The Limits of Model-Based Regulation

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ABSTRACT

We investigate how the introduction of model-based capital regulation affected credit risk of financial institutions. Model-based regulation was meant to enhance the stability of the financial sector by making capital charges more sensitive to risk. Exploiting the staggered introduction of the model-based approach in Germany and the richness of our loan-level data set, we show that (1) internal risk estimates employed for regulatory purposes systematically underpredict actual default rates by 0.5 to 1 percentage points; (2) both default rates and loss rates are higher for loans that were originated under the model-based approach, while corresponding risk weights are significantly lower; and (3) interest rates are higher for loans originated under the model-based approach, suggesting that banks were aware of higher risk associated with these loans and priced them accordingly. All in all, our findings suggest that, counter to the stated objectives, model-based capital regulation adversely affected financial stability.

Keywords: capital regulation, internal ratings, Basel regulation

JEL Classification: G01, G21, G28

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1. Introduction

Following the financial crisis of 2008, policy makers around the world have concentrated their efforts on designing a regulatory framework that increases the safety of individual institutions as well as the stability of the financial system as a whole. While there is relatively wide agreement on the necessity of such measures, a deeper debate has evolved on the optimal level and structure of financial regulation, with the design of banks’ capital charges at its core. In this context, the most important innovation in recent years has been the introduction of complex model-based capital regulation that was meant to promote the adoption of stronger risk management practices by financial intermediaries, and—ultimately—to strengthen the stability of the banking system (Basel Committee on Banking Supervision 2006). While proponents of such regulation argue that a complex financial system requires complex regulation to ensure an efficient allocation of resources, critics point out that complicated and often intransparent rules create high compliance costs and barriers to entry, while providing endless latitude for regulatory arbitrage.

In this paper, we examine how the introduction of model-based capital regulation affected banks’ credit risk and the overall stability of the financial system. Prior to the introduction of model-based regulation, the regulatory environment was considered to be too coarse, leading to excessive distortions in lending. Bank assets were bucketed into broad risk categories and each category was subject to a flat capital charge (a flat tax). In contrast, regulation under Basel II relies on a complex array of risk models, designed and calibrated by banks themselves and subsequently approved by the supervisor.\footnote{The latest revision of the regulatory framework, Basel III, retains the most important features of Basel II—most prominently the feature of model-based capital regulation—but introduces some corrective measures that are meant to address the most obvious problems with the previous framework.} As a consequence, many banks have more than 100 different risk models with several million parameters in place, all of which require constant validation and re-calibration by the bank’s risk management and surveillance by the supervisor.

Model-based regulation is based on the economic principle “He who pollutes should be taxed”: The higher the risk on a specific position, the higher the capital charge. By ty-
ing capital charges to actual asset risk, banks are no longer penalized for holding very safe assets on their balance sheets, so that the distortion in the allocation of credit that accompanied the simple flat tax feature of Basel I is eliminated. In a world with no informational and enforcement problems, such a sophisticated regulation should unambiguously improve welfare. The conclusion, however, becomes murkier in a world with informational and incentive constraints. As argued by Glaeser and Shleifer (2001), coarser regulation can be the optimal regulatory choice and may actually dominate more sophisticated forms of regulation in the presence of enforcement constraints. Given the wide prevalence of informational and enforcement constraints, the effect of sophisticated model-based regulation on banks’ credit risk remains an open question that we investigate in this paper.2

To study this question, we exploit the institutional details of the German Basel II introduction in 2007 as well as the great granularity of our loan-level data set obtained from Deutsche Bundesbank. Following the reform, banks were allowed to choose between the model-based approach (referred to as the internal ratings-based approach, short IRB) in which capital charges depend on internally estimated probabilities of default (PDs), and a more traditional approach that did not rely on internal risk parameters (referred to as the standard approach, short SA). The introduction of IRB required an extensive risk management system that had to be certified by the regulator, which imposed a significant compliance cost on the bank. Consequently, only very large banks found it worthwhile to introduce the new regulatory approach, while smaller regional banks opted for the standard approach to determine capital charges.

Clearly, banks that introduced the new approach were different from banks that remained under the traditional approach. Hence, a cross-sectional comparison between these two groups is likely to suffer from endogeneity bias. To circumvent this issue, we exploit variation in the regulatory approach within the group of banks that actually introduced

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2In the context of lending, it is now well understood that the quality of a the loan is not only a function of ‘hard’ and verifiable information, but also a function of ‘subjective’ and non-verifiable information. Model-based regulation induces a high weight on ‘hard’ information and thus provides perverse incentives to manipulate information on dimensions that reduce capital charges (Holmström and Milgrom 1991, Rajan et al. 2012). The inherent complexity of the model-based approach makes it very difficult—if not impossible—for the regulator to detect such behavior.
model-based regulation. Importantly for the identification strategy, the introduction of the model-based approach within German banks was staggered over time. Risk models needed to be certified by the regulator on a portfolio basis, and regulators delayed the approval of each model until they felt comfortable about the reliability of the model.\(^3\) In many cases, this meant waiting for more data on a specific portfolio of loans. We exploit this feature for identification, as illustrated in the following example: Consider a firm that has two loans, both from banks that opted to introduce the model-based approach. For one bank, the loan is in a portfolio that has already been shifted to the new approach, i.e., capital charges for this loan depend on the estimated PD. For the other bank the loan is in a portfolio that is awaiting approval from the regulator. Although the bank estimates and reports a PD for this loan, the risk estimate does not have an influence on capital charges. Comparing PDs and actual default rates for loans to the same firm, but under different regulatory approaches, allows us to identify the effects of model-based capital regulation on these parameters.\(^4\)

At the aggregate level, we find that average PDs and the corresponding risk weights, are significantly lower for portfolios that have already been shifted to the new approach (IRB) as compared with portfolios that are still waiting for approval (SA). In stark contrast, however, the ex-post default and loss rates go in the opposite direction—actual default rates and loan losses are significantly higher in the IRB portfolio compared with the SA portfolio. To dig deeper into the mechanism, we examine the interest rate that banks charge on these loans. In sharp contrast to PDs, we find that interest rates in the IRB portfolio are significantly higher than in the SA portfolio, suggesting that banks were well aware of the inherent riskiness of these loan portfolios, but chose not to pass on this information to the regulator.

We shift our analysis to the loan level to examine the robustness of our findings. Risk estimates for IRB loans systematically underpredict actual default rates by 0.5 to 1 percent, while there is no such effect in PDs for SA loans. Even for the same firm in the same year,\(^3\)

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\(^3\)See Section 2 for details. Banks made an implementation plan that specified the order of implementation several years in advance. They were not allowed to pick individual loans for IRB, but had to shift whole portfolios at the same time. Furthermore, they were not allowed to move IRB portfolios back to SA.

\(^4\)It should be noted that these estimates are likely to be biased downwards since one would expect that models that have not yet been certified by the regulator should perform worse. Our empirical strategy thus provides conservative estimates of the treatment effect.
if it has several loans from IRB banks, we find that both the reported PDs and the corresponding risk weights are systematically lower, and the prediction errors (i.e., the difference between a dummy for actual default and the PD of the loan) are significantly higher for loans that are subject to the IRB approach as compared with loans under SA. Furthermore, actual loan losses and corresponding interest rates charged on IRB loans seem to be higher, suggesting that banks are aware of the overall riskiness of these loans. The results are robust to the inclusion of bank interacted with year fixed effects that control for bank specific shocks and are quite persistent until the end of the sample period in 2012.

As an additional cut, we focus on variation over time within the portfolio of loans that has already been transferred to the new approach. For loans originated in 2005 or 2006, the average PD is close to the actual default rate. In contrast, for loans originated after the Basel II reform, in 2007 or 2008, the actual default rate is much higher than the average PD, indicating a significant underestimation of credit risk for this set of loans. The fact that the underestimation effect is much stronger for IRB loans that were originated after the reform as compared with IRB loans originated before the reform indicates that there is more manipulation on new loans rather than on existing loans.

All in all, our results suggests that model-based regulation has failed to meet its objective of tying a bank’s lending decisions to its risk-taking. Counter to the stated purpose of the reform, aggregate credit risk has increased, and complex model-based regulation has compromised financial stability. Furthermore, as discussed earlier, the IRB banks charged on average higher interest rates on IRB loans as compared to SA loans. Thus, even though regulatory capital charges of IRB loan portfolios were reduced, banks were aware of higher credit risk in these portfolios (as reflected in the higher rates).

Our paper connects several strands of the literature. A small but growing number of papers analyze how ratings used for regulatory purposes affect financial stability. As shown by Rajan et al. (2012) in the context of securitization, risk depends on the behavior of the parties involved, may change over time, and tracking it for regulatory purposes may be close to impossible. Most recently, the Basel Committee on Banking Supervision (2013) published

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Another example is given by Acharya (2011), who argues that low risk weights for residential mortgage-
an extensive study that showed a considerable impact of banks’ modeling choices on risk-weights, documenting that estimated risk parameters vary widely across banks, even for the same exposures.\textsuperscript{6} As a consequence, market participants seem to lose faith in the meaning of risk-based capital ratios (Demirgüç-Kunt et al. 2013).\textsuperscript{7} Further, Hellwig (2010) argues that model-based capital regulation suffers from the fact that many of the risks involved are not exogenously given, but endogenously determined. Acharya et al. (2013) question the predictive abilities of risk weights, as they are based on accounting data, can only be updated ex-post, and can easily be gamed by banks (see also Hoenig 2013). Our identification strategy in connection with the richness of our data set allows us to causally identify the effect of the shift towards model-based regulation on financial stability. To the best of our knowledge, our paper is the first to document that the introduction of model-based regulation actually compromised financial stability.

