and proxies for ex post credit risk, i.e. loan write-offs, using prudential data from Germany. Germany did not experience a credit boom over the last two decades. Nevertheless, individual banks have expanded their balance sheets and encountered distress or even collapsed. Hence, our data set is well-suited to identify those banks that engage in excessive lending as a rather small group compared to the whole banking system. Using a unique data set of bank loan portfolio data, we apply the HP filter to decompose a bank's loan growth into a trend and a cyclical component. Excessive credit growth is defined as a cyclical component, i.e. the difference between actual growth and the long term trend in credit growth. As our data set contains loan charge-offs for different lending sectors, we conduct our analysis for both total lending and lending at a sectoral loan portfolio level where we investigate banks' three largest lending portfolios. Using traditional measures of (excessive) loan growth, we show that the majority of banks are doing well in extending credit supply; i.e. banks are basically monitoring loan exposures sufficiently and do not lend excessively. Based on excessive credit growth measures derived from the HP filter, we identify those banks that extend too much credit and therefore experience significantly higher loan-write offs.

Our paper contributes to the empirical and theoretical literature linking excessive credit growth and future loan losses. [Salas and Saurina \(2002\)](#), [Jiménez and Saurina \(2006\)](#), and [Foos et al. \(2010\)](#) all find a positive relationship between abnormal credit growth and loan losses in subsequent years, but differ in the time lag between lending expansion and loan defaults. [Jiménez and Saurina \(2006\)](#) find that the major driver behind excessive credit growth is banks lowering their credit standards during boom periods. A deterioration in lending standards can be the product of bank managers' herding behavior ([Rajan, 1994](#)), increased collateral values during boom periods ([Asea and Blomberg, 1998](#)), the general opaqueness of information on borrowers' creditworthiness ([Dell'Ariccia and Marquez, 2006](#)), or macroeconomic drivers such as low interest rates, i.e. the risk-taking channel of monetary policy ([Dell'Ariccia et al., 2014](#); [Jiménez et al., 2014a](#)). Also, interbank competition can induce lower credit standards and fuel credit cycles ([Gorton and He, 2008](#); [Aikman et al., 2015](#)). [Broecker \(1990\)](#) and [Shaffer \(1998\)](#) address the problem of competition when new banks enter the market and find that borrowers' loan quality decreases with the number of banks previously rejected loan applicants can apply at.

Another strand of the empirical literature focuses on credit expansion (and contraction) as a consequence of the procyclical behavior of loan-loss provisioning and capital requirements (e.g., [Laeven and Majnoni, 2003](#); [Bikker and Metzmakers, 2005](#); [Behn et al., 2015](#)). Although credit risk builds up during booms, banks delay loan-loss provisioning for too long, and therefore have to write off a disproportionately large volume of loans during recessions ([Laeven and Majnoni, 2003](#)). [Berger and Udell \(2004\)](#) see the cause of the procyclicality of bank lending in the "institutional memory hypothesis." Institutions

forget about prior loan defaults, as older loan officers are replaced with officers who have never experienced a crisis. As a consequence, as more and more time passes since the last crisis, banks lower their credit standards and attract more borrowers of poor quality.

A small literature provides evidence at the bank level on how the enforcement of regulations can mitigate credit growth. [Aiyar et al. \(2014\)](#) investigate the time-varying bank-specific capital requirements imposed by the UK Financial Services Authority under the Basel I regime. The authors find that higher capital requirements reduce lending growth for regulated banks, whereas the opposite holds for unregulated banks. [Jiménez et al. \(2014b\)](#) investigate the impact of the dynamic loan loss provisioning regime in Spain on credit supply. They find that countercyclical dynamic provisioning mitigates credit supply cycles, but firms switch to receive credit supply from banks not covered under the provisioning scheme. Besides this form of regulatory arbitrage, affected banks lend to riskier borrowers during booms. [Basten and Koch \(2014\)](#) investigate the rates demanded by banks after the activation of the countercyclical capital buffer in Switzerland in February 2013. Capital-constrained banks with less excess capital are found to increase mortgage rates relatively more and rates to highly levered borrowers are increased overproportionally. While banks demand higher loan rates, the activation of the countercyclical capital buffer does not impact banks' willingness to accept new mortgage loans.

The remainder of this paper is organized as follows: Section 2 links the credit supply literature with auction pricing theory to provide the foundation of our Winner's Curse argument. Section 3 presents some institutional background on the German banking sector and explains the data and methodology underlying our empirical analysis. Results are presented in Section 4. Section 5 concludes.

2 Theoretical foundation of the argument

From the post-crisis perspective, the question arises as to why banks engage in excessive lending, subsequently leading to high loan charge-offs. [Williamson \(1987\)](#) shows that banks' expected cash flows from offering a standard debt contract decline when the nominal loan rate is set too high (i.e. sufficiently close to a borrower's maximum ability to pay) due to an increasing probability of borrower default. As a consequence, in a situation of costly state verification with ex-ante identical borrowers, a backward bending loan supply function and credit rationing appear due to the nature of an optimal loan contract design. In more formal terms: a bank's expected profit from lending rises in the nominal payment obligation R on loans as long as the payment obligation does not exceed a given threshold level R^* . Beyond R^* the expected profit falls when the nominal payment obligation is increased. This effect translates into a backward bending loan supply function which reaches a maximum at R^* .³

Given that both the common design of loan contracts as well as asymmetric informa-

³[Stiglitz and Weiss \(1981\)](#) present an alternative argument for the existence of backward bending loan supply functions based on asymmetric information about the quality of borrowers. When potential borrowers differ with respect to their individual risk levels and ability to meet payment obligations, adverse selection drives good borrowers out of the market if they are offered a standard debt contract. As a result, the average credit quality of the bank's loan portfolio decreases when loan supply is expanded. To a certain degree, banks are able to over-compensate this adverse selection effect by increasing borrowers' payment obligations. However, beyond a certain threshold the adverse selection effect dominates.

tion cause backward bending loan supply functions it cannot be optimal for individual banks to increase lending beyond the volume corresponding to the threshold payment obligation R^* . Additionally, credit rationing is also, at first glance, not compatible with excessive lending. Our model therefore combines banking theory, auction theory and decision making in situations of risk. We show that, regardless of the existence of credit rationing, uncertainty with respect to the general level of credit risk in the market distorts banks' lending decisions. This causes a Winner's Curse: a single bank's assessment of the general risk level turns out too optimistic ex post, resulting in excessive lending and extremely high write-offs on loans.

For a more formal representation of the argument we build on [Williamson \(1987\)](#): consider a credit market with a large number of ex-ante identical borrowers who need external funds to finance a profitable investment project with an uncertain outcome. Banks provide credit by offering identical standard debt contracts with a nominal payment obligation R to borrowers. That is, a representative borrower has to make a predefined repayment R to the bank when the debt contract matures. If, however, the borrower is not able to make this repayment, the bank takes possession of all available outcome of the borrower's project and incurs some fixed cost γ to monitor the project. Let $F(x|s)$ and $f(x|s) > 0$ denote the cumulative probability distribution function and the probability density function of the outcome x of a representative borrower's investment project conditional on the general level of risk s in the credit market.⁴ The bank's expected profit from such a standard debt contract $E(\pi(x|s))$ amounts to:

$$E(\pi(x|s)) = \int_0^R (x - \gamma) dF(x|s) + R(1 - F(R|s)). \quad (1)$$

There exists a certain R^* which maximizes $E(\pi(x|s))$. For all $R > R^*$ the function $E(\pi(x|s))$ is backward bending. That is, differentiating (1) with respect to R yields

$$\frac{d}{dR} E(\pi(x|s)) = (1 - F(R|s)) - \gamma f(R|s). \quad (2)$$

Due to $F(R|s) \in [0, 1]$ and $\gamma, f(R|s) > 0$ there exists a certain R^* for which the right-hand side of (2) becomes zero. Furthermore, the common features of cumulative probability distribution functions imply that $\frac{d}{dR} E(\pi(x|s))$ is positive (negative) for $R < R^*$ ($R > R^*$).

If we further assume that a bank's loan supply function L is an increasing function of the expected (conditional) profit of a representative standard debt contract, i.e.

$$L \equiv L(E(\pi(x|s))) \text{ with } L'(\cdot) \equiv \frac{d}{dE(\cdot)} L(E(\pi(x|s))) > 0, \quad (3)$$

then the previous observations translate into a backward-bending loan supply function of a bank with $L'(\cdot) \geq (<)0$ for $R \leq (>)R^*$ and $L'(\cdot) = 0$ for $R = R^*$. However, from (3) one easily observes that a bank's loan supply depends not only on R , but also on the general risk level s in the credit market. The risk level s represents a number of factors in the (macro) economic environment of borrowers with an impact on their project outcomes which they cannot directly affect by their behavior.

⁴Note that the general risk level s is treated as given, i.e. a scalar, for the moment. We generalize s being a random variable later on.

A higher general risk level s negatively affects borrowers' ability to meet payment obligations and, therefore, increases a bank's credit risk. We follow [Wong \(1996\)](#) and [Pausch and Welzel \(2012\)](#) and assume that s shifts the cumulative probability distribution function $F(x|s)$ in the sense of first-order stochastic dominance (FSD).⁵ In particular, we assume that a higher risk level s makes low realizations of the project outcome x more likely, formally:

$$\frac{d}{ds}F(x|s) > 0 \quad \forall x. \quad (4)$$

As a result a higher level of risk s causes a bank reduce its loan supply for any nominal payment obligation R , i.e.

$$\frac{d}{ds}L(\mathbb{E}(\pi(x|s))) = L'(\cdot)\frac{d}{ds}\mathbb{E}(\pi(x|s)) < 0 \quad \forall R. \quad (5)$$

The reason is that s reduces a bank's (conditional) expected profit from a representative standard debt contract:

$$\frac{d}{ds}\mathbb{E}(\pi(x|s)) = -\gamma\frac{d}{ds}F(R|s) - \int_0^R \frac{d}{ds}F(x|s)dx < 0 \quad \forall R \quad (6)$$

where the second term on the right-hand side of (6) is a result of integrating (1) by parts.⁶ Inequality follows from the fact that all terms are positive due to our earlier assumptions.

Finally we assume that a bank chooses R in a way to maximize total expected (conditional) profit from lending $\mathbb{E}(\Pi(x|s))$. It can, however, be easily shown that this is equivalent with maximizing the expected (conditional) profit of a representative standard debt contract.⁷

Based on previous considerations we are now able to formulate our Winner's Curse

⁵Note that by using FSD to model a shift in the general risk level we implicitly assume that the expected outcome from borrowers' investment projects decreases when s grows. That is, we do not apply a mean preserving spread à la [Rothschild and Stiglitz \(1970\)](#) to model changes in s . The reason for this is that we do not think it is plausible to leave the expected project outcome unchanged when the general risk level in the credit market grows.

⁶Partially integrating (1) yields

$$\mathbb{E}(\pi(x|s)) = R - \gamma F(R|s) - \int_0^R F(x|s)dx.$$

Differentiation of the latter equation with respect to s results in (6).

⁷Because $\mathbb{E}(\Pi(x|s))$ calculates

$$\mathbb{E}(\Pi(x|s)) = L(\mathbb{E}(\pi(x|s))) \cdot \mathbb{E}(\pi(x|s))$$

and optimality requires

$$\frac{\partial \mathbb{E}(\Pi(x|s))}{\partial R} = \frac{\partial \mathbb{E}(\pi(x|s))}{\partial R} (L'(\mathbb{E}(\pi(x|s))) \cdot \mathbb{E}(\pi(x|s)) + L(\mathbb{E}(\pi(x|s)))) = 0,$$

a bank's decision can only be optimal if

$$\frac{\partial \mathbb{E}(\pi(x|s))}{\partial R} = 0$$

due to $L(\cdot)$, $L'(\cdot)$, $\mathbb{E}(\pi(x|s)) > 0$.

conjecture. For this purpose we generalize the risk level s being a random variable in the following. In particular we assume, as is common in the auction theory literature, that each individual bank i in the credit market is uncertain about the actual general risk level s and observes just a noisy signal s_i , i.e. a specific realization of the random variable s , which is private information to bank i . Consequently, individual signals s_i are **not** independent between banks because they come out of a common random process $s_i = s + \epsilon_i$ where s is the actual general risk level and the ϵ_i 's represent iid noise terms of individual banks with $E(\epsilon_i) = 0 \forall i$.⁸ As a result, s_i is an unbiased estimator for the actual s of any individual bank i .

Now our Winner's Curse argument goes as follows: based on the private signal s_i , each individual bank i determines the expected conditional profit of a representative loan contract $E(x|s_i)$ and the corresponding R_i^* which ensures bank i a maximum expected profit from lending. As a result, depending on the individual signal s_i each bank observes a corresponding realization of the conditional expected profit $E(\pi(x|s))$ of a representative standard debt contract. Banks which observe very low signals s_i will hence infer that lending is highly profitable and any bank with a low signal s_i will supply more loans than any other bank observing a higher risk-level signal s_j .⁹

$$L_i(E(\pi(x|s_i))) > L_j(E(\pi(x|s_j))) \text{ because } E(\pi(x|s_i)) > E(\pi(x|s_j)) \forall s_i < s_j, i \neq j.$$

Ex post this is, however, bad news for all banks with individual signals below the true risk level s , i.e. $s_i < s$. All these banks overestimate expected profits from lending and supply more loans than would be optimal at the prevailing nominal loan payment R_i^* . Note that for any given R_i^* relations (5) and (6) imply

$$L(E(\pi(x|s))) < L(E(\pi(x|s_i))) \text{ because } E(\pi(x|s)) < E(\pi(x|s_i)) \forall s_i < s \text{ at given } R_i^*.$$

Figure 1 illustrates the case.

