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A comprehensive view on risk reporting: evidence from supervisory data

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NON-TECHNICAL SUMMARY

RESEARCH QUESTION

In this paper, we examine how banks that use internal ratings-based (IRB) approaches assign credit risk in the credit portfolio depending on their market risk exposure in the trading book.

CONTRIBUTION

Our paper contributes to the growing literature in banking that investigates the link between risk reporting and bank capital under current internal ratings-based regulation. While current studies focus solely on how banks report risk in one asset category to economize on regulatory capital, our paper is the first that takes a comprehensive view on different bank risk dimensions.

RESULTS

We find that banks report lower credit risk weights for their loan portfolio when they face higher risk exposure in their trading book. This relationship is especially strong for banks that have binding regulatory capital constraints. While our results suggest the existence of incentive spillovers across different risk categories, they do not imply an abusive application of banks' own models to assess risk. Rather, we view our findings to be within the scope of the allowed discretion of the IRB model framework. These results imply that supervision requires a comprehensive view on the different bank risk dimension.

NICHTTECHNISCHE ZUSAMMENFASSUNG

FORSCHUNGSFRAGE

In diesem Papier untersuchen wir, ob und wie Banken, die ihre Kreditrisiken auf Basis eines eignen Modells bestimmen (IRB-Banken), Risiken in ihrem Kreditportfolio in Abhängigkeit von ihrem Marktrisiko melden.

BEITRAG

Jüngste Studien zeigen, dass Banken im Rahmen der gegenwärtigen Regulierung Kapital einsparen, indem sie systematisch zu geringe Risiken melden. Diese Studien beschränken sich jedoch auf eine bestimme Anlageklasse. Im Gegensatz dazu nimmt unsere Studie eine gesamtheitliche Sicht auf verschiedene Risiken der Banken ein.

ERGEBNISSE

Wir finden, dass Banken geringere regulatorische Kreditrisikogewichte für ihr Kreditportfolio angeben, wenn sie höherem Marktrisiko im Handelsbuch ausgesetzt sind. Dies gilt verstärkt für Banken, die näher an ihrer regulatorische Kapitalgrenze operieren. Während unsere Ergebnisse für die Existenz von Wechselwirkungen über verschiedene Anlageklassen hinweg sprechen, implizieren sie keine Manipulation bestehender aufsichtsrechtlicher Regeln. Vielmehr gelten aus unserer Sicht diese Ergebnisse innerhalb der von der Aufsicht erlaubten Flexibilität des IRB-Modellrahmens. Diese Ergebnisse zeigen, dass für die laufende Überwachung eine Gesamtheitsbetrachtung der verschiedenen Risikoklassen notwendig ist.

Deutsche Bundesbank Discussion Paper No 08/2018

A COMPREHENSIVE VIEW ON RISK REPORTING: EVIDENCE FROM SUPERVISORY DATA*

PURIYA ABBASSI MICHAEL SCHMIDT

ABSTRACT

We show that banks' risk exposure in one asset category affects how they report regulatory risk weights for another asset category. Specifically, banks report lower credit risk weights for their loan portfolio when they face higher risk exposure in their trading book. This relationship is especially strong for banks that have binding regulatory capital constraints. Our results suggest the existence of incentive spillovers across different risk categories. We relate this behavior to the discretion inherent in internal ratings-based models which these banks use to assess risk. These findings imply that supervision should include a comprehensive view of different bank risk dimensions.

JEL CLASSIFICATION: G01, G21, G28

KEYWORDS: Internal ratings-based regulation, credit risk, market risk, incentive spillovers, capital regulation, comprehensive risk assessment

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I. INTRODUCTION

Since the mid-1990s, banking regulators globally have allowed banks the discretion to use their own models to assess risk and thus calculate capital needs. The financial crisis, however, has triggered a fundamental debate among scholars and regulators about this flexibility given to banks to scale their regulatory capital (e.g., Haldane, 2013). Many observers distrust the complicated models that banks use, which they say tend to make assets look safer than they really are. Therefore, recent initiatives by regulatory bodies are aiming for simpler rules which are harder to manipulate (BCBS, 2016; Coen, 2016) and closer to what is deemed optimal from a benevolent regulator's perspective (Glaeser and Shleifer, 2001). An important argument against new measures, though, is that simpler rules are less efficient with respect to capital allocation and thus more stringent. As a result, banks would have to increase their capital or reduce lending with potential real effects on the economy (Dombrovskis, 2016).[1] To address malfunctions in an efficient manner but prevent over-regulation, it is crucial to understand how and why banks potentially use the discretion inherent in their models.

Recent studies show that banks using the internal ratings-based (IRB) approach economize on capital by systemically reporting lower risk within a specific asset category, e.g., credit risk in the banking book (Mariathasan and Merrouche, 2014; Plosser and Santos, 2014, Behn, Haselmann, Vig 2016, Firestone and Rezende, 2016, Berg and Koziol, 2017), or market risk in the trading book (Begley, Purnanandam, and Zheng, 2016). We complement this literature by assessing different bank risk dimensions comprehensively and ask whether banks report lower risks in one asset category to cross-subsidize risks (and losses) in another asset category. The idea being that, if banks can economize on capital by strategic risk-reporting in the banking book, they could use the 'freed capital' to cross-subsidize risk associated with assets in the trading book and thereby insulate their official capital adequacy ratio. In essence, banks

[1] Behn, Haselmann, and Wachtel (2016) and Jiménez, Ongena, Peydró, and Saurina (2017) (among many others) document how capital regulation affects lending.

would be less capitalized than what official capital ratios suggest and thus create a more fragile banking system. The implications of such a comprehensive risk management would be threefold: first, banks would use the regulatory discretion to manage short-term adverse market risk fluctuations. Second, banks would optimize risk and thus regulatory risk weights at an aggregate overall risk level as opposed to an asset-specific risk level. Third, supervisors should include a comprehensive view of the different bank risk dimensions. To the best of our knowledge, this is the first study that examines the cross-subsidy incentivized risk reporting across regulatory asset charges.

To examine this question, we use a unique, proprietary dataset from the Deutsche Bundesbank (the German central bank), which collects supervisory information on internal credit risk ratings for the loan portfolio of all banks in Germany using the IRB approach (hereafter: IRB banks). In particular, the data comprises IRB banks' estimates of creditors' one-year probability of default (PD) and the creditor-specific risk-weighted asset at the borrower-bank-time level for the period between 2008:Q1 and 2012:Q4. The granularity of the internal credit risk ratings for the loan portfolio of each IRB bank allows us to examine the differential PD reporting by banks and across borrowers. Notably, we also have access to quarterly supervisory data on market risk-weighted assets for trading book assets (hereafter: mRWA or market RWA) for each IRB bank during each quarter (BCBS, 2013). This allows us to examine whether IRB banks report credit risk ratings depending on their market risk exposure. Our exhaustive dataset is matched with comprehensive balance sheet information.

The testable hypothesis, which we study in this paper, is that IRB banks report lower credit risk for their loan portfolio when they have higher market risk exposure (as compared to banks with lower market risk exposure). Our results suggest the existence of incentive spillovers across these two risk categories. On average, an IRB bank with a one-standard deviation higher market RWA reports lower PDs by 0.03 percentage points, which is equivalent to a reduction of risk weights by about 3.57 percentage points and thus economically significant. Conditioning on the level of the regulatory Tier 1 capital ratio, we find that this effect is more pronounced for banks with more binding capital constraints (lowest 25th percentile of Tier 1 ratio). These results are robust to an exhaustive set of various fixed effects and bank-level controls.

To tease out the potential channels behind this finding, we examine and discuss three mutually non-exclusive possibilities, all of which relate to the level of discretion inherent in the models used under the IRB approach. First, we find that our result only holds for banks using the Advanced-IRB approach but not for banks that employ the Foundation-IRB approach. These findings suggest that there is self-selection when banks decide which approach (A-IRB vs. F-IRB) they should choose. That is, especially those banks that tend to exploit the greater degree of discretion may choose the A-IRB approach over F-IRB.

Second, we find that incentive spillovers across these different risk categories are weaker when market discipline is higher and stronger for less transparent borrowers with respect to fundamental information. Third, we find that more stringent regulatory supervision hampers the use of IRB model discretion for some banks, but not for institutions with stricter capital constraints. However, the latter finding might also be a result of the fading effect of the financial crisis. Both interpretations nevertheless suggest a more comprehensive view of risk reporting is required in future supervisory practice.

While our results suggest the existence of incentive spillovers across different risk categories, they do not imply an abusive application of banks' own models to assess risk. Neither do they indicate that banks manipulate their models after approval has been granted by the national regulator. Rather, we view our findings to be within the scope of the discretion that the national regulatory authorities allow to exist in the IRB model framework. This also includes banks' choice to apply either a point-in-time or a through-the-cycle risk modelling approach.

