EUROPEAN CENTRAL BANK
EUROSYSTEM

Working Paper Series

Markus Behn,
Rainer Haselmann and
Vikrant Vig

The limits of model-based regulation

No 1928 / July 2016

ABSTRACT

In this paper, we investigate how the introduction of sophisticated, model-based capital regulation affected the measurement of credit risk by 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 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 the higher risk associated with these loans and priced them accordingly. Counter to the stated objective of the reform, financial institutions have lower capital charges and at the same time experience higher loan losses. Further, we document that large banks benefited from the reform as they experienced a reduction in capital charges and consequently expanded their lending at the expense of smaller banks that did not introduce the model-based approach. Overall, our results highlight that if the challenges that accompanies complex regulation are too high simpler rules may increase the efficacy of financial regulation.

Keywords: capital regulation, internal ratings, complexity of regulation, Basel regulation

JEL Classification: G01, G21, G28

Non-technical summary

In recent decades, 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. In this context, an important innovation 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 increase the stability of the banking system (Basel Committee on Banking Supervision 2006).

We investigate how the introduction of sophisticated, model-based capital regulation affected the measurement of credit risk by financial institutions. Prior to the introduction of model-based regulation, the regulatory environment was considered to be too coarse, leading to excessive distortions in lending. 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. By tying 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. However, a regulation that is based on banks' internal risk models may suffer from both informational and incentive problems. The overall effects of sophisticated, model-based regulation on banks' credit risk remain controversial, and this paper aims to contribute to the debate.

To examine the effects of model-based regulation on the measurement of credit risk, we exploit the institutional details of the German Basel II introduction in 2007, as well as the high 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, shortened to IRB) in which capital charges depend on internal risk estimates of the bank, and a more traditional approach that does not rely on internal risk parameters (referred to as the standard approach, shortened to SA). Importantly, among those banks that opted for the new approach (referred to as IRB banks), the introduction of the model-based approach was staggered over time. Risk models were certified by the supervisor on a portfolio basis, and supervisors delayed the approval of each model until they felt comfortable about the reliability of the model.

At the aggregate level, we find that reported probabilities of default (PDs) and risk weights are significantly lower for portfolios that were already shifted to the IRB approach compared with SA portfolios still waiting for approval. In stark contrast, however, ex-post default and loss rates go in the opposite direction — actual default rates and loan losses are significantly higher in the IRB pool compared with the SA pool. Interestingly, interest rates in the IRB pool are significantly higher than in the SA pool, suggesting that banks were aware of the inherent riskiness of these loan portfolios, even though reported PDs and risk weights did not reflect this. These results are present in every year until the end of the sample period in 2012 and are quite stable across the business cycle.

To address potential selection issues we also investigate differential effects on risk estimates for SA and IRB loans to the same firm. This within firm analysis mitigates concerns related to omitted variables (such as macro factors) which may differentially affect SA and IRB loans. The loan-level analysis yields very similar insights. Even for the same firm in the same year, we find that both the reported PDs and the risk weights are systematically lower, while the estimation bias (i.e., the difference between a dummy for actual default and the PD) are significantly higher for loans that are subject to the IRB approach vis-à-vis the SA approach. Again, the interest rates charged on IRB loans are higher despite the reported PDs and risk-weights being lower.

The high compliance costs associated with the model-based approach meant that only the larger banks adopted it. These large banks benefited from the new regulation and expanded their lending, potentially at the expense of smaller banks. We find that banks that opted for the introduction of the model-based approach experienced a reduction in capital charges and consequently increased their lending by about 9 percent relative to banks that remained under the traditional approach. Thus, this complex, model-based regulation created barriers to entry and subsidized larger banks.

All in all, counter to the stated objective of the reform, financial institutions have lower capital charges and at the same time experience higher loan losses under IRB. Furthermore, IRB banks charged on average higher interest rates on IRB loans 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). The gap between reported PDs and actual default rates has significant effects on the profitability of banks that applied the model-based approach. Back-of-the-envelope calculations (abstracting from risk-based pricing of the cost of capital) suggest that underreporting of PDs allowed banks to increase their return on equity by up to 16.7 percent.

1. Introduction

In recent decades, 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 increase 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 opaque 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 the measurement of banks' credit risk. Prior to the introduction of model-based regulation, the regulatory environment was considered to be too coarse, as bank assets were bucketed into broad risk categories and each category was subject to a flat capital charge (a flat tax). This simple flat tax feature, it was argued, incentivized banks to increase asset risk *within* each risk category, thus leading to a distortion in the allocation of credit. To establish a stronger link between capital charges and actual asset risk, regulation under Basel II relies on a complex array of risk models, designed and calibrated by banks themselves and subsequently approved by the supervisor. As a consequence, many banks have more than 100 different risk models with thousands of parameters in place, all of which require constant validation and re-calibration by the bank's risk management and surveillance by the supervisor.[1]

By tying capital charges to actual asset risk, model-based regulation aims to avoid situations where banks are penalized for holding safe assets on their balance sheet, thus reducing distortions in the allocation of credit. In a world with no informational and incentive problems, such a sophisticated

[1]The latest revision of the regulatory framework, Basel III, retains 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. These include, inter alia, a simpler leverage ratio requirement that is also meant to address model risk. Furthermore, the Basel Committee on Banking Supervision has recently established the high-level Task Force on Simplicity and Comparability which is mandated to reduce reliance on models for some risks and portfolios, and has consulted on a new capital floor framework that will limit the extent to which internal models can lower capital requirements relative to the standardised approach (see Basel Committee on Banking Supervision 2014).

regulation should unambiguously improve welfare. However, a regulation that is based on banks' internal risk models may suffer from both informational and incentive problems.[2] 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. The overall effects of sophisticated, model-based regulation on banks' credit risk remain controversial, and this paper aims to contribute to the debate.

To examine the effects of model-based regulation on the measurement of credit risk, we exploit the institutional details of the German Basel II introduction in 2007, as well as the high 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, shortened to IRB) in which capital charges depend on internal risk estimates of the bank, and a more traditional approach that does not rely on internal risk parameters (referred to as the standard approach, shortened to 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 (Basel Committee on Banking Supervision 2004). 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.

Importantly, among those banks that opted for the new approach (referred to as IRB banks), the introduction of the model-based approach was staggered over time. Risk models were certified by the supervisor on a portfolio basis, and supervisors 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 staggered implementation to identify the effects of model-based regulation within the group of IRB banks.

At the aggregate level, we find that reported probabilities of default (PDs) and risk-weights are significantly lower for portfolios that were already shifted to the IRB approach compared with SA portfolios still waiting for approval. In stark contrast, however, ex-post default and loss rates go in

[2]In the context of lending, it is now well understood that the quality of a 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. 2015). The inherent complexity of the model-based approach makes it very difficult—if not impossible—for the regulator to detect such behavior.

[3]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 (see Section 2).

the opposite direction—actual default rates and loan losses are significantly higher in the IRB pool compared with the SA pool. To dig deeper into the mechanism, we examine the interest rate that banks charge on these loans, as interest rates give us an opportunity to assess the perceived riskiness of these loans.[4] Interest rates in the IRB pool are significantly higher than in the SA pool, suggesting that banks were aware of the inherent riskiness of these loan portfolios, even though reported PDs and risk-weights did not reflect this. Putting it differently, while the PDs/risk-weights do a poor job of predicting defaults and losses, the interest rates seem to do a better job of measuring risk. Moreover, the results are present in every year until the end of the sample period in 2012 and are quite stable across the business cycle (during the period of our study the German economy underwent both a downturn and a recovery).

While aggregate results are striking, one may be concerned that loan portfolios that were shifted first to the model-based approach differ from portfolios that were shifted later. That is, a non-random assignment of loans within the group of IRB banks may raise concerns about the nature of omitted variables and their effect on statistical inference. As discussed, the supervisor typically approved the new regulatory approach for loan portfolios that had sufficient amount of data available.[5] Thus, any non-random assignment of loans is likely to generate a downward bias on our estimates, as one would expect models that have not yet been certified by the regulator to perform worse. Moreover, to address this issue we investigate differential effects on risk estimates for SA and IRB loans to the *same* firm. This *within* firm analysis mitigates concerns related to omitted variables (such as macro factors) which may differentially affect SA and IRB loans.

The following example illustrates our empirical strategy: Consider a firm that has two loans, both from IRB banks. For one bank, the loan is in a portfolio that has already been shifted to the new approach (IRB pool), while for the other bank the loan is in a portfolio that is awaiting approval from the regulator (SA pool). While both banks estimate the same variable—the firm's PD within the next year—capital charges depend on the estimated PD for loans in the IRB pool, but not for loans in the SA pool.[6] Comparing PDs, actual default rates and other contract terms for loans to the *same* firm but under different regulatory approaches allows us to identify the effects of model-based capital

[4]Since firms are not required to report the corresponding interest rates, we obtain effective interest rates from matching the credit register data with detailed income statement data from Deutsche Bundesbank (see Section 2 and Appendix A for details).

[5]Our results in Appendix B support the view that the discriminatory power of models that were shifted earlier to IRB is similar or even somewhat higher than that of SA models that were shifted later.

[6]Importantly, PDs are meant to estimate the firm's probability of default. They do not consider other parameters such as recovery rates or losses given default. Thus, both banks are expected to arrive at similar estimates for the PD.

regulation on the variable of interest. Furthermore, we are able to exploit within bank variation in the regulatory approach, which allows us to systematically control for bank specific shocks.

The loan-level analysis yields very similar insights. Even for the *same* firm in the *same* year, we find that both the reported PDs and the risk-weights are systematically lower, while the ESTIMATION BIAS (i.e., the difference between a dummy for actual default and the PD) is significantly higher for loans that are subject to the IRB approach vis-à-vis the SA approach. Again, the interest rates charged on IRB loans are higher despite the reported PDs and risk-weights being lower. The results are robust to the inclusion of bank interacted with year fixed effects that control for bank specific shocks.

The incongruence between reported PDs/risk-weights and interest rates suggests that the underperformance of IRB models vis-à-vis SA models was not driven by unanticipated events on the part of the bank. However, it is possible that other differences between IRB and SA portfolios (e.g., differences in the bank's market power) explain our finding. Put differently, market power in a specific portfolio of loans may allow a bank to charge interest rates that are higher than those that would be charged in a competitive market.[7]

To address this issue, we exploit the non-linearity in the mapping between PDs and risk-weights. The relationship between PDs and risk-weights is concave; it is very steep for low PDs and gradually flattens for high PDs (see Figure 1). This non-linearity generates differential incentives to misreport PDs. Specifically, a small decrease in the PD induces a reduction in risk-weights that is much larger for low PD loans than it is for high PD loans. In line with this observation, we find that while our results exist across the entire PD band, the effects are much larger for low PD loans for which small reductions in the PD imply large reductions in the risk-weight. Importantly, this specification systematically controls for time varying omitted factors that might explain the selection of loans into the IRB pool within a specific bank.[8]

We employ further cross-sectional tests to sharpen the analysis. It is natural to expect that more capital-constrained banks have higher incentives to underreport risk estimates, since the marginal benefit of relaxing regulatory constraints are higher for these banks. In line with this view, we find that the difference in ESTIMATION BIAS between IRB and SA loans is insignificant for well

[7]It should be noted that our saturated specification with bank interacted with year fixed effects already controls for time varying bank market power. The concern being highlighted relates to the portfolio-specific market power.

[8]The specification non-parametrically controls for differences that may exist between SA and IRB models.

capitalized banks, while it is both statistically and economically significant for banks that have a low capitalization.

There are two versions of the model-based approach, the foundation approach (F-IRB) and the advanced approach (A-IRB). Under the F-IRB approach, banks estimate only the PD while other parameters such as loss given default (LGD) or exposure at default (EAD) are provided by the regulator and hard wired into the risk-weight calculation. Under the A-IRB approach, banks may use their internal models to estimate not only the PD but also the loss given default (LGD) and the exposure at default (EAD). Interestingly, we find that the breakdown in the relationship between risk weights and actual loan losses is more severe the more discretion is given to the bank: while the same patterns are present for both F-IRB and A-IRB portfolios, the results are much more pronounced for loans under the A-IRB approach, which is clearly more complex and accords more autonomy to the bank.

Our findings can either be driven by direct manipulation of PDs of existing loans, after the portfolios have been shifted to the IRB approach, or by the new loans that banks granted after the reform. We document that IRB loans that were granted in the Basel II regime have significantly larger estimation biases than IRB loans that were originated before the reform. Further, we find that PDs are not manipulated downwards once a loan portfolio is transferred to the IRB regime. Thus, our results seem to be driven by the extension of new loans rather than outright manipulation of PDs. A reason could be that the introduction of IRB changed the incentives of banks to originate loans that score more favorably on dimensions that are captured by the model, while ignoring negative "soft" information that is vital in determining the credit risk of loans. Such a change in incentives may have altered the quality of loans originated by the bank, which in turn affected the performance of the models that have been approved by the regulator.[9]

The high compliance costs associated with the model-based approach meant that only the largest banks adopted it. These large banks benefited from the new regulation and expanded their lending, potentially at the expense of smaller banks. Specifically, we find that banks that opted for the introduction of the model-based approach experienced a reduction in capital charges and consequently increased their lending by about 9 percent relative to banks that remained under the traditional approach. IRB banks increased their lending to the same firm significantly more than SA banks when the firm's PD (and hence the capital charge) was relatively low, but not when the firm's PD was relatively high. Overall, complex model-based regulation created barriers to entry and sub-

[9] See Rajan et al. (2015) for an application of what is often termed as the Goodhart's Law.

sidized larger banks, which seems rather paradoxical given the negative externalities that such banks may exert on the financial system.