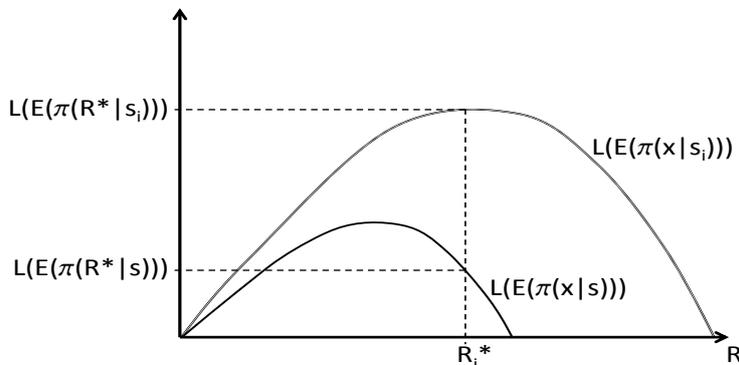
In other words, all banks with $s_i < s$ are too optimistic about the profit opportunities in the credit market. As a result their loan supply is too high and, ex post, they will find themselves in a situation where they face write-downs on loans even if their ex-ante decisions seem to credit-ration borrowers in the sense of [Stiglitz and Weiss \(1981\)](#) and [Williamson \(1987\)](#). A Winner's Curse situation – well known in auction theory – occurs in the credit market.¹⁰ Moreover, in highly competitive credit markets the previous arguments emphasize that particularly banks with very low signals s_i will behave very aggressive. This might encourage other banks to lower their credit standards and increase the volume of loans.

⁸For a similar setting to model banks' credit decisions depending on private signals on fundamentals, see [Aikman et al. \(2015\)](#).

⁹Note, this argument compares specific realizations of conditional expected profits $E(\pi(x|s_i))$ that are driven by realizations of the common random process $s_i = s + \epsilon_i$.

¹⁰Note, one may argue that banks that behave rational should be aware of this effect and therefore will take this into account when making decisions. However, there are two arguments for why the Winner's Curse will still prevail. First, because banks are modeled symmetrically, modifying the decision process for Winner's Curse will just reduce expectations on $E(\pi(x|s_i))$. Relative expectations among individual banks, which depend on the individual signals s_i , do not change, however. Second, it is absolutely rational for each individual bank to formulate expectations $E(\pi(x|s_i))$ based on private signals. This is because any bank is aware of the fact that due to the random process s_i is an unbiased estimator of the actual general risk level s .

Figure 1: Loan Supply with $s_i < s$



3 Institutional background, methodology and data

3.1 Institutional background

The German banking sector comprises three pillars of universal banks: the commercial, savings, and cooperative bank sector with 1,787 institutions and €6,064 billion in total assets in 2013. The largest pillar, the sector of commercial banks, is highly concentrated, with the four largest banks representing some 62% of total assets in this segment. In sum, all 277 commercial banks represent 46.0% of total assets in the system of universal banks.

The second-largest group, savings banks and their central institutions (DekaBank and nine Landesbanks), comprise banks which are mostly owned by cities, counties or state governments. Within this sector, each savings bank is closely linked to its respective central institution (Landesbank, DekaBank) which provides additional banking services (e.g., securities and international banking). The savings bank sector, including DekaBank and Landesbanks, is rather fractionalized, comprising 421 banks in all. In general, savings banks are smaller than private banks and are mainly restricted to the area of the city or county in which the bank is located. This “regional principle” makes competition between savings banks almost impossible. In 2013 the savings bank sector represented 36.9% of the total assets of universal banks in Germany.

The third and smallest pillar comprises cooperative banks. This sector is even more fractionalized than the savings bank pillar as cooperative central banks only hold 26.5% of total assets of the sector and, in addition, the number of banks is larger. Like savings banks, cooperative banks are also limited to specific geographic areas, enabling them to compete against commercial and savings banks, but restricting competition within the cooperative bank pillar. By law, cooperative banks are committed to promoting the economic interests of their members, which are also the owners of these banks. In 2013, the 1,078 cooperative banks in Germany together with the two central cooperative institutions accounted for 17.1% of total assets in the three-pillar system of universal banks.

3.2 Data and methodology

To analyze whether our Winner’s Curse can be demonstrated to exist in credit markets, we use a unique and confidential data set from the Bundesbank borrowers’ statistics which comprises information on domestic exposures to 24 corporate industry sectors and 3 household sectors and write-offs at the bank portfolio level.¹¹ Control variables are derived from the Bundesbank’s prudential data base (“BAKIS”). The portfolio-level data is complemented with bank-level data as well as with macroeconomic data at the county level obtained from the German Federal Statistical Office. In the data set we control for mergers in the most thorough way: following the merger of two (formerly) independently operating banks, a third (new) bank is artificially created.¹²

Figure 2 illustrates how often a given loan portfolio will appear in our regression analysis by being among the three largest portfolios for a given bank. For better visibility we confine ourselves to listing the ten most frequently included portfolios. The portfolio most often included is housing finance which includes mortgages backed by collateral. Hence, this category is usually assumed to be a safe portfolio. The second most frequently included portfolio is agricultural loans which are frequently issued by cooperative banks in rural areas and the third most frequently comprises installment loans (excluding housing). But also commercial industry sectors such as construction, commerce and communications appear in our regression analysis. By focussing on the three largest portfolios, we are including commercial loans to industry sectors, but the high share of relatively safe mortgage loans to households should bias our findings against finding significant results for loan growth on loan losses on the portfolio level.

Figure 3 links economic development and credit portfolio growth and shows the procyclicality of lending. The positive correlation indicates that credit growth is high when the economy is doing well and vice versa.

In general, our empirical analysis seeks to investigate the impact of credit growth on loan write-offs. For an analysis of our theoretical arguments we need to disentangle *adequate credit growth* from *excessive credit growth*. *Adequate credit growth* refers to situations when the prevailing risk characteristics in the credit market (i.e. the fundamentals represented by the probability distribution $f(x|s)$) allow the loan volume to be increased without a negative impact on banks’ risk exposure and earnings. In terms of our theoretical argument banks either increase lending along a specific loan supply function or switch from a lower to a higher loan supply function $L(E(x|s')) > L(E(x|s))$ with $s' > s$. What is crucial in this regard is that banks neither set the nominal payment requirement R to $R > R^*$ nor understate the general risk level in the lending market. *Excessive credit growth*, on the contrary, refers to situations in which banks understate the general level of risk in the lending market and/or set $R > R^*$. In both cases, increasing the lending volume is expected to negatively impact on banks’ total exposure to risk and earnings.

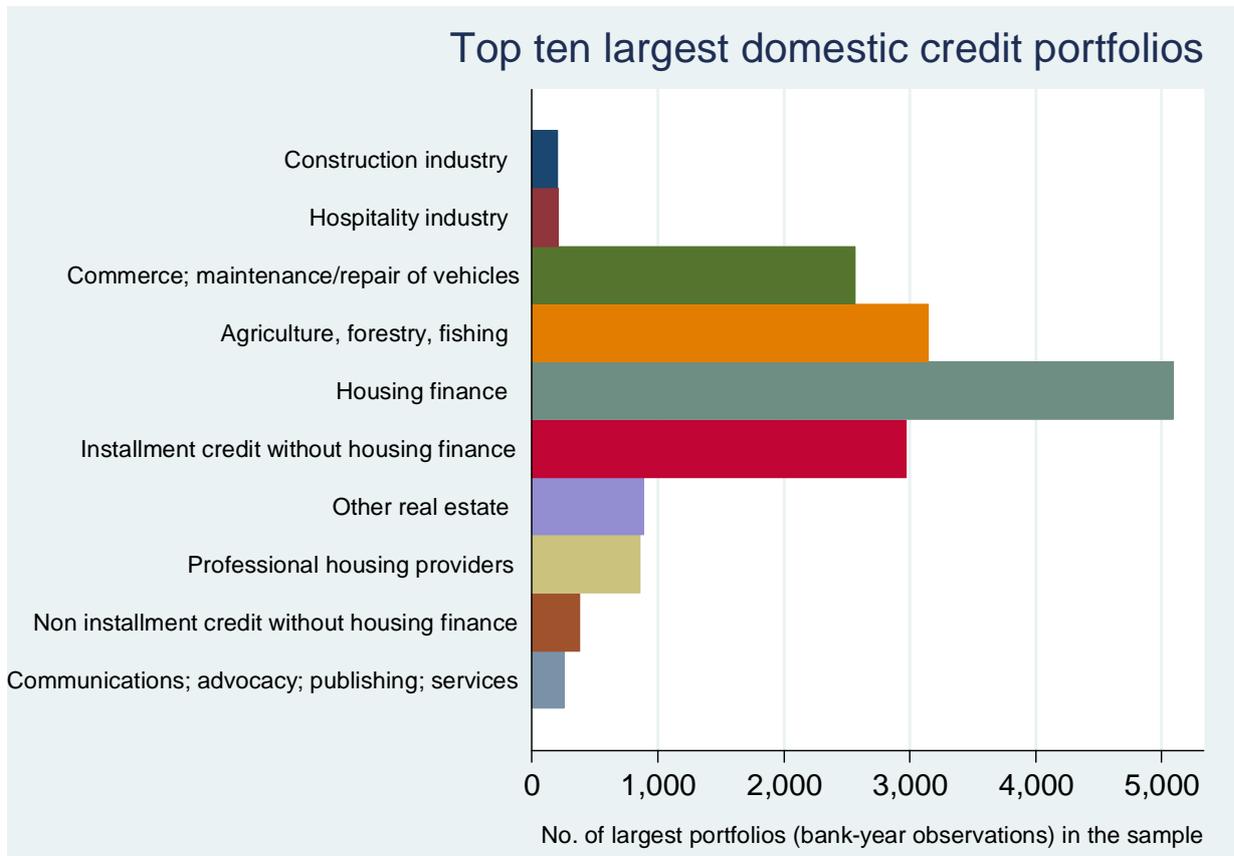
For the purpose of disentangling adequate from excessive credit growth we show three panels including different measures of annual credit growth.¹³

¹¹For a detailed description of the Bundesbank borrowers’ statistics see [Mommel et al. \(2015\)](#).

¹²Note that, due to the merger treatment applied to the data set, the total number of banks exceeds the maximum number of banks in a given year. For the importance of controlling for mergers and acquisitions in analyzing credit growth at the bank level, see [Dell’Ariccia and Garibaldi \(2005\)](#).

¹³For a detailed description of the variables see [Table A.1](#).

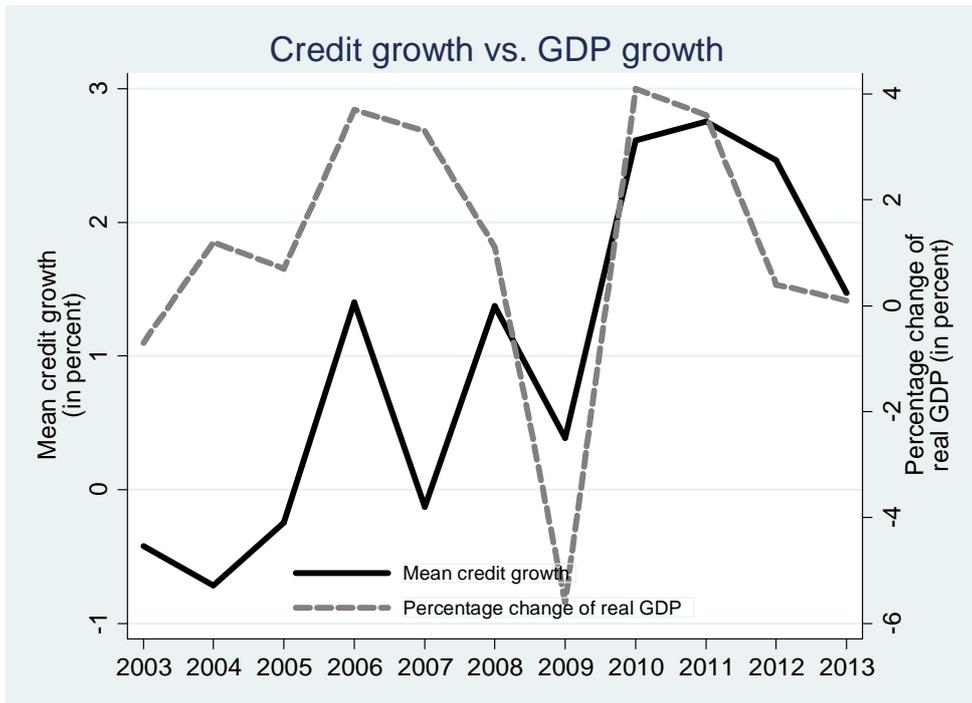
Figure 2: Top ten largest domestic credit portfolios



- **Panel A:** CREDIT GROWTH is measured as $\Delta \ln \text{credit}$ (if change in credit is positive)
- **Panel B:** DUMMY LARGE CREDIT GROWTH takes one when a bank increases its lending by more than the mean plus two times the standard deviation of the banking sector.
- **Panel C:** GAP EXCESSIVE CREDIT GROWTH measures the positive deviation from the long-run *bank-specific* trend in % derived by employing the HP filter.
- **Panel D:** REL. GAP EXCESSIVE CREDIT GROWTH measures the positive deviation from the long-run *banking sector* trend in % derived by employing the HP filter.