Our paper also adds to the literature on regulation, which can broadly be divided into two categories. The ‘public interest’ theory of regulation, championed by Pigou (1932), rests on two key assumptions: 1) market failures are quite common, and the the job of the government is to correct them, and 2) the government is benign and acts to enhance social efficiency. In line with this view, complex regulation might be needed to achieve an efficient allocation of resources. The ‘public interest’ theory has been challenged by the ‘public choice’ theory of regulation (see, e.g., Stigler 1971, Posner 1974, Peltzman 1976, Becker 1983, Laffont and Tirole 1991). According to this theory, the regulatory process may be captured by small interest groups with high stakes in its outcome. In the context of financial regulation, this would mean that the financial industry created complex regulatory rules mainly for its own benefit.\textsuperscript{8}

The high compliance costs associated with the model-based approach meant that only the larger banks adopted this new approach. These large banks benefited from the new regulation and expanded their lending, potentially at the expense of smaller banks. Thus, this backed securities made investment in this asset class attractive and endogenously turned it into a systemically important asset class.

\textsuperscript{6} See also Firestone and Rezende (2013) and Le Leslé and Avramova (2012).
\textsuperscript{7} See also Hagendorff and Vallasca (2013), Das and Sy (2012), or Mariathasan and Merrouche (2012).
\textsuperscript{8} See also the ‘grabbing hand’ view of regulation articulated in Shleifer and Vishny (2002).
complex model-based regulation created barriers to entry and subsidized larger banks. This seems rather paradoxical, given the systemic risk associated with larger banks. A regulation that was intended to reduce system risk, ended up subsidizing it. Regulators—impressed by sophisticated new risk modeling techniques—failed to observe that the preferential treatment of large institutions under the model-based approach actually increased systemic risk. Besides, they also benefited from the introduction of complex regulation, as it facilitates what can be termed as regulatory ‘empire building’ à la Jensen and Meckling (1976). Thus, our findings provide some support for the ‘public choice’ theory, where incumbents lobby for sophisticated regulation as it helps them in extracting rents (Stigler 1971, Buchanan and Tullock 1975).⁹

Our findings have important policy implications. As a response to the financial crisis in 2007/2008, the Basel committee has drafted a third revision of the regulatory framework for banks (Basel III). This framework continues to rely on model-based regulation, but further increases complexity by introducing—among other measures—capital conservation and countercyclical capital buffers. These new tools have been designed to address substantial weaknesses of the old framework that were identified in the recent crisis. While the measures might make sense individually, our results suggest that further increases in complexity are unlikely to increase financial stability. Although regulators at the national and at the European level are increasing their staff as a response to the reform, keeping track with ever-increasing complexity might prove to be difficult. The evidence presented in this paper provides support for the view that simpler and more transparent rules would be more effective in achieving the ultimate goal of financial stability.¹⁰

The rest of the paper is organized as follows. In the next section we describe the institutional details of the Basel II introduction in Germany, before we introduce our data set in Section 3. We explain our empirical strategy in Section 4 and present our main findings in Section 5. Afterwards we show additional results that support our argumentation in Sec-

⁹Sophisticated risk models can induce inefficiently low levels of regulation (Hakenes and Schnabel 2013), and regulatory reform in the financial sector is often driven by industry interests rather than public interest (Becker and Opp 2013).

tion 6 and analyze how the reform affected banks’ lending decisions in Section 7. Section 8 discusses the meaning of our results and concludes.

2. The introduction of model-based regulation in Germany

One of the main objectives of bank regulation in recent decades has been to establish a closer link between capital charges and actual asset risk. Regulators around the world promoted the adoption of stronger risk management practices by the banking industry in order to achieve the ultimate goal of a sound and stable international banking system.\(^{11}\) In 1988, the Basel I agreement introduced risk-based capital charges by assigning bank assets into different risk groups (or buckets) with pre-assigned risk-weights (Basel Committee on Banking Supervision 1988). Risk-weighted assets were calculated by multiplying these risk-weights (0, 20, 50, or 100 percent) with actual asset values, and capital requirements were defined in terms of risk-weighted assets.

The next revision of this regulatory framework, referred to as Basel II, tried to establish a more granular link between capital charges and individual asset risk. The new framework, introduced in Germany in 2007, allowed banks to use their own internal risk models to determine capital charges for credit risk (Basel Committee on Banking Supervision 2006). Under the internal ratings-based (IRB) approach, each exposure gets assigned an individual risk weight that crucially depends on the bank’s estimated probability of default (PD) for a specific borrower.\(^{12}\) Risk-weighted assets are calculated by multiplying the—loan-specific—risk-weights with actual assets values, and capital requirements are defined in terms of risk-weighted assets as under Basel I.

In Germany, Basel II was implemented by revision of the Solvabilitätsverordnung

\(^{11}\) The introduction of risk-weighted capital charges and potential problems related to them have been discussed in several papers, e.g. Behn et al. (2013), Brun et al. (2013), Hellwig (2010), Kashyap and Stein (2004), Danielsson et al. (2001), Jones (2000), Brinkmann and Horvitz (1995). For an assessment from the side of the regulator see Basel Committee on Banking Supervision (1999).

\(^{12}\) In the foundation IRB approach the bank estimates only the PD, while standard values are assumed for loss given default (LGD), exposure at default (EAD), and maturity of the loan. In the advanced IRB approach, the bank has to estimate all four parameters. As risk weights depend on the PD—our parameter of interest—in both approaches, we do not distinguish between the two in the empirical analysis.
(2006), which provides the foundation for national bank regulation. This code allows banks to choose between two broad methodologies for calculating their capital charges: The internal ratings-based approach described above and the so-called standard approach, that is basically equivalent to the old Basel I framework with fixed risk weights for corporate loans (100 percent of the loan amount net of collateral).\textsuperscript{13}

The Solvabilitätsverordnung (2006) provides a comprehensive set of rules and guidelines for banks that want to use internal risk models for calculating their capital charges: PD models used for regulatory purposes should estimate creditors’ one-year probability of default.\textsuperscript{14} As the bank could have incentives to report low PDs in order to economize on regulatory capital, internal risk models are subject to a strong supervisory review—including on-site audit (see also Bundesbank 2004). In particular, the regulator requires a precise and consistent estimation of credit risk, and proof that the model has been used for internal risk management and credit decisions for at least three years before it may be used for regulatory purposes. Furthermore, the bank has to constantly validate its models and adjust them if their estimates are inconsistent with realized default rates. The supervisor certifies rating systems, continuously monitors compliance with minimum standards, and assesses banks’ internal validation procedures (see also Bundesbank 2003).

PD models are estimated on a portfolio basis. For corporate loans, their most important determinant is accounting information from firms’ financial statements (see, e.g., Initiative für den Finanzstandort Deutschland 2006; Krahnen and Weber 2001). For loans to small and medium enterprises (SMEs), where there is often a significant publication lag for accounting information, also target financial ratios or industry characteristics may be used. Besides these quantitative factors, also qualitative information such as a firm’s management quality or its competitive situation can be included in the models. However, since such information is by definition hard to quantify its impact on the rating is rather limited. A prominent

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\textsuperscript{13}Exceptions are cases where borrowers have external credit ratings, as the SA allows banks to use these ratings to determine capital requirements. However, the German market for corporate bonds is very small; hence, very few companies have an external rating.

\textsuperscript{14}According to § 125 of the Solvabilitätsverordnung (2006), a creditor is in default if (a) the bank has valid indications that the creditor will not be able to fulfill his obligations, or (b) the creditor is more than 90 days past due on his obligations.
PD model used for the estimation of corporate credit risk is Moody’s RiskCalc™ model (Moody’s Analytics 2013). To obtain predicted probabilities of default for a given portfolio, historical information on corporate defaults is regressed on accounting information such as the equity ratio, capital structure, net debt ratio, sales growth, net profit ratio, personnel cost ratio, payables payment period, or cash flow per liabilities. In a second step, estimates from this model are used to attribute predicted PDs to current and new borrowers. In cases where loan officers consider model outputs to be unreasonable they have the option to overwrite the predicted PD. However, if such overwrites occur to frequently, the regulator may ask the bank to revise its model. Furthermore, a bank has to revise its model if the annual validation process reveals a considerable discrepancy between predicted PDs and actual default rates.

Besides loan-specific variables such as the loss given default, the exposure at default and the maturity of a loan, the firm-specific PD estimate is the key ingredient for the calculation of risk-weighted assets. Figure 1 shows the relationship between estimated PDs and corresponding risk-weights, assuming standard values for the remaining parameters. Risk-weight curves are relatively steep for the lowest PDs and become flatter for higher PDs. This is in line with the objectives of the new agreement: To provide banks with incentives to introduce IRB, risk-weight curves were calibrated in a way that ensured that capital requirements would be substantially lower under IRB than under SA (Basel Committee on Banking Supervision 2006, p. 12).

To be eligible for the model-based approach to capital regulation, banks need to fulfill certain conditions and minimum disclosure requirements. Since the organizational efforts as well as the administrative expenses for the introduction of the new approach are high, only large banks opted for its introduction (of our sample of 1,603 German banks, only 45 banks applied for an IRB license; nevertheless these banks account for about 50 percent of the loans in our sample). The introduction of new rating models is a complex process, so that banks did not apply the new approach to all loans at once; rather, they agreed on a gradual implementation plan with the regulator. The plan specified an order according to which different business units (loan portfolios) had to be shifted to IRB. As the calibration of a

15See Solvabilitätsverordnung (2006), §§ 64-67 for details on the implementation plan.
meaningful PD model requires a sufficient amount of data on past loan performance, banks typically started with loan portfolios in business units where they were relatively active. As mentioned before, banks have to prove that a specific model has been used internally for at least three years and does not over- or underpredict defaults before it can be used for regulatory purposes. Thus, models used for IRB loans are similar to those used for SA loans, as these will later be shifted to IRB. Subsequent changes in the model have to be certified by the regulator. The phased roll-out of IRB means that during the transition, which typically lasts for several years, banks have both IRB and SA loans in their portfolios. We exploit this feature of the implementation process in our empirical section, where we compare PD estimations with actual default rates for loans that are subject to different regulatory approaches.