These results contribute to the growing literature in banking that investigates the link between risk reporting and bank capital under current internal ratings-based regulation (Mariathasan and Merrouche, 2014; Plosser and Santos, 2014; Begley, Purnanandam, and Zheng, 2016; Behn, Haselmann, Vig, 2016; Behn, Haselmann, Wachtel, 2016; Firestone and Rezende, 2016; Berg and Koziol, 2017). While these studies focus solely on how banks report risk in one asset category to economize on regulatory capital, our paper reveals two new dimensions: first, we show that banks use their risk reporting as a device to manage risk across different asset categories and, second, that banks optimize risk weights at the risk-comprehensive level rather than at the specific-risk level. In this regard, our paper is also connected to current debates on banking (capital) regulation (e.g., see Kashyap, Rajan, and Stein, 2008; Admati and Hellwig, 2013; Admati, DeMarzo, Hellwig, and Pfleiderer, 2013; Haldane, 2013; Dombrovskis, 2016). Our findings suggest that regulators can curtail the documented strategic risk reporting by taking a comprehensive view on the different bank risk dimension in the ongoing supervision.

Our work also adds to the literature on risk-management practice in banking (e.g., see Ellul and Yerramilli, 2013), which examines the role of strong and independent risk management for the resilience of banks' exposure to tail risk. Our findings highlight, that strategic risk management can have severe consequences for the existence of an institution from a microprudential perspective. With incentive spillovers across different risk categories, banks reduce or even isolate the otherwise adverse effect on their official capital ratio, making the institution more prone to shocks, both with respect to the asset side (higher risk related to assets) and with respect to the liability side (less capitalized relative to the engaged risk). This is a form of incentive risk reporting unintended by the regulator. In this respect, our paper also relates to the literature on regulatory arbitrage (e.g., see Huizinga and Laeven 2012; Acharya, Schnabl, and Suarez, 2013; Boyson, Fahlenbrach, and Stulz, 2016).

At a broader level, our results also relate to the literature that examines the misreporting incentives in financial markets (e.g., Piskorski, Seru, and Witkin, 2015; and Griffin and Maturana, 2016) and the related role of incentives and information in the estimation of risk measures (Rajan, Seru, and Vig, 2010, and 2015). Our results highlight the importance of a regulatory design that elicits truthful disclosure of risk, which is a prerequisite step to the current discussion on the optimal level of regulatory capital banks need to hold. In this regard, our paper also contributes to the literature that examines the reliability and credibility of risk weights (e.g., Das and Sy, 2012; Le Leslé and Avramova, 2012, among others). Official capital adequacy ratios must reflect the actual truthful risks in order for them to be a proper regulatory tool for both the microprudential and macroprudential policy.

The remainder of the paper is structured as follows. In the next section, we will discuss the institutional details of current IRB-regulation. Section III presents our data set. Section IV shows our empirical strategy and presents our results. Section V concludes.

II. INSTITUTIONAL SETTING

The current regulatory framework (Basel II and Basel III) relies on the concept of risk-sensitivity and links capital charges to the risk associated with the assets held. More precisely, minimum capital charges are determined on the basis of core capital as a fraction of the (unweighted) sum of RWA across all sources of risk (total RWAs). On average, around 70% of bank's assets are allocated to lending and roughly 20% to securities investments (see Table 2). This means that both, credit risk (i.e., credit RWA) and market risk (i.e., mRWA) account for the largest part of the variation in bank's total RWA.

The regulator allows banks to use their own internal ratings-based (IRB) models to calculate risk weights (as opposed to standard risk weights, see BCBS, 2006). Under IRB, banks assess the risk weights in their credit portfolio such that each individual borrower receives a borrower-specific risk weight. The estimation of the borrower-specific risk weight relies on the bank's own borrower-specific estimated probability of default over the subsequent year. That is, reported PDs for a given creditor assess the credit risk over a one-year horizon irrespective of the loan-specific characteristics such as the actual maturity and the loss given default. Further, even though internal credit risk models are used on a portfolio basis, borrower-specific PD estimations are invariant to the bank's credit portfolio insofar that the capital required for a given loan depends only on the risk of that loan but not on the portfolio it is added to (BCBS, 2006).

The assessment of risk weights for trading book assets is somewhat different. For internal market risk weighting, IRB banks use internal Value-at-Risk (VaR) models that are based on their own assumptions with respect to correlation between all trading assets; that is, in contrast to credit risk, for market risk the required capital for a given trading asset depends on the portfolio it is added to. Also, in calculating value-at-risk, IRB banks typically assume an instantaneous price shock equivalent to a 10-day movement in prices. But in principle, the rationale remains the same insofar that a bank that uses the IRB approach can apply its own judgement on (i.e., use models to assess) how risky an investment is and thus on how much capital needs to be held. That is, under the IRB approach banks' capital charges are endogenous to banks' self-assessment of risk.

The regulator understands that this endogeneity provides banks the discretion to scale their regulatory capital. But at the same time, the supervisor imposes certain rules to ensure compliance with the regulatory framework. First, risk models under IRB have to be evaluated and certified by the respective national supervisor prior to its implementation. Before any bank is allowed to apply the IRB approach for regulatory purposes, it has to ensure that the specific model has been used for internal risk management purposes for at least three years, see (BCBS 2006). After the approval, banks validate their models on a regular frequency (in most cases annually) and adjust them if their assessment is not consonant with realized and materialized risk (e.g., realized default rates on loans). Second, the regulator conducts a back-testing approach to evaluate the accuracy of bank's self-assessed risks and imposes a penalty (e.g., higher capital requirements) on the institutions if their models prove to be inaccurate and imprecise, see Bundesbank (2004). That is, banks have generally the incentives to use and hold on to models that have passed the regulator's evaluation and validation check-up.

III. DATA

In Germany, IRB banks undertake the regulatory reporting on their credit portfolio as part of the quarterly credit register to the Deutsche Bundesbank, which (together with the German federal financial supervisory authority 'BaFin') is the micro and macro-prudential supervisor of the German banking system. We have access to this supervisory micro data on internal credit risk measures at the borrower level for each IRB bank in Germany on a quarterly frequency from the beginning of 2008 (which is also the start of the IRB approach to capital regulation) to the end of 2012.[2] For each borrower, the bank reports its estimation on the probability of default (PD over the subsequent year). In addition, the bank also provides information on its borrower-specific credit RWA, which is used to compute the required level of regulatory capital the bank needs to hold for that specific borrower.[3] Note that the PD-reporting is at the borrower level as opposed to at the loan level.

We also obtain quarterly supervisory data on each bank's internal market risk weights at the bank-time level. This data captures the market risk-weighted sum of trading book assets (mRWA) at the bank level during each quarter. We supplement this database on banks' internal credit risk and market risk weights with confidential supervisory balance sheet statistics at

[2] We restrict our baseline regressions to the period of the financial crisis for two main reasons. First, banks' incentives to exploit the discretion inherent to their models along the lines of our hypothesis should be more pronounced during periods of higher market risk. And second, it allows for complementary analysis vis-à-vis previous studies that we mentioned in our Introduction. However, in Section IV.3.3 we extend our sample to 2008-2016 and find similar effects.

[3] In our data set, there are 41,697 (out of 703,195) cases, where we have information on the borrower-specific PD but not on the borrower-specific credit RWA.

the bank level. In particular, we collect quarterly balance sheet items such as bank total assets, interbank borrowings, savings deposits, and total lending (both retail and wholesale) and supervisory data on bank Tier 1 capital ratio, which are maintained by the Bundesbank.

We complement this rich dataset further with confidential supervisory data at the bank level, notably on losses and risks associated with trading activities and securities investments, and also the size of the investment portfolio. More precisely, we compute quarterly statistics on bank's securities holdings as a fraction of total assets from the security register and collect confidential supervisory annual information on total profits and net losses from trading from the profit and loss statements, both of which are maintained by the Deutsche Bundesbank (e.g., Amann, Baltzer, and Schrape, 2012).

Our complete dataset comprises credit ratings on a total of 269 banks, including both IRB and non-IRB banks. We prune the data as follows. We first restrict our analysis to IRB banks only. Also, we exclude the top (and bottom) 5% largest (smallest) values of PD entries (i.e. PD values larger than 10% and equal to zero, respectively), to ensure that our results are not driven by outliers. Further, we exclude banks that have less than 50 borrowers with at least two PD reporting values during our complete sample. Note, however, that our results are completely robust to both of these sample restrictions. For identification, we further restrict our sample to those borrowers that have at least two credit relationships with (and thus two reported PDs from) different banks at the same time. The resulting data set comprises 17,339 distinct borrowers and 38 IRB banks providing more than 45% of credit of the total German banking system. Together, these banks' total assets account for half of total assets of all banks in Germany and 160% of annual German GDP as at the year of 2012.

IV. IDENTIFICATION STRATEGY AND RESULTS

In this section, we first discuss our identification strategy to examine banks' internal credit risk reporting depending on the level of market risk exposure related to trading assets. Second, we will present our results and, third, we will elaborate on various channels behind our findings.