Our first measure, CREDIT GROWTH, is simply the change in the log of credit and is set to zero if a bank reports a decline in lending. DUMMY LARGE CREDIT GROWTH is an indicator of extreme lending growth and assigns a value of one to banks that increase their lending more than two standard deviations above the mean of their banking sector. Growth rates were separately measured for private commercial, savings, and cooperative banks. This measure is only assigned to less than five percent of the banks with the highest credit growth. Nevertheless, our analysis will show that large loan growth does

Figure 3: Credit growth and the real economy



not necessarily mean excessive credit growth. Even the opposite might hold: a bank assigned a value of zero might have excessive credit growth if it is undercapitalized or its loan monitoring techniques are inadequate. Excessive credit growth is calculated as the deviation from the long-run trend when applying the the HP filter. Using quarterly data, the smoothing parameter is set to 1,600. Based on credit data from the first quarter of 1999 until the end of 2013 we calculate GAP EXCESSIVE CREDIT GROWTH as the percentage of positive deviation from the bank-individual trend and REL. GAP EXCESSIVE CREDIT GROWTH as the percentage positive deviation from the industry trend,¹⁴ i.e. the aggregated growth trend in the banking sector of private commercial, savings or cooperative banks. Excessive growth rates are calculated for total domestic lending as well as the three largest domestic sectoral portfolios. For banks experiencing credit growth below their long-run trend, GAP EXCESSIVE CREDIT GROWTH is set to zero. We exclude banks and bank portfolios which do not exist for at least ten successive quarters in the sample period. Following [Mendoza and Terrones \(2008, 2012\)](#), we employ the standard form of the HP filter and do not use an expanding HP filter as the standard version proved to be superior in identifying the timing of credit booms. Their approach also proved to be suitable for separating the development of bank-level variables — such as profitability, non-performing loans, loan expansion and capital adequacy — of a country’s median bank into boom and bust phases. As the HP filter estimates the cyclical and trend components inaccurately at endpoints ([Mise et al., 2005](#)) the standard version is preferable. Moreover, using previous year-end lagged values of (REL.) GAP EXCESSIVE CREDIT GROWTH excludes the last four less accurately estimated quarterly observations of excess credit growth from our analysis. Hence, applying the standard

¹⁴This measure is similar to that of [Dell’Ariccia and Garibaldi \(2005\)](#).

version of the HP filter seems suitable for measuring and timing excessive credit growth at a micro-prudential bank level that might translate into a macroeconomic credit boom.

Furthermore, we consider a set of control variables which help to validate our results. The two most important ones we will focus on are a proxy for pricing or market power – the LERNER INDEX — and a proxy for monitoring costs γ which we will call MONITORING ABILITY. Adjusting the LERNER INDEX for inefficiencies (see, [Koetter et al., 2012](#)) allows us to incorporate the idea that banks might exercise even higher market power than their observed profits and costs would suggest but forego some of these profits due to non-optimal and therefore inefficient behavior. A higher LERNER INDEX indicates that banks enjoy more price-setting power in the credit market. Banks are, in turn, able to enforce higher nominal payment requirements R in loan contracts. Against the background of our theoretical considerations the LERNER INDEX helps to analyze whether banks operate to the left or to the right of the optimal R^* on a given loan supply function. Operating on the left would result in a negative coefficient and is consistent with the franchise value theory of competition (e.g., [Keeley, 1990](#)), i.e. that lower competition decreases the risk of default as banks limit risk-taking in order not to lose the franchise value of their operations. On the other hand, if we observe a positive impact of the LERNER INDEX on loan losses, a bank would operate to the right of the optimal R^* . This is in line with the risk-shifting hypothesis of competition developed by [Boyd and De Nicolo \(2005\)](#) which is based on moral hazard behavior of borrowers similar to that modeled in [Stiglitz and Weiss \(1981\)](#). If banks use their price-setting power to increase the nominal repayment obligation R close to borrowers' maximum ability to repay, the corresponding increase in the probability of borrowers defaulting on loan repayment would outweigh the positive margin effect of higher loan repayment. By allowing for imperfectly correlated loan defaults, [Martinez-Miera and Repullo \(2010\)](#) demonstrate the existence of a U-shaped relationship between competition and bank failure. For low levels of competition the risk-shifting effect dominates and an increase in competition reduces bank failure, whereas in markets with a high degree of competition the margin effect of higher interest income on performing loans dominates and a further increase in competition makes bank failure more likely. These non-linearities can be captured empirically by including a squared term of the Lerner index (SQUARED LERNER INDEX) ([Jiménez et al., 2013](#)). We expect LERNER INDEX to show a negative coefficient, i.e. higher market power allows banks to choose high-quality borrowers and reduces their charge-off rates. For the SQUARED term we expect a positive coefficient as banks that try to extract excessively high rates from their borrowers will observe moral hazard.

MONITORING ABILITY is a proxy for the intensity and the amount of monitoring costs a bank incurs when checking loan exposures. The variable is the ratio of full-time employees to total loans. A higher value indicates a higher monitoring intensity and lower monitoring costs due to borrower default. As a result, we expect a negative relationship between MONITORING ABILITY and loan write-offs, i.e. more intensive monitoring should reduce moral hazard and will positively affect bank earnings.

Our regression framework has the following form and includes a set of further control variables:

$$LWO = f(CG, BS, C, ME, u), \quad (7)$$

where LWO is a vector of loan write-offs. In each panel we compare two model specifications: (1) an ordinary least squares (OLS) model with the deviation of loss rate to

overall loss rate (at the bank or the bank-portfolio level for domestic loans), and (2) a Tobit model with the loss rate (i.e., the total write-offs to total credit in the domestic credit portfolio) as the dependent variable. In order to separate the effect of the total domestic loan portfolio from the effect of a bank’s three largest portfolios we estimate models for both “Total domestic credit” and the “Three largest portfolios of domestic credit”. All regressions are run for the whole banking system as well as separately for the private, savings and cooperative banking pillars. Loan write-offs are a function of a vector CG of three lagged values of the credit growth proxies introduced above. We include lagged values to mitigate endogeneity concerns and control for the fact that borrowers do not necessarily default in the first year. Instead, contemporaneous write-offs can be the consequence of credit supply dating back several years. Taking lagged values of up to three periods is supported by other empirical studies (e.g., [Foos et al., 2010](#); [Jiménez et al., 2014a](#)). BS is a vector of bank-specific control variables, C is a vector that captures the stance of credit market competition, and ME controls for the macroeconomic environment. Bank-specific control variables include EQUITY CAPITAL RATIO, the ratio of Tier 1 capital to risk-weighted assets (RWA). Equity serves as a measure of a bank’s risk-aversion but also controls for a bank’s ability to lend. CUSTOMER LOANS RATIO is the percentage of customer loans to total assets and controls for the fact that loans to households and corporates have on average higher default rates. SHARE FEE INCOME is the percentage of fee and commission income to total income and is a proxy for a bank’s engagement in other than the traditional banking activities. Finally, LOAN PORTFOLIO HHI is the Herfindahl-Hirschman Index (HHI) calculated over 8 grouped credit sectors. Competition C includes the LERNER INDEX and its SQUARED term. ME includes REGIONAL GDP at the county level. All other macroeconomic developments at the national level are captured using YEAR DUMMIES. Finally, u represents the error term.

From a micro-prudential perspective we want to know whether excessive loan growth makes banks more risky. Therefore, we replace LWO in further regressions at the bank level by the ZSCORE, interpreted as a bank’s distance to default. If excessive lending increases bank risk, we would expect a negative coefficient on lagged loan growth, i.e. we would observe a shrinking distance to default. Moreover, we investigate whether excessive lenders are more likely to need capital support (DISTRESS) or to go into outright default (DEFAULT). The latter two regressions are run as probit models and we expect a positive coefficient on lagged loan growth. In order to address unobserved bank characteristics in our regressions, in evaluating the significance of the results, we report standard errors clustered on the bank level.

Table 1 presents summary statistics of these variables for the sample between 1999 and 2013. The average loss rate for total lending is 0.461%, and slightly higher for the largest loan portfolio at 0.693%. Annual loan growth for total credit is around 3%, but significantly higher for the largest portfolio at around 9%. Hence, banks are more likely to increase lending to those industry sectors they already have a large experience in. Using our DUMMY LARGE CREDIT GROWTH, we find that between 3% and 4% of banks show credit growth in excess of average growth + two standard deviations. Both GAP and REL. GAP EXCESSIVE CREDIT GROWTH are on average around 1% for total credit and 4% for the largest portfolio.

4 Results

4.1 Adequate credit growth

As shown in Tables 2 for OLS and 3 for Tobit models, analyzing the effect of CREDIT GROWTH in general, i.e. without making corrections for certain thresholds or the long-term trend, does not support our Winner’s Curse conjecture and we observe significantly negative or insignificant coefficients on lagged CREDIT GROWTH. This suggests that in general, increasing the loan volume reduces banks’ loan write-offs, and loan growth is *adequate*. Coefficients for the three largest portfolios are less pronounced than for total domestic credit, but increasing the number of observations by almost three times improves statistical significance. Results are robust to different kind of estimations (OLS vs. Tobit).¹⁵

Taking a look at the control variables, we find that a higher CUSTOMER LOANS RATIO increases loan write-offs. This is consistent with loans to households and corporates being on average riskier than those to financial institutions. For small, local banks (i.e. savings and cooperative banks) we find support for the model of [Martinez-Miera and Repullo \(2010\)](#). We find that a higher LERNER INDEX decreases loan defaults but, as the SQUARED term is positive, the relationship changes for high levels of LERNER INDEX. For savings and cooperative banks higher market power increases loan defaults at a level of 0.88. Hence, only banks that try to exploit very high margins with a LERNER INDEX more than five standard deviations above the mean (mean: 0.48; std: 0.07) will experience situations in which the risk-shifting channel dominates the margin channel. At the portfolio level this result only holds for cooperative banks and for the total sample, whereas for savings banks the SQUARED term becomes insignificant. Consequently, banks appear to be able to exploit price-setting power in order to stabilize earnings from lending, and only those banks that charge excessively high rates suffer disproportionately large losses. The coefficients OBS ACTIVITIES and MONITORING ABILITY remain insignificant.

The previous results basically hold even when we consider a relatively high threshold of two standard deviations above the mean growth rate for a banking sector. Two observations are, however, noteworthy: on the one hand, the coefficients of the control variables appear robust in terms of sign, magnitude and significance. On the other hand, although the signs of the DUMMY LARGE CREDIT GROWTH coefficients are basically the same as those for positive credit growth above, significance appears weaker. The F-statistics of joint significance of the coefficients still indicate significantly negative effects but are lower in magnitude than the corresponding F-statistics for CREDIT GROWTH. The latter observations, therefore, indicate that results may change when credit growth becomes extraordinarily large (see Tables 4 and 5). In contrast, previous studies found significant effects of lagged (abnormal) loan growth measures on loan losses. [Salas and Saurina \(2002\)](#) and [Jiménez and Saurina \(2006\)](#) find that even lagged normal loan growth has a positive impact on non-performing loans. [Foos et al. \(2010\)](#) find that their lags of abnormal loan growth — defined as the difference of bank-specific to a country’s aggregate loan growth — is positive and statistically significant.

¹⁵For robustness, we replace CREDIT GROWTH, for which loan contraction has been set to zero with a variable that allows for negative loan growth. Results are robust and lagged loan growth has an even larger positive impact.

Table 2: Panel A1. Pooled OLS model with CREDIT GROWTH

This table presents results from pooled OLS regressions with DEVIATION LOSS RATE (SECTOR): deviation of loss rate (sector) from the industry aggregate (commercial bank sector, public bank sector, cooperative bank sector) per year as the dependent variable; CREDIT GROWTH is defined as delta \ln credit for positive changes; L1 - L3 denote lag-operators; *Bank-specific control variables* are measured in percent (REGIONAL GDP as a percentage change) and averaged over three years. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; standard errors clustered at bank level (bank-portfolio level) in parentheses.