All in all, counter to the stated objective of the reform, financial institutions have lower capital charges and at the same time experience higher loan losses. Furthermore, IRB banks charged on average higher interest rates on IRB loans 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). The gap between reported PDs and actual default rates has significant effects on the profitability of banks that applied the model-based approach. Back-of-the-envelope calculations suggest that underreporting of PDs allowed banks to increase their ROE on large corporate loan portfolios by around 16.1 percent.

Our paper connects several strands of the literature. The literature on regulatory complexity is the obvious starting point. Some argue that complex and sophisticated rules are often dominated by simpler regulation that is easier to enforce (Glaeser and Shleifer 2001). Complex regulation imposes a significant enforcement cost on society and provides incentives to regulated entities to find ways around the regulation.[10] Recent empirical evidence on the impact of complex regulation regulation in the insurance sector is provided by Koijen and Yogo (2015, 2016). Similarly, the public economics literature has discussed the merits of a flat tax schedule. In an recent paper Gorodnichenko et al. (2009) document that a move towards a flat tax regime in Russia reduced tax evasion and increased tax revenues in Russia, suggesting that in countries where tax evasion is significant, a flat tax regime may be beneficial.[11] We add to this literature by highlight how simpler rules may increase the efficacy of financial regulation.

A small but growing number of papers analyzes how ratings used for regulatory purposes affect financial stability. As shown by Rajan et al. (2015) in the context of securitization, risk depends on the behavior of the parties involved, it may change over time, and tracking it for regulatory purposes may be near-impossible.[12] The Basel Committee on Banking Supervision (2013) published

[10]As formulated by Kane (1977), complex rules in credit markets are likely to initiate "a dialectical process of adjustments and counter-adjustments [in which] bureaucratic controls and market adaptation chase each other round and round, generating additional problems, confrontations, and costs for society at large."

[11]Since the model-based regulation can be viewed as a move away from the flat tax regime (Basel I), our results support the view that a simple flat tax regulation might be optimal in cases where manipulation ('tax evasion') is possible.

[12]Another example is given by Acharya (2011), who argues that low risk-weights for residential mortgage-backed securities made investment in this asset class attractive and endogenously turned it into a systemically important asset class. Goel and Thakor (2015) develop a theory of coarse credit ratings to explain how coarse credit ratings are better for incentive compatibility than more precise ratings when involved parties have incentives to manipulate reported information.

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. As a consequence, market participants seem to lose faith in the meaning of risk-based capital ratios (Demirgüç-Kunt et al. 2013). 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. (2014) 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 combined with the richness of our data set allows us to identify the effect of the shift towards model-based regulation on measurement of credit risk. To the best of our knowledge, our paper is the first to demonstrate how banks exploited complex regulation to economize on regulatory capital.[13]

Importantly, our paper is not about explicit manipulation, outright fraud, or the complexity of models per se. Rather, we think that our findings illustrate that banks will always try to circumvent regulation, optimizing from a private perspective, and that complex regulation can be accompanied by considerable enforcement challenges. As such, our findings have important policy implications. As a response to the financial crisis in 2007-08, 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 arguably simplifies regulation by introducing leverage back stops. While it is hard to evaluate the efficacy of the new regulation, the evidence presented in this paper provides support for the view that simpler and more transparent rules could be more effective in achieving the ultimate goal of financial stability.[14]

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 present additional results in Section 6 and analyze how the reform affected banks' lending decisions and the structure of financing in Section 7. Section 8 discusses remaining concerns and Section 9 concludes.

[13] Two recent papers, Plosser and Santos (2014) and Begley et al. (2015), confirm our findings in different settings.

[14] See, e.g., Glaeser and Shleifer (2001), Hellwig (2010), Hoenig (2010), Haldane (2012), Admati and Hellwig (2013), Haldane (2013), Hoenig (2013), and Acharya et al. (2014). Most recently, debates in policy circles have focused on ways to constrain banks' regulatory discretion, also to prevent 'gaming' of internal risk models (see, for instance, Constâncio 2015 or Fender and Lewrick 2015).

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.[15] 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, 10, 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—Basel II, which was introduced in 2007—allowed banks to choose between two broad methodologies for calculating capital charges for credit risk: The so-called standard approach (SA) which was basically equivalent to the old Basel I framework with fixed risk-weights for corporate loans (100 percent of the loan amount);[16] and the model- or internal ratings-based (IRB) approach—with an additional distinction between Foundation IRB (F-IRB) and Advanced IRB (A-IRB)—that tried to establish a more granular link between capital charges and individual asset risk. Under IRB, loans get assigned individual risk-weights that crucially depend on the bank's internal risk estimates. Risk-weighted assets are calculated by multiplying these risk-weights with actual assets values, and capital requirements are defined in terms of risk-weighted assets as under Basel I (Basel Committee on Banking Supervision 2006).

Under both versions of the model-based approach, the F-IRB and the A-IRB, the firm-specific probability of default (PD)—our main variable of interest—has to be estimated by the bank. Therefore, we do not distinguish between the two approaches in large parts of the empirical analysis (we investigate differences between F-IRB and A-IRB in Section 6.3). Under the F-IRB approach, the bank estimates only the firm-specific PD, while loan-specific loss given default (LGD), exposure at

[15] The introduction of risk-weighted capital charges and the potential problems related to them have been discussed in several papers, e.g. Brinkmann and Horvitz (1995), Jones (2000), Daníelsson et al. (2001), Kashyap and Stein (2004), Hellwig (2010), and Behn et al. (2016). For an assessment from the side of the regulator see Basel Committee on Banking Supervision (1999).

[16] Risk mitigation instruments (i.e., collateral and guarantees that are eligible according to Basel II) can be used to decrease capital requirements. Exceptions to the fixed risk-weights 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. In unreported regressions we find that our results are less pronounced in the small subsample of firms with external credit ratings. Since external ratings may serve as a useful benchmark for regulators assessing the bank's internal risk models banks could be reluctant to underreport risk estimates for firms with external credit ratings, as misreporting would be more likely to be detected by the supervisor.

default (EAD), and maturity are given by the regulator and hard-wired into the calculation of risk-weights. Under the A-IRB approach—which may be chosen by the most sophisticated banks—banks plug calculated effective maturities and their own estimates for LGD and EAD (instead of the F-IRB standard values) into the formula and obtain similar mappings between PDs and regulatory risk-weights. The mapping between banks' internal risk estimates and regulatory risk-weights (using the standard parameters of the F-IRB approach) is illustrated in Figure 1. The risk-weight curve is relatively steep for the lowest PDs and becomes flatter for higher PDs. To provide banks with incentives to introduce IRB, it was calibrated in a way that ensured that capital requirements were somewhat lower under IRB than under SA (Basel Committee on Banking Supervision 2006, p. 12).

PD models used for regulatory purposes are meant to estimate borrowers' one-year probability of default.[17] Although models are estimated on a portfolio basis, PDs should be portfolio invariant in the sense that the capital required for a given loan depends only on the risk of that loan and not on the portfolio it is added to (Basel Committee on Banking Supervision 2005).[18] For corporate loans, the most important determinant of the PD is accounting information from firms' financial statements (see, e.g., Krahnen and Weber 2001). For loans to small and medium enterprises (SMEs), where there is often a significant publication lag for accounting information, target financial ratios or industry characteristics may also be used. Besides these quantitative factors, qualitative information such as a firm's management quality or its competitive situation can also be included in the models. However, since such information is by definition hard to quantify its impact on the risk estimate is rather limited. A prominent PD model used for the estimation of corporate credit risk is Moody's RiskCalc^{TM} 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. The borrower-specific PD estimates from banks' internal models have to be updated at least once a year to incorporate new information that becomes available. In cases where loan officers consider model outputs to be unreasonable they have the option of overwriting the predicted PD. However, if such overwrites occur too frequently,

[17] The German Solvabilitätsverordnung (2006) specifies that 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.

[18] As noted in the BIS document, "taking into account the actual portfolio composition when determining capital for each loan [...] would have been a too complex task for most banks and supervisors alike, [as] diversification effects would depend on how well a new loan fits into an existing portfolio. As a result, the 'Revised Framework' was calibrated to well diversified banks" (Basel Committee on Banking Supervision 2005, p.4).

the regulator may ask the bank to revise its model.

While the Basel framework was meant to harmonize international bank regulation, the implementation process of the new framework differed between countries. In Germany, Basel II was implemented by revision of the Solvabilitätsverordnung (2006), which provides the foundation for national bank regulation. The law specifies a strong supervisory review that includes on-site audits to ensure compliance with the regulatory framework (see also Deutsche Bundesbank 2004). Banks have to validate their models on an annual basis and adjust them if their estimates are inconsistent with realized default rates (see also Deutsche Bundesbank 2003). Further, risk models have to be certified by the supervisor and banks have to prove that a specific model has been used for internal risk management and credit decisions for at least three years before it can be used for regulatory purposes. Since the introduction of the IRB approach imposes sizeable organizational efforts and administrative expenses and also requires a certain degree of sophistication (Basel Committee on Banking Supervision 2004), it was only implemented by the largest banks.[19] Of our sample of 1,603 German banks, only 45 banks applied for an IRB license, but these banks account for about 50 percent of the loans in our sample. Of the 45 banks that introduced the IRB approach, 17 introduced F-IRB, 18 introduced A-IRB, and 10 use F-IRB for some portfolios and A-IRB for other portfolios.

The banks that opted for model-based regulation did not apply the new approach to all loans at once, but agreed on a gradual implementation plan with the supervisor. The plan specified an order according to which different loan portfolios were shifted to IRB. As the calibration of a 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. Other portfolios remained under SA until banks were able to prove that the respective model had been used internally for at least three years and did not over- or underpredict defaults. Otherwise, regulators delayed the approval of the model until they felt comfortable about the reliability of the model. The phased roll-out of IRB meant that during the transition, which typically lasted for several years, banks had 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.

[19]To be eligible for the model-based approach to capital regulation, banks need to prove that "their rating and risk estimation systems and processes provide for a meaningful assessment of borrower and transaction characteristics; a meaningful differentiation of risk; and reasonably accurate and consistent quantitative estimates of risk" (Basel Committee on Banking Supervision 2006).

3. Data

Our principal source of data is the German credit register compiled by Deutsche Bundesbank (MiMiK, see Schmieder 2006). As part of its supervisory role, the central bank collects data each quarter on all outstanding loans of at least € 1.5 million.[20] 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. In 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 loan-level information on the regulatory approach (SA or IRB) and the estimated probability of default (PD). Moreover, the database contains information on risk-weighted assets and actual loan losses. For the empirical analysis, we combine this loan-level data with annual bank balance sheet information from Deutsche Bundesbank's BAKIS database and annual firm balance sheet information from Deutsche Bundesbank's USTAN database.

Our sample includes 1,603 German banks, 45 of which opted for IRB following the introduction of Basel II (we will refer to these 45 banks as 'IRB banks'). 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. As mentioned before, only large and internationally active banks introduced IRB, while smaller regional banks remained under the standard approach.

Our loan-level data set contains three types of loans: (1) loans provided by SA banks; (2) loans provided by IRB banks that are still subject to SA; and (3) loans provided by IRB banks that are already subject to the new approach.[21] In large parts of the empirical analysis, we use only loans provided by IRB banks. 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 of PDs for IRB loans.

Descriptive statistics for SA and IRB loans provided by IRB banks during our sample period from 2008 to 2012 are presented in Panel B of Table 1, where we classify a given loan as IRB or SA depending on whether the reported PD for the loan was generated under the IRB or the SA regime. To understand this better, imagine a portfolio that was shifted to the IRB approach in 2009. At that time,

[20]Since we focus on corporate loans, this cut-off does not constitute a big issue for our analysis. The average loan amount in our sample is € 23 million, well above the cut-off, which makes it unlikely that we miss out on many loans.

[21]In Section 6.3, we break these loans down into those under Foundation IRB (F-IRB) and Advanced IRB (A-IRB).

the submitted PDs (which were also used in the process of approving the IRB model) were generated under the SA regime, and correspondigly the loans are still classified as SA loans. However, once the PDs are updated in 2010 (the updating generally happens just once a year), the entire loan portfolio is shifted from SA to IRB, since the updated PDs were generated under the IRB regime. Moreover, if for a given bank-firm relationship a new loan was issued in the interim (in the example above between 2009 and 2010), the bank generally updates the borrower's PD and we classify that relationship as IRB from the issuance of the loan onward because the PD for the respective borrower was generated under the IRB regime.

Although information in the credit register is available on a quarterly basis, PDs are updated only once a year unless there is some dramatic event or adverse news. Thus, to 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.[22]

The first line of Table 1, Panel B shows that the average PD is higher for SA loans (2.6 percent) 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 information (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.[23] 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 actual losses for loans (i.e., realized losses in a given period) in default to the credit register. 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 direct information on interest rates, we back out effective interest rates as described in detail in the Appendix A. Specifically, the simple structure of most German loan contracts allows us to infer the repayment schedules from the quarterly data on loan amounts. We match this contract-level information with firm-level data on aggregate interest payments obtained

[22]Results for the remaining quarters are very similar to the results we report.