IV.1. EMPIRICAL STRATEGY AND IDENTIFICATION

Our testable hypothesis is that IRB banks with higher market risk exposure (as compared to banks with lower market risk exposure) will assign lower PDs (and thus also lower risk weights) to the same borrowers at the same time in their credit portfolio in order to cross-subsidize the risk (or loss) of trading book assets. We examine this using the following econometric model[4]:

$$PD_{i,j,t} = \beta \cdot mRWA_{i,t-1} + \delta' controls_{i,t-1} + \delta_{i,j} + \nu_{j,t} + \varepsilon_{i,j,t} \qquad (1)$$

where *PD* refers to the probability to default over the next year that bank 'i' assigns to borrower 'j' during quarter 't'. 'mRWA' measures bank 'i's market risk exposure of its trading book assets (BCBS, 2013). For identification, we include borrower*time fixed effects ($\nu_{j,t}$) to account for time-varying, unobserved borrower fundamentals (e.g., risk and growth opportunities). Note that this identification strategy imposes that each borrower has at least two credit relationships with different banks at the same time. This identification is crucial for us to examine the differential PD reporting depending on key bank characteristics. We also include bank*borrower fixed effects ($\delta_{i,j}$) to control for time-invariant, unobserved bank-borrower-specific characteristics such as geographical distance (Degryse and Ongena, 2005), relationship lending (Petersen and Rajan, 1995), and reasons related to the regulatory framework (Behn, Haselmann, and Vig, 2016). Note that the inclusion of bank*borrower fixed effects at the same time controls for all observed and unobserved time-invariant bank-level heterogeneity. Thus, we can compare the internal credit risk assigned to the same borrower at the same time by different banks depending on their market risk exposure. 'controls' is a vector

[4] Our results do not depend on this specification. In alternative estimations (not reported), we have also used PDs in logarithms. But our results remain qualitatively unchanged.

of (lagged) time-varying bank variables, notably size, interbank borrowing over total assets, deposits over total assets, bank and non-bank lending over total assets, securities portfolio over total assets, ROE, and profits from trading over total income. We include these time-varying bank variables as our specification does not allow us to include bank*time fixed effects to control extensively for any observed and unobserved time-varying bank heterogeneity.[5]

If banks report lower risk for the sake of incentive spillover, the PD adjustment should affect the borrower-specific credit risk weight, and thus overall credit RWA. We test this with the following econometric model:

$$\mathrm{RW(PD\text{-}implied)}_{i,j,t} = (\mathrm{RWA}^{credit}_{i,j,t} / \mathrm{Loan}_{i,j,t})^{fitted} = \beta \cdot \mathrm{mRWA}_{i,t-1} + \delta' \mathrm{controls} + \delta_{i,j} + \nu_{j,t} + \varepsilon_{i,j,t} \qquad (2)$$

where the dependent variable refers to the borrower-specific credit risk weight that bank ‘i’ assigns to borrower ’j’ during quarter ‘t’, as *implied by the bank’s PD reporting*. To measure the effect of the PD reporting on credit risk weight, we use the fitted values from the following auxiliary regression[6]:

$$\mathrm{RWA}^{credit}_{i,j,t} / \mathrm{Loan}_{i,j,t} = \alpha + \beta \cdot \mathrm{RW(PD)}^{credit}_{i,j,t} + \varepsilon_{i,j,t} \qquad (3)$$

where the dependent variable is the credit RWA that bank ‘i’ reports for borrower ’j’ in quarter ‘t’ (in addition to the individual PD, as explained above) as a fraction of the respective borrower-specific loan exposure. The fitted values of this regression, i.e., $(\mathrm{RWA}^{credit}_{i,j,t} / \mathrm{Loan}_{i,j,t})^{fitted}$, then capture the part of the observed credit risk weight that can be explained by the reported PD, hence the PD-implied credit risk weight. $\mathrm{RW(PD)}^{credit}_{i,j,t}$ is computed

[5] For instance, we cannot control for the risk-taking behaviour of managers over time across banks; different managers may be willing to take more risk for reasons such as higher risk tolerance or incentive contracts. One may argue that such managers may end up being too aggressive in both trading book and lending book causing higher mRWA and lower PD. We do not consider this to be an issue in our analysis for the following reasons. First, it is not straightforward why an ‘aggressive’ manager’ should primarily manifest in higher market risk exposure but not in higher credit risk exposure. Second, risk-taking in the lending book should be reflective in higher PDs. But as we will discuss below, the marginal effect of an incremental increase in PDs on risk weights are much less pronounced for higher levels of PDs. Third, it is not clear whether managers’ risk-taking behaviour is systematically correlated with bank's Tier 1 capital position. In fact, persistent risk-taking on the asset side should rather incentivize managers to operate with higher Tier 1 capital buffers to avoid scrutiny by regulators.

[6] We modelled the functional relationship between credit risk weights and PDs in several ways (e.g., using logs, polynomial of n-th order). Our results do not depend on the specification choice.

on the basis of the Basel formula (BCBS, 2005 and 2006) using the reported PD (see Appendix Figure A1). Our coefficient of interest, β, in Equation (2) then measures the PD-elasticity and allows us to infer the economic magnitude and significance of our results from Equation (1). The explanatory variables and our fixed effects strategy are similar in both Equation (2) and Equation (1). We estimate our regressions using OLS and cluster standard errors at bank and borrower level. Our results are also robust to multi-way clustering of standard errors at bank, borrower and time level (not reported).

IV.2. MAIN RESULTS

We start by taking a first look at the cross-sectional variation in PDs (around the median PD) for the same borrower at the same time during our sample period. In Figure 1, we can see that PDs vary substantially and reach levels ranging from – 2.5 to +2.5 percentage points around the median PD. At the face of it, these numbers may seem small. But, for instance, Moody's ratings of one-year PDs are AAA (for PD=0%), AA (PD=0.01%), A (PD=0.02%), Baa (PD=0.18%), Ba (PD=1.2%), B (PD=5.23%), and Caa-C (PD=19.47%), see e.g., Moody's Analytics (2007). This suggests that the variation in PDs is economically meaningful.[7] Yet, the interesting question, which will be at the centre of our analysis, is whether banks with specific key characteristics are systematically associated with PDs (for the same borrower at the same time) at the lower tail of this PD distribution.

Table 2 presents summary statistics on reported PDs and balance sheet variables of banks using IRB approaches. We can see that the average creditor PD is 0.72%, which is equivalent to the Moody's rating bucket 'Baa to Ba'. The average credit risk weight for a borrower is 49% and the share of credit RWA accounts, on average, for 88.63% of total bank RWA. This highlights the role of credit risk for total risk and thus for the level of regulatory capital. The share of mRWA to total RWA amounts on average to 4.62%. The IRB banks' mRWA

[7] Note however that the variation in our PDs cannot be directly translated into changes across rating classes as this categorisation is non-linear and would require a geometric mapping.

amounts to 1.81% of total assets, which is equivalent to 8.79% of total securities (i.e., [mRWA/TA]/[Securities/TA], which corresponds to [1.81%]/[20.57%]). Similar levels are reported in BCBS (2013). This highlights the role of credit RWA and mRWA for total RWA, and thus for the level of required capital.

We use Equation (1) as baseline and modify it based on the hypothesis we are testing. In column 1 of Table 3, we start to examine the differential PD reporting for the same borrower at the same time at the borrower-bank-quarter level, depending on their level of market RWA (mRWA) and Tier 1 capital ratio during the previous quarter. There are two findings. First, a bank with a lower Tier 1 capital ratio reports significantly lower PDs for the same borrower at the same time as compared to a bank with a higher Tier 1 capital ratio. In this regard, our finding is in line with previous work (Plosser and Santos, 2014; Behn, Haselmann, and Vig, 2016; Berg and Koziol, 2017). And second, we can see that for the same borrower at the same time, IRB banks with higher mRWAs report lower PDs as compared to banks with lower mRWAs in the previous quarter. The magnitude of the different reporting is substantial. An IRB bank with a one-standard deviation higher market RWA reports lower PDs by 0.03 percentage points. This translates into a reduction of risk weights by about 3.57 percentage points.[8] In column 2, we add bank*borrower fixed effects and find similar coefficients as in column 1. Note that in both columns, we include bank*time controls (i.e., bank size, interbank borrowing, deposits, ROE, profits from trading/total income, and overall size of the credit and securities portfolio), which we absorbed for consolidated representation reasons. In the appendix, we further show that our main finding on incentive spillover is not a mere result of banks reporting higher PDs in response to lower mRWAs, see Table A1. Also, the fact that we do not find a significant (neither statistically nor economically) effect for periods of decreasing mar-

[8] In order to calculate the marginal effect of an increase in PDs we use the Basel formula as stated in BCBS (2006) and assume an LGD of 45% and a maturity of 2.5 years. The resulting average marginal effect across all borrowers is 127.254. We multiply this average marginal effect by the standard deviation of 0.0214 and the coefficient of 0.0131, which then equals to 3.57 percentage points. These assumptions are rather conservative as they rely on Basel (2006) parameters for senior corporate debt such that our economic results represent a lower bound.

ket risk exposure suggests that our main finding is not a mechanical effect caused by the choice of the bank's IRB model (i.e., point-in-time vs. through-the-cycle). Moreover, Table A2 shows that this behaviour is more pronounced during times of higher market risk (i.e., when the VIX is particularly high).

Given these two independent set of results, one might be concerned with the question of how much of these effects are essentially coming from the same channel and how much are actually independent effects. For example, economically it might be argued that banks which experience a decline in Tier 1 capital *due to* losses in their trading book are more likely to report lower PDs for the same borrower at the same time. We examine this by using trading losses as an instrument for Tier 1 capital in a first-stage regression, and then use the predicted value of Tier 1 capital from this regression in the second stage with PD as the dependent variable. The results of the second stage regression are presented in column 3. While the predicted Tier 1 is not significant, neither statistically and nor economically, the coefficient of mRWA remains both quantitatively and qualitatively unchanged. This suggests that our results presented in columns 1 and 2 rather point to two independent effects.