Variable	Total domestic credit				Three largest portfolios of domestic credit			
	All	Private	Savings	Coops	All	Private	Savings	Coops
	<i>Credit growth</i>							
L1.CREDIT GROWTH	-0.0105*** [-5.9443]	-0.0094*** [-3.2577]	-0.0160** [-2.5632]	-0.0157*** [-7.3843]	-0.0018*** [-5.3463]	-0.0025* [-1.7753]	-0.0040*** [-5.6380]	-0.0017*** [-4.7691]
L2.CREDIT GROWTH	-0.0060*** [-3.2949]	-0.0094*** [-3.4186]	-0.0087* [-1.6664]	-0.0029 [-1.4499]	-0.0011*** [-3.9894]	-0.0011 [-0.7858]	-0.0023*** [-4.0348]	-0.0009*** [-3.3870]
L3.CREDIT GROWTH	0.0030** [2.1270]	0.0025 [0.8568]	-0.0004 [-0.1182]	0.0022 [1.5904]	-0.0007*** [-2.9390]	-0.0014* [-1.9618]	-0.0002 [-0.2469]	-0.0008*** [-3.3049]
	<i>Bank-specific control variables (averaged over three years)</i>							
EQUITY CAPITAL RATIO	0.0018 [0.2556]	0.0120 [1.2813]	-0.0443*** [-2.9621]	-0.0127 [-1.2697]	-0.0147** [-2.4516]	0.0000 [0.0022]	-0.0803*** [-4.3627]	-0.0381*** [-4.5382]
CUSTOMER LOANS RATIO	0.0032*** [3.8652]	0.0042** [2.1051]	0.0049** [2.4486]	0.0015* [1.9340]	0.0050*** [6.0884]	0.0057*** [3.3403]	0.0094*** [4.2559]	0.0021** [2.1464]
OBS ACTIVITIES	0.0024 [1.0663]	-0.0014 [-0.6499]	0.0030 [0.6493]	0.0121* [1.8762]	-0.0003 [-0.2131]	-0.0012 [-0.7436]	-0.0031 [-0.5838]	-0.0003 [-0.0634]
SHARE FEE INCOME	0.0007 [0.3723]	0.0006 [0.2134]	-0.0208** [-2.2746]	0.0002 [0.0629]	-0.0008 [-0.5037]	0.0004 [0.1627]	-0.0186* [-1.8537]	0.0006 [0.2016]
LOAN PORTFOLIO HHI	-0.0050*** [-2.9182]	-0.0011 [-0.4990]	-0.0058 [-0.7258]	-0.0092*** [-2.9883]	-0.0047*** [-3.2795]	0.0004 [0.1674]	-0.0170** [-2.2191]	-0.0105*** [-5.3532]
LERNER INDEX	-0.1643 [-0.4015]	-0.0078 [-0.0281]	-5.2876** [-2.0767]	-3.1018*** [-8.0958]	-0.5247** [-2.0873]	-0.2343 [-0.8946]	-4.8329 [-1.5918]	-5.1450*** [-6.2237]
SQUARED LERNER INDEX	0.1759 [0.5276]	-0.1645 [-1.2102]	6.0162** [2.1598]	3.5352*** [9.1311]	-0.0588 [-1.2880]	-0.0957 [-1.2676]	4.9792 [1.5109]	5.1910*** [5.7865]
MONITORING ABILITY	-0.0151 [-1.3160]	-0.0190 [-1.3744]	0.3285 [1.1524]	-0.1273 [-1.4730]	-0.0294 [-1.2105]	-0.0089 [-0.4560]	0.8298** [2.4066]	-0.4569*** [-4.6955]
	<i>Macroeconomic control variables</i>							
REGIONAL GDP	0.0049 [1.3542]	0.0302 [1.1996]	0.0096 [1.4742]	0.0007 [0.1938]	0.0005 [0.1230]	0.0108 [0.3868]	0.0115 [1.4234]	-0.0069 [-1.4124]
STATE/YEAR DUMMIES			YES				YES	
	<i>Banking group dummies and constant</i>							
DUMMY SAVINGS BANKS	-0.4390*** [-6.1001]				-0.3871*** [-6.9579]			
DUMMY COOP. BANKS	-0.3868*** [-5.8363]				-0.2938*** [-5.5937]			
Constant	0.4335** [2.5764]	0.4091 [1.5004]	1.4673*** [2.6505]	1.1079*** [5.6157]	1.4080*** [11.5283]	0.5583** [2.2785]	1.5455** [2.2434]	2.2021*** [9.4927]
Observations	17,590	1,302	4,621	11,667	52,314	3,538	13,863	34,913
Number of banks / portfolios	2,361	184	571	1,607	10,706	818	2,660	7,231
Adjusted R-squared	0.088	0.065	0.147	0.102	0.040	0.033	0.074	0.051
L1-3.CREDIT GROWTH (F stat)	20.553	8.815	3.845	23.481	19.891	3.027	15.436	15.211
L1-3.CREDIT GROWTH (p value)	0.000	0.000	0.010	0.000	0.000	0.029	0.000	0.000

Table 3: Panel A2. Pooled Tobit model with CREDIT GROWTH

This table presents results from pooled Tobit regressions with LOSS RATE: write-offs (portfolio) to credit (portfolio) in the domestic credit portfolio as the dependent variable; CREDIT GROWTH is defined as delta \ln credit for positive changes; L1 - L3 denote lag-operators; *Bank-specific control variables* are measured in percent (REGIONAL GDP as a percentage change) and averaged over three years. *** p<0.01, ** p<0.05, * p<0.1; standard errors clustered at bank level (bank-portfolio level) in parentheses.

Variable	Total domestic credit				Three largest portfolios of domestic credit			
	All	Private	Savings	Coops	All	Private	Savings	Coops
<i>Credit growth</i>								
L1.CREDIT GROWTH	-0.0130*** [-5.8323]	-0.0150*** [-3.2678]	-0.0169*** [-2.5890]	-0.0185*** [-6.8008]	-0.0026*** [-4.4963]	-0.0064*** [-8.4181]	-0.0047*** [-4.8412]	-0.0022*** [-3.6935]
L2.CREDIT GROWTH	-0.0083*** [-3.7045]	-0.0131*** [-3.1839]	-0.0087 [-1.5987]	-0.0059** [-2.4360]	-0.0013*** [-2.7022]	-0.0029*** [-3.5407]	-0.0019** [-2.3838]	-0.0009* [-1.8428]
L3.CREDIT GROWTH	0.0026 [1.5715]	-0.0001 [-0.0219]	-0.0007 [-0.1859]	0.0024 [1.5787]	-0.0008* [-1.9288]	-0.0038*** [-5.2849]	-0.0003 [-0.3364]	-0.0004 [-0.8168]
<i>Bank-specific control variables (averaged over three years)</i>								
EQUITY CAPITAL RATIO	-0.0033 [-0.3491]	0.0182 [1.1877]	-0.0442*** [-2.8180]	-0.0268** [-2.0040]	-0.0659*** [-4.3809]	-0.0170*** [-2.9330]	-0.0716*** [-2.9112]	-0.1375*** [-6.8199]
CUSTOMER LOANS RATIO	0.0047*** [4.5162]	0.0111*** [3.5970]	0.0050** [2.4347]	0.0016 [1.4639]	0.0120*** [7.8139]	0.0282*** [31.9429]	0.0103*** [3.6036]	0.0024 [1.1312]
OBS ACTIVITIES	0.0033 [1.0901]	-0.0034 [-0.7438]	0.0034 [0.6960]	0.0152* [1.8737]	0.0031 [0.8078]	0.0012 [0.7802]	0.0020 [0.2970]	0.0067 [0.7709]
SHARE FEE INCOME	0.0006 [0.2400]	0.0002 [0.0343]	-0.0220** [-2.2838]	0.0007 [0.1933]	0.0033 [0.8538]	-0.0038** [-2.2973]	-0.0249* [-1.9222]	0.0166** [2.4755]
LOAN PORTFOLIO HHI	-0.0081*** [-3.4590]	-0.0055 [-1.5356]	-0.0055 [-0.6718]	-0.0139*** [-3.0165]	-0.0195*** [-6.1980]	-0.0107*** [-7.6197]	-0.0184* [-1.6989]	-0.0342*** [-5.8826]
LERNER INDEX	-0.1811 [-0.3672]	0.6729 [0.5012]	-4.9583* [-1.8331]	-3.3497*** [-8.1010]	-1.2266*** [-2.6283]	0.5370*** [3.8227]	0.8992 [0.2212]	-6.1180*** [-7.5555]
SQUARED LERNER INDEX	0.2099 [0.5451]	-0.9442 [-0.5500]	5.6265* [1.9071]	3.8092*** [8.6413]	0.0816 [0.5072]	-1.7392*** [-6.9808]	-2.1498 [-0.4897]	5.5685*** [5.9033]
MONITORING ABILITY	-0.0368 [-0.7565]	-0.0489 [-1.3267]	0.3649 [1.2442]	-0.2405** [-2.0067]	-0.4734** [-2.4678]	-0.0926*** [-2.8334]	0.5726 [1.3396]	-1.3798*** [-4.7430]
<i>Macroeconomic control variables</i>								
REGIONAL GDP	0.0047 [1.1313]	0.0451 [1.5883]	0.0091 [1.3300]	0.0003 [0.0593]	-0.0071 [-1.0440]	0.0267** [2.3189]	0.0046 [0.4372]	-0.0159* [-1.9408]
STATE/YEAR DUMMIES			YES				YES	
INDUSTRY SECTOR DUMMIES			NO				YES	
<i>Banking group dummies, and constant</i>								
DUMMY SAVINGS BANKS	-0.3657*** [-4.1645]				-0.1301 [-1.3389]			
DUMMY COOP. BANKS	-0.4687*** [-5.7898]				-0.5419*** [-5.8582]			
Constant	0.6114*** [2.8496]	-0.2395 [-0.4979]	1.5468*** [2.6617]	1.2273*** [4.6084]	0.4416 [1.0599]	-16.3037*** [-238.9051]	0.3728 [0.4065]	2.1565*** [4.1017]
Observations	17,590	1,302	4,621	11,667	52,314	3,538	13,863	34,913
Number of banks / portfolios	2,361	184	571	1,607	10,706	818	2,660	7,231
Pseudo R-squared	0.070	0.066	0.115	0.080	0.045	0.064	0.042	0.047
L1-3.CREDIT GROWTH (F stat)	20.565	7.683	3.815	20.340	9.214	367.670	9.079	5.046
L1-3.CREDIT GROWTH (p value)	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.002

Table 4: Panel B1. Pooled OLS model with DUMMY LARGE CREDIT GROWTH (mean + 2 Std)

This table presents results from pooled OLS regressions with DEVIATION LOSS RATE (SECTOR): deviation of loss rate (sector) from the industry aggregate (commercial bank sector, public bank sector, cooperative bank sector) per year as the dependent variable; DUMMY LARGE CREDIT GROWTH is a dummy variable that takes on the value of one when the threshold per banking group (mean growth + 2 standard deviations) is exceeded; L1 - L3 denote lag-operators; *Bank-specific control variables* are measured in percent (REGIONAL GDP as a percentage change) and averaged over three years. *** p<0.01, ** p<0.05, * p<0.1; standard errors clustered at bank level (bank-portfolio level) in parentheses.

Variable	Total domestic credit				Three largest portfolios of domestic credit			
	All	Private	Savings	Coops	All	Private	Savings	Coops
<i>DUMMY LARGE CREDIT GROWTH (threshold per banking group: mean growth + 2 standard deviations)</i>								
L1.DUMMY LARGE CG	-0.0877*** [-3.2588]	-0.2272*** [-2.8874]	-0.1020* [-1.7942]	-0.0947*** [-3.7006]	-0.1150*** [-4.1395]	-0.2299** [-2.1638]	-0.1756*** [-3.3632]	-0.1087*** [-3.1849]
L2.DUMMY LARGE CG	-0.0528 [-1.6306]	-0.2663*** [-3.4939]	-0.0685 [-1.1136]	0.0011 [0.0346]	-0.0799*** [-3.1093]	-0.1356 [-1.1842]	-0.1230*** [-3.0274]	-0.0692** [-2.1897]
L3.DUMMY LARGE CG	0.0445* [1.7313]	0.0198 [0.1996]	0.0137 [0.2299]	0.0440* [1.7313]	-0.0643** [-2.3077]	-0.1509* [-1.6936]	-0.0634 [-1.2694]	-0.0770** [-2.4077]
<i>Bank-specific control variables (averaged over three years)</i>								
EQUITY CAPITAL RATIO	0.0024 [0.3338]	0.0134 [1.3828]	-0.0400*** [-2.6456]	-0.0093 [-0.9047]	-0.0149** [-2.4911]	-0.0003 [-0.0477]	-0.0789*** [-4.2845]	-0.0382*** [-4.5351]
CUSTOMER LOANS RATIO	0.0030*** [3.5631]	0.0033* [1.7007]	0.0048** [2.4570]	0.0013* [1.6515]	0.0050*** [6.0132]	0.0056*** [3.2756]	0.0095*** [4.3083]	0.0020** [2.0543]
OBS ACTIVITIES	0.0021 [0.9517]	-0.0011 [-0.5283]	0.0021 [0.4382]	0.0099 [1.5504]	-0.0004 [-0.2817]	-0.0012 [-0.7301]	-0.0034 [-0.6306]	-0.0005 [-0.1250]
SHARE FEE INCOME	0.0007 [0.3759]	0.0006 [0.2231]	-0.0219** [-2.4053]	0.0017 [0.6281]	-0.0008 [-0.4916]	0.0003 [0.1237]	-0.0194* [-1.9323]	0.0011 [0.3551]
LOAN PORTFOLIO HHI	-0.0058*** [-3.4145]	-0.0010 [-0.4609]	-0.0085 [-1.0983]	-0.0101*** [-3.2623]	-0.0049*** [-3.4550]	0.0003 [0.1093]	-0.0180** [-2.3574]	-0.0106*** [-5.4299]
LERNER INDEX	-0.1499 [-0.3752]	-0.0291 [-0.1052]	-5.1155** [-1.9874]	-2.9098*** [-6.8736]	-0.5287** [-2.1063]	-0.2177 [-0.8291]	-4.7509 [-1.5684]	-5.1401*** [-6.1995]
SQUARED LERNER INDEX	0.1469 [0.4532]	-0.1792 [-1.3000]	5.7221** [2.0284]	3.2480*** [7.8680]	-0.0603 [-1.3245]	-0.0905 [-1.1923]	4.8623 [1.4786]	5.1569*** [5.7320]
MONITORING ABILITY	-0.0152 [-1.2823]	-0.0227 [-1.5991]	0.3651 [1.2705]	-0.1265 [-1.4379]	-0.0285 [-1.1848]	-0.0085 [-0.4361]	0.8691** [2.5077]	-0.4574*** [-4.6871]
<i>Macroeconomic control variables</i>								
REGIONAL GDP	0.0050 [1.3638]	0.0291 [1.1681]	0.0090 [1.3577]	0.0005 [0.1460]	0.0012 [0.2691]	0.0115 [0.4115]	0.0112 [1.3798]	-0.0061 [-1.2487]
STATE/YEAR DUMMIES			YES				YES	
<i>Banking group dummies and constant</i>								
DUMMY SAVINGS BANKS	-0.3847*** [-5.4764]				-0.3631*** [-6.5405]			
DUMMY COOP. BANKS	-0.3419*** [-5.3244]				-0.2761*** [-5.2726]			
Constant	0.4160*** [2.6005]	0.3751 [1.3664]	1.3846** [2.4851]	0.8067*** [3.7341]	1.0264*** [8.5898]	0.5130** [2.0832]	1.5008** [2.1837]	2.1805*** [9.3847]
Observations	17,590	1,302	4,621	11,667	52,314	3,538	13,863	34,913
Number of banks / portfolios	2,361	184	571	1,607	10,706	818	2,660	7,231
Adjusted R-squared	0.082	0.058	0.143	0.094	0.039	0.031	0.072	0.050
L1-3.DUMMY LARGE CG (F stat)	5.823	6.723	1.485	4.931	10.238	2.447	6.714	7.062
L1-3.DUMMY LARGE CG (p value)	0.001	0.000	0.218	0.002	0.000	0.063	0.000	0.000