3. Data

Our principal source of data is the German credit register compiled by Deutsche Bundesbank. As part of its supervisory role, the central bank collects data each quarter on all outstanding loans of at least €1.5 million. The data set starts in 1993 and includes information on the lender’s and the borrower’s identity, the amount of the loan outstanding and several other loan characteristics. As a response to the Basel II reform, reporting requirements for the credit register have been expanded considerably from 2008 onwards. In addition to the previous information, banks now also report exposure-level information on the regulatory approach (SA or IRB) and the estimated probability of default (PD). For loans under the IRB approach, the reported PD is the one that is used to determine regulatory capital charges. For loans under SA, banks also have to report PDs if they are estimated internally. As IRB banks aim to transfer all eligible loan portfolios to the new approach once the respective model is certified by the regulator, they report PDs for both IRB loans and SA loans. We use PDs for SA loans as a benchmark against which we evaluate the performance

16Since we focus on corporate lending, this cut-off does not constitute a big issue for our analysis. When matching firm balance sheet information from the Bundesbank USTAN database to the credit register, we find that—in the matched sample—lending recorded in the credit register makes up about 80-90 percent of firms’ overall bank debt on average.
of PDs for IRB loans. Further, the database contains information on risk-weighted assets and actual loan losses. We combine this exposure-level data with annual bank balance sheet information from Bundesbank’s BAKIS database and annual firm balance sheet information from Bundesbank’s USTAN database.

Our sample includes 1,603 German banks, 45 of which opted for IRB following the introduction of Basel II. Panel A of Table 1 shows that the average IRB bank is larger and less capitalized than the average SA bank, whereas average ROA is similar in the two groups of banks. Further, there are relatively more cooperative banks among the group of SA banks, whereas IRB banks are mostly large and internationally active commercial banks. Our empirical setup allows us to analyze the predictive abilities of PDs for loans subject to different regulatory approaches within the group of IRB banks only.

Descriptive statistics on the loan level are presented in Panel B of Table 1 and grouped by the regulatory approach used for the determination of capital charges, where loans are classified according to the approach under which they were issued.\textsuperscript{17} The panel provides summary statistics for all loans that we include in the regression analysis, i.e., IRB loans and SA loans from IRB banks in the period from 2008 to 2012. Although information in the credit register is available on a quarterly basis, PDs tend to be relatively sticky and are updated only once a year. Thus, to be conservative and avoid the duplication of observations, we include only one quarter per year in large parts of the empirical analysis. Specifically, we restrict ourselves to the fourth quarter of each year, as most German companies report their earnings in the second or third quarter of the year and this information is typically used by the bank to update the PD.\textsuperscript{18}

The first line of the table shows that the average PD is higher for SA loans (2.6 percent) as compared with IRB loans (1.8 percent). While the PD estimates the firm-specific probability of default, the risk weight for a specific loan also incorporates loan-specific infor-

\textsuperscript{17}Specifically, new lending relationships are classified according to the regulatory approach used at issuance. Existing relationships may be re-classified whenever there is a large increase in the loan amount (i.e., an increase of at least 30 percent). They are then classified according to the regulatory approach used for the relationship at the time of the increase in the loan amount.

\textsuperscript{18}Results for the remaining quarters are very similar to the results we report.
ation (e.g., the collateralization of the loan). For SA loans the corresponding risk weight does not depend on the PD and is equal to 100 percent of the unsecured fraction of the loan amount.\(^{19}\) Overall, this translates into an average risk weight of 61.6 percent for SA loans, which is considerably higher than the average risk weight for IRB loans (49.0 percent). Furthermore, banks are required to report loan losses for loans in default. Since certain loans are backed by collateral or guarantees, the consequences of a borrower’s default may vary. For both SA loans and IRB loans, the actual loan loss rate is around 0.5 percent. Since the German credit register does not contain information on interest rates, we follow a procedure developed by Haselmann et al. (2013) to back out interest rates from the data that is available in the credit register. Specifically, we infer the repayment structure of the loan contract (e.g., whether it is repaid at the end of the contract period, linearly, or de-/progressively) from the quarterly data on loan amounts. We match this contract-level information with firm-level data on aggregate interest payments obtained from Bundesbank’s USTAN database. This procedure allows us to back out effective annual interest rates on the loan contract level.\(^{20}\) As shown in the table, interest rates for loans under the standard approach are on average slightly lower (7.7 percent) than interest rates for loans under IRB (8.9 percent). The last line of Panel B shows the average change in the amount of loans outstanding around the introduction of Basel II.\(^{21}\) The average IRB loan in our sample was increased by about 6.4 percent over the Basel II introduction, while the average SA loan was increased by about 1.6 percent.

Finally, Panel C of Table 1 contains descriptives for firm-level variables. Several accounting variables are obtained by a hand-match of the Bundesbank USTAN database with the credit register.\(^{22}\) The match was conducted based on company name, location, and in-

\(^{19}\)The Basel regulations include a discount for loans to small and medium enterprises (SMEs) as the regulator wants to promote lending to these firms. Specifically, under Basel II, loans to firms with a turnover of €50 million or less are subject to lower capital charges, as regular risk weights are multiplied with a correction factor depending on the exact amount of the turnover.

\(^{20}\)See Haselmann et al. (2013) for further details.

\(^{21}\)The sample includes all loans in the credit register that have an observation both before and after the reform. We calculate the change in lending around the reform by collapsing all quarterly data for a given exposure into single pre-event and post-event periods by taking the average of the two years before and the two years after the Basel II introduction. The change in lending is defined as the difference in the logarithm of these averages, so that there is one observation per loan.

\(^{22}\)Even though the credit register and the accounting information all come from Deutsche Bundesbank, the
dustry segment that are available in both data sources. The matched dataset contains detailed information on lending relationships and balance sheet items for 5,961 distinct firms. We report summary statistics on total assets, debt to assets and return on assets (ROA) for this sample. The average size of our sample firms is 154 million euros, the average debt to asset ratio is 34.3 percent, and the average return on assets is 7.9 percent.

4. Empirical strategy

In this section, we carefully explain the empirical strategy employed in order to validate the main argument of our paper: That the introduction of model-based capital regulation led to a systematic failure of banks’ internal risk models and compromised financial stability. We start by estimating loan-level equations of the following type:

\[ y_{ijtk} = \alpha + \delta \cdot 1_{(k \in R)} + \varepsilon_{ijtk}, \]

where \( j \) denotes the individual bank, \( i \) denotes the individual firm, \( t \) time, and \( k \) indicates whether the loan belongs to an SA or to an IRB portfolio within the bank. The dependent variable \( y_{ijtk} \) is the loan-specific ESTIMATION ERROR at time \( t \), i.e., the difference between a dummy for ACTUAL DEFAULT and the PD; alternatively, we use the PD itself, the ratio of RWA TO LOAN, the actual LOSS RATE, or the INTEREST RATE as a dependent variable. The indicator variable \( 1_{(k \in R)} \) takes a value of 1 if loans to firm \( i \) belong to the IRB portfolio of bank \( j \), and 0 if they belong to the SA portfolio. Further, the equation includes a constant \( \alpha \) and a random error term \( \varepsilon_{ijtk} \). In order to allow for potential correlation among default events for loans to the same firm or from the same bank, standard errors are double clustered at the firm-period and at the bank-period level in all regressions.

Interpreting \( \delta \) as the causal impact of the regulatory approach on \( y_{ijtk} \) requires that the covariance between \( 1_{(k \in R)} \) and \( \varepsilon_{ijtk} \) is equal to 0, i.e., \( Cov(\varepsilon_{ijtk}, 1_{(k \in R)}) = 0 \). As banks that introduced the model-based approach tend to be larger, internationally more active and more sophisticated than banks that remained under the traditional approach, an estimation two datasets have no unique identifier. For a detailed description of the USTAN database see Bachmann and Bayer (2013).
based on loans from both types of banks would have biased our coefficients. Fortunately, the institutional details of the German Basel II introduction described in Section 2 allow us to circumvent this concern by using within-bank variation in the regulatory approach. IRB institutions did not shift all their portfolios to the new approach at the same time, so that we can restrict the sample to IRB banks and use variation between loans that have already been shifted to IRB and loans that are still under SA to identify \( \delta \) in Equation (1).

Although the approach described above addresses many concerns, coefficients could be biased if firms that obtain SA loans are systematically different from firms that obtain IRB loans. To address this issue, we focus on firms that borrow from at least two banks at the same time, one bank where loans to the firm belong to a portfolio that has already been shifted to IRB and one bank where they are still under SA. Using this sample of firms, we estimate:

\[
y_{ijtk} = \alpha_{it} + \alpha_{jt} + \delta \cdot 1_{(k \in R)} + \epsilon_{ijtk},
\]

where \( \alpha_{it} \) and \( \alpha_{jt} \) denote firm \( \times \) period and bank \( \times \) period interactions, respectively, and the remaining variables are defined as in Equation (1). By adding \( \alpha_{it} \) we are able to systematically control for time-varying heterogeneity across firms. That is, we can check whether the ESTIMATION ERROR for loans under IRB is larger than the ESTIMATION ERROR for loans under SA to the same firm in the same period. Additionally, the inclusion of \( \alpha_{jt} \) allows us to control for time-varying heterogeneity across banks; i.e., we can rule out that differences between banks are driving our results. Our identification strategy is illustrated in Figure 2.

The identification strategy described above relies on the assumption that there is no systematic relationship between the point in time at which a specific portfolio is shifted to IRB and the bank’s ability to estimate PDs for loans in that portfolio. As described in Section 2, banks typically shifted those portfolios first for which they had a sufficient amount of data to calibrate a meaningful PD model that could be certified by the regulator. Hence, any bias from selection of IRB portfolios should work against us: If anything, banks should be better able to predict actual default rates for those loan portfolios that have been certified by the regulator (i.e., those portfolios for which they have sufficient data and experience).
Nevertheless, we further refine the identification strategy to remove any remaining doubts.