In addition to these individual effects, the relationship between the PD reporting and the market risk of the bank inherent to its trading book assets might depend on the ex-ante level of its Tier 1 capital ratio. The idea being that banks, for which the regulatory capital limits are more binding, might report lower PDs in order to cross-subsidize the risk of their trading book assets as compared to other banks (i.e., less capital constrained banks). To examine this, in columns 4 and 5 we replicate our analysis of column 2 but condition on IRB banks with the lowest (bottom 25th percentile of Tier 1 capital ratio) and highest (top 25th percentile of Tier 1 capital ratio) ex-ante regulatory capital ratio, respectively. From column 4, we can see that IRB banks with more binding regulatory capital limits report lower PDs when they have higher ex-ante market risk exposure. Economically, for an IRB bank with a one-standard deviation higher share of mRWA, the bank reports lower PDs to an extent that corresponds to 24.56% of the total Tier 1 capital ratio.[9] We find that the effects are not significant for high-Tier 1-capital IRB banks (top 25th percentile), compare column 5. In fact, note that the estimated coefficient of mRWA in the regressions for low-Tier 1 capital-ratio banks differs by a factor of more than 7 as compared to the regressions for high-Tier 1 capital-ratio banks (compare e.g., column 4 and 5). In Table 4, we replicate the analysis of Table 3 for borrower-specific PD-implied risk weights to examine the importance of our results. The columns 1 to 5 confirm the two results from Table 3: banks with higher market risk report lower credit risk weights and the result is stronger for lower ex-ante capital banks. Economically, an IRB bank with a one-standard-deviation higher market risk exposure reports lower PD-implied risk weights by 4.91 percentage points when capital constraints are more binding (bottom 25th percentile Tier 1 ratio). These results suggest incentive risk reporting across different risk categories.

IV.3. TEASING OUT THE ECONOMIC CHANNEL

Our robust result on incentive spillovers across different asset categories raises one important question: what is the economic channel behind it? The answer to this question allows us to put our findings into perspective and thus draw the proper conclusions. In this section, we will therefore discuss three different, mutually non-exclusive, possibilities and tease out their importance.

IV.3.1. FOUNDATION-IRB VS ADVANCED-IRB APPROACH

Under IRB, banks can choose between two approaches to determine capital charges, i.e., the 'Foundation IRB' (F-IRB, hereafter) and the 'Advanced IRB' (A-IRB, hereafter). Under both approaches, banks use their own PD estimates (BCBS, 2006). But in contrast to F-IRB, under A-IRB, banks provide also own estimates on other parameters such as the loss given

[9] This results from multiplying the standard deviation of mRWA/TA by the coefficient from column 4 of Table 3 times the average marginal effect (assuming standard Basel values for LGD and maturity) as a fraction of the borrower specific credit risk weight. More precisely, we first compute the change in RWA-to-Loan ratio, i.e., (0.0625*0.0214*127.254)= 0.17 percentage point. Then, we determine the relative change in the RWA to-Loan ratio, i.e., (0.0625*0.0214*127.254)/0.4773=0.3565. The credit RWA accounts for 68.87% of total RWA, which translates to an relative change of total RWA of 35,65%*68.87% = 24,56%

default (LGD), the exposure at default (EAD), and the effective maturity. Since banks may choose between either one of these approaches, there could be a self-selection involved. That is, especially those banks may choose the A-IRB approach over F-IRB, which intend to exploit the greater discretion.

We examine this in Table 5 and replicate our estimation from Table 3 (and 4 for credit risk weights) but restrict ourselves to banks that use the F-IRB and the A-IRB approach, respectively. In column 1, we can see that for banks that use the F-IRB approach the coefficient on mRWA is not significant. Moreover, the magnitude of the estimated coefficient is substantially smaller. For banks using the A-IRB approach, however, the coefficient of mRWA is highly significant, both statistically and economically. In fact, the estimated coefficient is considerably larger in absolute terms. The estimated coefficient suggests that under the A-IRB approach, a bank with a one-standard deviation higher market RWA reports lower PDs by 0.05 percentage points, which translates into a reduction of risk weights by about 6.84 percentage points.

Columns 3 and 4 show similar results for the credit risk weights. This result suggests that banks are not engaging in outright manipulation of PD estimates. That is to say, if bank's ultimate goal was to manipulate their PD estimations, we should also (or especially) find IRB banks to report lower PDs under F-IRB approach where (i) PDs are the only parameter that can be estimated, and (ii) PDs could be used to over-compensate the rather conservative estimates of the regulator with respect to the LGD and the maturity. But instead, our results seem to highlight the role of the greater discretion inherent to the approved models that banks employ under the A-IRB approach, which banks seem to systematically exploit for incentive spillovers across different risk categories. Our results therefore suggest that there is a self-selection in the decision of which approach (A-IRB vs. F-IRB) to choose.

IV.3.2. TRANSPARENCY VS MARKET DISCIPLINE

The behaviour of incentive risk reporting can also depend on the borrower type. For instance, one may argue that bank's discretion in assessing the PD is greater for borrowers from sectors that are less transparent with respect to fundamental information. The notion being that, PD estimations might be more sensitive to the bank's own assessment when borrower fundamentals are less traceable. An alternative view could be that the bank's discretion decreases when transparency and thus market discipline is high. Large shareholders of listed firms, for instance, might bring more market discipline on the bank as compared to firms that are not listed, thus limiting the discretion of a bank vis-à-vis its credit risk assessment for that firm. We elaborate on these two different economic forces in Table 6. In column 1 and 2 of Table 6 Panel A, we distinguish between listed and non-listed borrowers. We can see that the estimation coefficient in both columns is negative and significant. However, we can reject the null hypothesis of parameter equality suggesting that incentive spillovers are larger for non-listed borrowers (F-test provided in the lower panel of Table 6). In columns 3 and 4, we replicate the regression from column 2 but condition on borrowers from the MFI sector and from the non-MFI sector, respectively. If opacity is also a driving force behind our results, we would expect IRB banks to report especially lower PDs for borrowers from the non-listed non-MFI sector (i.e., non-banks), which is very probably less transparent with respect to fundamental information as compared to borrowers from the not-listed MFI sector (i.e., banks). We can see that the coefficient on mRWA is negative and significant for borrowers from both the MFI and non-MFI sector, but statistically (weakly) larger for non-MFI borrowers as compared to MFI creditors (null of parameter equality can be rejected at 10% level of significance). In columns 5 to 8, we examine the heterogeneity within the not-listed, non-MFI sector more narrowly. We do not find significant effects for borrowers from the financial industry, while effects from the corporate and the real-estate sector are statistically highly significant. The F-Test presented in the lower part of the table shows that the null of parameter equality can be rejected at the 5% level of significance. In Panel B of Table 6, we show that these results hold also for the PD-implied risk weight.

Our results on listed vs. not-listed firms highlight the role of market discipline in limiting the bank's discretion. Yet, we can see that banks do report lower PDs for borrowers from segments that are less transparent with respect to fundamental information. Together, these findings indicate that two forces are at play: opacity and market discipline.

IV.3.3. VARIATION IN REGULATORY SUPERVISION

Our results presented above rely on a sample that spans the period of Basel II. In the period after 2013 though, regulatory supervision has become more stringent as regards supervisory assessments, stress tests, and the introduction of newer regulatory rules including several key trading book measures. More precisely, the Basel Committee's phase-in period for higher and better quality capital requirements began from January 2013. Moreover, the Fundamental Review of the Trading Book, for instance, was meant to replace the crop of measures implemented through Basel 2.5 with a more coherent and consistent set of requirements, and to reduce the variability in the capital numbers generated by banks for market risk. By the end of 2013, the European Central Bank conducted the largest-ever supervisory comprehensive assessment including an EU-wide stress test exercise (e.g., Abbassi, Iyer, Peydró, and Soto, 2017). In November 2014, a new single supervisory authority (i.e., the Single supervisory mechanism, SSM) for the Eurozone was launched with the goal of supervising and monitoring all banks in the euro area more narrowly. One may have the notion that before 2013, regulation was relatively lax as compared to the period thereafter. We examine the impact of the variation in the regulatory supervision as of 2013 on incentive spillover across different categories. To that aim, we have collected additional data and expand our sample to also cover the period from 2013:Q1 through 2016:Q4. In Table 7, we replicate our regression from Table 3 for the full sample running from 2008 until 2016. The aim of this analysis is twofold. First, it will allow us to examine whether our results are robust to the full sample, and second, whether this behaviour is different depending on the period of more stringent regulatory supervision as compared to the time before 2013.

In column 1 of Table 7, we can see that the coefficient on mRWA is still significant and economically meaningful. We find that an IRB bank with a one-standard-deviation higher market risk exposure reports lower PD-implied risk weights by 0.02 percentage points, which translates into a reduction of risk weights by about 2.67 percentage points. The estimated coefficient suggests that our finding on the incentive spillover across different categories is robust to the extension of the sample. To examine whether there is a differential effect between the two periods, i.e., before vs. after 2012, we interact our main variable mRWA/TA (and Tier 1-ratio) with a factor variable that equals the value of one for all quarters from 2013:Q1 until 2016:Q4, and zero otherwise. Interestingly, in column 2 of Table 7 we can see that this relationship is positive (negative for Tier 1-ratio) and statistically significant during the period after 2012. The overall effect for the post-2013 period is then the sum of the estimated coefficient on mRWA/TA and the interaction term, which together is statistically not different from zero. The respective F-test (not reported) cannot reject the null that β(mRWA/TA) – β(mRWA/TA*Basel III phase in) = 0 at any conventional significance level. This implies that our finding is particularly present during the period before 2013. Interestingly, we find similar results also for the Tier 1-ratio. In column 3 and 4, we replicate our analysis but condition on IRB banks with the lowest (bottom 25th percentile of Tier 1 capital ratio) and highest (top 25th percentile of Tier 1 capital ratio) ex-ante regulatory capital ratio, respectively. We thus mimic our analysis from column 4 and 5 of Table 3. However, we find that during the post-2013 period our finding is still present for banks with more binding capital constraints. These findings suggest that the increasing regulatory pressure as of 2013 might have hampered the use of IRB model discretion for some banks, but not for banks with more binding capital constraints.