Table 5: Panel B2. Pooled Tobit model with DUMMY LARGE CREDIT GROWTH (mean + 2 Std)

This table presents results from pooled Tobit regressions with LOSS RATE (SECTOR): write-offs (sector) to credit (sector) in the domestic credit portfolio as the dependent variable; DUMMY LARGE CREDIT GROWTH is a dummy variable that takes on the value of one when the threshold per banking group (mean growth + 2 standard deviations) is exceeded; L1 - L3 denote lag-operators; *Bank-specific control variables* are measured in percent (REGIONAL GDP as a percentage change) and averaged over three years. *** p<0.01, ** p<0.05, * p<0.1; standard errors clustered at bank level (bank-portfolio level) in parentheses.

Variable	Total domestic credit				Three largest portfolios of domestic credit			
	All	Private	Savings	Coops	All	Private	Savings	Coops
	<i>DUMMY LARGE CREDIT GROWTH (threshold per banking group: mean growth + 2 standard deviations)</i>							
L1.DUMMY LARGE CG	-0.1251*** [-3.5197]	-0.5085*** [-3.3451]	-0.1067* [-1.7657]	-0.1219*** [-3.3581]	-0.1545*** [-3.0977]	-0.7110*** [-13.7419]	-0.2006*** [-2.7958]	-0.1268* [-1.9152]
L2.DUMMY LARGE CG	-0.0827** [-2.0641]	-0.4344*** [-3.3011]	-0.0793 [-1.2075]	-0.0204 [-0.5336]	-0.0813* [-1.6831]	-0.5412*** [-10.3688]	-0.0883 [-1.4380]	-0.0342 [-0.5246]
L3.DUMMY LARGE CG	0.0425 [1.4383]	-0.0981 [-0.5929]	0.0123 [0.2011]	0.0498* [1.7178]	-0.0999** [-1.9816]	-0.4935*** [-9.9051]	-0.0695 [-0.9817]	-0.0639 [-0.9731]
	<i>Bank-specific control variables (averaged over three years)</i>							
EQUITY CAPITAL RATIO	-0.0025 [-0.2653]	0.0211 [1.3651]	-0.0399** [-2.5160]	-0.0222 [-1.6136]	-0.0668*** [-4.4296]	-0.0186*** [-3.2116]	-0.0710*** [-2.8826]	-0.1380*** [-6.8236]
CUSTOMER LOANS RATIO	0.0044*** [4.1608]	0.0096*** [3.0764]	0.0050** [2.4470]	0.0012 [1.1295]	0.0120*** [7.7494]	0.0279*** [31.8010]	0.0102*** [3.5782]	0.0024 [1.0896]
OBS ACTIVITIES	0.0029 [0.9799]	-0.0030 [-0.6640]	0.0024 [0.4886]	0.0125 [1.5465]	0.0030 [0.8000]	0.0013 [0.8557]	0.0023 [0.3270]	0.0065 [0.7478]
SHARE FEE INCOME	0.0007 [0.2614]	0.0003 [0.0564]	-0.0232** [-2.4233]	0.0026 [0.7100]	0.0033 [0.8467]	-0.0041** [-2.4834]	-0.0260** [-1.9990]	0.0171** [2.5440]
LOAN PORTFOLIO HHI	-0.0092*** [-3.9263]	-0.0052 [-1.4655]	-0.0082 [-1.0314]	-0.0153*** [-3.2553]	-0.0198*** [-6.2964]	-0.0109*** [-7.8290]	-0.0189* [-1.7423]	-0.0345*** [-5.9091]
LERNER INDEX	-0.1657 [-0.3472]	0.5356 [0.4291]	-4.7802* [-1.7485]	-3.1207*** [-6.8195]	-1.2348*** [-2.6440]	0.6172*** [4.4144]	0.9706 [0.2388]	-6.1165*** [-7.5502]
SQUARED LERNER INDEX	0.1688 [0.4531]	-0.8461 [-0.5297]	5.3229* [1.7819]	3.4448*** [7.4441]	0.0745 [0.4578]	-1.7890*** [-7.2001]	-2.2695 [-0.5169]	5.5282*** [5.8572]
MONITORING ABILITY	-0.0329 [-0.8180]	-0.0556 [-1.4817]	0.4024 [1.3612]	-0.2391** [-1.9619]	-0.4705** [-2.4586]	-0.0876*** [-2.7891]	0.5876 [1.3686]	-1.3831*** [-4.7408]
	<i>Macroeconomic control variables</i>							
REGIONAL GDP	0.0047 [1.1291]	0.0443 [1.6101]	0.0084 [1.2160]	0.0000 [0.0110]	-0.0065 [-0.9538]	0.0285** [2.4804]	0.0040 [0.3797]	-0.0151* [-1.8339]
STATE/YEAR DUMMIES			YES				YES	
INDUSTRY SECTOR DUMMIES			NO				YES	
	<i>Banking group dummies, and constant</i>							
DUMMY SAVINGS BANKS	-0.2901*** [-3.3592]				-0.1039 [-1.0673]			
DUMMY COOP. BANKS	-0.4071*** [-5.1591]				-0.5259*** [-5.6775]			
Constant	0.5305** [2.4450]	-0.2960 [-0.6184]	1.5031** [2.5671]	1.1431*** [4.0641]	0.4123 [0.9891]	-16.1552*** [-238.4865]	0.3454 [0.3767]	2.1413*** [4.0646]
Observations	17,590	1,302	4,621	11,667	52,314	3,538	13,863	34,913
Number of banks / portfolios	2,361	184	571	1,607	10,706	818	2,660	7,231
Pseudo R-squared	0.066	0.067	0.113	0.076	0.045	0.064	0.041	0.046
L1-3.DUMMY LARGE CG (F stat)	6.469	6.440	1.495	4.452	4.448	158.600	3.187	1.366
L1-3.DUMMY LARGE CG (p value)	0.000	0.000	0.214	0.004	0.004	0.000	0.023	0.251

To conclude, normal credit growth and even very large credit growth being two standard deviations above the industry mean cannot (necessarily) be considered excessive as increasing loan volumes are consistent with decreasing loan loss rates. Therefore, credit growth cannot simply be regarded as excessive only because it is large in magnitude, but has to take banks' previous growth rates into account. The measures of (abnormal) loan growth used in the literature so far are therefore likely not to assist supervisors in identifying weak banks.

4.2 Excessive credit growth

Application of our credit growth measures based on the cyclical deviation from the long-run trend, dramatically changes the results. The GAP EXCESSIVE CREDIT GROWTH coefficients are positive and significant. Credit growth beyond the long-term trend increases banks' loan write-offs. The control variables prove to be robust in terms of sign, magnitude and significance, which suggests that credit growth beyond the long-term trend corresponds to a situation of *excessive credit growth*.

Moreover, our results suggest that banks find themselves in a Winner's Curse situation if they engage in *excessive credit growth*, as the sign and size of the LERNER INDEX and its SQUARED term coefficients are robust to our findings for adequate credit growth measures. This suggests that banks operate in the region of credit rationing where the margin channel outweighs the negative effects of borrower moral hazard. Therefore, the losses stem solely from banks taking on poorer-quality borrowers and not from banks driving borrowers into default by charging excessively high lending rates. Banks seem to mistakenly assume that they operate in the region of credit rationing, and the only explanation in line with rational bank behavior is the underestimation of loan riskiness, as presented by our Winner's Curse argument. (REL.) GAP EXCESSIVE CREDIT GROWTH that goes beyond the long-term trend of a bank's total credit portfolio or of its major sectoral portfolio will lead to disproportionately large write-offs in subsequent years. Banks following business strategies which are centered around such *excessive credit growth* will find themselves in a situation of Winner's Curse as their lending standards are too lax in light of an overly optimistic evaluation of the general risk level in the credit market (see Tables 6 and 7 for GAP EXCESS CREDIT GROWTH and Tables 8 and 9 for REL. GAP EXCESS CREDIT GROWTH).

Table 6: Panel C1. Pooled OLS model with GAP EXCESSIVE CREDIT GROWTH

This table presents results from pooled OLS regressions with DEVIATION LOSS RATE (SECTOR): deviation of loss rate (sector) from the industry aggregate (commercial bank sector, public bank sector, cooperative bank sector) per year as the dependent variable; GAP EXCESSIVE CREDIT GROWTH is the positive deviation from the long-run trend (measured in %); L1 - L3 denote lag-operators; *Bank-specific control variables* are measured in percent (REGIONAL GDP as a percentage change) and averaged over three years. *** p<0.01, ** p<0.05, * p<0.1; standard errors clustered at bank level (bank-portfolio level) in parentheses.