We argue that model-based regulation changes incentives for banks, eventually leading to a systematic failure of PD models. As a consequence, underestimation effects should be particularly pronounced for loans that were originated after the introduction of model-based regulation. For those loans, capital charges depended on PD estimates at the time of loan origination, while they did not for loans that were originated before the reform and shifted to IRB later on. We exploit this time series variation in the loan issuance date to circumvent the selection concern. Specifically, we restrict ourselves to loans that actually use the IRB approach and check whether the underestimation of actual default rates is greater for loans that were originated after the reform as compared with loans that were originated before the reform. We estimate the following equation:

\[ y_{ij} = \alpha_j + \delta \cdot 1_{(l \in B)} + \epsilon_{ij}, \]  

where \( y_{ij} \) is the loan-specific ESTIMATION ERROR as before and \( 1_{(l \in B)} \) is an indicator variable that takes a value of 1 if the IRB loan was issued in the two years following the implementation of Basel II (i.e., 2007 or 2008) and 0 if it was issued in the two years prior to the reform (i.e., 2005 or 2006). Loans are evaluated either in 2009 or four years after the issuance date. Note that this specification is not prone to selection concerns and therefore allows for an unbiased estimate of the effect of the regulatory approach on the functioning of PD models.\textsuperscript{23}

5. Empirical results

5.1. Descriptive analysis

Table 2 and Figure 3 show average values of key variables for SA and IRB loans from IRB banks between 2008 and 2012. There are 66,045 lending relationships in 2008, 14,713 under SA and 51,332 under IRB. Additional portfolios are shifted to IRB throughout our sample.

\textsuperscript{23}In contrast to previous estimations it is difficult to include also firm fixed effects in these regressions, as there are relatively few firms that obtained new loans both before and after the reform.
period, which is why the number of SA loans declines to 8,907 in 2012.

We start by assessing how PD estimates from banks’ internal risk models compare with actual default rates for loans under SA and IRB. As stated in Section 2, PDs should estimate one-year default rates and a loan is considered to be in default if the borrower is 90 days past due on his obligations. Accordingly, the dummy variable ACTUAL DEFAULT captures whether a loan is in default in at least one of the four quarters following the one in which the PD is evaluated. Importantly, all loans that are already in default in a respective quarter are excluded from the analysis.

In line with our expectation, average PDs for IRB loans are always lower than average PDs for SA loans. As shown at the bottom of Table 2, the difference between the two groups lies between 0.7 and 1.1 percentage points and is highly significant. Kernel density plots for PDs further illustrate this point (see Figure 4). Clearly, the distribution for IRB loans is to the left of the distribution for SA loans in all years. This is confirmed in a Kolmogorov-Smirnov test for equality of distributions: The hypothesis that the distributions for SA loans and IRB loans are equal can be rejected at the 1 percent level in all cases.

In sharp contrast, actual default rates for IRB loans are higher than those for SA loans in all years. They fluctuate between 1.9 and 2.6 percent for SA loans, and between 2.1 and 3.0 percent for IRB loans. For each of our five sample years, model-based PDs for IRB loans are lower than actual default rates. For SA loans, we observe a close match of PDs and default rates in the first year and an slight overprediction of default rates in the remaining years.

Although startling in themselves, the results for PDs and actual default rates do not necessarily mean that aggregate credit risk is higher for loans under IRB. Apart from the PD, risk-weights in the model-based approach also depend on loan-specific factors such as the loss given default (LGD), exposure at default (EAD), and the maturity (M) of the loan. Risk-weights in the advanced IRB approach will be lower the better the estimate on any of these variables. Hence, the reform provides additional incentives for banks to invest into the quality of these parameters. Consequently, overall loan quality might have improved,
despite the fact that default rates are higher for IRB loans. An assessment of the reform on overall credit risk and bank stability needs to take all loan-specific factors into account.

The data from the credit register allows us to address this issue. Apart from information on the PD, it also contains exposure-level information on risk-weighted assets and actual loan losses. The risk-weight includes all firm-specific as well as loan-specific information relevant for a loan’s regulatory capital charge. Loan losses capture the actual amount the bank has to write off in case of default of a specific loan (see Section 3). Comparing regulatory risk-weights to actual losses for loans under SA and loans under IRB allows us to evaluate the reform’s overall impact on credit risk.

Average values for the ratio of RWA TO LOAN and the actual LOSS RATE are displayed in Table 2 and Figure 3. Risk weights for IRB loans are about 10 to 15 percent lower than risk weights for SA loans, which means that banks have to hold much less capital for IRB exposures. At the same time, actual loss rates are similar among both groups; if anything, they tend to be slightly higher for loans under IRB in most years. In the latter empirical analysis we will show that loan losses are higher for IRB loans than for SA loans to the same firm. Although banks have lower capital charges on average, they actually lose more money with loans under IRB.

Taken together, findings on PDs, actual defaults, risk weights and loss rates suggest that credit risk has increased under model-based regulation. But do these findings mean that banks misjudged credit risk under the new approach? Or were they aware of higher credit risk in portfolios under the model-based approach, and simply used the new regulation to economize on regulatory capital? Average interest rates provide evidence in favor of the latter explanation. As shown in Table 2 and Figure 3, and in stark contrast to PD estimates, interest rates for loans under IRB are significantly higher than interest rates for loans under SA. This suggests that banks were aware of the actual risk involved with loans under the model-based approach. We proceed by testing our assertions more formally in a regression framework below.
5.2. Regression framework: IRB versus SA loans

Results for Equations (1) and (2), using the logarithm of the loan-specific PD as a dependent variable, are presented in Table 3. Column 1 shows that PDs for IRB loans are considerably lower than PDs for SA loans. This finding is expected as one objective of the reform was to promote lending to low PD borrowers. However, column 2 includes firm fixed effects and shows that banks assign significantly lower PDs to the same borrower if the loan is part of an IRB portfolio as compared with an SA portfolio. This result is robust to the inclusion of period fixed effects in column 3. In column 4, we include firm × period interactions. In this test, the sample is constrained to firm-period observations where the respective firm has at least one IRB loan and at least one SA loan from an IRB bank. The negative coefficient implies that PDs for IRB loans are significantly lower than PDs for SA loans to the same firm in the same period. Finally, the result is also robust to the inclusion of bank × period interactions in column 5: PDs from the same bank in the same period are significantly lower for loans under IRB. Magnitudes are large: PDs for IRB loans are 22 to 45 percent smaller than PDs for SA loans. These findings strongly suggest that the introduction of model-based regulation had a direct impact on banks’ ability to evaluate credit risk. Under the new regulation, banks have incentives to understate PDs, which is illustrated by lower PDs assigned to the same firm in the same period.

In Table 4 we use the loan-specific ESTIMATION ERROR, defined as the difference between the ACTUAL DEFAULT dummy and the PD, as a dependent variable. Column 1 shows that PDs for IRB loans underestimate actual default rates by about 0.8 percent on average, whereas the estimation error for SA loans is not significantly different from 0. As expected, the difference between the two groups of loans is significant in specifications that include firm fixed effects (column 2), period fixed effects (column 3), firm × period interactions (column 4), and bank × period interactions (column 5). Compared with SA loans, PDs for IRB loans underestimate actual default rates by 0.5 to 1.3 percentage points.

Next, we once more look at risk-weights and actual loan losses. Applying the same

\[ \text{The effect is equal to } \exp(\delta) - 1 \] (Halvorsen and Palmquist 1980).
estimations as for the PD and the ESTIMATION ERROR, we find that the ratio of RWA
TO LOAN is 10 to 15 percent lower for loans under IRB, even for loans to the same firm in
the same period (Table 5). This result is not surprising, as the regulator wanted to provide
incentives to banks to introduce the model-based approach and therefore calibrated capital
charges in a way that ensured that they were lower for loans under IRB. However, as already
documented in the previous section, actual loan losses are similar in the two groups of loans.
If anything, they are higher for loans under IRB, which is indicated by the significantly
positive coefficients for D(IRB LOAN) in column 2-4 of Table 6.

Finally, results in Table 7 reveal that banks were fully aware of higher risks associated
with loans under IRB. Interest rates for these loans are about 0.9 percent higher than interest
rates for loans under SA (column 1). Also in the remainder of the table we get—in most
cases—significant coefficients for the IRB loan dummy, which is a remarkable finding. In
sharp contrast to PDs, interest rates on IRB loans are significantly higher than interest rates
on SA loans to the same firm in the same period, which suggests that banks are well aware
of the higher risks associated with these loans.

5.3. Regression framework: IRB loans issued before and after the event

In this section we provide additional results that help to understand the mechanism behind
our findings. We argue that our results are driven by new loan issuances as bankers have
lower incentives to report bad information that increases the PD for a specific borrower
following the reform. Alternatively, it could be that banks simply adjusted existing PDs
downwards in order to save on regulatory capital. In the latter case, we would expect a
uniform effect for all IRB exposures, whereas in the former case we would expect a stronger
effect for new lending relationships. Restricting ourselves to loans that actually use the IRB
approach, we check whether the underestimation of actual default rates is greater for loans
that were originated after the reform as compared with loans that were originated before the
reform.

Additionally, this test allows us to address potential selection concerns arising from
the order in which IRB banks shifted their loan portfolios from SA to IRB. As discussed in detail in Section 4, the selection of IRB portfolios was based on data quality and experience of the bank and should therefore result—if at all—in a downward bias of our coefficients. Nevertheless, exploiting variation in the loan issuance date allows us to provide evidence that is independent of the regulatory classification. Within the portfolio of IRB loans, we can check whether the underestimation effect is more severe for those loans that were issued under the new regime.