Yet, an alternative interpretation could be that the weaker result observed during the post-2013 period relates to the fading effect of the financial crisis, suggesting that incentive spillovers of the kind we document in this paper should be more pronounced during periods of higher market risk and more binding capital constraints, respectively. Common to both interpretations though is that regulators and supervisors are advised to use a comprehensive view on risk reporting in future supervisory practice.

V. CONCLUSION

In this paper, we examine whether banks that use the internal ratings-based approach to capital regulation strategically report lower credit risks for their credit portfolio when they are more exposed to market risk. We find that IRB banks report lower PDs when they have more risk exposure in their trading book (as compared to banks with lower market risk). This result is especially strong for banks that face regulatory capital constraints. We find that this behaviour affects risk weights and thus the level of required capital to an economically meaningful extent. An IRB bank with a one-standard-deviation higher market risk exposure reports lower credit risk weights by 4.91 percentage points for the same borrower at the same time. Given that IRB banks are mostly larger banks in Germany, and their total asset size accounts for 160% of German GDP (as at 2012), our results suggest a significant risk to financial stability.

To understand the economic channel behind these results, we relate the observed behaviour to the discretion inherent to the models that IRB banks use under the IRB approach. For instance, we examine whether lower PDs are reported under both the A-IRB and F-IRB. We find that our result only holds for banks using the Advanced-IRB approach but not for banks that employ the Foundation-IRB approach, which suggest that there is a self-selection in the decision of which approach (A-IRB vs. F-IRB) to choose. That is, especially those banks may choose the A-IRB approach over F-IRB, which intend to exploit the greater discretion. Also, we find that the systematic incentive spillover is weaker when market discipline is higher and stronger for non-transparent borrowers with respect to fundamental information. Further, we find that more stringent regulatory supervision hampers the use of IRB model discretion for some banks, but not for institutions with more binding capital constraints.

Our findings have important policy implications. First, they show that banks use the discretion inherent to their models to manage adverse fluctuations across different asset categories. Second, they reveal that banks optimize risk and thus regulatory risk weights at an aggregate overall-risk level as opposed to the asset-specific-risk level. Our results therefore suggest that regulators should continue fostering the comprehensive view on the different bank risk dimensions in their ongoing supervisory task.

REFERENCES

Abbassi, P., Iyer, R., Peydró, J.L., and P.E. Soto (2018). Dressing up for the regulator: evidence from the largest-ever supervisory exercise, Deutsche Bundesbank Discussion Paper, forthcoming.

Acharya, V. V., Schnabl, P. and G. Suarez (2013). Securitization without risk transfer, *Journal of Financial Economics*, 107(3):515–536.

Admati, A. and M. Hellwig (2013). The bankers' new clothes: What's wrong with banking and what to do about it. Princeton University Press, Princeton, New Jersey.

Admati, A., DeMarzo, P., Hellwig, M., and P. Pfleiderer (2013). Fallacies, irrelevant facts, and myths in the discussion of capital regulation. Stanford Graduate School of Business Working Paper No 2065.

Amann, M., Baltzer, M., and M. Schrape (2012). Microdatabase: Securities holdings statistics. Deutsche Bundesbank Technical Documentation.

Basel Committee on Banking Supervision (2005). An explanatory note on the Basel II IRB risk weight functions. Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision (2006). International convergence of capital measurement and capital standards – A revised framework. Bank for International Settlements, Basel, Switzerland.

Begley, T. A., Purnanandam, A. K. and K.C. Zheng (2016). The strategic under-reporting of bank risk, *Review of Financial Studies*, 30(10):3376-3415..

Behn, M., Haselmann, R. and V. Vig (2016). The limits of model-based regulation, European Central Bank Working Paper No 1928.

Behn, M., Haselmann, R. and P. Wachtel (2016). Procyclical capital regulation and lending, *Journal of Finance*, 71(2):919–956.

Berg, T. and P. Koziol (2017). An analysis of the consistency of banks' internal ratings, *Journal of Banking and Finance*, 78(C):27–41.

Boyson, N., Fahlenbrach, R. and R. M. Stulz (2016). Why don't all banks practice regulatory arbitrage? Evidence from usage of trust-preferred securities, *Review of Financial Studies,* 29(7):1821–1859.

Coen, W. (2016). Bank capital: a revised Basel framework, Available online: https://www.bis.org/speeches/sp161007.htm. Bank of International Settlement, Speech on 7 October.

Das, S. and A.N.R. Sy (2012). How risky are banks' risk-weighted assets? Evidence from the financial crisis", International Monetary Fund Working Paper No 12/36.

Degryse, H. and S. Ongena (2005). Distance, lending relationships, and competition, *Journal of Finance*, 60(1):231–266.

Dombrovskis, V. (2016). European Banking Federation Conference: Embracing Disruptions. Available online: https://ec.europa.eu/commission/2014-2019/dombrovskis/announcements/speech-vp-dombrovskis-european-banking-federation-conference-embracing-disruption_en. European Commission, Keynote Speech on 29 September.

Ellul, A. and V. Yerramilli (2013). Stronger risk controls, lower risk: evidence from U.S. bank holding companies. *Journal of Finance*, 68(5): 1757–1803.

Firestone, S. and M. Rezende (2016). Are banks' internal risk parameters consistent? Evidence from syndicated loans, *Journal of Financial Services Research*, 50(2):211–242.

Glaeser, E. L. and A. Shleifer (2001). A Reason for quantity regulation, *American Economic Review*, 91(2):431–435.

Griffin, J. M. and G. Maturana (2016). Who facilitates misreporting in securitized loans?, *Review of Financial studies*, 29(2):384–419.

Haldane, A. G. (2013). Constraining discretion in bank regulation, Available online: http://www.bankofengland.co.uk/publications/Documents/speeches/2013/speech657.pdf. Bank of England, Speech on 9 April.

Huizinga, H., and L. Laeven (2012). Bank valuation and accounting discretion during a financial crisis, *Journal of Financial Economics*, 106(3):614–634.

Jiménez, G., Ongena, S., Peydró, J.-L., and J. Saurina (2017). Macroprudential policy, countercyclical bank capital buffers and credit supply: Evidence from the Spanish dynamic provisioning experiments, *Journal of Political Economy*, 125(6):2126-2177.

Kashyap, A. K., Rajan, R. G., and J. C. Stein (2008). Rethinking capital regulation. Available online: http://www.kansascityfed.org/publicat/sympos/2008/KashyapRajanStein.03.12.09.pdf. Economic symposium on 12 March.

Le Leslé, V. and S. Avramova (2012). Revisiting risk-weighted assets, International Monetary Fund Working Paper No 12/90.

Mariathasan, M. and O. Merrouche (2014). The manipulation of Basel risk-weights, *Journal of Financial Intermediation*, 23(3):300–321.

Moody's Analytics (2007). Confidence intervals for corporate default rates. Available online: https://www.moodys.com/sites/products/DefaultResearch/2006600000426807.pdf.

Petersen, M. A. and R. G. Rajan (1995). The effect of credit market competition on lending relationships, *Quarterly Journal of Economics*, 110(2):407–443.

Piskorski, T., Seru, A., and J. Witkin (2015). Asset quality misrepresentation by financial intermediaries: evidence from the RMBS market. *Journal of Finance*, 70(6):2635–2678.

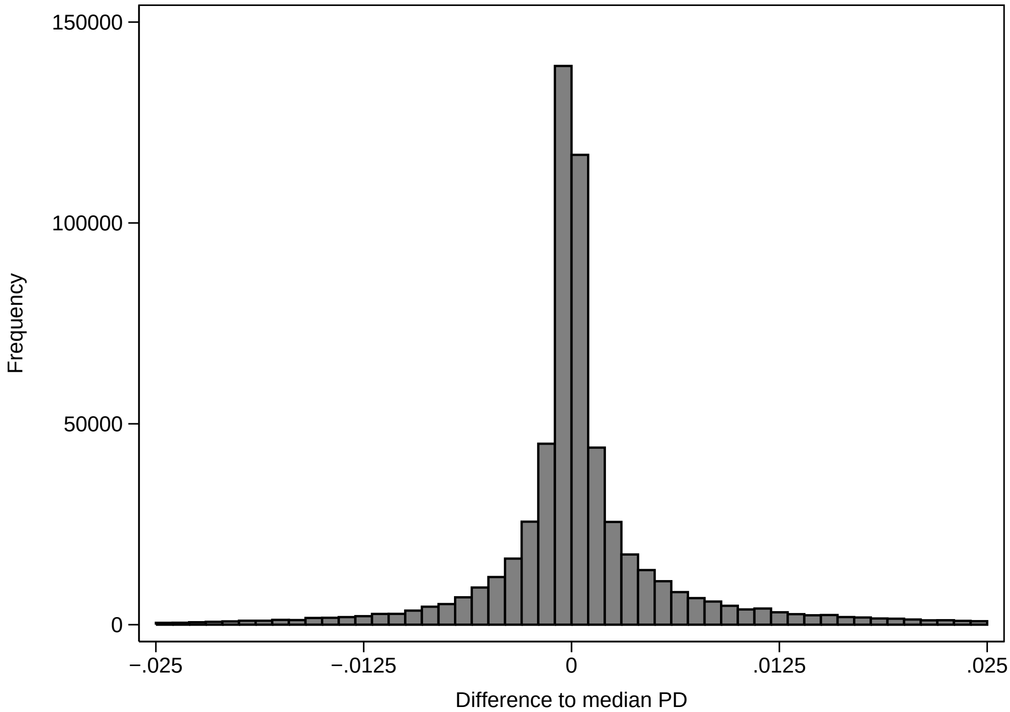
Plosser, M. C. and J. A. Santos (2014). Banks' incentives and the quality of internal risk Models, Federal Reserve Bank of New York Staff Reports No 704.