Variable	Total domestic credit				Three largest portfolios of domestic credit				
	All	Private	Savings	Coops	All	Private	Savings	Coops	
	<i>Gap excessive credit growth</i>								
L1.GAP EXCESSIVE CG	0.0249*** [4.9653]	0.0101 [1.3663]	0.0564*** [5.0111]	0.0386*** [5.4383]	0.0015** [2.0219]	0.0030 [1.1115]	-0.0042** [-2.4893]	0.0019** [2.2579]	
L2.GAP EXCESSIVE CG	0.0162*** [3.3120]	0.0095 [1.2712]	0.0269** [2.0498]	0.0215*** [3.9291]	0.0013* [1.6477]	0.0005 [0.2162]	0.0018 [1.0366]	0.0016* [1.6881]	
L3.GAP EXCESSIVE CG	0.0196*** [5.2845]	0.0247*** [3.2154]	0.0236** [2.4328]	0.0162*** [4.5387]	0.0034*** [3.8266]	0.0051* [1.8821]	0.0044** [2.3288]	0.0022** [2.0907]	
	<i>Bank-specific control variables (averaged over three years)</i>								
EQUITY CAPITAL RATIO	0.0010 [0.1371]	0.0094 [0.9787]	-0.0309** [-2.0249]	-0.0089 [-0.9026]	-0.0157*** [-2.6071]	-0.0011 [-0.1553]	-0.0798*** [-4.3465]	-0.0389*** [-4.6030]	
CUSTOMER LOANS RATIO	0.0031*** [3.8044]	0.0046** [2.4378]	0.0042** [2.2065]	0.0009 [1.1807]	0.0050*** [6.0600]	0.0059*** [3.4668]	0.0096*** [4.3476]	0.0020** [2.0090]	
OBS ACTIVITIES	0.0006 [0.2914]	-0.0024 [-1.1045]	0.0009 [0.1904]	0.0078 [1.3267]	-0.0006 [-0.4105]	-0.0017 [-1.0646]	-0.0029 [-0.5461]	-0.0005 [-0.1140]	
SHARE FEE INCOME	0.0005 [0.2493]	0.0003 [0.1054]	-0.0188** [-2.1132]	0.0037 [1.4291]	-0.0008 [-0.5194]	-0.0002 [-0.0715]	-0.0205** [-2.0390]	0.0018 [0.5686]	
LOAN PORTFOLIO HHI	-0.0068*** [-4.0677]	-0.0027 [-1.2094]	-0.0146** [-2.0992]	-0.0100*** [-3.4509]	-0.0055*** [-3.8636]	-0.0005 [-0.2317]	-0.0187** [-2.4241]	-0.0110*** [-5.6143]	
LERNER INDEX	-0.1168 [-0.3017]	0.0171 [0.0628]	-4.4307* [-1.7791]	-2.7771*** [-5.9403]	-0.5190** [-2.0730]	-0.2059 [-0.7877]	-4.6379 [-1.5330]	-5.1049*** [-6.1482]	
SQUARED LERNER INDEX	0.1932 [0.6305]	-0.0900 [-0.6741]	4.9999* [1.8270]	3.1165*** [6.9349]	-0.0571 [-1.2549]	-0.0854 [-1.1196]	4.7538 [1.4465]	5.1202*** [5.6935]	
MONITORING ABILITY	-0.0248** [-2.0308]	-0.0278** [-1.9831]	0.4270 [1.4858]	-0.1426* [-1.6764]	-0.0306 [-1.2616]	-0.0112 [-0.5974]	0.9123*** [2.6340]	-0.4567*** [-4.7040]	
	<i>Macroeconomic control variables</i>								
REGIONAL GDP	0.0049 [1.3724]	0.0303 [1.2131]	0.0090 [1.3746]	0.0004 [0.1119]	0.0021 [0.4701]	0.0095 [0.3401]	0.0122 [1.4999]	-0.0050 [-1.0312]	
STATE/YEAR DUMMIES		YES					YES		
	<i>Banking group dummies and constant</i>								
DUMMY SAVINGS BANKS	-0.2491*** [-3.5381]				-0.3549*** [-6.4025]				
DUMMY COOP. BANKS	-0.2195*** [-3.4170]				-0.2656*** [-5.0809]				
Constant	0.2459 [1.5468]	0.2783 [1.0189]	1.1603** [2.1544]	0.7985*** [3.9415]	0.9830*** [8.2337]	0.4717* [1.9241]	1.4510** [2.1152]	2.1315*** [9.1596]	
Observations	17,590	1,302	4,621	11,667	52,314	3,538	13,863	34,913	
Number of banks / portfolios	2,361	184	571	1,607	10,706	818	2,660	7,231	
Adjusted R-squared	0.099	0.070	0.159	0.116	0.039	0.030	0.072	0.050	
L1-3.GAP EXCESSIVE CG (F stat)	23.694	5.087	13.170	17.694	6.711	1.426	4.996	3.617	
L1-3.GAP EXCESSIVE CG (p value)	0.000	0.002	0.000	0.000	0.000	0.234	0.002	0.013	

Table 7: Panel C2. Pooled Tobit model with GAP EXCESSIVE CREDIT GROWTH

This table presents results from pooled Tobit regressions with LOSS RATE (SECTOR): write-offs (sector) to credit (sector) in the domestic credit portfolio as the dependent variable; GAP EXCESSIVE CREDIT GROWTH is the positive deviation from the long-run trend (measured in %); L1 - L3 denote lag-operators; *Bank-specific control variables* are measured in percent (REGIONAL GDP as a percentage change) and averaged over three years. *** p<0.01, ** p<0.05, * p<0.1; standard errors clustered at bank level (bank-portfolio level) in parentheses.

Variable	Total domestic credit				Three largest portfolios of domestic credit			
	All	Private	Savings	Coops	All	Private	Savings	Coops
	<i>Gap excessive credit growth</i>							
L1.GAP EXCESSIVE CG	0.0250*** [4.2466]	0.0084 [0.7838]	0.0573*** [4.9621]	0.0375*** [4.6397]	0.0018 [1.4625]	-0.0001 [-0.0716]	-0.0062*** [-2.7852]	0.0043*** [2.8655]
L2.GAP EXCESSIVE CG	0.0175*** [3.1124]	0.0135 [1.3076]	0.0275** [2.0557]	0.0208*** [3.4251]	0.0023* [1.7580]	-0.0009 [-0.4078]	0.0040* [1.8194]	0.0034** [2.1217]
L3.GAP EXCESSIVE CG	0.0204*** [4.7782]	0.0289*** [2.7780]	0.0232** [2.2929]	0.0178*** [4.4261]	0.0043*** [2.9746]	0.0062*** [3.0325]	0.0075*** [3.1558]	0.0028 [1.5913]
	<i>Bank-specific control variables (averaged over three years)</i>							
EQUITY CAPITAL RATIO	-0.0043 [-0.4753]	0.0136 [0.8733]	-0.0303* [-1.8970]	-0.0215 [-1.6222]	-0.0684*** [-4.5254]	-0.0224*** [-3.7729]	-0.0728*** [-2.9665]	-0.1394*** [-6.8768]
CUSTOMER LOANS RATIO	0.0045*** [4.3490]	0.0114*** [3.7787]	0.0044** [2.1941]	0.0009 [0.7827]	0.0119*** [7.7206]	0.0280*** [31.4225]	0.0101*** [3.5388]	0.0022 [1.0198]
OBS ACTIVITIES	0.0012 [0.4165]	-0.0049 [-1.0330]	0.0011 [0.2255]	0.0101 [1.3409]	0.0031 [0.8178]	0.0008 [0.4796]	0.0032 [0.4638]	0.0070 [0.8032]
SHARE FEE INCOME	0.0004 [0.1576]	-0.0004 [-0.0818]	-0.0200** [-2.1382]	0.0048 [1.3175]	0.0033 [0.8501]	-0.0048*** [-2.8092]	-0.0268** [-2.0694]	0.0179*** [2.6658]
LOAN PORTFOLIO HHI	-0.0103*** [-4.4789]	-0.0078** [-2.1993]	-0.0146** [-2.0328]	-0.0152*** [-3.3996]	-0.0204*** [-6.4572]	-0.0126*** [-8.7915]	-0.0195* [-1.7770]	-0.0349*** [-5.9703]
LERNER INDEX	-0.1141 [-0.2483]	0.7795 [0.5947]	-4.0745 [-1.5331]	-2.9600*** [-5.8972]	-1.2397*** [-2.6622]	0.6730*** [4.7222]	1.0564 [0.2595]	-6.1025*** [-7.5617]
SQUARED LERNER INDEX	0.2114 [0.5981]	-0.9393 [-0.5569]	4.5735 [1.5716]	3.2811*** [6.6374]	0.0828 [0.5121]	-1.7842*** [-7.0526]	-2.3619 [-0.5371]	5.4856*** [5.8475]
MONITORING ABILITY	-0.0390 [-1.3063]	-0.0574* [-1.6749]	0.4659 [1.5764]	-0.2519** [-2.1335]	-0.4809** [-2.5223]	-0.0991*** [-2.8049]	0.6070 [1.4145]	-1.3986*** [-4.7875]
	<i>Macroeconomic control variables</i>							
REGIONAL GDP	0.0048 [1.1643]	0.0454 [1.6066]	0.0084 [1.2261]	-0.0001 [-0.0175]	-0.0057 [-0.8297]	0.0231** [1.9787]	0.0054 [0.5114]	-0.0140* [-1.7055]
STATE/YEAR DUMMIES		YES				YES		
INDUSTRY SECTOR DUMMIES		NO				YES		
	<i>Banking group dummies, and constant</i>							
DUMMY SAVINGS BANKS	-0.1524* [-1.7623]				-0.0929 [-0.9524]			
DUMMY COOP. BANKS	-0.2824*** [-3.5816]				-0.5203*** [-5.6094]			
Constant	0.3496 [1.6292]	-0.4160 [-0.8669]	1.2635** [2.2140]	1.0537*** [3.7662]	0.3903 [0.9418]	-16.5865*** [-238.9773]	0.2996 [0.3264]	2.1078*** [4.0022]
Observations	17,590	1,302	4,621	11,667	52,314	3,538	13,863	34,913
Number of banks / portfolios	2,361	184	571	1,607	10,706	818	2,660	7,231
Pseudo R-squared	0.073	0.064	0.122	0.084	0.045	0.062	0.042	0.047
L1-3.GAP EXCESSIVE CG (F stat)	19.978	4.089	12.848	13.830	4.191	134.840	8.567	4.377
L1-3.GAP EXCESSIVE CG (p value)	0.000	0.007	0.000	0.000	0.006	0.000	0.000	0.004

Table 8: Panel D1. Pooled OLS model with REL. GAP EXCESSIVE CREDIT GROWTH

This table presents results from pooled OLS regressions with DEVIATION LOSS RATE (SECTOR): deviation of loss rate (sector) from the industry aggregate (commercial bank sector, public bank sector, cooperative bank sector) per year as the dependent variable; Rel. GAP EXCESSIVE CREDIT GROWTH is the positive deviation from the long-run trend (measured in %) adjusted by the industry aggregate (i.e. the positive deviation from the long-run trend for the commercial bank sector, savings bank sector, cooperative bank sector); L1 - L3 denote lag-operators; *Bank-specific control variables* are measured in percent (REGIONAL GDP as a percentage change) and averaged over three years. *** p<0.01, ** p<0.05, * p<0.1; standard errors clustered at bank level (bank-portfolio level) in parentheses.

Variable	Total domestic credit				Three largest portfolios of domestic credit			
	All	Private	Savings	Coops	All	Private	Savings	Coops
	<i>Relative gap excessive credit growth (industry adjusted)</i>							
L1.REL. GAP EXCESSIVE CG	0.0234*** [4.8348]	0.0100 [1.3791]	0.0494*** [4.6094]	0.0331*** [5.2421]	0.0015* [1.8326]	0.0030 [1.0628]	-0.0034* [-1.8406]	0.0022** [2.2419]
L2.REL. GAP EXCESSIVE CG	0.0132*** [2.9494]	0.0069 [0.9694]	0.0211* [1.7374]	0.0194*** [3.9272]	0.0014* [1.7376]	-0.0010 [-0.3938]	0.0033* [1.7777]	0.0017* [1.7493]
L3.REL. GAP EXCESSIVE CG	0.0191*** [5.2294]	0.0239*** [3.1165]	0.0194** [2.1502]	0.0162*** [4.6382]	0.0029*** [3.2417]	0.0050* [1.8775]	0.0033* [1.6570]	0.0022** [2.1029]
	<i>Bank-specific control variables (averaged over three years)</i>							
EQUITY CAPITAL RATIO	0.0011 [0.1518]	0.0097 [1.0112]	-0.0321** [-2.0938]	-0.0088 [-0.8853]	-0.0156*** [-2.5936]	-0.0010 [-0.1462]	-0.0794*** [-4.3223]	-0.0388*** [-4.5906]
CUSTOMER LOANS RATIO	0.0030*** [3.6957]	0.0044** [2.3440]	0.0043** [2.2322]	0.0009 [1.1037]	0.0050*** [6.0592]	0.0059*** [3.4447]	0.0096*** [4.3424]	0.0019** [2.0013]
OBS ACTIVITIES	0.0010 [0.4660]	-0.0020 [-0.9410]	0.0010 [0.2064]	0.0081 [1.3444]	-0.0006 [-0.3843]	-0.0016 [-1.0085]	-0.0030 [-0.5557]	-0.0004 [-0.0989]
SHARE FEE INCOME	0.0006 [0.3147]	0.0003 [0.1294]	-0.0194** [-2.1575]	0.0038 [1.4373]	-0.0009 [-0.5289]	-0.0001 [-0.0578]	-0.0207** [-2.0534]	0.0018 [0.5761]
LOAN PORTFOLIO HHI	-0.0067*** [-4.0200]	-0.0027 [-1.1735]	-0.0142* [-1.9634]	-0.0101*** [-3.4363]	-0.0055*** [-3.8600]	-0.0005 [-0.2108]	-0.0191** [-2.4630]	-0.0110*** [-5.6384]
LERNER INDEX	-0.1141 [-0.2948]	0.0218 [0.0798]	-4.5944* [-1.7783]	-2.7646*** [-5.9025]	-0.5197** [-2.0752]	-0.2058 [-0.7854]	-4.6542 [-1.5386]	-5.1075*** [-6.1536]
SQUARED LERNER INDEX	0.1759 [0.5735]	-0.1086 [-0.8125]	5.1358* [1.8166]	3.0916*** [6.8558]	-0.0582 [-1.2791]	-0.0877 [-1.1460]	4.7638 [1.4499]	5.1172*** [5.6918]
MONITORING ABILITY	-0.0226* [-1.8310]	-0.0264* [-1.8794]	0.4027 [1.4069]	-0.1433* [-1.6664]	-0.0299 [-1.2330]	-0.0102 [-0.5509]	0.9097*** [2.6244]	-0.4573*** [-4.7066]
	<i>Macroeconomic control variables</i>							
REGIONAL GDP	0.0053 [1.4854]	0.0316 [1.2621]	0.0086 [1.3069]	0.0005 [0.1501]	0.0020 [0.4486]	0.0098 [0.3518]	0.0121 [1.4892]	-0.0051 [-1.0565]
STATE/YEAR DUMMIES		YES				YES		
	<i>Banking group dummies and constant</i>							
DUMMY SAVINGS BANKS	-0.2587*** [-3.6605]				-0.3533*** [-6.3656]			
DUMMY COOP. BANKS	-0.2297*** [-3.5533]				-0.2658*** [-5.0779]			
Constant	0.2552 [1.6125]	0.2938 [1.0829]	1.2825** [2.2958]	0.7486*** [3.4458]	0.9816*** [8.2338]	0.4776* [1.9487]	1.4616** [2.1305]	2.1381*** [9.1929]
Observations	17,590	1,302	4,621	11,667	52,314	3,538	13,863	34,913
Number of banks / portfolios	2,361	184	571	1,607	10,706	818	2,660	7,231
Adjusted R-squared	0.096	0.065	0.153	0.113	0.039	0.030	0.071	0.050
L1-3.REL. GAP EXCESSIVE CG (F stat)	22.368	4.608	10.804	17.744	5.443	1.363	3.946	3.932
L1-3.REL. GAP EXCESSIVE CG (p value)	0.000	0.004	0.000	0.000	0.001	0.253	0.008	0.008

Table 9: Panel D2. Pooled Tobit model with REL. GAP EXCESSIVE CREDIT GROWTH

This table presents results from pooled Tobit regressions with LOSS RATE (SECTOR): write-offs (sector) to credit (sector) in the domestic credit portfolio as the dependent variable; REL. GAP EXCESSIVE CREDIT GROWTH is the positive deviation from the long-run trend (measured in %) adjusted by the industry aggregate (i.e. the positive deviation from the long-run trend for the commercial bank sector, savings bank sector, cooperative bank sector); L1 - L3 denote lag-operators; *Bank-specific control variables* are measured in percent (REGIONAL GDP as a percentage change) and averaged over three years. *** p<0.01, ** p<0.05, * p<0.1; standard errors clustered at bank level (bank-portfolio level) in parentheses.