Specifically, we evaluate the performance of a sample of loans that were originated between 2005 and 2008, within two years before and after the reform. As our data is on the bank-firm level (and not on the contract level), we define the year of a loan issuance as follows: First, a new loan was originated in a given year if a new bank-firm relationship was formed in that year. Second, for existing bank-firm relationships, we assume that a new loan was granted if we see an increase of at least 30 percent of the amount already outstanding in a given quarter.\footnote{We focus on large increases in the outstanding loan amount of a given bank-firm relationship since most firms keep a checking account with their banks whose balances keep varying around a certain level quarter by quarter. Importantly, our results do not depend on the exact definition of a new loan issuance, i.e., we have tried different cutoff values and obtained similar results.}

Table 8 provides regression results for Equation (3). We use the ESTIMATION ERROR as a dependent variable and evaluate loan performance in 2009.\footnote{Evaluating loans in 2009 allows us to include loans that were originated within a two-year window around the reform, with the sample being relatively balanced between loans that were originated before and after the reform. The same test in 2010 yields similar results, but is less balanced since the share of loans originated before the reform is considerably lower.} We find a significant difference between the two regimes, i.e., PDs for loans originated under Basel II are significantly more likely to underestimate actual default rates than PDs for loans originated before the reform. Column 2 shows that this result is robust to the inclusion of bank fixed effects. Compared with IRB loans originated before the reform, IRB loans originated after the reform underestimate actual default rates by about 0.6 percentage points.

Since loans are evaluated in 2009, they differ in the time elapsed since their origination. To rule out that the length of a specific relationship explains part of our findings we repeat the analysis using a different evaluation horizon. In particular, we evaluate loan performance
four years after origination. That is, loans originated in 2005 are evaluated in 2009, loans originated in 2006 are evaluated in 2010, and so on.\footnote{We also tried alternative evaluation horizons (three years, five years) and obtained similar results.} Using this alternative evaluation horizon we obtain similar results (Table 8, columns 3 and 4).

Results in this section suggest that indeed our findings are driven by lower incentives for banks to report information that increases the PD for a specific borrower following the reform. They are not consistent with a simple manipulation story in which banks simply adjust all their existing PDs downwards in order to save on regulatory capital. Further, the results confirm that our findings in the previous section are not driven by the selection of IRB loan portfolios. We find a stronger underestimation effect for IRB loans that were originated after the reform as compared with IRB loans that were originated before the reform. While these loans differ in the time of origination, they find themselves within the same loan portfolios within IRB banks, i.e., those portfolios for which the new approach has already been implemented.

6. Further results

The broad array of results so far provides support for the view that the introduction of model-based regulation negatively affected credit risk measurement, thus undermining financial stability. In this section, we provide additional results that support this view.

6.1. Business cycle fluctuations and measurement of credit risk

A wide literature has documented that credit risk varies over the business cycle.\footnote{E.g., Berndt et al. (2008) document that credit risk is considerably higher during recessions.} Thus, changes in economic conditions are likely to affect loan defaults which in turn might affect the ability of a credit risk model to predict defaults. If economic condition turn out to be worse than expected (i.e., there are more defaults than expected), even a well-functioning default model is likely to underpredict defaults (and vice versa if economic conditions turn out better than expected).
Importantly, our previous loan-level analysis compares the relative ESTIMATION ERROR for loans to the same firm by different banks and should therefore not be affected by any macro factors. Nevertheless, we now investigate whether underestimation of actual default rates is present in both downswing and upswing periods. In Figure 5, we plot German GDP (seasonally adjusted, 2005 prices) as obtained from the Federal Statistical Office as well as corporate default rates obtained from Duellmann and Koziol (2014). These two graphs document that our sample period comprises a downswing period (2008Q1 until 2009Q1) and an upswing period (2009Q2 until 2012Q3). GDP decreased, while defaults increased during the downswing period. Thereafter, GDP recovered and the default rate constantly decreased until the end of our sample period.

We split our sample into these subperiods and present mean values for the ESTIMATION ERROR of IRB and SA loans (of IRB banks) in columns 1 and 4 of Table 9. For SA loans, the sign of the ESTIMATION ERROR is as expected in both subperiods. During the downswing, PDs for SA loans underpredicted actual default rates by about 0.1 percent (although the effect is statistically not significant). During the upswing, however, PDs for these loans overpredict defaults by about 0.6 percent (again, the effect is not significant). For IRB loans, we find consistent underprediction in both subperiods. For loans under IRB, PDs underpredict actual default rates even in a period in which the default rate is constantly decreasing. As before, we can also test the difference between the two types of loans. Coefficients suggest that underprediction is more severe for loans under IRB in both subperiods (columns 2 and 4).

6.2. Bank portfolio analysis

We argue that model-based regulation adversely affected bank stability. It is possible that documented loan losses occur within well diversified portfolios, thus weakening the threat to a specific bank. To investigate this issue, we replicate our empirical analysis on the bank

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29 Alternatively, we could have shown the default series from our own data set. This data, however, starts only in 2008.
portfolio level. Specifically, we form two portfolios for each bank in each period: one portfolio includes all IRB loans and the other one includes all SA loans. Loans are weighted equally, but results are very similar when weight each loan by its respective amount. Regression results are reported in Table 10.31

The average PD is about 0.4 percent smaller in IRB portfolios as compared with SA portfolios, a result that is robust to the inclusion of bank and period fixed effects or bank × period interactions (columns 1-3). The same bank reports smaller PDs in its IRB portfolio as compared with its SA portfolio in the same period. ACTUAL DEFAULT is somewhat higher for IRB portfolios (columns 4-6; once bank or bank × period fixed effects are included the effect is not significant anymore), resulting in a significant underprediction of actual default rates in IRB portfolios (columns 7-9).

Also the results on financial stability can be shown on the portfolio level. IRB portfolios require significantly less regulatory capital (as indicated by the RWA TO LOAN ratio in columns 10-12) but exhibit a higher LOSS RATE than SA portfolios (columns 13-15). Interestingly, the INTEREST RATE reflects the higher risk of IRB portfolios (columns 16-18). This suggests that banks were aware of higher risk taking within IRB portfolios, but did not pass this information on to the regulator when reporting PDs.

7. Bank lending around the introduction of model based regulation

In a final step, we try to identify potential winners and losers of the reform. While large banks had the ability to spread the compliance costs associated with the implementation of the model-based approach over a large portfolio of loans, small banks did not introduce the new regulation. Thus, banks that introduced IRB experienced a significant reduction in capital requirements for loans—both in absolute terms and relative to SA banks that did not introduce the new approach. In this section, we analyze whether the reform’s differential

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31These regressions include all quarterly data as the problem of sticky PDs is less severe at the portfolio level (each quarter a part of the PDs in the portfolio is updated). Reported standard errors are corrected for autocorrelation.
impact on capital requirements had consequences for banks’ lending behavior.

We have previously documented significantly lower PDs as well as lower average risk weights for loan portfolios under IRB. Figure 6 shows that, following the reform, banks that introduced the model-based approach expanded their lending to corporate borrowers in Germany.\(^{32}\) Prior to the reform the development of aggregate loans was relatively similar for the two groups of banks. Following the reform, however, we see a sharp increase in aggregate loans for IRB banks, while the loans of SA banks remain relatively constant or even decline.

To formalize the analysis, we collapse quarterly bank-level loans into single pre-event and post-event time periods by taking the average of the two years before and the two years after the reform and regress the change in this variable on a dummy that indicates whether the bank has introduced the model-based approach. Table 11 shows that IRB banks increased their lending by about 9 percent as compared with SA banks (column 1).\(^{33}\) In column 2 we add several bank-level control variables (i.e., the pre-event logarithm of assets, ratio of equity to assets, ROA and bank ownership dummies), and find that larger banks, better capitalized banks, and more profitable banks increased their lending relatively more following the reform, while state banks reduced their lending relative to commercial banks and cooperative banks. The coefficient for the IRB bank dummy remains significantly positive. This finding is in line with results documented by Brun et al. (2013), who show that French banks increased their lending by similar magnitudes following the introduction of Basel II. To sum up, larger banks drastically expanded their lending relative to smaller banks, resulting in a further concentration of market shares in the market for corporate loans.

Under IRB, the capital charge for a specific loan depends on the estimated PD for that loan (see Section 2 for details). Hence, we expect that IRB banks increase lending particularly to those firms where PDs are relatively low. To test this assertion, we collapse the quarterly loan-level data into single pre-event and post-event time periods by taking the averages of the two years before and the two years after the reform, and regress the change

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\(^{32}\)For each group of banks—SA banks and IRB banks—we sum all loans in a given quarter to obtain aggregate loans. The figure shows the logarithm of aggregate loans—scaled by its value in 2007Q1—for SA and IRB banks (see Khwaja and Mian 2008 for a similar graphical illustration).

\(^{33}\)According to Halvorsen and Palmquist (1980), the effect of dummy variables in semi-logarithmic equations is equal to \(exp(\beta) - 1\).
in this variable on an interaction between the IRB bank dummy and the firm’s PD. Formally, we run the following regression:

$$\Delta \log(\text{loans})_{ij} = \alpha_i + \alpha_j + D(\text{IRB bank})_i \times \text{Firm PD}_j \times \gamma + \epsilon_{ij},$$

(4)

where \(i\) denotes the individual bank, and \(j\) denotes the individual firm. We use the average PD banks report for each firm in 2008Q1, the first quarter for which this information is available (see Section 3). The variable is interacted with the dummy that indicates whether the bank adopted IRB during our sample period. Firm fixed effects are denoted by \(\alpha_i\). Bank fixed effects are denoted by \(\alpha_j\). To allow for potential correlation among changes in lending from the same bank we cluster standard errors at the bank level in all loan-level regressions. As we are trying to identify a supply side effect, it is important to control for a firm’s demand for credit by including firm fixed effects (see Khwaja and Mian 2008). The 44,784 observations in the loan-level regressions correspond to all loans to firms with at least one loan from an IRB bank and at least one loan from an SA bank. Additionally, we include bank fixed effects that allow us to systematically control for heterogeneity across banks. That is, we test whether the same bank increases its lending relatively more to firms with low PDs, and whether this effect depends on whether the bank is an IRB bank or not.