Rajan, U., Seru, A., and V. Vig (2010). Statistical default models and incentives. *American Economic Review*, 100(2):506–510

Rajan, U., Seru, A., and V. Vig (2015). The failure of models that predict failure: Distance, incentives, and defaults. *Journal of Financial Economics*, 115(2):237–260

FIGURE 1:

DISTRIBUTION OF PD REPORTING ACROSS BANKS



This figure shows the cross-sectional variation in PDs (relative to the median PD) for the same borrower at the same time during our sample period 2008:Q1 to 2012:Q4. The PDs for the same borrower in the same quarter vary around the median value (i.e., the spread between the PD and the median PD is not zero). The x-axis refers to the spread between the reported PD minus the mean of the PD of a given borrower at the same time, across all banks. Source: German credit register, authors' own calculations

TABLE 1:

DEFINITION OF MAIN VARIABLES

Variable	Definition
$PD_{(i,j,t)}$	Probability of default which bank 'i' assigns to borrower 'j' in quarter 't'.
PD-implied risk $weight_{(i,j,t)}$	Fitted value of credit risk weight, which is explained by the probability of default that bank 'i' assigns to borrower 'j' in quarter 't'.
Credit $amount_{(i,j,t)}$	Logarithm of the credit amount outstanding (in EUR thousand) between bank 'i' and borrower 'j' at time 't'.
Credit RWA/total $RWA_{(i,t-1)}$	Share of total credit RWA to total RWA of bank 'i' in quarter 't-1'.
mRWA/total $RWA_{(i,t-1)}$	Share of total mRWA to total RWA of bank 'i' in quarter 't-1'.
$mRWA/TA_{(i,t-1)}$	Share of mRWA to total assets of bank 'i' in quarter 't-1'.
Tier1-$ratio_{(i,t-1)}$	Share of core capital to total RWA of bank 'i' in quarter 't-1'.
$Size_{(i,t-1)}$	Logarithm of the total balance sheet size (in EUR thousand) of bank 'i' in quarter 't-1'.
$Securities/TA_{(i,t-1)}$	Share of total securities holdings (in nominal values) to total assets of bank 'i' in quarter 't-1'.
$Credit/TA_{(i,t-1)}$	Share of total lending to total assets of bank 'i' in quarter 't-1'.
Interbank $borrowing/TA_{(i,t-1)}$	Share of total interbank borrowing to total assets of bank 'i' in quarter 't-1'.
$Deposits/TA_{(i,t-1)}$	Share of total deposits to total assets of bank 'i' in quarter 't-1'.
$ROE_{(i,t-1)}$	Share of total profits to equity of bank 'i' in quarter 't-1'.
Net losses from trading/total $income_{(i,t-1)}$	Share of net losses from trading with securities, derivatives and commodities to total income of bank 'i' in quarter 't-1'.

TABLE 2:

SUMMARY STATISTICS

	All IRB banks			IRB banks with more binding capital limits			IRB banks with less binding capital limits		
	Mean	Std.	Obs.	Mean	Std.	Obs.	Mean	Std.	Obs.
PD	0.0072	0.0121	578853	0.0060	0.0103	65097	0.0092	0.0147	190885
PD-implied risk weight	0.4918	0.2021	578853	0.4668	0.1939	65097	0.5223	0.2205	190885
Credit amount (in log of EUR thousand)	8.5982	2.1359	578853	8.9307	1.9172	65097	8.4764	2.2833	190885
Credit RWA/total RWA	0.8863	0.0784	666	0.9180	0.0577	146	0.8709	0.0902	184
mRWA/total RWA	0.0462	0.0549	666	0.0276	0.0441	146	0.0409	0.0502	184
mRWA/TA	0.0181	0.0214	666	0.0137	0.0214	146	0.0135	0.0164	184
Tier1-ratio	0.1105	0.0560	666	0.0722	0.0108	146	0.1673	0.0766	184
Size (in log of EUR thousand)	17.8823	1.3286	666	17.4521	1.2860	146	17.9458	1.3524	184
Securities/TA	0.2057	0.1053	666	0.2290	0.0927	146	0.1833	0.1288	184
Credit/TA	0.6886	0.1278	666	0.7021	0.1022	146	0.7028	0.1468	184

This table reports the summary statistics of the variables used in the paper, across our sample from 2008:Q1 to 2012:Q4. We define ‘All IRB banks’ (all banks in our sample of IRB banks), ‘IRB banks with more binding capital limits’ (banks in bottom 25th percentile Tier 1-ratio), and ‘IRB banks with less binding capital limits’ (banks in top 25th percentile Tier 1-ratio). ‘PD’ refers to the probability of default, which a respective bank assigns to its borrower in a given quarter. ‘PD-implied risk weight’ denotes the fitted value of the borrower-specific credit risk weight, which is explained by the probability of default that a given bank assigns to its borrower in a given quarter. ‘Credit RWA/total RWA’ denotes the share of total credit RWA to total RWA for each bank during each quarter. ‘mRWA/total RWA’ denotes the share of total market RWA to total RWA for each bank during each quarter. ‘mRWA/TA’ denotes the share of total market RWA to total assets for each bank during each quarter. ‘Tier1-ratio’ denotes the share of Tier 1 core capital to total RWA for each bank during each quarter. The definition of the other variables can be found in Table 1. Source: German credit register, German security register, monthly balance sheet statistics, supervisory balance sheet information, profit and loss statements, authors’ own calculations.

TABLE 3:

PD REPORTING DEPENDING ON EX-ANTE MARKET RISK EXPOSURE

	Dependent variable: Probability of default				
	All banks			IRB banks with more binding capital limits	IRB banks with less binding capital limits
	(1)	(2)	(3)	(4)	(5)
$mRWA/TA_{(i,t-1)}$	-0.0131***	-0.0136***	-0.0157***	-0.0625**	-0.0080
	[0.0048]	[0.0043]	[0.0050]	[0.0220]	[0.0072]
$Tier1\text{-}ratio_{(i,t-1)}$	0.0035***	0.0027***	-0.0048	0.0105	0.0014
	[0.0010]	[0.0007]	[0.0094]	[0.0167]	[0.0013]
Observations	580,196	578,853	578,853	19,047	102,189
R-squared	0.6701	0.8660	0.8659	0.9184	0.8872
Bank*Time controls	Y	Y	Y	Y	Y
Bank FE	Y	--	--	--	--
Borrower*Time FE	Y	Y	Y	Y	Y
Bank*Borrower FE	N	Y	Y	Y	Y

The dependent variable is the reported PD by bank ‘i’ for borrower ‘j’ during quarter ‘t’ in the period 2008:Q1 to 2012:Q4. In column 3, the variable ‘Tier1-ratio’ refers to the predicted value of Tier 1 core capital from a first stage regression, where trading losses are used as an instrument for Tier 1 core capital. In column 4 (5), we restrict our sample to banks that had more (less) binding capital limits, i.e., banks in bottom (top) 25th percentile Tier 1-ratio, in the previous quarter. ‘Tier1-ratio’ denotes the share of Tier 1 core capital to total RWA for each bank during the previous quarter ‘t-1’. All regressions are estimated using ordinary least squares. Lagged, time-varying bank controls (Size, Securities/TA, Credit/TA, Interbank borrowing/TA, Deposits/TA, ROE, Net losses from trading/total income) and fixed effects are either included (‘Y’), not included (‘N’), or spanned by another set of fixed effects (‘-’). The definition of the main independent variables can be found in Table 1. Robust standard errors clustered at bank and borrower level are reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level. Source: German credit register, German security register, monthly balance sheet statistics, supervisory balance sheet information, profit and loss statements, authors’ own calculations.