[23]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.

from Deutsche Bundesbank's USTAN database and back out effective annual interest rates on the loan contract level.[24] As shown in the table, interest rates for loans under the standard approach are on average lower (7.9 percent) than interest rates for loans under IRB (8.8 percent). The last line of Panel B shows the average change in the amount of loans outstanding around the introduction of Basel II.[25] 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 Deutsche Bundesbank's USTAN database with the credit register.[26] The match was conducted based on company name, location, and industry segment, which 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

As discussed earlier, the introduction of Basel II was staggered over time, allowing us to exploit cross-sectional variation in the regulatory approach within a bank variation at each point in time. Restricting ourselves to the sample of loans from IRB banks, we estimate loan-level equations of the following type:

$$y_{ijt} = \alpha + \delta \cdot \mathbb{1}_{jpt} + \varepsilon_{ijt}, \tag{1}$$

where i denotes the individual bank, j denotes the individual firm, p denotes the loan pool within the bank (IRB or SA), and t denotes time. The dependent variable y_{ijt} is the logarithm of the loan-

[24] As we have to match the data from the credit register with firm balance sheet information for this procedure, the sample size for interest rates is considerably lower than for the remaining variables. We are able to back out interest rates for 11,759 loan-year observations. For a small sample we can compare the interest rates we have backed out with the actual interest rates and find that these match very closely (see Appendix A for details). The characteristics of loans in the interest rate sample, and in particular the differences between SA and IRB loans, are similar to those in the full sample, suggesting that it is unlikely that there is a significant selection bias in the interest rate sample.

[25] 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 seven quarters after the Basel II introduction (see Section 7.2 for more information). The change in lending is defined as the difference in the logarithm of these averages, so that there is one observation per loan.

[26] Even though the credit register and the accounting information all come from Deutsche Bundesbank, the two datasets have no unique identifier. For a detailed description of the USTAN data see Stoess (2001) or Bachmann and Bayer (2014).

specific PD reported at time t by the bank to the supervisor (LOG(PD)); alternatively, we use the ESTIMATION BIAS (i.e., the difference between a dummy for ACTUAL DEFAULT and the PD), the ratio of RWA TO LOAN (i.e., the ratio of a loan's risk-weighted assets by the corresponding loan amount), the actual LOSS RATE, or the INTEREST RATE as a dependent variable. The dummy $\mathbb{1}_{jpt}$ takes on a value of 1 if the PD for the respective loan of bank j at time t is classified as IRB and 0 if it is classified as SA (see Section 3). Furthermore, the equation includes a constant α and a random error term ε_{ijt}. In order to allow for potential correlation among default events for loans from the same bank or in the same year, standard errors are clustered at the bank $\times$ year level in all regressions.

Interpreting δ as the causal impact of the regulatory approach on y_{ijt} requires that the covariance between $\mathbb{1}_{jpt}$ and ε_{ijt} is equal to 0, i.e., $Cov(\mathbb{1}_{jpt}, \varepsilon_{ijt}) = 0$. Clearly, loans that were shifted first to the model-based approach could be different from loans that remained under the traditional approach and were shifted later. This non-random assignment of loans to IRB and SA pools raises endogeneity concerns, so that our coefficients could potentially be biased. To test for structural differences between IRB and SA models, we analyze their discriminatory power relative to each other (see Appendix B). The discriminatory power for SA and IRB models is in the same ballpark, where the models for IRB portfolios slightly outperform those for portfolios that are still under SA. This confirms our prior that regulators approved rather well performing models first.

To systematically 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:

$$y_{ijt} = \alpha_{it} + \alpha_{jt} + \delta \cdot \mathbb{1}_{jpt} + \varepsilon_{ijt}, \tag{2}$$

where α_{it} and α_{jt} denote firm $\times$ year and bank $\times$ year interactions, respectively, and the remaining variables are defined as in Equation (1). By adding α_{it} we are able to systematically control for time-varying heterogeneity across firms. That is, we can check whether the PD reported by different banks for the *same* firm in the *same* year is lower if a loan is part of the IRB pool as compared with the SA pool.[27] A similar analysis can be done for the other dependent variables (i.e., ESTIMATION BIAS,

[27]One could think about adding also bank $\times$ firm interactions, as this would allow to control for bank-firm specific factors. While this is statistically possible, we refrain from including bank $\times$ firm interactions in our main specifications, since it would induce a mechanical survivorship bias forcing us to find an effect even if none exists. We further discuss the issue in Section 6.4.

RWA TO LOAN, LOSS RATE, and INTEREST RATE). Further, the inclusion of α_{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.

While the identification strategy described above controls for bank specific shocks (α_{jt}), it is unable to control for time varying omitted factors that might influence the selection of loans into the IRB pool within a bank. For example, one may still be concerned about differences between the IRB loans (e.g., with respect to credit risk or contract terms) in portfolios that have already been shifted to the IRB approach and those that are shifted at a later point in time. To control for such concerns, one would have to include bank $\times$ year $\times$ loan pool (SA vs. IRB) interactions, α_{jpt}, which would absorb the variable of interest, $\mathbb{1}_{jpt}$. To circumvent this issue, we further refine the identification strategy and make use of the non-linear shape of the risk-weight formula and other cross-sectional information. Incentives to underreport borrowers' PD are particularly pronounced for firms with relatively low PDs, as the shape of the risk-weight curve implies that small increases in the PD lead to large increases in capital charges for loans to these firms (see Figure 1). By including an interaction between firm PDs and and the IRB dummy in Equation (2) we can test whether underreporting is indeed more pronounced for firms with low PDs. Importantly, such a test allows for the inclusion of bank $\times$ year $\times$ loan pool interactions that control for time varying omitted factors that could potentially influence the selection of loans into the IRB pool within a specific bank. Furthermore, we examine whether the degree of underreporting depends on certain bank characteristics such as capitalization (since less capitalized banks have higher incentives to economize on regulatory capital). Such cross-sectional tests allow us to further strengthen the rationale behind our findings.

5. Empirical results

5.1. Aggregate analysis

Table 2 and Figure 2 show average values of key variables between 2008 and 2012 for SA and IRB loans from the 45 banks that adopted the IRB approach (IRB banks). 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 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 explained in Section 2, PDs are meant to estimate one-year default rates. 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.

We find that 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. In sharp contrast, actual default rates for IRB loans are higher than those for SA loans in all years (see Table 2). 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 a slight overprediction of default rates in the remaining years. During our sample period, the German economy underwent a slowdown and a recovery. As documented in Figure 3, GDP decreased and aggregate default rates increased until the first quarter of 2009. For the rest of our sample period GDP recovered and the default rate constantly decreased. While these business cycle fluctuations affected the level of default rates, the difference in ESTIMATION BIAS between IRB models and SA models is relatively stable over the business cycle.[28] The difference in ESTIMATION BIAS between IRB and SA loans is a striking result, also given that IRB models tend to have a slightly higher discriminatory power than SA models (see Appendix B).

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. The data from the credit register allows us to examine 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.

Average values for the ratio of RWA TO LOAN and the actual LOSS RATE are also displayed in Table 2 and Figure 2. 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

[28]The difference in ESTIMATION BIAS between the IRB and SA loan pool is 1.6 percentage points (PP) in 2008; 1.4 PP in 2009; 1.2 PP in 2010; 1.3 PP in 2011, and 1.0 PP in 2012. See also lower right panel of Figure 2.

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. Although banks have lower capital charges on average, they actually tend to lose more money with loans under IRB.

Taken together, financial institutions have lower capital charges and at the same time experience higher loan losses under model-based regulation. But do these findings mean that banks misjudged credit risk under the new approach? Or were they aware of the higher level of risk in portfolios under the model-based approach, and did they simply use 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 2, and in stark contrast to PD and risk-weight estimates, interest rates for loans under IRB are 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.

5.2. Regression framework: IRB versus SA loans

We will now test our assertions more formally in a regression framework. Regression results using the logarithm of the loan-specific PD as a dependent variable are presented in Table 3, Panel A.[29] Column 1 shows that PDs for IRB loans are considerably lower than PDs for SA loans. As already noted, PDs do not capture recovery rates that might also vary from bank to bank. Thus, all banks that are providing loans to a specific firm should arrive at similar PD estimates, even though they may have very different financial contracts with the firm.[30] However, including firm fixed effects in column 2 we find 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 year fixed effects in column 3. In column 4, we include firm $\times$ year interactions. In this test, the sample is constrained to firm-year 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 year. Finally, the result is also robust to the inclusion of bank $\times$ year interactions in column 5: PDs from the same bank in the same year are significantly lower for loans under IRB. The magnitudes are large: PDs for IRB loans are

[29]The distribution of PDs in logarithms looks more Gaussian and is less prone to outliers, thus improving the properties of the OLS estimation. We also used the PD in levels as a dependent variable, winsorized at the 5 percent level to take care of the outliers, and obtained very similar results.

[30]For example, a bank giving a secured loan to a firm and another bank giving an unsecured loan to the same firm should arrive at similar PDs even though exposures at default and recovery rates are likely to be different.

22 to 30 percent smaller than PDs for SA loans.[31] A back-of-the-envelope calculation indicates that the estimate in column 5 translates into a 16.1 percent increase in ROE for the IRB loan portfolio.[32] This illustrates that the 'perceived benefits' from gaming risk-weighted assets for credit risk under the IRB approach can be quite sizable.

In Panel B of Table 3 we use the loan-specific ESTIMATION BIAS, 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 percentage points on average, whereas the ESTIMATION BIAS 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), year fixed effects (column 3), firm × year interactions (column 4), and bank × year 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 look again at risk-weights and actual loan losses. Applying the same estimation strategy as before, we find that the ratio of RWA TO LOAN is 10 to 15 percentage points lower for loans under IRB, even for loans to the same firm in the same year (Table 3, Panel C). 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 columns 2-4 of Table 3, Panel D.

Finally, interest rates for these loans are about 0.9 percentage points higher than interest rates for loans under SA (Table 3, Panel E, column 1). Also, in the remainder of the table, we get highly significant coefficients for the IRB loan dummy, which is a remarkable finding. In sharp contrast to

[31] Following Halvorsen and Palmquist (1980), Kennedy (1981), and van Garderen and Shah (2002), when interpreting the effects of dummy variables in semi-logarithmic equations coefficients should be adjusted as

$$\hat{M}_{Kennedy} = 100 \ exp\left(\hat{\delta} - \frac{1}{2}\hat{Var}(\hat{\delta})\right) - 1$$

while standard errors can be obtained as

$$SE(\hat{M}_{Kennedy}) = 100 \sqrt{exp\left(2 \ \hat{\delta}\right)\left[exp\left(-\hat{Var}(\hat{\delta})\right) - exp\left(-2 \ \hat{Var}(\hat{\delta})\right)\right]}.$$

[32]This approximation is based on the following accounting identity: $ROE = \frac{NetIncome}{Equity} = \frac{ROA \times Assets}{Equity} = ROA \times \frac{Assets}{RWA} \times \frac{RWA}{Equity}$. Assuming a roughly fixed ROA and a fixed target Tier 1 ratio, it follows that: $\widehat{ROE} \approx -\left(\frac{\widehat{RWA}}{Assets}\right)$. The median PD for IRB loans is 0.38 percent, and an underestimation of 25 percent (Table 3, panel A, column 5) would translate into a PD of 0.285 percent. Under the F-IRB approach, this corresponds to a decrease in risk weights from 0.65 to 0.56 of the loan amount. Given that the percentage change in ROE is equal to the negative of the percentage change in the average risk-weight, this implies a 16.1 percent increase in ROE.

PDs and RWA TO LOAN, interest rates on IRB loans are significantly higher than interest rates on SA loans to the same firm in the same year. It is important to note that we only have interest rates on a small subset of loans which explains the drop in the number of observations.[33]

6. Additional results

6.1. Exploiting the non-linearity of the Basel function ('curvature test')

In this section we further refine the identification strategy 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 2, 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, to address any remaining concerns, we saturate Equation (2) with bank $\times$ year $\times$ loan pool (SA vs. IRB) interactions and exploit the non-linear shape of the mapping from PDs into regulatory risk-weights (recall Figure 1). Specifically, we evaluate credit risk models for IRB loans relative to those for SA loans, distinguishing between firms with relatively low PDs and firms with relatively high PDs. The shape of the risk-weight function implies that incentives to underreport PDs are higher for loans to the former group of firms.[34]

Panel A of Table 4 provides the corresponding regression results. We first use the PD as a dependent variable and estimate the difference in PDs between loans under SA and IRB, distinguishing between firms with an average initial PD below and above the median. We either use the whole sample of firms (columns 1 and 2), or the restricted sample of firms that have both IRB and SA loans from IRB banks (columns 5 and 6). As before, PDs for loans under IRB are lower than PDs for loans under SA, particularly for firms with below median PDs (more negative coefficient). This means that banks report lower PDs for precisely those loans where small reductions in the PD translate into large reductions in risk-weighted assets. In columns 3 and 7 we interact the firm's average PD with the IRB loan dummy and find a significant effect for the interaction term. The magnitude of the coefficient implies that underreporting of PDs for loans under the model-based approach as compared with loans under the traditional approach is about 14.5 percent larger for firms at the 25^{th} percentile

[33]We have re-estimated all specifications on the subset of loans for which we have the interest rates and the patterns we find are very similar to those seen in the full sample.