Estimation results for Equation (4) are presented in Table 11, columns 3 to 6. We interact the IRB bank dummy with the firm PD variable and find that IRB banks increase lending to the same firm relatively more, but less so when the firm’s PD is higher (column 3). This effect is robust to the inclusion of firm fixed effects in column 4, bank fixed effects in column 5, and both firm and bank fixed effects in column 6. Economically, the coefficients indicate that an increase of one standard deviation in \(\text{Firm PD} (0.031)\) induces a 1.2 to 2.5 percent smaller increase in loans from IRB banks. In line with our assertion, we find that IRB banks increase lending to the same firm significantly more than SA banks when the firm’s PD is relatively low, but not when the firm’s PD is relatively high.

Overall, we document that indeed the reform changed the quantity and the composition of bank lending. While the reform achieved a tighter link between estimated PDs and a bank’s lending decision, the crucial link between PDs and actual default rates was lost in the
8. Concluding Remarks

In this paper, we use data from the German credit register to show that the introduction of model-based capital regulation under Basel II affected the validity of internal risk estimates. We find that risk estimates for loans under the model-based approach (IRB) systematically underestimate actual default rates, while there is no such effect for loans under the traditional approach. Moreover, the underestimation effect is worse for IRB loans that were originated after the reform as compared with loans that are subject to IRB but were originated before the reform. Based on this evidence, we argue that model-based capital regulation is unable to adequately capture the risk of financial institutions, as it changes banks’ incentives and leads to a systematic failure of internal risk models. We further show that the introduction of model-based regulation induced lower aggregate capital charges, but higher actual losses. Thus, we conclude that the reform has failed to meet its ultimate objective of strengthening the soundness and stability of the international banking system.

Overall, our paper provides support to regulatory capture view of regulation (Stigler 1971, Posner 1974, Peltzman 1976, Becker 1983) and questions the rationale behind complex regulation. The high compliance costs associated with the model-based approach meant that only the larger banks adopted this new approach. These large banks benefited from the new regulation and expanded their lending. Consistent with the view espoused in Hellwig (2010), large banks exploited the model-based approach to ‘economize on equity’, reducing regulatory capital to a bare minimum and capturing the excess returns on equity associated with a high leverage ratio. While this behavior might have been privately optimal, it came at the expense of smaller banks that did not introduce the model-based approach, and ultimately at the expense of society, which had to bear the costs of financial instability in the form of bank bailouts. Regulators—impressed by sophisticated new risk modeling techniques—failed to observe that the preferential treatment of large institutions under the model-based approach actually increased systemic risk. Besides, one could argue, they also
benefited from the introduction of complex regulation, as it facilitates what can be termed as regulatory ‘empire building’ à la Jensen and Meckling (1976). In recent years, the number of financial supervisors has dramatically increased across the world, at a much faster pace than the number of people working in the financial industry (Haldane 2013). The most recent step in this direction was the creation of about 1,000 new supervisory positions at the European Central Bank.

The regulation of bank capital requirements is one of the most controversial topics in today’s world of banking. In recent years, a fundamental debate has evolved on whether current regulation is heading into the right direction. The financial system is complex in itself, and Basel II-type model-based regulation has added to this complexity by requiring the estimation of thousands of parameters for the determination of capital charges at a large bank. Model-based regulation is inherently complex and thus difficult to enforce. As pointed out by Haldane (2013), already the number of pages in regulatory documents reveals ever-increasing complexity: Basel I in 1988 consisted of only 30 pages, while Basel II in 2007 had 347 pages, and Basel III doubled to 616 pages. The enforcement problem arises from the sheer amount of parameters that have to be estimated, and from the fact that banks have incentives to keep capital charges rather low.

Basel III retains the trend towards more and more complex regulation and can, as expressed by Haldane (2011), easily be summarized as “more of the same – and better”. Many have questioned whether such complex regulation actually benefits the financial system, and calls for simpler rules and guidelines are becoming louder in the regulatory community and even among banks themselves. Our paper illustrates that complex regulation may fail to adequately capture credit risk, hence supporting the view that coarser regulation may have its benefits.

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34 A recent study by McKinsey estimates that a large bank needs to create 200 new full-time jobs to ensure compliance with regulatory rules (Härle et al. 2010).
References


Moody’s Analytics (2013). Riskcalc™ plus.


The figure shows how estimated PDs map into regulatory risk-weights for loans in the corporate sector, assuming standard values for loss given default (45 percent) and loan maturity (2.5 years). The figure plots risk weights for loans to firms with a turnover larger than €50 million. For loans to smaller firms, risk weights are multiplied with a correction factor depending on the exact amount of the turnover.

The figure illustrates our identification strategy. As the implementation of IRB occurs gradually, IRB banks have both IRB and SA loans in their portfolios. In the regression analysis, we rely on firms that have at least two loans from different IRB banks: one bank where the loan is in an IRB portfolio and one bank where the loan is still under SA.
The figure shows average PDs, actual default rates, loan loss rates, the ratio of RWA TO LOAN, and interest rates for SA loans and IRB loans during the period from 2008 to 2012. The sample includes all loans that are not in default in the respective year.
The figure shows Epanechnikov kernel densities for PDs from 2008 to 2012. PDs are reported in logarithms for reasons of presentability. The smoothing parameter in the density estimation is set to 0.4. The blue line corresponds to PDs for SA loans of IRB banks, the red line corresponds to IRB loans of IRB banks. Dashed vertical lines represent the respective mean of the distribution.

Figure 4: PD kernel densities

The figure shows Epanechnikov kernel densities for PDs from 2008 to 2012. PDs are reported in logarithms for reasons of presentability. The smoothing parameter in the density estimation is set to 0.4. The blue line corresponds to PDs for SA loans of IRB banks, the red line corresponds to IRB loans of IRB banks. Dashed vertical lines represent the respective mean of the distribution.
Panel A shows the development of seasonally adjusted German GDP index between 2005Q1 and 2012Q4 (Source: German Federal Statistical Office). Panel B shows the development of default rates in the German corporate sector as obtained from a paper by Duellmann and Koziol (2014).

The figure shows the development of aggregate lending in our sample for SA banks and IRB banks around the Basel II introduction in the first quarter of 2007. Aggregate numbers are obtained from the German credit register and calculated by summing all loans from the respective group of banks within a given quarter. Aggregate loans are standardized by their value in 2007Q1, and the figure shows the logarithm of this ratio (see Khwaja and Mian 2008 for a similar graphical illustration).
Table 1: Descriptives

Panel A: Bank descriptives

<table>
<thead>
<tr>
<th></th>
<th>SA banks (1,558 banks)</th>
<th>IRB banks (45 banks)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>BANK ASSETS (2006, in mn €)</td>
<td>1,330</td>
<td>3,750</td>
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<tr>
<td>BANK ROA (2006)</td>
<td>0.680</td>
<td>0.464</td>
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<tr>
<td>Bank type</td>
<td></td>
<td></td>
</tr>
<tr>
<td>... commercial</td>
<td>14.0</td>
<td>–</td>
</tr>
<tr>
<td>... state</td>
<td>29.4</td>
<td>–</td>
</tr>
<tr>
<td>... cooperative</td>
<td>56.7</td>
<td>–</td>
</tr>
</tbody>
</table>

Panel B: Loan descriptives

<table>
<thead>
<tr>
<th></th>
<th>SA loans (59,000 loans)</th>
<th>IRB loans (237,985 loans)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S.D.</td>
</tr>
<tr>
<td>PD</td>
<td>0.0262</td>
<td>0.0564</td>
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<tr>
<td>RWA TO LOAN</td>
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<tr>
<td>LOSS RATE</td>
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<tr>
<td>INTEREST RATE</td>
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<td>Δ LOG(LOANS)</td>
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<td>0.3582</td>
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Panel C: Firm descriptives

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<th>(5,961 firms)</th>
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<tr>
<td></td>
<td>Mean</td>
</tr>
<tr>
<td>FIRM ASSETS (2006, in mn €)</td>
<td>154</td>
</tr>
<tr>
<td>FIRM DEBT TO ASSETS (2006)</td>
<td>0.343</td>
</tr>
<tr>
<td>LOG FIRM ASSETS (2006)</td>
<td>10.363</td>
</tr>
<tr>
<td>FIRM ROA (2006)</td>
<td>7.909</td>
</tr>
</tbody>
</table>

Panel A shows descriptive statistics for the groups of SA and IRB banks. An IRB bank is defined as a bank that uses the internal ratings-based approach for some loans during our sample period, whereas an SA bank is defined as a bank that uses the Basel II standard approach in all its lending relationships. Panel B shows summary statistics for loans in the German credit register. Data are restricted to (a) loans that are larger than € 1.5 million (b) loans from commercial, state, or cooperative banks that are subject to the Basel II capital regulation (c) loans that have an observation both before and after the introduction of Basel II in 2007. Δ LOG(LOANS) refers to the change in the log of loans around the Basel II reform (average of two years after minus average of two years before the reform). The remaining variables include observations from 2008 to 2012. Panel C contains information on the firm level for a matched sample of 5,961 firms. Firm balance sheet information is obtained from Bundesbank’s USTAN database.
Table 2: Characteristics of SA and IRB loans within IRB banks