TABLE 4:

PD-IMPLIED RISK WEIGHTS DEPENDING ON EX-ANTE MARKET RISK EXPOSURE

	Dependent variable: PD-implied risk weight				
	All banks			IRB banks with more binding capital limits	IRB banks with less binding capital limits
	(1)	(2)	(3)	(4)	(5)
mRWA/TA$_{(i,t-1)}$	-0.3865**	-0.3461**	-0.4121***	-2.2929***	-0.2182
	[0.1514]	[0.1300]	[0.1453]	[0.7773]	[0.1268]
Tier1-ratio$_{(i,t-1)}$	0.0828***	0.0688***	-0.2846	-0.1846	-0.0152
	[0.0230]	[0.0224]	[0.1780]	[0.4093]	[0.0223]
Observations	580,196	578,853	578,853	19,047	102,189
R-squared	0.7660	0.9148	0.9148	0.9472	0.9364
Bank*Time controls	Y	Y	Y	Y	Y
Bank FE	Y	--	--	--	--
Borrower*Time FE	Y	Y	Y	Y	Y
Bank*Borrower FE	N	Y	Y	Y	Y

The dependent variable is the PD-implied risk weight , i.e., the fitted value of credit risk weight, which is explained by the probability of default that bank 'i' assigns to borrower 'j' during quarter 't' in the period 2008:Q1 to 2012:Q4. In column 3, the variable 'Tier1-ratio' refers to the predicted value of Tier 1 core capital from a first stage regression, where trading losses are used as an instrument for Tier 1 core capital. In column 4 (5), we restrict our sample to banks that had more (less) binding capital limits, i.e., banks in bottom (top) 25th percentile Tier 1-ratio, in the previous quarter. 'Tier1-ratio' denotes the share of Tier 1 core capital to total RWA for each bank during the previous quarter 't-1'. All regressions are estimated using ordinary least squares. Lagged, time-varying bank controls (Size, Securities/TA, Credit/TA, Interbank borrowing/TA, Deposits/TA, ROE, Net losses from trading/total income) and fixed effects are either included ('Y'), not included ('N'), or spanned by another set of fixed effects ('-'). The definition of the main independent variables can be found in Table 1. Robust standard errors clustered at bank and borrower level are reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level. Source: German credit register, German security register, monthly balance sheet statistics, supervisory balance sheet information, profit and loss statements, authors' own calculations.

TABLE 5:

TEASING OUT THE ECONOMIC CHANNEL

FOUNDATION-IRB VS. ADVANCED-IRB APPROACH

	Dependent variable:			
	Probability of default		PD-implied risk weight	
	(1)	(2)	(3)	(4)
	F-IRB	A-IRB	F-IRB	A-IRB
mRWA/TA$_{(i,t-1)}$	0.0007	-0.0251***	-0.0136	-0.8449***
	[0.0022]	[0.0042]	[0.0891]	[0.2256]
Tier1-ratio$_{(i,t-1)}$	-0.0020	0.0031***	-0.1706**	0.0699**
	[0.0026]	[0.0010]	[0.0795]	[0.0282]
Observations	203,441	240,807	203,441	240,807
R-squared	0.9010	0.8676	0.9387	0.9099
Bank*Time controls	Y	Y	Y	Y
Borrower*Time FE	Y	Y	Y	Y
Bank*Borrower FE	Y	Y	Y	Y

This table replicates column 2 of Table 2 and 3 respectively, but restricts the sample to those banks that use different IRB approaches (Foundation-IRB vs. Advanced-IRB). The dependent variable in columns 1 and 2 is the reported PD by bank 'i' for borrower 'j' during quarter 't' in the period 2008:Q1 to 2012:Q4. The dependent variable in columns 3 and 4 is the PD-implied risk weight, i.e., the fitted value of credit risk weight, which is explained by the probability of default that bank 'i' assigns to borrower 'j' in quarter 't'. 'mRWA/TA' denotes the share of total market RWA to total assets for each bank during the previous quarter 't-1'. All regressions are estimated using ordinary least squares. Lagged, time-varying bank controls (Size, Securities/TA, Credit/TA, Interbank borrowing/TA, Deposits/TA, ROE, Net losses from trading/total income) and fixed effects are either included ('Y'), not included ('N'). The definition of the main independent variables can be found in Table 1. Robust standard errors clustered at bank and borrower level are reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level. Source: German credit register, German security register, monthly balance sheet statistics, supervisory balance sheet information, profit and loss statements, authors' own calculations.

TABLE 6 PANEL A:

TEASING OUT THE ECONOMIC CHANNEL

TRANSPARENCY VS. MARKET DISCIPLINE

	Dependent variable: Probability of default							
			Not-listed borrowers					
					Non-MFI sector			
	Listed	Not-listed	MFI sector	Non-MFI sector	Financial industry (excl. MFIs)	Corporate industry sector	Corporate service sector	Real-estate sector
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
mRWA/TA$_{(i,t-1)}$	-0.0073**	-0.0168***	-0.0117***	-0.0183***	-0.0043	-0.0262***	-0.0211***	-0.0128*
	[0.0036]	[0.0047]	[0.0034]	[0.0052]	[0.0067]	[0.0085]	[0.0056]	[0.0070]
Tier1-ratio$_{(i,t-1)}$	0.0030***	0.0026***	0.0009	0.0031***	0.0049***	0.0024**	0.0047***	-0.0000
	[0.0006]	[0.0008]	[0.0007]	[0.0009]	[0.0012]	[0.0012]	[0.0017]	[0.0022]
Observations	163,258	415,595	60,262	355,333	58,283	122,331	89,669	44,286
R-squared	0.8318	0.8725	0.9020	0.8667	0.8466	0.8645	0.8596	0.8641
Bank*Time controls	Y	Y	Y	Y	Y	Y	Y	Y
Borrower*Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank*Borrower FE	Y	Y	Y	Y	Y	Y	Y	Y
Test of Parameter Equality:								
Null Hypothesis:	$\beta_{listed} = \beta_{non\text{-}listed}$		$\beta_{mfi} = \beta_{non\text{-}mfi}$		$\beta_{financial\ industry} = \beta_{corporate\ industry} = \beta_{corporate\ service} = \beta_{real\text{-}estate}$			
F-statistic	10.11		2.86		3.86			
p-value	0.003		0.0994		0.0169			

This table replicates column 2 of Table 2 *conditional* on the borrower type. ‘mRWA/TA’ denotes the share of total market RWA to total assets for each bank during the previous quarter ‘t-1’. All regressions are estimated using ordinary least squares. Lagged, time-varying bank controls (Size, Securities/TA, Credit/TA, Interbank borrowing/TA, Deposits/TA, ROE, Net losses from trading/total income) and fixed effects are either included (‘Y’), or not included (‘N’). The definition of the main independent variables can be found in Table 1. Robust standard errors clustered at bank and borrower level are reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level. Source: German credit register, German security register, monthly balance sheet statistics, supervisory balance sheet information, profit and loss statements, authors’ own calculations.

TABLE 6 PANEL B:

TEASING OUT THE ECONOMIC CHANNEL

TRANSPARENCY VS. MARKET DISCIPLINE (CONT'D)

	Dependent variable: PD-implied risk weight							
			Not-listed borrowers					
					Non-MFI sector			
	Listed	Not-listed	MFI sector	Non-MFI sector	Financial industry (excl. MFIs)	Corporate industry sector	Corporate service sector	Real-estate sector
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mRWA/TA$_{(i,t-1)}$	-0.2463*	-0.4002***	-0.2665*	-0.4377***	-0.3160**	-0.5161***	-0.5367***	-0.3307
	[0.1353]	[0.1279]	[0.1373]	[0.1247]	[0.1202]	[0.1307]	[0.1487]	[0.1966]
Tier1-ratio$_{(i,t-1)}$	0.0621**	0.0720***	0.0187	0.0888***	0.1040***	0.0690***	0.1202***	0.0393
	[0.0251]	[0.0231]	[0.0253]	[0.0242]	[0.0244]	[0.0212]	[0.0368]	[0.0432]
Observations	163,258	415,595	60,262	355,333	58,283	122,331	89,669	44,286
R-squared	0.9013	0.9157	0.9253	0.9107	0.9011	0.9118	0.8979	0.9077
Bank*Time controls	Y	Y	Y	Y	Y	Y	Y	Y
Borrower*Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank*Borrower FE	Y	Y	Y	Y	Y	Y	Y	Y

Test of Parameter Equality:

Null Hypothesis:	$\beta_{listed} = \beta_{non\text{-}listed}$	$\beta_{mfi} = \beta_{non\text{-}mfi}$	$\beta_{financial\ industry} = \beta_{corporate\ industry} = \beta_{corporate\ service} = \beta_{real\text{-}estate}$
F-statistic	7.7	4.34	2.14
p-value	0.0086	0.0442	0.1117

This table replicates column 2 of Table 3 *conditional* on the borrower type. 'mRWA/TA' denotes the share of total market RWA to total assets for each bank during the previous quarter 't-1'. All regressions are estimated using ordinary least squares. Lagged, time-varying bank controls (Size, Securities/TA, Credit/TA, Interbank borrowing/TA, Deposits/TA, ROE, Net losses from trading/total income) and fixed effects are either included ('Y'), or not included ('N'). The definition of the main independent variables can be found in Table 1. Robust standard errors clustered at bank and borrower level are reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level. Source: German credit register, German security register, monthly balance sheet statistics, supervisory balance sheet information, profit and loss statements, authors' own calculations.