[34]This can be illustrated with a simple example: Assume that a firm has a PD of 1 percent; applying standard parameters for LGD, EaD, and M, reducing the firm's PD by 0.5 percentage points (PP) reduces risk-weighted assets by about 30 PP. In contrast, for a firm with a PD of 3 percent, a reduction by 0.5 PP reduces risk-weighted assets by 8 PP.

compared with firms at the 75^{th} percentile of FIRM PD (column 3). Including firm fixed effects and restricting the sample to firms with multiple relationships under IRB and SA, the magnitude is about 6.8 percent (column 7). Finally, we add bank $\times$ year $\times$ loan pool interactions that control for any differences between SA and IRB portfolios of a specific bank (columns 4 and 8). Results are unaffected.

In Panel B of Table 4, we use the ESTIMATION BIAS as a dependent variable. There are considerable differences in the ESTIMATION BIAS between IRB and SA loans for firms with below median average PDs (columns 1 and 5). Within this sample, the underestimation effect is about 1 percentage point larger for loans under IRB, a significant effect given the sample median of 0.9 percent for the average PD. For firms with above median average PDs, i.e., firms in the flat section of the PD-to-risk-weight mapping, there is no statistically significant difference between loans under the new and old regulatory regimes. Interaction terms are highly significant and economically meaningful: The difference in ESTIMATION BIAS between IRB and SA loans is 0.3 to 0.5 percentage points larger for firms at 25^{th} percentile as compared with firms at the 75^{th} percentile of FIRM PD (column 3 and 7). As above, the inclusion of bank $\times$ year $\times$ loan pool interactions does not affect the results (columns 4 and 8).

Results in this section suggest that our findings are driven by incentives to underreport PDs in order to economize on regulatory capital, as the underestimation effect is stronger for those loans where small decreases in the PD imply large decreases in the risk weight. The inclusion of bank $\times$ year $\times$ loan pool interactions non-parametrically controls for time-varying omitted factors which could affect the selection of loans into the IRB pool within a specific bank. Furthermore, as the test compares the differential performance of IRB models along the PD band (low PD vs. high PD) with that of SA models along the same band, it allays concerns regarding any potential differences between SA and IRB models that could bias the analysis.

6.2. Differences in bank capitalization

Banks that are sufficiently capitalized have less incentives to economize on regulatory capital since the marginal benefit of relaxing regulatory constraints is smaller. To test whether such cross-sectional variation affects the degree of underreporting, we introduce sample splits based on differences in banks' capitalization (measured by the capital adequacy ratio) and run our main regressions separately for each subsample. As for all our balance sheet variables, we use pre-reform values for bank capitalization, since current values would be affected by the treatment (IRB implementation).

Table 5 summarizes our findings on the effects of bank capitalization. For banks with lower capitalization regulatory capital requirements are more likely to become a binding constraint. Consequently, incentives to underreport PDs are considerably higher for these banks. In line with this argument, we find that the underreporting of PDs for IRB loans relative to SA loans is particularly pronounced for banks with a capital ratio below the median. Controlling for bank $\times$ year interactions, PDs for IRB loans are 27 percent lower than PDs for SA loans in the group of less capitalized banks, whereas the effect is only 18 percent in the group of better capitalized banks (Table 5, Panel A, columns 4 and 5). More importantly, for banks with a high capitalization the difference in ESTIMATION BIAS between IRB and SA loans is statistically insignificant (Panel B, column 4). In contrast, the same difference amounts to a full percentage point and is highly significant for banks with a low capitalization (column 5). Overall, these results suggest that the level of misreporting is higher the more the respective bank benefits from relaxing regulatory capital requirements.

6.3. Foundation versus Advanced IRB approach

As explained in Section 2, banks that opted for the new regulatory approach could choose between two alternatives to determine capital charges for their loan portfolios: The Foundation IRB (F-IRB) approach and the Advanced IRB (A-IRB) approach. Compared to the F-IRB approach, the A-IRB approach gives banks more flexibility in determining capital charges since it requires them to estimate not only the borrower's PD, but also loan-specific factors such as loss given default (LGD) and exposure at default (EAD). Under the F-IRB approach these loan-specific parameters are provided by the regulator and hard-wired into the calculation of risk-weights. Consequently, the PD is the only parameter that banks can adjust in the F-IRB approach, whereas under A-IRB they can adjust other parameters as well. Incentives to underreport PDs might therefore be higher under F-IRB, since it could be preferable for banks to underreport LGDs or other risk parameters rather than PDs under the more complex A-IRB approach (e.g. in case deviations of reported and actual PD are easier to detect than deviations of reported and actual LGDs).

For the years from 2008 to 2012, our sample includes 100,616 loans under F-IRB and 132,171 loans under A-IRB.[35] Average values of estimated PDs, actual defaults, risk weights, loan losses, interest rates and the estimation bias for these loans are shown in Figure 4. Compared with the F-IRB approach, reported PDs (as well as actual defaults and loss rates) are higher for loans under the A-IRB approach, while risk weights tend to be lower. This is consistent with a story in which there is less manipulation of PDs, but more manipulation of other parameters for loans under the A-IRB approach. That is, more discretion on the side of banks seems to come along with more manipulation. In line with this story, interest rates charged on A-IRB loans are higher (although the reported risk-weights are lower) than those for loans under F-IRB, suggesting that banks are aware of the higher risks associated with these loans. Unfortunately, power issues prevent us from doing a fully-fledged regression analysis, as coefficients tend to be insignificant in saturated specifications with bank $\times$ year and firm $\times$ year interactions (although the magnitudes of coefficients are quite sizable).

6.4. Mechanism and origin of the underestimation of default rates

Underestimation of actual default rates for IRB loans can either originate from direct manipulation of PDs of existing loans, after the portfolios have been shifted to the IRB approach, or from new loans that are granted by the bank. While IRB models themselves cannot be adjusted (without permission from the regulator), it is perhaps possible to manipulate the inputs that go into these models to the extent that the inputs require some degree of subjectivity, that is, contain what is often referred to as "soft" information. Model-based regulation may change the incentives of banks to originate loans that score more favorably on dimensions that are captured by the model, while ignoring negative "soft" information that is vital in determining the credit risk of loans. This change in incentives may alter the quality of loans originated by the bank, which in turn affects the performance of the models that have been approved by the regulator.

To shed light on the underlying mechanism behind our findings we conduct two additional tests. First, we compare estimation biases of loans that were originated in the SA regime and the IRB regime ('cohort test'). Second, we examine whether banks reduce reported PDs once a portfolio has been shifted to the IRB regime (to save on regulatory capital).

For the 'cohort test', we restrict ourselves to loans using the IRB approach that were granted in the 12 months before and after the reform in 2007. That is, we include bank-firm relationships under

[35] As mentioned in Section 2, of the 45 banks that introduced the IRB approach, 17 introduced F-IRB, 18 introduced A-IRB, and 10 use F-IRB for some portfolios and A-IRB for other portfolios.

the IRB approach (a) that newly appear in our dataset in either 2006 or 2007, or (b) that already existed before but exhibit a new loan issuance in either 2006 or 2007. Using this subsample, we check whether the underestimation of actual default rates at a given point in time is greater for loans that were originated after the reform as compared with loans that were originated before the reform. Specifically, we estimate the following equation:

$$y_{ij} = \alpha_j + \delta \times \mathbb{1}_{(l \in B)} + \varepsilon_{ij}, \tag{3}$$

where y_{ij} is the relationship-specific estimation bias as before and $\mathbb{1}_{(l \in B)}$ is an indicator variable that takes a value of 1 if the IRB loan was issued in the 12 months following the implementation of Basel II (i.e., 2007) and 0 if it was issued in the year prior to the reform (i.e., 2006). We evaluate the ESTIMATION BIAS for these loans in 2009 and 2010 (we could also do that in the years 2011 and 2012 – however given that some loan mature before, the number of observations is decreasing with every year we move forward). 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 in the 12 month both before and after the reform. We also run the same specification for the sample of SA loans, which serve as a control group.

Table 6 provides regression results for Equation (3). We find a significant difference in ESTIMATION BIAS between the two regimes both in 2009 (columns 1 to 4) and 2010 (columns 5 to 8). That is, PDs for IRB loans *originated* under Basel II are significantly more likely to underestimate actual default rates than PDs for IRB loans *originated* before the reform. Columns 2 and 5 show 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 0.8 percentage points more in 2009 and by about 1 percentage point more in 2010. As a placebo test, we replicate Equation (3) using SA loans only. Here, we find no statistical difference between loans issued in 2006 and 2007. Note that this specification is not prone to selection concerns with respect to the order in which IRB banks transfer their portfolios to the new regulatory approach, since the coefficient of interest is estimated within the sample of IRB loans only.

In the second test, we examine how the PD of existing relationships changes once our classification switches from SA to IRB (i.e., once the PD of a loan whose portfolio switched from SA to IRB has been updated, see Section 3). In other words, we estimate our main specification on the sample of loans for which the classification switches from SA to IRB throughout our sample period, adding bank $\times$ firm interactions that ensure that the coefficient of interest is identified from within-relationship variation. There is no significant change in PD once the classification for a relationship changes from SA to IRB.[36]

Overall, the results in this section suggest that our main findings are driven by new loan origination following the introduction of model-based regulation. We document that loans originated under the IRB regime have a significantly larger ESTIMATION BIAS than loans originated under the SA regime. Further, PDs are not manipulated downwards once the loan portfolio is transferred to the IRB regime.[37] Instead, the introduction of model-based regulation changed banks' incentives and in turn affected the performance of the models that are used to measure credit risk.

7. Effects on lending and the structure of financing

7.1. Bank-level evidence

In this section, we try to identify potential winners and losers of the reform. 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. 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 were unable to bear the cost and did not introduce the new approach. Here, we analyze whether the reform's differential impact on capital requirements had consequences for banks' lending behavior.

The left-hand panel of figure Figure 5 illustrates that the aggregate supply of credit to domestic non-banks by all German banks increased considerably around the Basel II reform in 2007. Interestingly, specifically those banks that introduced the model-based approach expanded their lending to corporate borrowers in Germany following the reform (see right-hand panel of Figure 5).[38] Prior to the reform, the development of loan growth 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

[36]Results are available upon request.

[37]This is perhaps not very surprising, as a systematic downward correction in PDs after a portfolio is transferred to IRB would attract the attention of the supervisors.

[38]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.

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 7, columns 1 and 2, shows that IRB banks increased their lending by about 9 percent as compared with SA banks.[39] Thus, larger banks drastically expanded their lending relative to smaller banks, resulting in a concentration of market shares in the market for corporate loans.

7.2. Loan-level evidence

Under IRB, the capital charge for a specific loan depends on the estimated PD for that loan. 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 in this variable on an interaction between an IRB bank dummy and the firm's PD. Formally, we run the following regression:

$$\Delta LOG(LOANS)_{ij} = \alpha_i + \alpha_j + \gamma \cdot \left[\mathbb{1}_j \times pd_i\right] + \varepsilon_{ij}, \tag{4}$$

where i denotes the individual firm, and j denotes the individual bank. Following Khwaja and Mian (2008), the dependent variable is constructed by collapsing the quarterly data for a given firm-bank relationship into single pre-event and post-event observations. Specifically, we calculate the average loan amounts in the two years before and the seven quarters after the Basel II introduction and use the log difference between the two as dependent variable. We are not including the last quarter of 2008 in the post event period, since average PDs considerably increased in Germany following the Lehman collapse at the time which resulted in a considerable increase of capital requirements of IRB loans (see Behn et al. 2016, and the right-hand panel of Figure 5, which shows that IRB banks reduced their lending more than SA banks following the Lehman collapse). As an independent variable, we use the average PD banks report for each firm in 2008Q1, the first quarter for which this information is available. The variable is interacted with the dummy $\mathbb{1}_j$ that indicates whether the bank adopted IRB during our sample period. 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, α_i (see Khwaja and Mian 2008). The 44,784 observations in the loan-level regressions correspond to all loans to firms with at least one

[39] 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). The coefficient for the IRB bank dummy remains significantly positive.

loan from an IRB bank and at least one loan from an SA bank. Bank fixed effects, α_j, systematically control for heterogeneity across banks (e.g. differences in bailout expectations). 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 7, 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 FIRM PD 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 the reform did indeed change the quantity and the composition of bank lending.

To overcome potential identification issues we apply a similar identification strategy as in the main part of the paper. Specifically, we exploit variation in the regulatory approach (IRB vs. SA) within the sample of banks that have adopted the IRB approach (IRB banks). Restricting the sample to IRB banks and distinguishing between the IRB and SA portfolios of these banks, we estimate:

$$\Delta LOG(LOANS)_{ij} = \alpha_i + \alpha_j + \delta \, \mathbb{1}_{jp} + X_{ij}'\gamma + \varepsilon_{ij}, \qquad (5)$$

where p denotes the regulatory approach of the loan and $\mathbb{1}_{jp}$ takes the value of one if the respective loan is in the IRB pool and zero if it is in the SA pool of bank j. As before, firm and bank fixed effects allow to control for firm-specific credit demand shocks, bank-specific credit supply shocks, and other sources of heterogeneity across firms or banks. Our sample is restricted to firms that borrow from at least two IRB banks—one bank where the loan is in the IRB pool and another where the loan is subject to the SA.