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>PD</th>
<th>ACTUAL DEFAULT</th>
<th>RWA TO LOAN</th>
<th>LOSS RATE</th>
<th>INTEREST RATE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>S.D.</td>
<td>Mean</td>
<td>S.D.</td>
<td>Mean</td>
</tr>
<tr>
<td>SA loans</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>14,713</td>
<td>0.0265</td>
<td>0.0504</td>
<td>0.0257</td>
<td>0.1582</td>
<td>0.5832</td>
</tr>
<tr>
<td>2009</td>
<td>13,734</td>
<td>0.0292</td>
<td>0.0647</td>
<td>0.0248</td>
<td>0.1554</td>
<td>0.6144</td>
</tr>
<tr>
<td>2010</td>
<td>11,154</td>
<td>0.0264</td>
<td>0.0572</td>
<td>0.0173</td>
<td>0.1304</td>
<td>0.6237</td>
</tr>
<tr>
<td>2011</td>
<td>10,492</td>
<td>0.0239</td>
<td>0.0518</td>
<td>0.0188</td>
<td>0.1357</td>
<td>0.6316</td>
</tr>
<tr>
<td>2012</td>
<td>8,907</td>
<td>0.0237</td>
<td>0.0560</td>
<td>0.0193</td>
<td>0.1376</td>
<td>0.6419</td>
</tr>
<tr>
<td>IRB loans</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td>51,332</td>
<td>0.0153</td>
<td>0.0443</td>
<td>0.0305</td>
<td>0.1720</td>
<td>0.5269</td>
</tr>
<tr>
<td>2009</td>
<td>48,816</td>
<td>0.0193</td>
<td>0.0552</td>
<td>0.0289</td>
<td>0.1675</td>
<td>0.5259</td>
</tr>
<tr>
<td>2010</td>
<td>45,078</td>
<td>0.0199</td>
<td>0.0596</td>
<td>0.0230</td>
<td>0.1500</td>
<td>0.5278</td>
</tr>
<tr>
<td>2011</td>
<td>47,592</td>
<td>0.0174</td>
<td>0.0482</td>
<td>0.0251</td>
<td>0.1564</td>
<td>0.5008</td>
</tr>
<tr>
<td>2012</td>
<td>45,167</td>
<td>0.0160</td>
<td>0.0441</td>
<td>0.0213</td>
<td>0.1445</td>
<td>0.4750</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Difference</th>
<th>t-stat</th>
<th>Difference</th>
<th>t-stat</th>
<th>Difference</th>
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<th>Difference</th>
<th>t-stat</th>
<th>Difference</th>
<th>t-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>66,045</td>
<td>26.1907</td>
<td>-0.0048</td>
<td>3.0368</td>
<td>0.0562</td>
<td>8.5052</td>
<td>0.0006</td>
<td>1.0990</td>
<td>-0.0111</td>
<td>-4.7954</td>
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<td>2009</td>
<td>62,550</td>
<td>17.8498</td>
<td>-0.0041</td>
<td>3.0368</td>
<td>0.0886</td>
<td>11.4931</td>
<td>-0.0001</td>
<td>-0.3800</td>
<td>-0.0138</td>
<td>-5.3734</td>
</tr>
<tr>
<td>2010</td>
<td>56,232</td>
<td>10.3944</td>
<td>-0.0057</td>
<td>3.6836</td>
<td>0.0959</td>
<td>12.3742</td>
<td>-0.0015</td>
<td>-2.7691</td>
<td>-0.0119</td>
<td>-4.2753</td>
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<td>2011</td>
<td>58,084</td>
<td>12.3322</td>
<td>-0.0063</td>
<td>3.8211</td>
<td>0.1309</td>
<td>24.2272</td>
<td>-0.0005</td>
<td>-0.9968</td>
<td>-0.0156</td>
<td>-5.1638</td>
</tr>
<tr>
<td>2012</td>
<td>54,074</td>
<td>14.3537</td>
<td>-0.0020</td>
<td>1.2031</td>
<td>0.1669</td>
<td>29.7199</td>
<td>0.0000</td>
<td>-0.1842</td>
<td>-0.0097</td>
<td>-3.1216</td>
</tr>
</tbody>
</table>

The table shows average values for the estimated PD, the ACTUAL DEFAULT rate, the LOSS RATE, the ratio of RWA TO LOAN, and the INTEREST RATE for SA loans and IRB loans in 2008, 2009, 2010, 2011, and 2012, respectively. Further, the table shows the difference between the two groups of loans for each year and reports statistics for two-sample mean-comparison t-tests.
Table 3: PD

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>LOG(PD)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>D(IRB LOAN)</td>
<td>-5.5494***</td>
</tr>
<tr>
<td></td>
<td>(0.0495)</td>
</tr>
<tr>
<td>D(SA LOAN)</td>
<td>-4.9515***</td>
</tr>
<tr>
<td></td>
<td>(0.1052)</td>
</tr>
</tbody>
</table>

Constant

| Firm FE | YES |
| Period FE | YES |
| Firm × Period FE | YES |
| Bank × Period FE | YES |
| Observations | 296,985 |
| R-squared | 0.0192 |

The sample includes loans from IRB banks in 2008, 2009, 2010, 2011, and 2012. The dependent variable in all regressions is the logarithm of the loan-specific PD. In columns 4 and 5 the sample is restricted to firm-year observations in which the respective firm has at least one IRB loan and at least one SA loan. D(IRB LOAN) indicates the regulatory approach under which a specific loan was issued and is equal to 1 if the loan was issued under IRB. Similarly, D(SA LOAN) is equal to 1 if the loan was issued under SA and 0 otherwise. Robust standard errors adjusted for double clustering at the firm-period and bank-period level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.
Table 4: Estimation error

<table>
<thead>
<tr>
<th></th>
<th>ESTIMATION ERROR (ACTUAL DEFAULT – PD)</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>D(IRB LOAN)</td>
<td>0.0084***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0024)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D(SA LOAN)</td>
<td>-0.0045</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0047)</td>
<td></td>
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</tr>
<tr>
<td>Constant</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Firm FE     NO YES YES — —
Period FE   NO NO YES — —
Firm × Period FE NO NO NO YES YES
Bank × Period FE NO NO NO YES YES
Observations 296,985 296,985 296,985 50,798 50,798
R-squared 0.0011 0.4937 0.4975 0.6241 0.6312

The sample includes loans from IRB banks in 2008, 2009, 2010, 2011, and 2012. The dependent variable in all regressions is the loan-specific ESTIMATION ERROR, defined as the difference between an ACTUAL DEFAULT dummy that indicates whether the loan defaults within the next four quarters and the PD. In columns 4 and 5 the sample is restricted to firm-year observations in which the respective firm has at least one IRB loan and at least one SA loan. D(IRB LOAN) indicates the regulatory approach under which a specific loan was issued and is equal to 1 if the loan was issued under IRB. Similarly, D(SA LOAN) is equal to 1 if the loan was issued under SA and 0 otherwise. Robust standard errors adjusted for double clustering at the firm-period and bank-period level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.
### Table 5: RWA TO LOAN

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>RWA TO LOAN</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>D(IRB LOAN)</td>
<td></td>
<td>0.5114***</td>
<td>-0.1408***</td>
<td>-0.1410***</td>
<td>-0.1268***</td>
<td>-0.1522***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0186)</td>
<td>(0.0050)</td>
<td>(0.0050)</td>
<td>(0.0088)</td>
<td>(0.0110)</td>
</tr>
<tr>
<td>D(SA LOAN)</td>
<td></td>
<td>0.6155***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0305)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Constant

| Firm FE | NO | YES | YES | —   | —   |
| Period FE | NO | NO  | YES | —   | —   |
| Firm × Period FE | NO | NO  | NO  | YES | YES |
| Bank × Period FE | NO | NO  | NO  | NO  | YES |
| Observations      | 281,565 | 281,565 | 281,565 | 47,469 | 47,469 |
| R-squared          | 0.0039  | 0.5589  | 0.5591  | 0.2738  | 0.2983  |

The sample includes loans from IRB banks in 2008, 2009, 2010, 2011, and 2012. The dependent variable in all regressions is the loan-specific ratio of RWA TO LOAN. In columns 4 and 5 the sample is restricted to firm-year observations in which the respective firm has at least one IRB loan and at least one SA loan. D(IRB LOAN) indicates the regulatory approach under which a specific loan was issued and is equal to 1 if the loan was issued under IRB. Similarly, D(SA LOAN) is equal to 1 if the loan was issued under SA and 0 otherwise. Robust standard errors adjusted for double clustering at the firm-period and bank-period level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.
Table 6: Loss rate

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>LOSS RATE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>D(IRB LOAN)</td>
<td>0.0051***</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
</tr>
<tr>
<td>D(SA LOAN)</td>
<td>0.0049***</td>
</tr>
<tr>
<td></td>
<td>(0.0013)</td>
</tr>
</tbody>
</table>

Constant

| Firm FE | NO | YES | YES | — | — |
| Period FE | NO | NO | YES | — | — |
| Firm × Period FE | NO | NO | NO | YES | YES |
| Bank × Period FE | NO | NO | NO | NO | YES |
| Observations | 294,592 | 294,592 | 294,592 | 50,543 | 50,543 |
| R-squared | 0.0084 | 0.5830 | 0.5847 | 0.7050 | 0.7076 |

The sample includes loans from IRB banks in 2008, 2009, 2010, 2011, and 2012. The dependent variable in all regressions is the loan-specific LOSS RATE. In columns 4 and 5 the sample is restricted to firm-year observations in which the respective firm has at least one IRB loan and at least one SA loan. D(IRB LOAN) indicates the regulatory approach under which a specific loan was issued and is equal to 1 if the loan was issued under IRB. Similarly, D(SA LOAN) is equal to 1 if the loan was issued under SA and 0 otherwise. Robust standard errors adjusted for double clustering at the firm-period and bank-period level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.
Table 7: Interest rate

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>INTEREST RATE</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>D(IRB LOAN)</td>
<td>0.0885***</td>
<td>0.0054</td>
<td>0.0078**</td>
<td>0.0097***</td>
<td>0.0198***</td>
</tr>
<tr>
<td></td>
<td>(0.0013)</td>
<td>(0.0036)</td>
<td>(0.0031)</td>
<td>(0.0025)</td>
<td>(0.0039)</td>
</tr>
<tr>
<td>D(SA LOAN)</td>
<td>0.0798***</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.0022)</td>
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</tr>
<tr>
<td>Constant</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Firm FE NO YES YES — —
Period FE NO NO YES — —
Firm × Period FE NO NO NO YES YES
Bank × Period FE NO NO NO NO YES
Observations 11,811 11,811 11,811 1.677 1.677
R-squared 0.0027 0.6927 0.7016 0.8037 0.8279