TABLE 7:

TEASING OUT THE ECONOMIC CHANNEL

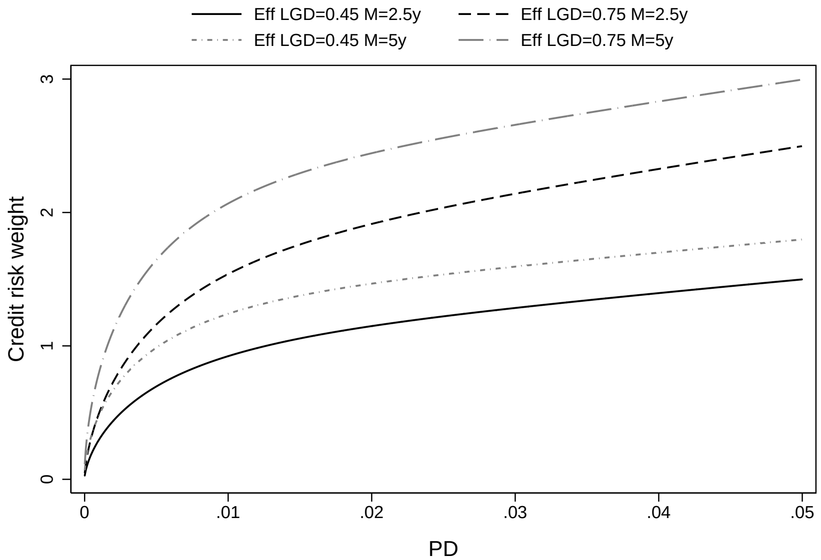
VARIATION IN REGULATORY SUPERVISION

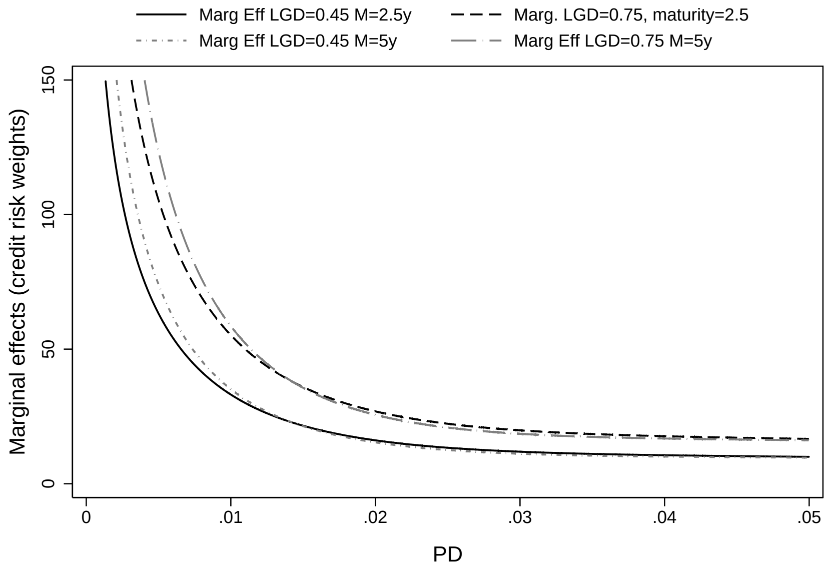
	Dependent variable:							
	Probability of default				PD-implied risk weight			
	All banks		IRB banks with more binding capital limits	IRB banks with less binding capital limits	All banks		IRB banks with more binding capital limits	IRB banks with less binding capital limits
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
mRWA/TA$_{(i,t-1)}$	-0.0098**	-0.0141***	-0.0685***	0.0001	-0.2152**	-0.3151**	-1.9808**	0.0634
	[0.0043]	[0.0048]	[0.0218]	[0.0068]	[0.1010]	[0.1248]	[0.7624]	[0.1142]
mRWA/TA$_{(i,t-1)}$*post2013$_{(t)}$		0.0146**	0.0176	-0.0197		0.3395**	1.0112**	-0.1882
		[0.0059]	[0.0123]	[0.0193]		[0.1335]	[0.3697]	[0.3178]
Tier1-ratio$_{(i,t-1)}$	0.0025***	0.0045***	0.0188	0.0038**	0.0635***	0.0994***	0.0613	0.0420*
	[0.0005]	[0.0016]	[0.0160]	[0.0014]	[0.0208]	[0.0324]	[0.3703]	[0.0233]
Tier1-ratio(i,t-1)*post2013(t)		-0.0150**	-0.0451*	-0.0091		-0.2809**	-0.0825	-0.2278
		[0.0072]	[0.0224]	[0.0089]		[0.1320]	[0.4548]	[0.1802]
Observations	1,127,766	1,127,766	39,167	158,348	1,127,766	1,127,766	39,167	158,348
R-squared	0.8637	0.8639	0.9183	0.8806	0.9148	0.9151	0.9519	0.9336
Bank*Time controls	Y	Y	Y	Y	Y	Y	Y	Y
Borrower*Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Bank*Borrower FE	Y	Y	Y	Y	Y	Y	Y	Y

This table replicates column 2 of Table 2 and 3, respectively, covering the period from 2008:Q1 through 2016:Q4. 'mRWA/TA' denotes the share of total market RWA to total assets for each bank during the previous quarter 't-1'. 'post2013' is an indicator variable that takes the value of one for all quarters from 2013:Q1 until 2016:Q4. All regressions are estimated using ordinary least squares. Lagged, time-varying bank controls (Size, Securities/TA, Credit/TA, Interbank borrowing/TA, Deposits/TA, ROE, Net losses from trading/total income) and fixed effects are either included ('Y'), or not included ('N'). The definition of the main independent variables can be found in Table 1. Robust standard errors clustered at bank and borrower level are reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level. Source: German credit register, German security register, monthly balance sheet statistics, supervisory balance sheet information,

APPENDIX FIGURE A1:

PD-ELASTICITY OF CREDIT RISK WEIGHTS AND AVERAGE MARGINAL EFFECTS





(A) PDS AND CREDIT RISK WEIGHTS

(B) PDS AND MARGINAL EFFECTS

Subfigure (A) shows the relationship between PDs and the respective regulatory risk weight for loans in the credit portfolio, assuming different values for the loss given default (LGD) and the loan maturity. The solid black line assumes LGD=45% and maturity of 2.5 years (standard Basel values for corporate loans, see BCBS, 2006), the dashed black line assumes LGD=75% and maturity of 2.5 years, the dotted grey line assumes LGD=45% and maturity of 5 years, and long-dashed grey line assumes LGD=75% and maturity of 5 years. Subfigure (B) plots the respective marginal effects, derived from the Basel formula as depicted in Equation (2) (BCBS, 2005).
Source: Authors' own calculations

APPENDIX TABLE A1:
PD REPORTING DEPENDING ON EX-ANTE MARKET RISK EXPOSURE (ROBUSTNESS)

	Dependent variable:	
	Probability of default	
	Market risk increase (ΔmRWA >0)	Market risk decrease (ΔmRWA <0)
	(1)	(2)
mRWA/TA$_{(i,t-1)}$	-0.0182**	0.0063
	[0.0079]	[0.0066]
Tier1-ratio$_{(i,t-1)}$	0.0041***	0.0134
	[0.0011]	[0.0090]
Observations	145,462	264,716
R-squared	0.8932	0.8802
Bank*Time controls	Y	Y
Borrower*Time FE	Y	Y
Bank*Borrower FE	Y	Y

This table replicates column 2 of Table 2 *conditional* on the change in market risk. 'mRWA/TA' denotes the share of total market RWA to total assets for each bank during the previous quarter 't-1'. All regressions are estimated using ordinary least squares. Lagged, time-varying bank controls (Size, Interbank borrowing/TA, Deposits/TA, Credit/TA, Securities portfolio/TA, ROE, Profits from trading/total income) and fixed effects are either included ('Y'), or not included ('N'). The definition of the main independent variables can be found in Table 7. Robust standard errors clustered at bank and borrower level are reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level. Source: German credit register, German security register, monthly balance sheet statistics, supervisory balance sheet information, profit and loss statements, authors' own calculations.

APPENDIX TABLE A2:
PD REPORTING DEPENDING ON EX-ANTE MARKET RISK EXPOSURE
(ROBUSTNESS CONT'D)

	Dependent variable: Probability of default	
	IRB banks with more binding capital limits	IRB banks with less binding capital limits
	(1)	(2)
$mRWA/TA_{(i,t-1)}$	-0.0767***	-0.0106*
	[0.0245]	[0.0062]
$mRWA/TA_{(i,t-1)}*VIX_{(t-1)}$	-0.0388**	0.0515*
	[0.0150]	[0.0262]
$Tier1\text{-}ratio_{(i,t-1)}$	0.0233	0.0007
	[0.0162]	[0.0010]
Observations	19,047	102,189
R-squared	0.9188	0.8873
Bank*Time controls	Y	Y
Borrower*Time FE	Y	Y
Bank*Borrower FE	Y	Y

This table replicates column 2 of Table 2 but controls for time-varying aggregate market risk. 'mRWA/TA' denotes the share of total market RWA to total assets for each bank during the previous quarter 't-1'. 'VIX' refers to the standardized implied volatility of S&P 500 index options. All regressions are estimated using ordinary least squares. Lagged, time-varying bank controls (Size, Securities/TA, Credit/TA, Interbank borrowing/TA, Deposits/TA, ROE, Net losses from trading/total income) and fixed effects are either included ('Y'), or not included ('N'). The definition of the main independent variables can be found in Table 1. Robust standard errors clustered at bank and borrower level are reported in parentheses. ***: Significant at 1% level; **: Significant at 5% level; *: Significant at 10% level. Source: German credit register, German security register, monthly balance sheet statistics, supervisory balance sheet information, profit and loss statements, authors' own calculations.