Regression results for Equation (5) are shown in Table 8, columns 1-3. Recall that risk weights for IRB loans are on average 12 percentage points lower than risk weights for SA loans (Table 1), which translates into a reduction in capital requirements of about 1 percentage point (since capital requirements are 8 percent of RWA: $0.08 \times 0.12 = 0.0096$). In response, loans in the IRB portfolios are increased by about 8 percent more than loans in the SA portfolios of IRB banks (column 1). Interestingly, the constant (which indicates the average change for SA loans) is positive, so that both

IRB and SA loans increased on average over the reform. This illustrates that the reform had a positive effect on aggregate lending. Results are robust to the inclusion of bank fixed effects in column 2 and firm fixed effects in column 3. The coefficient in column 3 implies that loans in portfolios that were transferred to IRB following the introduction of Basel II were increased by more than 5 percent more than loans in portfolios that were not transferred.[40] Overall, results suggests that the reform caused an increase in lending on the intensive margin.

In Section 6.3, we argue that the ESTIMATION BIAS for portfolios under model-based regulation is mainly driven by new loans. To test whether IRB banks extended more new loans in the IRB portfolios, we construct a dummy variable (NEW LOAN) that takes the value of one if—either for an existing or a new bank-firm relationship—a new loan was issued during the post-event period. We then reestimate Equation (5), using NEW LOAN instead of ΔLOG(LOANS) as a dependent variable. Results are shown in columns 4-6 of Table 8. In line with our argumentation, the issuance of a new loan for a given borrower is 5 to 12 percent more likely if the firm finds itself in a portfolio that has already been shifted to the IRB approach.

8. Discussion

The broad array of results suggests that the introduction of Basel II-type model-based capital regulation affected the validity of banks' internal risk estimates and that banks have lower capital charges and at the same time experience higher loan losses. Our findings can be explained by incentives for banks to underreport PDs in order to economize on regulatory capital. In this section, we discuss some remaining concerns and alternative stories that may seem consistent with our findings.

8.1. Conservatism of SA models

Our empirical analysis benchmarks the performance of IRB models with SA models. This raises a natural concern: what if the benchmark is incorrect? In other words, if banks take a more conservative approach when estimating PDs for SA loans in order to get these models approved by the regulator, then this would obfuscate the identification strategy. There are several reasons why we

[40]The magnitudes of the effects are consistent with findings by Aiyar et al. (2014), who find for the U.K. that a one-percentage-point increase in capital requirements induces a decline in bank-level loan growth of 6.5 to 7.2 percentage points. Studies estimating the effect of higher bank capital ratios on loan growth usually find somewhat smaller effects (see Carlson et al. 2013 for an overview).

do not consider this a cause for concern. To begin with, it should be noted that prior to regulatory approval, banks need to prove that a specific model has been used internally for at least three years and does not under- or overpredict actual default rates (see Section 2).[41] Thus, strategic conservatism does not really help their cause and only delays the transfer process. Our empirical analysis confirms this view, as we do not find any evidence of strategic behavior. As reported earlier, the coefficient for the SA loan dummy in column 1 of Table 3, Panel B is not different from zero. Moreover, we do not observe a systematic downward adjustment of PDs once a loan portfolio is shifted from SA to IRB. But most importantly, the 'curvature test' in Section 6.1 directly address any concerns that relate to potential differences between SA and IRB models, as it allows for the inclusion of bank $\times$ year $\times$ loan pool interactions that systematically account for such effects. If conservative estimates on SA loans were driving our results, one would not expect the underestimation effect to be stronger for low PD loans.

8.2. Regulatory rigidity

It could also be that the failure of credit risk models was caused by the need to comply with rigid regulatory standards, rather than by misaligned incentives. Regulators required banks to stick to the models that were approved and this took away some discretion from the banks and reduced their ability to adapt to changing times. While banks had the flexibility to adjust the PDs and other parameters if banks felt they were incorrect, a large amount of such adjustments would draw some flak from the regulator. Thus, it could be the lack of discretion that came with the regulation which led to the failure of models, rather than misaligned incentives. It could further be that interest rates did a better job at predicting defaults because banks had the flexibility to adjust their own risk models to the new information. Our results speak against such a story. We find that more discretion given to banks implies worse underperformance of credit risk models. Under the F-IRB approach, banks only use model-based PDs, while LGD and EAD are given by the regulator and hard-wired into the risk-weight calculation. Under the A-IRB approach, banks use their own model-based parameters also for LGD and EAD and thus have more discretion in determining capital charges. We find that more autonomy implies a higher degree of incongruence between reported risk weights and actual loan losses.

[41] Based on conversations with supervisors, there is no evidence of banks overreporting estimated default rates during the approval process.

9. Conclusion

Using data from the German credit register, we show that the introduction of Basel II-type, model-based capital regulation affected the validity of banks' internal risk estimates. We find that for the *same* firm in the *same* year, both reported PDs and risk-weights are significantly lower, while estimation biases and loan losses are significantly higher for loans under the new regulatory approach. Thus, risk estimates for loans under the model-based approach systematically underestimate actual default rates. There is an incongruence between the reported PDs/risk-weights and interest rates charged for loans under model-based regulation, suggesting that banks were aware of the inherent riskiness of these loan portfolios. To account for potential differences in the correlation structure in the IRB and SA pools, we look at aggregate results. We find a significant underestimation of default rates and higher loss rates in the IRB pool, which tells us that better diversification in IRB portfolios compared with SA portfolios does not solve the underestimation problem. All in all, our results suggest that simpler rules may have their benefits, and encourage caution against the current trend towards higher complexity of financial regulation.

Importantly, our paper does not make any welfare statements about model-based regulation. While we observe that banks underestimate the level of risk, it could be that the reform positively affected the cross-sectional predictability of defaults within the pool of IRB loans. Moreover, we demonstrated that lower capital charges for loans under model-based regulation promoted lending by large banks, with potentially beneficial effects for certain borrowers. Also, the regulation may have lowered distortions in the cross-section as the capital charge was more tied to a particular loan risk. We do not make a judgment on these aspects of model-based regulation. Rather, we benchmark the reform against its stated objectives and conclude that, following the reform financial institutions have lower capital charges and at the same time experience higher loan losses.

Our findings can be explained by incentives for banks to underreport PDs in order to economize on regulatory capital. This interpretation is supported by the fact that interest rates, in contrast to PDs/risk-weights, seem to reflect borrowers' actual default risk, and by the fact that the underreporting of PDs is more severe for low PD loans, for which small reductions in the PD translate into large reductions in risk-weights. While we do not analyze the effect of model-based regulation on overall systemic risk, it is very likely that the stability of the financial sector as a whole has been adversely affected. Clearly, the reform induced a considerable reduction in capital requirements while actual loan losses have been higher for loans under the new regulation. It is likely that lower capital buffers under the new regime increased banks' vulnerability to credit risk shocks. Furthermore, our results on market segmentation (Section 7.3), suggest that IRB banks have become more interconnected. This increase in interconnectedness of IRB banks may further compromise financial stability, a rather unintended effect of the reform.

Finally, one may argue that not model-based regulation in itself, but rather the way in which it was implemented (self-reporting of risks) caused the problems we document. Certainly, one would expect less of a downward bias in risk estimates if model outputs were generated by the regulator and not the banks themselves, although such an approach could be subject to other problems. However, we note that also under the current regulation banks only propose models, while the final decision on model approval rests with the supervisors. In other words, supervisors are already heavily involved in the process, and still we observe the patterns documented above. In interpreting our findings, one should keep in mind Goodhart's Law (or the Lucas critique): "When a measure becomes a target, it ceases to be a good measure;" or, applied to our case: once the rules are in place, banks have incentives to change their behavior, which will adversely affect the performance also of models implemented by the supervisor. Thus, we have doubts whether the problems documented in our paper would be solved if complex models were implemented by regulators or supervisors instead of the banks themselves.

Our findings raise important questions about political economy factors that might play a role in the introduction of complex regulation. While the political economy side of complexity is not the focus of this paper, our results support the regulatory capture view of regulation (Stigler 1971, Posner 1975, Peltzman 1976, Becker 1983, Shleifer and Vishny 2002). The high compliance costs associated with the model-based approach meant that only the larger banks adopted this new approach and consequently benefited from lower capital charges. Moreover, one could argue that regulators and supervisors 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). The number of financial supervisors has dramatically increased around the world, at a much faster pace than the number of people working in the financial industry (Haldane 2013), where the most recent step in this direction was the creation of about 1,000 new supervisory positions at the European Central Bank. The political economy of complex financial regulation remains an interesting topic for further research.

References

Acharya, V. (2011). Ring-fencing is good, but no panacea. In *The Future of Banking (edited by Thorsten Beck)*. Vox eBook.

Acharya, V., Engle, R., and Pierret, D. (2014). Testing macroprudential stress tests: The risk of regulatory risk weights. *Journal of Monetary Economics*, 65.

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

Aiyar, S., Calomiris, C., and Wieladek, T. (2014). Does macro-prudential regulation leak? evidence from a uk policy experiment. *Journal of Money, Credit and Banking*, 46(s1):181–214.

Bachmann, R. and Bayer, C. (2014). Investment dispersion and the business cycle. *American Economic Review*, 104(4):1392–1416.

Basel Committee on Banking Supervision (1988). *International convergence of capital measurement and capital standards*. Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision (1999). *Capital requirements and bank behaviour: The impact of the Basle Accord*. Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision (2004). *Implementation of Basel II: Practical considerations*. Bank for International Settlements, Basel, Switzerland.

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

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

Basel Committee on Banking Supervision (2013). *Regulatory consistency assessment programme (RCAP): Analysis of risk-weighted assets for credit risk in the banking book*. Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision (2014). *Capital floors: the design of a framework based on standardised approaches*. Bank for International Settlements, Basel, Switzerland.

Becker, G. (1983). A theory of competition among pressure groups for political influence. *Quarterly Journal of Economics*, 98(3):371–400.

Begley, T., Purnanandam, A., and Zheng, K. (2015). The strategic under-reporting of bank risk. *Ross*

School of Business Paper.

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

Brinkmann, E. J. and Horvitz, P. M. (1995). Risk-based capital standards and the credit crunch. *Journal of Money, Credit and Banking*, 27(3):848–863.

Brunner, A. and Krahnen, J. P. (2008). Multiple lenders and corporate distress: Evidence on debt restructuring. *Review of Economic Studies*, 75(2):415–442.

Brunner, A. and Krahnen, J. P. (2013). Hold-up in multiple banking: Evidence from sme lending. *International Journal of Banking, Accounting and Finance*, 5(1):78–101.

Carlson, M., Shan, H., and Warusawitharana, M. (2013). Capital ratios and bank lending: A matched bank approach. *Journal of Financial Intermediation*, 22(4):663–687.

Constâncio, V. (2015). Financial regulation and the global recovery. Available online: https://www.ecb.europa.eu/press/key/date/2015/html/sp150416.en.html. Speech at the 24th Annual Hyman P. Minsky Conference, Washington.

Daníelsson, J., Embrechts, P., Goodhart, C., Keating, C., Muennich, F., Renault, O., and Shin, H. S. (2001). An academic response to Basel II. LSE Financial Markets Group, Special Paper No. 130.

Demirgüç-Kunt, A., Detragiache, E., and Merrouche, O. (2013). Bank capital: Lessons from the financial crisis. *Journal of Money, Credit and Banking*, 45(6):1147–1164.

Deutsche Bundesbank (2003). Approaches to the validation of internal rating systems. *Monthly Report September*, pages 59–71.

Deutsche Bundesbank (2004). New capital requirements for credit institutions (Basel II). *Monthly Report September*, pages 73–94.

Duellmann, K. and Koziol, P. (2014). Are SME loans less risky than regulatory capital requirements suggest? *Journal of Fixed Income*, 23(4):89–103.

Fender, I. and Lewrick, U. (2015). Calibrating the leverage ratio. *BIS Quarterly Review*, Bank for International Settlements, Basel, Switzerland.

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

Goel, A. and Thakor, A. (2015). Information reliability and welfare: A theory of coarse credit ratings. *Journal of Financial Economics*, 115:541–557.

Gorodnichenko, Y., Martinez-Vazquez, J., and Sabirianova Peter, K. (2009). Myth and reality of flat tax reform: Micro estimates of tax evasion response and welfare effects in Russia. *Journal of Political Economy*, 117(3):504–554.

Haldane, A. (2012). The dog and the frisbee. Available online: http://www.bankofengland.co.uk/publications/Documents/speeches/2012/speech596.pdf. Bank of England, Speech on 31 August.

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

Halvorsen, R. and Palmquist, R. (1980). The interpretation of dummy variables in semilogarithmic equations. *American Economic Review*, 70(3):474–475.

Hellwig, M. (2010). Capital regulation after the crisis: Business as usual? *CESifo DICE Report*, 8(2):40–46.

Hoenig, T. (2010). Banking: From Bagehot to Basel, and back again. Available online: http://www.bankofengland.co.uk/publications/Documents/speeches/2010/speech455.pdf. Bank of England, Speech on 25 October.

Hoenig, T. (2013). Basel III capital: A well-intended illusion. Available online: http://www.fdic.gov/news/news/speeches/spapr0913.html. FDIC, Speech on 9 April.

Holmström, B. and Milgrom, P. (1991). Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, and Organization*, 7:24–52.

Jensen, M. C. and Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 3(4):305–360.

Jones, D. (2000). Emerging problems with the Basel capital accord: Regulatory capital arbitrage and related issues. *Journal of Banking and Finance*, 24(1):35–58.

Kane, E. (1977). Good intentions and unintended evil: The case against selective credit allocation. *Journal of Money, Credit and Banking*, 9(1):55–69.

Kashyap, A. K. and Stein, J. C. (2004). Cyclical implications of the Basel II capital standards. *Federal Reserve Bank of Chicago: Economic Perspectives*, (1):18–31.