Variable	Total domestic credit				Three largest portfolios of domestic credit			
	All	Private	Savings	Coops	All	Private	Savings	Coops
	<i>Relative gap excessive credit growth (industry adjusted)</i>							
L1.REL. GAP EXCESSIVE CG	0.0233*** [4.0935]	0.0085 [0.7984]	0.0499*** [4.5030]	0.0321*** [4.4730]	0.0019 [1.4005]	0.0002 [0.0824]	-0.0035 [-1.4665]	0.0038** [2.3531]
L2.REL. GAP EXCESSIVE CG	0.0135*** [2.5903]	0.0104 [1.0362]	0.0223* [1.8033]	0.0187*** [3.3992]	0.0027** [2.0926]	-0.0030 [-1.3159]	0.0067*** [2.8453]	0.0035** [2.2390]
L3.REL. GAP EXCESSIVE CG	0.0200*** [4.7454]	0.0265** [2.5454]	0.0186** [1.9626]	0.0181*** [4.5698]	0.0041*** [2.8202]	0.0046** [2.1861]	0.0074*** [2.9878]	0.0033* [1.8622]
	<i>Bank-specific control variables (averaged over three years)</i>							
EQUITY CAPITAL RATIO	-0.0042 [-0.4620]	0.0139 [0.8934]	-0.0316** [-1.9640]	-0.0215 [-1.6087]	-0.0685*** [-4.5275]	-0.0221*** [-3.7193]	-0.0718*** [-2.9279]	-0.1392*** [-6.8663]
CUSTOMER LOANS RATIO	0.0045*** [4.2659]	0.0112*** [3.7014]	0.0045** [2.2220]	0.0008 [0.7282]	0.0119*** [7.7297]	0.0279*** [31.2897]	0.0101*** [3.5231]	0.0022 [1.0202]
OBS ACTIVITIES	0.0017 [0.5591]	-0.0044 [-0.9339]	0.0012 [0.2415]	0.0104 [1.3548]	0.0031 [0.8261]	0.0008 [0.5206]	0.0032 [0.4562]	0.0071 [0.8120]
SHARE FEE INCOME	0.0005 [0.2037]	-0.0003 [-0.0607]	-0.0206** [-2.1801]	0.0048 [1.3178]	0.0033 [0.8394]	-0.0047*** [-2.7798]	-0.0273** [-2.1056]	0.0179*** [2.6689]
LOAN PORTFOLIO HHI	-0.0103*** [-4.4364]	-0.0078** [-2.1541]	-0.0141* [-1.8981]	-0.0154*** [-3.3874]	-0.0204*** [-6.4700]	-0.0125*** [-8.7267]	-0.0207* [-1.8909]	-0.0350*** [-5.9788]
LERNER INDEX	-0.1120 [-0.2438]	0.7317 [0.5694]	-4.2445 [-1.5433]	-2.9462*** [-5.8489]	-1.2383*** [-2.6586]	0.6543*** [4.5871]	1.0486 [0.2576]	-6.1049*** [-7.5716]
SQUARED LERNER INDEX	0.1924 [0.5438]	-0.9033 [-0.5444]	4.7146 [1.5713]	3.2562*** [6.5510]	0.0810 [0.5002]	-1.7788*** [-7.0249]	-2.3708 [-0.5393]	5.4820*** [5.8455]
MONITORING ABILITY	-0.0367 [-1.1827]	-0.0558 [-1.5956]	0.4415 [1.4994]	-0.2526** [-2.1147]	-0.4795** [-2.5127]	-0.0971*** [-2.7643]	0.6019 [1.4007]	-1.3981*** [-4.7827]
	<i>Macroeconomic control variables</i>							
REGIONAL GDP	0.0052 [1.2667]	0.0471* [1.6665]	0.0080 [1.1566]	0.0001 [0.0175]	-0.0058 [-0.8457]	0.0232** [1.9876]	0.0055 [0.5147]	-0.0143* [-1.7440]
STATE/YEAR DUMMIES			YES				YES	
INDUSTRY SECTOR DUMMIES			NO				YES	
	<i>Banking group dummies, and constant</i>							
DUMMY SAVINGS BANKS	-0.1646* [-1.8982]				-0.0890 [-0.9124]			
DUMMY COOP. BANKS	-0.2952*** [-3.7234]				-0.5197*** [-5.5997]			
Constant	0.3788* [1.7743]	-0.4206 [-0.8861]	1.3658** [2.3120]	1.0765*** [3.8290]	0.4001 [0.9654]	-16.4831*** [-237.3262]	0.3039 [0.3310]	2.1270*** [4.0424]
Observations	17,590	1,302	4,621	11,667	52,314	3,538	13,863	34,913
Number of banks / portfolios	2,361	184	571	1,607	10,706	818	2,660	7,231
Pseudo R-squared	0.072	0.063	0.119	0.083	0.045	0.062	0.042	0.047
L1-3.REL. GAP EXCESSIVE CG (F stat)	18.171	3.353	10.519	14.093	4.482	115.940	8.087	4.284
L1-3.REL. GAP EXCESSIVE CG (p value)	0.000	0.018	0.000	0.000	0.004	0.000	0.000	0.005

4.3 Bank stability

High loan losses are a threat to banks, but as long as the losses are overcompensated by the credit risk premia charged, bank stability is not in danger. In line with the model of [Martinez-Miera and Repullo \(2010\)](#) we analyze whether the risk-shifting channel of moral hazard or the margin channel of higher interest income dominates for banks that attract large credit growth. We replace loan write-offs as our dependent variable with more comprehensive bank stability measures, such as DISTRESS (i.e. which identifies banks receiving capital support measures from the deposit insurance funds, or exiting the market in a distressed merger/in a moratorium), DEFAULT (i.e. which identifies banks exiting the market in a distressed merger/in a moratorium), and the ZSCORE (i.e. banks' distance to default) as dependent variables at the bank level. Whereas a positive coefficient on the lagged values of our four credit growth measures indicates increased risk (i.e. a higher likelihood) for DISTRESS and DEFAULT, the opposite holds for the ZSCORE, as a negative coefficient indicates a shorter distance to default. For most German banks — especially the savings and cooperative banks that are bound by the regional principle — domestic credit is the largest and most important portfolio and contributes the largest share of overall RWA. Therefore, it seems justified to draw conclusions whether the risk-shifting or the margin channel dominates when comparing our previous results to the financial stability indicators.

Table 10 confirms that excessive credit growth is consistent with reduced bank stability. Whereas the joint significance of the coefficients for *adequate credit growth* measures (see the bottom of the table) only leads to a reduced ZSCORE¹⁶ but has no significant effect on the likelihood of DISTRESS or DEFAULT, our measures of *excessive credit growth* indicate that the HP filter is able to identify banks with a higher likelihood of default. In contrast, for Spanish banks [Jiménez and Saurina \(2006\)](#) could show that measures of normal credit growth forecast bank defaults two to four years ahead. Therefore, the methodology we propose for identifying excessive credit suppliers has clear predictive power for micro-prudential regulation and additional capital charges can be justified based on them. Moreover, the results for DISTRESS and the ZSCORE provide evidence that higher pricing power in the market (i.e. a higher LERNER INDEX) ensures a more stable banking system (see also [Kick and Prieto, 2015](#)).¹⁷ Surprisingly, our analysis reveals that a better MONITORING ABILITY leads to a higher risk of DEFAULT (when adequate credit growth measures are used) and lower ZSCORES. This stands in contrast to our expectations that loan monitoring enhances financial stability. However, the costs associated with hiring more employees seem to outweigh the benefits of lower loan losses.

¹⁶This finding is confirmed by [Foos et al. \(2010\)](#) using their abnormal growth measure.

¹⁷For DEFAULT the result only holds when excessive credit growth measures are used.

Table 10: Panel E. Bank Stability

This table presents results from pooled Probit regressions with DISTRESS: a dummy variable that takes on the value of one for banks receiving capital support measures from the deposit insurance funds, or exiting the market in a distressed merger/in a moratorium / DEFAULT: a dummy variable that takes on the value of one for banks exiting the market in a distressed merger/in a moratorium as the dependent variable; moreover, pooled OLS regressions with ZSCORE: the ln of the z-score calculated as the ratio of equity capital and operating profits to the standard deviation of operating profits (all components scaled by total assets) as the dependent variable are shown. CREDIT GROWTH is defined as delta ln credit for positive changes; DUMMY LARGE CREDIT GROWTH is a dummy variable that takes on the value of one when the threshold per banking group (mean growth + 2 standard deviations) is exceeded; GAP EXCESSIVE CREDIT GROWTH is the positive deviation from the long-run trend (measured in %); REL. GAP EXCESSIVE CREDIT GROWTH is the positive deviation from the long-run trend (measured in %) adjusted by the industry aggregate (i.e. the positive deviation from the long-run trend for the commercial bank sector, public bank sector, cooperative bank sector); L1 - L3 denote lag-operators; *Bank-specific control variables* are measured in percent (REGIONAL GDP as a percentage change) and averaged over three years. *** p<0.01, ** p<0.05, * p<0.1; standard errors clustered at bank level (bank-portfolio level) in parentheses.