The sample includes loans from IRB banks in 2008, 2009, 2010, 2011, and 2012. The dependent variable in all regressions is the loan-specific INTEREST RATE. In columns 4 and 5 the sample is restricted to firm-year observations in which the respective firm has at least one IRB loan and at least one SA loan. D(IRB LOAN) indicates the regulatory approach under which a specific loan was issued and is equal to 1 if the loan was issued under IRB. Similarly, D(SA LOAN) is equal to 1 if the loan was issued under SA and 0 otherwise. Robust standard errors adjusted for double clustering at the firm-period and bank-period level are reported in parentheses. Note: * indicates statistical significance at the 10% level, ** at the 5% level and *** at the 1% level.
Table 8: Estimation error by cohorts

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>ESTIMATION ERROR (ACTUAL DEFAULT – PD)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Evaluation in 2009</td>
<td>Evaluation after four years</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>BASEL II</td>
<td>0.0057***</td>
<td>0.0062***</td>
<td>0.0067**</td>
</tr>
<tr>
<td></td>
<td>(0.0020)</td>
<td>(0.0023)</td>
<td>(0.0034)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.0080</td>
<td>0.0030</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0058)</td>
<td></td>
<td>(0.0041)</td>
</tr>
<tr>
<td>Bank FE</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>Observations</td>
<td>64,695</td>
<td>64,695</td>
<td>47,144</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.0003</td>
<td>0.0381</td>
<td>0.0005</td>
</tr>
</tbody>
</table>

The sample includes loans that were originated in the years around the Basel II introduction, i.e., bank-firm-relationships that did not exist before or that display a large increase (at least 30% of existing loan amount) in the respective year. The dependent variable in all regressions is the difference between the dummy for ACTUAL DEFAULT and the estimated PD. The dummy BASEL II is equal to 1 if the loan was originated after the Basel II introduction (i.e., in 2007 or 2008) and equal to 0 if it was originated before (i.e., in 2005 or 2006). In columns 1 and 2, loans are evaluated in 2009Q4. In columns 3 and 4, loans are evaluated four years after their origination, i.e., loans originated in 2005 are evaluated in 2009Q4, loans originated in 2006 are evaluated in 2010Q4, and so on. Robust standard errors adjusted for clustering at the firm and bank level are reported in parentheses. Note: * indicates statistical significance at the 10% level, ** at the 5% level and *** at the 1% level.
Table 9: Business cycle

<table>
<thead>
<tr>
<th>Dependent variable: ESTIMATION ERROR (ACTUAL DEFAULT – PD)</th>
<th>Downswing</th>
<th>Upswing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>D(IRB LOAN)</td>
<td>0.0139***</td>
<td>0.0080**</td>
</tr>
<tr>
<td></td>
<td>(0.0048)</td>
<td>(0.0041)</td>
</tr>
<tr>
<td>D(SA LOAN)</td>
<td>0.0012</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0112)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Firm × Period FE NO YES NO YES
Observations 117,509 23,314 168,390 24,886
R-squared 0.0010 0.6073 0.0010 0.6334

The sample includes loans from IRB banks in 2008 and early 2009 in columns 1-2 and loans from IRB banks in 2010, 2011, and 2012 in columns 3-4. The dependent variable in all regressions is the loan-specific ESTIMATION ERROR, defined as the difference between an ACTUAL DEFAULT dummy that indicates whether the loan defaults within the next four quarters and the PD. In columns 2 and 4 the sample is restricted to firm-year observations in which the respective firm has at least one IRB loan and at least one SA loan. D(IRB LOAN) indicates the regulatory approach under which a specific loan was issued and is equal to 1 if the loan was issued under IRB. Similarly, D(SA LOAN) is equal to 1 if the loan was issued under SA and 0 otherwise. Robust standard errors adjusted for double clustering at the firm-period and bank-period level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.
Table 10: Portfolio level

<table>
<thead>
<tr>
<th></th>
<th>PD</th>
<th></th>
<th>ACTUAL DEFAULT</th>
<th></th>
<th>ESTIMATION ERROR</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>IRB PORTFOLIO</td>
<td>0.023***</td>
<td>-0.004***</td>
<td>-0.004**</td>
<td>0.028***</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>SA PORTFOLIO</td>
<td>0.027***</td>
<td></td>
<td>0.024***</td>
<td></td>
<td>-0.003</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td>(0.002)</td>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Period FE</td>
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<td>YES</td>
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<td>NO</td>
<td>YES</td>
<td>—</td>
</tr>
<tr>
<td>Bank FE</td>
<td>NO</td>
<td>YES</td>
<td>—</td>
<td>NO</td>
<td>YES</td>
<td>—</td>
</tr>
<tr>
<td>Bank × Period FE</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
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<tr>
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<td>1,546</td>
<td>1,546</td>
<td>1,546</td>
<td>1,546</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.004</td>
<td>0.658</td>
<td>0.802</td>
<td>0.002</td>
<td>0.328</td>
<td>0.747</td>
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</table>

<table>
<thead>
<tr>
<th></th>
<th>RWA TO LOAN</th>
<th>LOSS RATE</th>
<th>INTEREST RATE</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(10)</td>
<td>(11)</td>
<td>(12)</td>
</tr>
<tr>
<td></td>
<td>(13)</td>
<td>(14)</td>
<td>(15)</td>
</tr>
<tr>
<td></td>
<td>(16)</td>
<td>(17)</td>
<td>(18)</td>
</tr>
<tr>
<td>IRB PORTFOLIO</td>
<td>0.480***</td>
<td>-0.210***</td>
<td>-0.216***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.016)</td>
<td>(0.022)</td>
</tr>
<tr>
<td></td>
<td>0.006***</td>
<td>0.004***</td>
<td>0.003*</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td></td>
<td>0.081***</td>
<td>0.014***</td>
<td>0.012***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>SA PORTFOLIO</td>
<td>0.701***</td>
<td></td>
<td>0.003***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td></td>
<td>(0.000)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.071***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>Period FE</td>
<td>NO</td>
<td>YES</td>
<td>—</td>
</tr>
<tr>
<td>Bank FE</td>
<td>NO</td>
<td>YES</td>
<td>—</td>
</tr>
<tr>
<td>Bank × Period FE</td>
<td>NO</td>
<td>NO</td>
<td>YES</td>
</tr>
<tr>
<td>Observations</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.115</td>
<td>0.467</td>
<td>0.628</td>
</tr>
<tr>
<td></td>
<td>0.005</td>
<td>0.342</td>
<td>0.578</td>
</tr>
<tr>
<td></td>
<td>0.029</td>
<td>0.534</td>
<td>0.805</td>
</tr>
</tbody>
</table>

The sample includes portfolio level data for IRB banks from 2008Q1 to 2012Q4, i.e., for each bank there are two observations per quarter, one for the SA and one for the IRB portfolio. The dependent variables are collapsed at the portfolio level by taking the average value within the respective bank-quarter. Robust standard errors adjusted for clustering at the bank-period level and autocorrelation are reported in parentheses. Note: * indicates statistical significance at the 10% level, ** at the 5% level and *** at the 1% level.
<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>$\Delta \log(\text{BANK LOANS})$</th>
<th>$\Delta \log(\text{LOANS})$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>D(IRB BANK)</td>
<td>0.0867**</td>
<td>0.1115**</td>
</tr>
<tr>
<td></td>
<td>(0.0346)</td>
<td>(0.0505)</td>
</tr>
<tr>
<td>D(IRB BANK) × FIRM PD</td>
<td>-0.5740***</td>
<td>-0.5519***</td>
</tr>
<tr>
<td></td>
<td>(0.1473)</td>
<td>(0.1580)</td>
</tr>
<tr>
<td>FIRM PD</td>
<td>-0.2615***</td>
<td>-0.2990***</td>
</tr>
<tr>
<td></td>
<td>(0.0811)</td>
<td>(0.0890)</td>
</tr>
<tr>
<td>LOG BANK ASSETS</td>
<td>0.0073</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0086)</td>
<td></td>
</tr>
<tr>
<td>BANK EQUITY RATIO</td>
<td>0.0067*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0039)</td>
<td></td>
</tr>
<tr>
<td>BANK ROA</td>
<td>0.0498**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0239)</td>
<td></td>
</tr>
<tr>
<td>D(STATE BANK)</td>
<td>-0.0772**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0355)</td>
<td></td>
</tr>
<tr>
<td>D(COOPERATIVE BANK)</td>
<td>0.0461</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0345)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.1901***</td>
<td>-0.0411</td>
</tr>
<tr>
<td></td>
<td>(0.0096)</td>
<td>(0.1856)</td>
</tr>
<tr>
<td>Firm FE</td>
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<td>NO</td>
</tr>
<tr>
<td>Bank FE</td>
<td>NO</td>
<td>NO</td>
</tr>
<tr>
<td>Observations</td>
<td>1,603</td>
<td>1,547</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.0015</td>
<td>0.0336</td>
</tr>
</tbody>
</table>

The dependent variable in columns 1 and 2 is the change in the logarithm of aggregate bank lending over the Basel II introduction in 2007Q1. For each bank, we calculate aggregate lending by summing all loans in a respective period. We then collapse all quarterly data for a given bank into single pre-event and post-event periods by taking the average of the two years before and the two years after the Basel II introduction. The dependent variable in the regressions above is the difference in the logarithm of these averages, so that there is one observation per bank. The dummy variable D(IRB BANK) indicates whether the respective bank adopted the Basel II internal ratings-based approach during our sample period. Columns 3-6 show results on the loan level. For each bank-firm relationship, we collapse all quarterly data into single pre-event and post-event periods by taking the average of the two years before and the two years after the Basel II introduction. The dependent variable in the regressions above is the difference in the logarithm of these averages, so that there is one observation per bank-firm relationship. Data are restricted to (a) loans that are larger than €1.5 million, (b) loans from commercial, state, or cooperative banks that are subject to the Basel II capital regulation, (c) loans that have an observation in both the pre- and the post-event period, and (d) loans to firms that have at least one loan from an SA bank and one loan from an IRB bank. FIRM PD is the firm’s average PD in 2008Q1, the first quarter for which this information is available. Robust standard errors adjusted for clustering at the firm and bank level are reported in parentheses. Note: * indicates statistical significance at the 10% level, ** at the 5% level and *** at the 1% level.