Kennedy, P. (1981). Estimation with correctly interpreted dummy variables in semilogarithmic equations. *American Economic Review*, 71(4):801.

Khwaja, A. I. and Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–1442.

Koijen, R. and Yogo, M. (2015). The cost of financial frictions for life insurers. *American Economic Review*, 105:445–475.

Koijen, R. and Yogo, M. (2016). Shadow insurance. *Econometrica*, forthcoming.

Krahnen, J. P. and Weber, M. (2001). Generally accepted rating principles: A primer. *Journal of Banking and Finance*, 25(1):3–23.

Moody's Analytics (2013). RiskCalc^{TM} Plus. Available online: http://www.moodysanalytics.com/~/media/Brochures/Enterprise-Risk-Solutions/RiskCalc/RiskCalcPlus-Fact-Sheet.ashx.

Peltzman, S. (1976). Toward a more general theory of regulation. *Journal of Law and Economics*, 19(2):211–240.

Plosser, M. and Santos, J. (2014). Banks' incentives and the quality of internal risk models. *Federal Reserve Bank of New York Staff Report*, (704).

Posner, R. (1975). Social costs of monopoly and regulation. *Journal of Political Economy*, 83(4):807–827.

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

Satchell, S. and Xia, W. (2007). Analytic models of the receiver operating characteristic curve: Applications to credit rating model validation. *Journal of Risk Management in Financial Institutions*, 1(1):90–106.

Schmieder, C. (2006). The Deutsche Bundesbank's large credit database (BAKIS-M and MiMiK). *Schmollers Jahrbuch*, 126:653–662.

Shleifer, A. and Vishny, R. (2002). *The grabbing hand: Government pathologies and their cures*. Harvard University Press, Cambridge, Massachusetts.

Solvabilitätsverordnung (2006). *Verordnung über die angemessene Eigenmittelausstattung von Instituten, Institutsgruppen und Finanzholding-Gruppen*. Bundesministerium für Finanzen, Berlin, Germany.

Stigler, G. J. (1971). The theory of economic regulation. *The Bell Journal of Economics and Management Science*, 2(1):3–21.

Stoess, E. (2001). Deutsche Bundesbank's corporate balance sheet statistics and areas of application. *Schmollers Jahrbuch*, 121:131–137.

van Garderen, K. and Shah, C. (2002). Exact interpretation of dummy variables in semilogarithmic equations. *The Econometrics Journal*, 5(1):149–159.

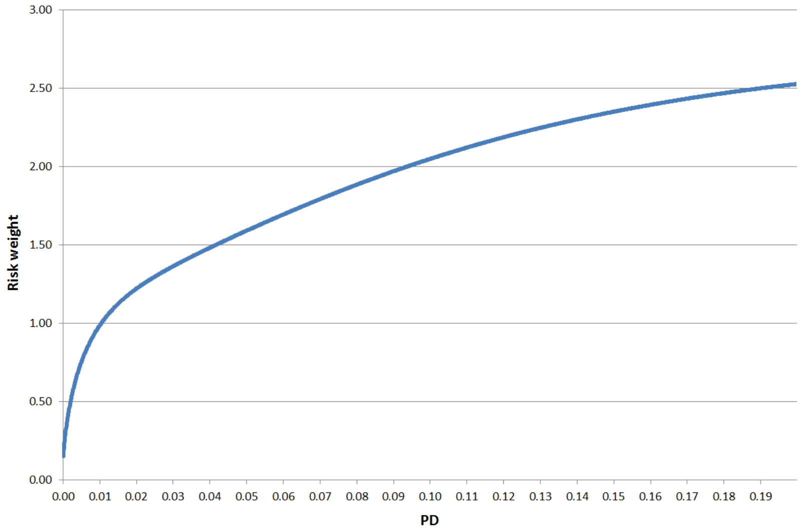


Figure 1: PDs and regulatory risk-weights

This 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. (Source: own calculations based on the formulas in Basel Committee on Banking Supervision 2006).

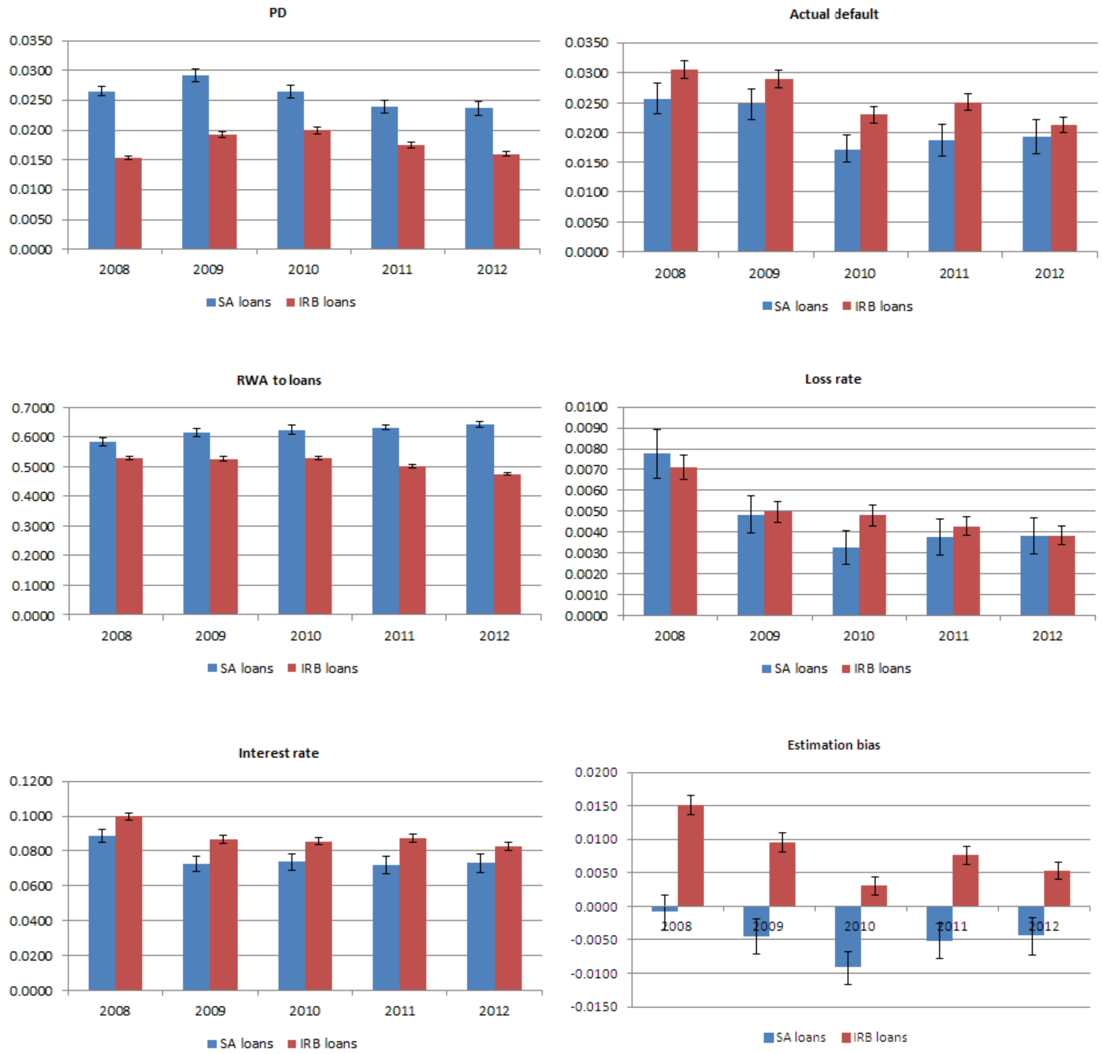


Figure 2: Average PDs and actual default rates

The figure shows average values for PDs, actual default rates, loan loss rates, the ratio of RWA to loans, interest rates, and the estimation bias for SA and IRB loans during the period from 2008 to 2012. The sample includes all loans that are not in default in the respective year. Confidence intervals are at the 95 %-level. (Source: Deutsche Bundesbank).

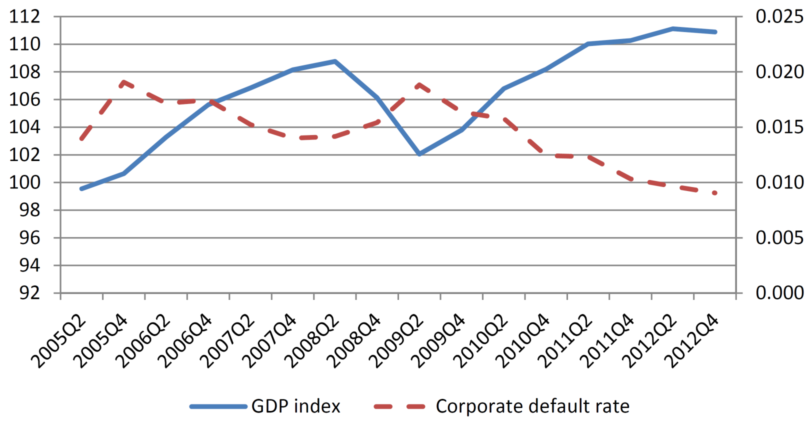


Figure 3: Business cycle

This figure shows the development of the seasonally adjusted German GDP index between 2005Q1 and 2012Q4 (left axis; source: German Federal Statistical Office) and the development of default rates in the German corporate sector (right axis; source: Duellmann and Koziol 2014).

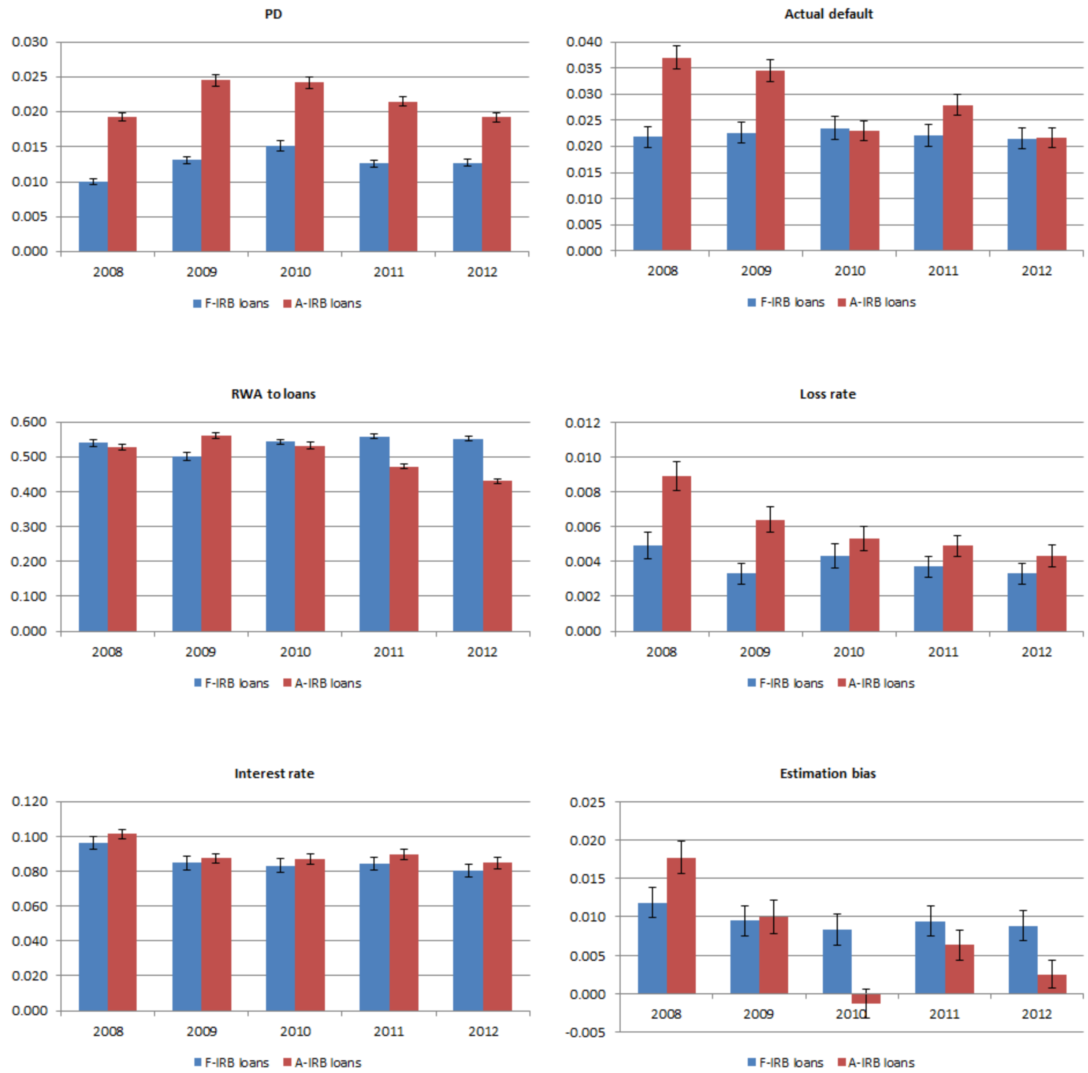


Figure 4: Basic vs. advanced IRB approach

The figure shows average values for PDs, actual default rates, loan loss rates, the ratio of RWA to loans, interest rates, and the estimation bias for loans under the Foundation and the Advanced IRB approach during the period from 2008 to 2012. The sample includes all loans that are not in default in the respective year. Confidence intervals are at the 95 %-level. (Source: Deutsche Bundesbank).