Variable	(1) CREDIT GROWTH			(2) DUMMY LARGE CREDIT GROWTH			(3) GAP EXCESSIVE CREDIT GROWTH			(4) REL. GAP EXCESSIVE CREDIT GROWTH		
	DISTRESS	DEFAULT	ZSCORE	DISTRESS	DEFAULT	ZSCORE	DISTRESS	DEFAULT	ZSCORE	DISTRESS	DEFAULT	ZSCORE
L1.(1) (2) (3) (4)	-0.0203*	-0.0319	0.0007	-0.1365	-0.4784	-0.0522*	0.0723***	0.0555***	-0.0206***	0.0740***	0.0530***	-0.0169***
L2.(1) (2) (3) (4)	[-1.7913]	[-1.6420]	[0.4604]	[-0.7735]	[-1.2335]	[-1.6938]	[5.7075]	[3.3155]	[-5.1318]	[5.7509]	[3.1518]	[-4.5097]
L3.(1) (2) (3) (4)	-0.0046	0.0057	-0.0000	0.1451	0.1900	-0.0636**	0.0106	0.0214	-0.0073***	0.0070	0.0268	-0.0051*
	[-0.3879]	[0.4338]	[-0.0343]	[0.8545]	[0.7456]	[-2.1595]	[0.8164]	[1.3346]	[-2.6795]	[0.4935]	[1.5043]	[-1.9176]
	0.0057	0.0011	-0.0048***	0.1192	0.0812	-0.1078***	0.0455***	0.0090	-0.0169***	0.0517***	0.0090	-0.0168***
	[1.0013]	[0.1704]	[-4.5372]	[1.1283]	[0.6025]	[-5.2104]	[4.5124]	[0.6468]	[-6.5014]	[4.8211]	[0.5717]	[-6.3540]
	<i>Bank-specific control variables (averaged over three years)</i>											
EQUITY CAPITAL RATIO	-0.1159***	-0.1176**	0.0603***	-0.1117***	-0.1107**	0.0606***	-0.1164***	-0.1034**	0.0613***	-0.1191***	-0.1074**	0.0612***
CUSTOMER LOANS RATIO	[0.0071*]	[0.0056]	[0.0022**]	[0.0071*]	[0.0053]	[0.0020**]	[0.0078**]	[0.0058]	[0.0019*]	[0.0078**]	[0.0056]	[0.0020**]
OBS ACTIVITIES	-0.0006	-0.0022	-0.0041***	-0.0006	-0.0019	-0.0039**	-0.0050	-0.0040	-0.0034**	-0.0041	-0.0036	-0.0037**
SHARE FEE INCOME	[-0.1255]	[-0.6829]	[-2.7213]	[-0.1304]	[-0.5985]	[-2.5454]	[-0.9776]	[-0.9728]	[-2.3610]	[-0.8175]	[-0.8741]	[-2.5657]
LOAN PORTFOLIO HHI	0.0094	0.0169***	-0.0081***	0.0085	0.0165***	-0.0082***	0.0067	0.0170***	-0.0081***	0.0066	0.0171***	-0.0082***
LERNER INDEX	[-0.6985]	[1.5275]	[-0.9570]	[-1.1055]	[1.3125]	[-0.8401]	[-1.3801]	[0.8483]	[-0.8692]	[-1.3874]	[0.8311]	[-0.8863]
SQUARED LERNER INDEX	-1.9674**	-8.3036	0.0640	-2.3077***	-8.7058	0.0702	-2.2362***	-11.0824*	0.0262	-2.2553***	-11.1243*	0.0396
MONITORING ABILITY	[-2.3916]	[-1.6173]	[0.3541]	[-2.8957]	[-1.6164]	[0.3920]	[-2.8005]	[-1.7941]	[0.1453]	[-2.8644]	[-1.8208]	[0.2181]
REGIONAL GDP	-0.1066	0.0574*	-0.0308***	-0.0676	0.0604*	-0.0316***	-0.0648	0.0460	-0.0234**	-0.0563	0.0492	-0.0249***
STATE/YEAR DUMMIES	[-0.7582]	[1.6553]	[-3.4406]	[-0.4889]	[1.7919]	[-3.5635]	[-0.5122]	[1.3457]	[-2.4773]	[-0.4453]	[1.4418]	[-2.6711]
	<i>Macroeconomic control variables</i>											
DUMMY SAVINGS BANKS	-0.6476***	-0.3381*	0.2612***	-0.6015***	-0.2868	0.2824***	-0.2517	0.0281	0.1878**	-0.2335	0.0465	0.1997**
DUMMY COOP. BANKS	[-3.1269]	[-1.7474]	[3.1002]	[-2.9004]	[-1.4784]	[3.4662]	[-1.0242]	[0.1215]	[2.3499]	[-0.9613]	[0.2005]	[2.4936]
Constant	-0.2536	0.0615	0.2885***	-0.2126	0.1076	0.3050***	0.0981	0.3973*	0.2208***	0.1038	0.3998*	0.2328***
	[-1.4757]	[0.3735]	[3.8058]	[-1.2567]	[0.6524]	[4.1448]	[0.4554]	[1.9156]	[3.0633]	[0.4879]	[1.9257]	[3.2212]
	-0.3642	-3.6346***	2.2915***	-0.5067	-3.7932***	1.9108***	-0.8958**	-4.4740***	2.3916***	-0.8860**	-4.4623***	1.9938***
	[-0.8756]	[-4.8007]	[16.1937]	[-1.2128]	[-4.6822]	[14.9028]	[-2.0848]	[-4.6453]	[17.2460]	[-2.0592]	[-4.7058]	[15.3760]
Observations	17,590	17,590	17,024	17,590	17,590	17,024	17,590	17,590	17,024	17,590	17,590	17,024
Number of banks / portfolios	2,361	2,361	2,224	2,361	2,361	2,224	2,361	2,361	2,224	2,361	2,361	2,224
(Adj. / Pseudo) R-squared	0.132	0.158	0.169	0.130	0.155	0.170	0.157	0.168	0.176	0.159	0.169	0.174
L1-3.(1) (2) (3) (4) (chi2/F stat)	4.608	2.808	7.286	2.451	1.751	9.403	50.050	25.838	17.996	52.774	25.992	16.095
L1-3.(1) (2) (3) (4) (p value)	0.203	0.422	0.000	0.484	0.626	0.000	0.000	0.000	0.000	0.000	0.000	0.000

5 Conclusion

Excessive credit growth has preceded many banking crises and can put the financial system as a whole in danger. From a micro-prudential perspective a limited number of banks may engage in excessive lending even though domestic credit growth is fairly adequate. Banks engaging in excessive lending usually lower their lending standards and tend to accept borrowers that are unable to repay their loans in subsequent years, leading to loan write-offs. Finally, the losses generated lead to a deterioration of the bank's equity capital and bank failure.

Extending insights from classical banking theory models to include overoptimistic behavior from auction theory, we show that excessive lending can affect a subgroup of overoptimistic banks while the majority of banks still sticks to sound lending standards and engages in credit rationing. Using a unique data set of loan volume and write-offs at the aggregated bank level as well as at specific industry portfolio levels, we empirically test the implications of our model. We find that, in general, standard measures of loan growth are associated with falling levels of loan loss provisioning in subsequent years. Hence, German commercial banks seem to be doing well in monitoring loan portfolio credit risk. However, by estimating the deviations of banks' credit growth from their (bank-specific or industry) long-term trend using a Hodrick-Prescott (HP) filter — a technique frequently used in macroeconomic time series to identify credit booms — we distinguish overoptimistic banks from those with adequate credit growth based on sound lending standards. For overoptimistic banks we find that loan growth is associated with abnormal loan write-offs in later years. This finding supports the Winners' Curse conjecture in loan market competition developed in our theoretical model.

Moreover, the excessive credit growth measures that build on the HP filter have predictive power in identifying weak banks — as demanded by [BCBS \(2015\)](#) — whose distance to default is shrinking, which need capital support or which will simply default outright. The Basel Committee proposes using the HP filter at an aggregate level in order to determine when to activate the countercyclical capital buffer. We show that applying the same filtering technique to microeconomic bank-level data helps to identify banks that might suffer loan losses and collapse in subsequent years. Therefore, our empirical method is useful to banking supervisors as a tool for monitoring the institutions in the Supervisory Review Process of Pillar 2 more closely and for justifying additional capital requirements.

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A Appendix

A.1 Variable description

Table A1: Variable description

<i>Dependent variables</i>	
LOSS RATE	Total write-offs to total credit in the domestic credit portfolio
DEVIATION LOSS RATE	Deviation of loss rate from the industry aggregate (commercial bank sector, public bank sector, cooperative bank sector) per year
LOSS RATE PORTFOLIO	Total write-offs to total credit per portfolio (i.e. industry sector as part of the domestic credit portfolio)
DEVIATION LOSS RATE PORTFOLIO	Deviation of loss rate per portfolio from the industry aggregate (commercial bank sector, public bank sector, cooperative bank sector) per year
DISTRESS	Dummy variable that takes on the value of one for banks receiving capital support measures from the deposit insurance funds, or exiting the market in a distressed merger/in a moratorium
DEFAULT	Dummy variable that takes on the value of one for banks exiting the market in a distressed merger/in a moratorium
ZSCORE	Ln of the z-score calculated as the ratio of equity capital and operating profits to the standard deviation of operating profits (all components scaled by total assets)
<i>Credit growth and gap excessive credit growth</i>	
L1.-L3.CREDIT GROWTH	Credit growth, measured as delta \ln credit (if change in credit is positive)
L1.-L3.DUMMY LARGE CREDIT GROWTH	A dummy variable that takes on the value of one when the threshold per banking group (mean growth + 2 standard deviations) is exceeded
L1.-L3.GAP EXCESSIVE CG	Gap excessive credit growth: positive deviation from the long-run trend in % (measured by HP filter, quarterly data)
L1.-L3.REL. GAP EXCESSIVE CG	Rel. gap excessive credit growth: positive deviation from the long-run trend in % (measured by HP filter, quarterly data) adjusted by the industry aggregate (i.e. the positive deviation from the long-run trend for the commercial bank sector, savings bank sector, cooperative bank sector)
<i>Bank-specific control variables (averaged over three years)</i>	
EQUITY CAPITAL RATIO	Tier 1 capital to risk-weighted assets
CUSTOMER LOANS RATIO	Customer loans to total assets
OBS ACTIVITIES	
SHARE FEE INCOME	Fee income to total operative income (interest income, fee income, trading income)
LOAN PORTFOLIO HHI	Herfindahl-Hirschman Index (HHI) of the domestic loan portfolio (27-sector classification, higher values indicate a higher concentration in the domestic loan portfolio)
LERNER INDEX	Cost and income efficiency-adjusted Lerner index (reflecting a bank's price setting power)
SQUARED LERNER INDEX	Squared cost and income efficiency-adjusted Lerner index
MONITORING ABILITY	Number of bank employees to deflated total assets (in million euros)
<i>Macroeconomic control variables</i>	
REGIONAL GDP	Growth of real regional GDP per capita per county
STATE DUMMIES	State dummy identifies banks in each of the 16 German states ("Bundeslands")
YEAR DUMMIES	Dummy identifies the specific economic situation ("business cycle") for each year
<i>Banking group dummies</i>	
DUMMY SAVINGS BANKS	Dummy for savings banks and Landesbanks (base group = private banks)
DUMMY COOP. BANKS	Dummy for cooperative banks and cooperative central banks (base group = private banks)

A.2 Lerner index

We proxy market power using an efficiency-adjusted Lerner index (Koetter et al., 2012), defined as the mark-up — price minus marginal cost — to the level of the output price, i.e. $(p - mc)/p$.¹⁸ As marginal cost cannot be observed, we estimate a translog cost function of the total output (TOUT) a bank generates, which we define as the sum of loan and security portfolios. Total operating costs are included as the dependent variable of the cost function.

$$\begin{aligned}
\ln TOC_{it} = & \gamma_i + \gamma_O \ln TOUT_{it} + \frac{1}{2} \gamma_{OO} (\ln TOUT_{it})^2 + \sum_{h=1}^3 \gamma_h \ln w_{hit} \\
& + \frac{1}{2} \sum_{h=1}^3 \sum_{m=1}^3 \gamma_{hm} \ln w_{hit} \ln w_{mit} + \sum_{h=1}^3 \gamma_{hO} \ln w_{hit} \ln TOUT_{it} + \gamma_E \ln Eq_{it} \\
& + \frac{1}{2} \gamma_{EE} (\ln Eq_{it})^2 + \gamma_{EO} \ln Eq_{it} \ln TOUT_{it} + \sum_{h=1}^3 \gamma_{hE} \ln w_{hit} \ln Eq_{it} \\
& + \gamma_T Tr + \frac{1}{2} \gamma_{TT} (Tr)^2 + \gamma_{TO} Tr \ln TOUT_{it} \\
& + \sum_{h=1}^3 \gamma_{Th} Tr \ln w_{hit} + \gamma_{TEq} Tr \ln Eq_{it} + \epsilon_{it}.
\end{aligned} \tag{A.1}$$

Marginal costs mc_{it} are derived from

$$mc_{it} = \left[\gamma_O + \gamma_{OO} \ln TOUT_{it} + \sum_{h=1}^3 \gamma_{hO} \ln w_{hit} + \gamma_{EO} \ln Eq_{it} + \gamma_{TO} Tr \right] \frac{TOC_{it}}{TOUT_{it}}. \tag{A.2}$$

The translog cost function is estimated based on a stochastic frontier analysis panel approach, where cost inefficiency is the difference between potential minimum and observed costs. The error term $\epsilon_{it} = v_{it} + u_{it}$. The random error term v_{it} is assumed to be i.i.d. normally distributed with mean zero and variance σ_v , whereas the component u_{it} captures the systematic deviation from the optimal cost structure due to inefficiency and is assumed to be i.i.d. with a truncated-normal distribution and a variance σ_u that is independent of the v_{it} 's. Equation (A.1) is estimated using maximum likelihood (Battese and Coelli, 1988).

In line with the majority of the literature, we assume that the output is generated using three different inputs: (i) borrowed funds, (ii) labor, and (iii) physical capital. Taking borrowed funds, such as deposits, as an input rather than an output of the banking firm is consistent with the financial intermediation approach (Sealey and Lindley, 1977). We include equity capital as a netput that can be used to fund income generating output and additionally captures differing risk attitudes. Technical change in the production technology of a bank is controlled for by including a time trend. In order to deal with outliers, we winsorize input prices at the upper and lower percentile. Homogeneity of degree one in input prices is imposed by dividing the price of labor and physical capital,

¹⁸For a detailed description of the Lerner index variables see Table A2.

as well as total operating cost by the price of borrowed funds. Output prices are assumed to be exogenously determined and given by total revenues to total assets.

The Lerner index can alternatively be written as $(AR - MC)/AR$, where AR represents average revenues and equals average profit plus average costs. In order to also integrate profit inefficiencies into the Lerner index, we substitute total operating costs by profits before tax (PBT) in Equation (A.1). Using predicted total operating costs and profits before tax from these estimations, the Lerner index is calculated as $(PBT + TOC - mc \times TOUT)/(PBT + TOC)$.

The following table explains the variables included in the estimation:

Table A2: **Variable description for Lerner index**

<i>Symbol</i>	<i>Variable name</i>	<i>Description</i>
TOC	Total operating cost	Sum of interest, fee and administrative expenses
PBT	Profits before tax	Profit before tax
$TOUT$	Total output	Total earning output measured as the sum of interest-bearing assets and securities
w_1	Cost of fixed assets	Other administrative expenses excluding personnel expenses
w_2	Cost of labor	Personnel expenditures to number of full time employee equivalents
w_3	Cost of borrowed funds	Interest expenses to total interest-paying liabilities
Eq	Total equity capital	Total regulatory capital
Tr	Time trend	Time trend starting with 0 in the year 1999
p	Output price	Total operating revenue to total assets