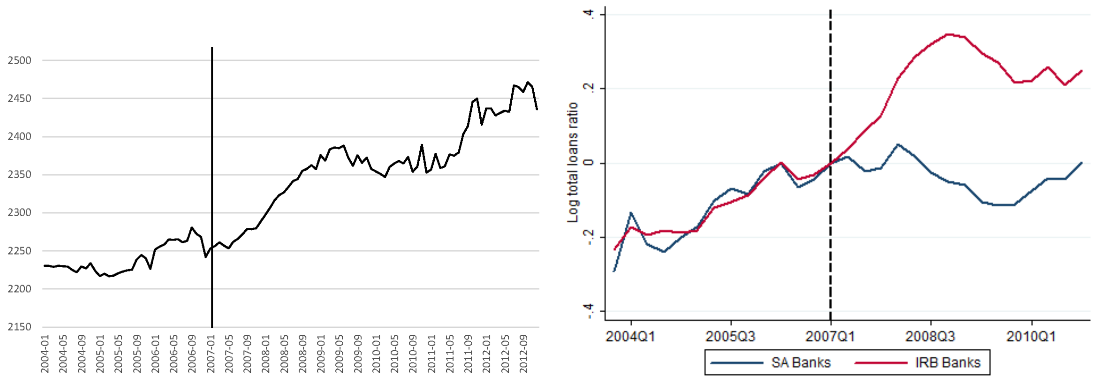


Figure 5: Aggregate lending around the Basel II introduction

The left hand side figure plots aggregate credit supply by all German banks to domestic non-banks (Source: Deutsche Bundesbank). The right hand side 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

	SA banks (1,558 banks)		IRB banks (45 banks)	
	Mean	S.D.	Mean	S.D.
BANK ASSETS (2006, in mn €)	1,330	3,750	133,000	259,000
LOG BANK ASSETS (2006)	20.158	1.162	24.196	1.937
BANK EQUITY RATIO (2006)	6.366	4.202	4.246	2.471
BANK ROA (2006)	0.680	0.464	0.673	0.584

Panel B: Loan descriptives

	SA loans (59,000 loans)		IRB loans (237,985 loans)	
	Mean	S.D.	Mean	S.D.
PD	0.0262	0.0564	0.0176	0.0506
RWA TO LOAN	0.6155	0.7558	0.4900	0.5374
LOSS RATE	0.0049	0.0542	0.0051	0.0546
INTEREST RATE	0.0792	0.0560	0.0876	0.0589
Δ LOG(LOANS)	0.0159	0.3582	0.0644	0.5697

Panel C: Firm descriptives

	(5,961 firms)	
	Mean	S.D.
FIRM ASSETS (2006, in mn €)	154	817
FIRM DEBT TO ASSETS (2006)	0.343	0.202
LOG FIRM ASSETS (2006)	10.363	1.428
FIRM ROA (2006)	7.909	6.982

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. Δ LOG(LOANS) refers to the change in the log of loans around the Basel II reform (average of seven quarters 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 Deutsche Bundesbank's USTAN database.

Table 2: Characteristics of SA and IRB loans within IRB banks

	Observations	PD		ACTUAL DEFAULT		RWA TO LOAN		LOSS RATE		INTEREST RATE	
SA loans		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2008	14,713	0.0265	0.0504	0.0257	0.1582	0.5832	0.7442	0.0078	0.0725	0.0876	0.0527
2009	13,734	0.0292	0.0647	0.0248	0.1554	0.6144	0.9132	0.0048	0.0530	0.0786	0.0587
2010	11,154	0.0264	0.0572	0.0173	0.1304	0.6237	0.9336	0.0033	0.0433	0.0750	0.0557
2011	10,492	0.0239	0.0518	0.0188	0.1357	0.6316	0.4302	0.0038	0.0442	0.0749	0.0556
2012	8,907	0.0237	0.0560	0.0193	0.1376	0.6419	0.5326	0.0038	0.0422	0.0748	0.0577
IRB loans		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2008	51,332	0.0153	0.0443	0.0305	0.1720	0.5269	0.6971	0.0071	0.0668	0.0968	0.0571
2009	48,816	0.0193	0.0552	0.0289	0.1675	0.5259	0.7614	0.0050	0.0549	0.0858	0.0596
2010	45,078	0.0199	0.0596	0.0230	0.1500	0.5278	0.6740	0.0048	0.0530	0.0857	0.0597
2011	47,592	0.0174	0.0482	0.0251	0.1564	0.5008	0.5148	0.0043	0.0470	0.0862	0.0588
2012	45,167	0.0160	0.0441	0.0213	0.1445	0.4750	0.4743	0.0039	0.0477	0.0832	0.0585
Difference		Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
2008	66,045	0.0112	26.1907	-0.0048	-3.0368	0.0562	8.5052	0.0006	1.0990	-0.0092	-3.1929
2009	62,550	0.0099	17.8498	-0.0041	-3.0368	0.0886	11.4931	-0.0001	-0.3800	-0.0072	-2.1869
2010	56,232	0.0065	10.3944	-0.0057	-3.6836	0.0959	12.3742	-0.0015	-2.7691	-0.0107	-3.1220
2011	58,084	0.0065	12.3322	-0.0063	-3.8211	0.1309	24.2272	-0.0005	-0.9968	-0.0113	-2.9616
2012	54,074	0.0077	14.3537	-0.0020	-1.2031	0.1669	29.7199	0.0000	-0.1842	-0.0084	-2.1039

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

Table 3: Main results

Panel A					
Dependent variable:	LOG(PD)				
	(1)	(2)	(3)	(4)	(5)
D(IRB LOAN)	-5.5494***	-0.3363***	-0.3538***	-0.3453***	-0.2516***
	(0.0494)	(0.0378)	(0.0401)	(0.0360)	(0.0345)
D(SA LOAN)	-4.9515***				
	(0.1052)				
Firm FE	NO	YES	YES	—	—
Year FE	NO	NO	YES	—	—
Firm × year FE	NO	NO	NO	YES	YES
Bank × year FE	NO	NO	NO	NO	YES
Observations	296,985	296,985	296,985	50,798	50,798
R-squared	0.0192	0.7280	0.7321	0.7117	0.7508
Kennedy estimator	—	-0.2865	-0.2988	-0.2930	-0.2235
Standard error	—	0.06121	0.0598	0.0657	0.0686
Panel B					
Dependent variable:	ESTIMATION BIAS (ACTUAL DEFAULT – PD)				
	(1)	(2)	(3)	(4)	(5)
D(IRB LOAN)	0.0084***	0.0066***	0.0046**	0.0071***	0.0052**
	(0.0024)	(0.0020)	(0.0019)	(0.0021)	(0.0021)
D(SA LOAN)	-0.0045				
	(0.0047)				
Firm FE	NO	YES	YES	—	—
Year FE	NO	NO	YES	—	—
Firm × year FE	NO	NO	NO	YES	YES
Bank × year FE	NO	NO	NO	NO	YES
Observations	296,985	296,985	296,985	50,798	50,798
R-squared	0.0011	0.4937	0.4975	0.6241	0.6312
Panel C					
Dependent variable:	RWA TO LOAN				
	(1)	(2)	(3)	(4)	(5)
D(IRB LOAN)	0.5114***	-0.1371***	-0.1372***	-0.1268***	-0.1522***
	(0.0186)	(0.0307)	(0.0308)	(0.0330)	(0.0329)
D(SA LOAN)	0.6155***				
	(0.0305)				
Firm FE	NO	YES	YES	—	—
Year FE	NO	NO	YES	—	—
Firm × year FE	NO	NO	NO	YES	YES
Bank × year 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

Table 3 continued...

Panel D					
Dependent variable:	LOSS RATE				
	(1)	(2)	(3)	(4)	(5)
D(IRB LOAN)	0.0051***	0.0013**	0.0009*	0.0012**	0.0008
	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0006)
D(SA LOAN)	0.0049***				
	(0.0013)				
Firm FE	NO	YES	YES	—	—
Year FE	NO	NO	YES	—	—
Firm × year FE	NO	NO	NO	YES	YES
Bank × year 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

Panel E					
Dependent variable:	INTEREST RATE				
	(1)	(2)	(3)	(4)	(5)
D(IRB LOAN)	0.0877***	0.0053**	0.0074***	0.0089**	0.0146**
	(0.0011)	(0.0025)	(0.0018)	(0.0038)	(0.0060)
D(SA LOAN)	0.0792***				
	(0.0020)				
Firm FE	NO	YES	YES	—	—
Year FE	NO	NO	YES	—	—
Firm × year FE	NO	NO	NO	YES	YES
Bank × year FE	NO	NO	NO	NO	YES
Observations	11,759	11,759	11,759	1,677	1,677
R-squared	0.0027	0.6841	0.6925	0.8605	0.8672

The sample includes loans from IRB banks in 2008, 2009, 2010, 2011, and 2012. The dependent variable is logarithm of the loan-specific PD in Panel A, the loan-specific ESTIMATION BIAS (defined as the difference between an ACTUAL DEFAULT dummy that indicates whether the loan defaults within the next four quarters and the PD) in Panel B, the loan-specific ratio of RWA TO LOAN in Panel C, the loan-specific LOSS RATE in Panel D, and the loan-specific INTEREST RATE in Panel E. 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 the PD for the respective loan was generated and is equal to 1 if the PD was generated under IRB. Similarly, D(SA LOAN) is equal to 1 if the PD for the loan was generated under SA and 0 otherwise. The last two lines of Panel A include adjusted coefficients and estimates for the standard errors, following the reasoning of Halvorsen and Palmquist (1980), Kennedy (1981), and van Garderen and Shah (2002) (see footnote 31). Robust standard errors adjusted for clustering at the bank × year level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table 4: Curvature test – PDs

Panel A								
Dependent variable:	LOG(PD)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	low pd	high pd	all	all	low pd	high pd	all	all
D(IRB LOAN)	-0.2644***	-0.2119***	-0.6080***		-0.3552***	-0.1232**	-0.3573***	
	(0.0945)	(0.0422)	(0.0851)		(0.0430)	(0.0495)	(0.0327)	
D(IRB LOAN) × FIRM PD			13.8880***	13.8993***			8.4063***	8.0937***
			(1.0799)	(1.1192)			(1.3610)	(1.3548)
Bank × year FE	YES	YES	YES	—	YES	YES	YES	—
Firm × year FE	NO	NO	NO	NO	YES	YES	YES	YES
Bank × year × loan pool FE	NO	NO	NO	YES	NO	NO	NO	YES
Observations	148,461	148,524	296,985	296,985	25,414	25,384	50,798	50,798
R-squared	0.1379	0.1256	0.2170	0.2321	0.6848	0.7053	0.7546	0.7603
Panel B								
Dependent variable:	ESTIMATION BIAS (ACTUAL DEFAULT – PD)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	low pd	high pd	all	all	low pd	high pd	all	all
D(IRB LOAN)	0.0124***	0.0038	0.0115***		0.0101***	-0.0001	0.0115***	
	(0.0035)	(0.0033)	(0.0027)		(0.0020)	(0.0034)	(0.0020)	
D(IRB LOAN) × FIRM PD			-0.3012***	-0.2965***			-0.4978***	-0.5002***
			(0.0390)	(0.0397)			(0.0658)	(0.0641)
Bank × year FE	YES	YES	YES	—	YES	YES	YES	—
Firm × year FE	NO	NO	NO	NO	YES	YES	YES	YES
Bank × year × loan pool FE	NO	NO	NO	YES	NO	NO	NO	YES
Observations	148,461	148,524	296,985	296,985	25,414	25,384	50,798	50,798
R-squared	0.0374	0.0365	0.0378	0.0418	0.7009	0.6052	0.6337	0.6385

The sample includes loans from IRB banks in 2008, 2009, 2010, 2011, and 2012. The dependent variable in Panel A is the logarithm of the PD and the ESTIMATION BIAS (defined as the difference between an ACTUAL DEFAULT dummy and the PD) in Panel B. D(IRB LOAN) indicates the regulatory approach under which the PD for the respective loan was generated and is equal to 1 if the PD was generated under IRB. Similarly, D(SA LOAN) is equal to 1 if the PD for the loan was generated under SA and 0 otherwise. FIRM PD is the firm's average PD in the first quarter in which this information is available. In columns 5-8, 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. Robust standard errors adjusted for clustering at the bank × year level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table 5: Cross-sectional bank variation – Bank capitalisation

Panel A						
Dependent variable:	LOG(PD)					
	(1)	(2)	(3)	(4)	(5)	(6)
	HIGH	LOW	ALL	HIGH	LOW	ALL
D(IRB LOAN)	-0.2918***	-0.3627***		-0.1799***	-0.2744***	
	(0.0351)	(0.0760)		(0.0439)	(0.0648)	
D(IRB LOAN) × HIGH			-0.3118***			-0.1841***
			(0.0341)			(0.0456)
D(IRB LOAN) × LOW			-0.3380***			-0.2714***
			(0.0617)			(0.0591)
Firm × year FE	YES	YES	YES	YES	YES	YES
Bank × year FE	NO	NO	NO	YES	YES	YES
Observations	15,776	14,480	30,256	15,776	14,480	30,256
R-squared	0.7506	0.6673	0.7116	0.7713	0.7391	0.7561
Panel B						
Dependent variable:	ESTIMATION BIAS (ACTUAL DEFAULT – PD)					
	(1)	(2)	(3)	(4)	(5)	(6)
	HIGH	LOW	ALL	HIGH	LOW	ALL
D(IRB LOAN)	0.0049*	0.0078**		0.0008	0.0102***	
	(0.0026)	(0.0033)		(0.0030)	(0.0036)	
D(IRB LOAN) × HIGH			0.0041*			0.0012
			(0.0023)			(0.0029)
D(IRB LOAN) × LOW			0.0085***			0.0096**
			(0.0027)			(0.0037)
Firm × year FE	YES	YES	YES	YES	YES	YES
Bank × year FE	NO	NO	NO	YES	YES	YES
Observations	15,776	14,480	30,256	15,776	14,480	30,256
R-squared	0.6125	0.6615	0.6292	0.6215	0.6687	0.6371

The table investigates how the difference in PDs (Panel A) and ESTIMATION BIAS (Panel B) between SA and IRB loans depends on bank capitalisation. Columns 1 and 4 include only observations from banks where bank capitalization is higher than the median, while columns 2 and 5 include only observations from banks where bank capitalization is lower than the median. In both cases, the sample is restricted to firms that have at least one IRB loan and at least one SA loan from banks in the respective subsample. Columns 3 and 6 include both subsamples, where HIGH and LOW are dummy variables that indicate whether bank capitalization for the bank is higher or lower than the median. Robust standard errors adjusted for clustering at the bank × year level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table 6: Cohort analysis

Dependent variable:	ESTIMATION BIAS (ACTUAL DEFAULT – PD)							
	2009				2010			
	IRB		SA		IRB		SA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
BASEL II	0.0079**	0.0086**	0.0009	0.0035	0.0104***	0.0094**	-0.0109	-0.0056
	(0.0037)	(0.0041)	(0.0138)	(0.0073)	(0.0037)	(0.0042)	(0.0082)	(0.0053)
Constant	0.0165*		0.0176**		0.0008		0.0028	
	(0.0098)		(0.0086)		(0.0055)		(0.0053)	
Bank FE	NO	YES	NO	YES	NO	YES	NO	YES
Observations	24,242	24,242	16,066	16,066	19,554	19,554	13,074	13,074
R-squared	0.0004	0.0410	0.0000	0.0385	0.0010	0.0306	0.0008	0.0323

The sample is restricted to loans using the IRB approach that were granted in the 12 months before and after the reform in 2007, i.e., bank-firm relationships under the IRB approach (a) that newly appear in our dataset in either 2006 or 2007, or (b) that already existed before but exhibit a new loan issuance in either 2006 or 2007. BASEL II is an indicator variable that takes a value of 1 if the IRB loan was issued in the 12 months following the implementation of Basel II (i.e., 2007) and 0 if it was issued in the year prior to the reform (i.e., 2006). The dependent variable is the ESTIMATION BIAS as defined before. Robust standard errors adjusted for clustering at the bank $\times$ year level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table 7: Lending around the reform – SA versus IRB institutions

Dependent variable:	Δ LOG(BANK LOANS)		Δ LOG(LOANS)			
	(1)	(2)	(3)	(4)	(5)	(6)
D(IRB BANK)	0.0867**	0.1115**	0.0649***	0.0591***		
	(0.0346)	(0.0505)	(0.0195)	(0.0202)		
D(IRB BANK) $\times$ FIRM PD			-0.8740***	-0.7011***	-0.7546***	-0.5184***
			(0.1785)	(0.1753)	(0.1723)	(0.1780)
FIRM PD			-0.2426**		-0.2217***	
			(0.0942)		(0.0942)	
Constant	0.1901***	-0.0411	0.0316***			
	(0.0096)	(0.1856)	(0.0071)			
Bank controls	NO	YES	NO	NO	NO	NO
Firm FE	NO	NO	NO	YES	NO	YES
Bank FE	NO	NO	NO	NO	YES	YES
Observations	1,603	1,547	45,430	45,430	45,430	45,430
R-squared	0.0015	0.0336	0.0049	0.2248	0.0423	0.2612

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, where all quarterly data for a given bank is collapsed 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 dummy variable D(IRB BANK) indicates whether the respective bank adopted the internal ratings-based approach during our sample period. Columns 3-6 show results on the loan level, where the dependent variable is the difference in the logarithm of the loan amount. 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 seven quarters after the Basel II introduction. Data are restricted to 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 bank level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table 8: Lending around the reform – within IRB institutions

Dependent variable:	Δ LOG(LOANS)			NEW LOAN		
	(1)	(2)	(3)	(4)	(5)	(6)
D(IRB LOAN)	0.0781**	0.1126***	0.0531**	0.1028***	0.1221***	0.0540**
	(0.0365)	(0.0390)	(0.0263)	(0.0207)	(0.0310)	(0.0230)
Constant	0.0188			0.1189***		
	(0.0268)			(0.0162)		
Firm FE	NO	NO	YES	NO	NO	YES
Bank FE	NO	YES	YES	NO	YES	YES
Observations	19,362	19,362	19,362	18,039	18,039	18,039
R-squared	0.0038	0.0292	0.3719	0.0152	0.0592	0.4060

The table shows the relationship between the increase in lending over the Basel II reform and the regulatory approach used by the bank. We collapse all quarterly data for a given bank-firm relationship into single pre- and post-event periods as before. The dependent variable is the difference in LOG(LOANS) between the pre- and post-event periods in columns 1-3, and a dummy variable indicating whether a new loan was issued for a specific bank-firm relationship (new or existing) in the seven quarters following the reform in columns 4-6. The sample is restricted to IRB banks and includes only firms that have at least one SA loan and at least one IRB loan from an IRB bank. Robust standard errors adjusted for clustering at the bank level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Appendix A: Computation of Interest Rates

Combining the quarterly Bundesbank credit register with annual firm-level accounting information from USTAN allows us to back out effective annual interest rates on the loan contract level.

Step 1: As a first step, we use quarterly information from the credit register on the bank-firm relationship level to identify individual loan contracts. From the repayment structure of the initial loan amount, we can infer the maturity of the loan contract (e.g., whether it is repaid at the end of the contract period; linearly or de/progressively). If the outstanding loan of a lending relationship increases, we identify a new loan contract. Some lending relationships include a current account for the client with a loan amount that fluctuates around a fairly stable mean. Therefore, we only identify a new loan contract if the increase in total loans per firm-bank relationship exceeds 33.33 percentage points. Following this procedure, we extract all individual loan contracts per firm from the credit register (see Table A.1, Panel A).[42]

Table A.1: Contract Extraction

A - Quarterly Data	I	II	III	IV	V
Quarter	Bank A	Bank B	Contract 1 (A)	Contract 2 (A)	Contract 3 (B)
1998 Q4	12000	-	12000	-	-
1999 Q1	10000	-	10000	-	-
1999 Q2	8000	-	8000	-	-
1999 Q3	6000	-	6000	-	-
1999 Q4	11000	-	4000	7000	-
2000 Q1	9000	-	2000	7000	-
2000 Q2	7000	-	-	7000	-
2000 Q3	7000	-	-	7000	-
2000 Q4	7000	-	-	7000	-
2001 Q1	7000	-	-	7000	-
2001 Q2	7000	-	-	7000	-
2001 Q3	7000	5000	-	7000	5000
2001 Q4	-	4000	-	-	4000
2002 Q1	-	3000	-	-	3000
2002 Q2	-	2000	-	-	2000
2002 Q3	-	1000	-	-	1000
B - Annualized Data	I	II	III	IV	V
Year	IR	Spread	Contract 1 (A)	Contract 2 (A)	Contract 3 (B)
1999	0.0700	0.0381	9000	-	-
2000	0.0853	0.0367	1500	7000	-
2001	0.0803	0.0399	-	7000	1250
2002	0.0800	0.0451	-	-	2500

Panel A of this table lists a firm's total loans from Bank A in column I and Bank B in column II derived from the credit register. Columns III to V display the contracts extracted from the quarterly loan information. Panel B depicts the annualized data. Column I shows the annual firm-level interest rate from balance sheet data, column II the spread of the interest rate over the EURIBOR. Columns III to V lists the average annual loan for Contracts 1 to 3. Details on the identification of loan contracts can be found in the text.

[42] The tables in this section help to guide the reader through the computation of interest rates by illustrating one hypothetical example.

To match loan and balance sheet data, we annualize the loan data by averaging the loan amount over four quarters (December$_{t-1}$, March$_t$, June$_t$, September$_t$). We match contract-level information with interest payments derived from balance sheet information[43] (see Table A.1, Panel B). In rare cases, firms have interest-relevant debt in excess of bank loans. In this case, the sum of all bank loans from the credit register does not sum up to the amount of loans reported in a firm's balance sheet. We deal with this discrepancy by treating the difference as an additional lending relationship.

Step 2: The combination of both datasets allows us to compute contract-level interest rates by solving the equation system:

$$r_{jt} = \sum_{d=1}^{D} \frac{x_{djt}}{\sum_{d=1}^{D} x_{djt}} \cdot r_{dj}, \tag{A.1}$$

$$for\ t = t - int(D/2), ..., t, ..., t + int((D-1)/2)$$

where D is the number of relationships. The variable r_{jt} is the average interest rate paid by firm j in year t. We winsorize firm-level interest rates at the 5/95 percent percentile to account for unduly extreme outliers. The individual contract volume for firm j's contracts is denoted by x_{djt}, and thus, $\frac{x_{djt}}{\sum_{d=1}^{D} x_{djt}}$ is contract d's share in firm j's total borrowing. The variable of interest is r_{dj}, the interest rate on the individual loan contract.[44]

Each contract can either be a fixed or floating rate contract.[45] Equation system (A.1) can also be solved for floating rate contracts by replacing r_{dj} by $(s_{dj} + EURIBOR_t)$, where s_{dj} is the spread over the EURIBOR for contract d. As we do not have information about the type of contract, we allow all possible combinations for each firm at every point in time. For a firm with D contracts at a given point in time, we solve 2^{D} different equation systems. Additionally, for D contracts to solve the equation system for r_{dj}, D independent equations are required. Solving the equation system provides us with contract-specific interest rates/spreads (see Table A.2).

Step 3: To identify the correct combination of contract types, we first calculate the average

[43] Annual firm-level interest rates are defined as interest expenses minus interest expenses to related firms (ap174-ap175) divided by the average loan amount in the same year.

[44] In the example from Table A.1, the equation system for the year 2000 with fixed interest rates is:
$\begin{bmatrix} 0.0853 \\ 0.0803 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0.1765 & 0.8235 \end{bmatrix} \times \begin{bmatrix} r_1 \\ r_2 \end{bmatrix}.$

[45] In Germany, floating rate contracts use the FIBOR as base rate until 1998 and the EURIBOR as of 1999.

absolute deviation from the mean interest rate/spread for each contract:

$$\sigma_{djt} = \frac{1}{T} \cdot \sum_{t=1}^{T} \left| r_{djt} - \sum_{t=1}^{T} \frac{r_{djt}}{T} \right| \quad \text{(A.1)}$$

where T is the maturity of contract d in years. Next, we compute the average deviation for each of the 2^{D} equation systems as the average deviation over all contracts as ς_j. For each firm, we pick the combination of fixed and floating rate contracts that leads to the lowest value of ς_j (see Table A.2). Finally, we calculate the annual firm-bank relationship level interest rate as the value-weighted interest rate of all contracts of a firm-bank relationship for a given year. This approach allows us to compute firm-bank level interest rates for a subsample of lending relationships for which equation system (A.1) is solvable.

Table A.2: Solutions

	(r,r,r)	(s,s,s)	(r,s,s)	(r,r,s)	(r,s,r)	(s,r,r)	(s,r,s)	(s,s,r)
1999								
Contract 1 (A)	0.0700	0.0381	0.0700	0.0700	0.0700	0.0381	0.0381	0.0381
Contract 2 (A)	-	-	-	-	-	-	-	-
Contract 3 (B)	-	-	-	-	-	-	-	-
2000								
Contract 1 (A)	0.0700	0.0381	0.0700	0.0700	0.0700	0.0381	0.0381	0.0381
Contract 2 (A)	0.0886	0.0364	0.0400	0.0886	0.0400	0.0850	0.0850	0.0364
Contract 3 (B)	-	-	-	-	-	-	-	-
2001								
Contract 1 (A)	0.0700	0.0381	0.0700	0.0700	0.0700	0.0381	0.0381	0.0381
Contract 2 (A)	0.0886	0.0364	0.0400	0.0886	0.0400	0.0850	0.0850	0.0364
Contract 3 (B)	0.0339	0.0595	0.0395	-0.0065	0.0799	0.0540	0.0136	0.0999
2002								
Contract 1 (A)	-	-	-	-	-	-	-	-
Contract 2 (A)	0.0804	0.0390	0.0390	0.0794	0.0400	0.0804	0.0794	0.0462
Contract 3 (B)	0.0800	0.0451	0.0451	0.0451	0.0800	0.0800	0.0451	0.0451
σ(Contract 1 (A))	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
σ(Contract 2 (A))	0.0101	0.0031	0.0012	0.0113	0.0000	0.0057	0.0069	0.0120
σ(Contract 3 (B))	0.0345	0.0108	0.0042	0.0387	0.0001	0.0195	0.0236	0.0411
ς	0.0149	0.0046	0.0018	0.0166	0.0000	0.0084	0.0102	0.0177

The first line of the table indicates the combination of fixed rate contracts (r) and floating rate contracts (s). The optimal combination of contracts to solve the equation system is (r,s,r). The interest rate for Contract 1 is 0.08, the spread for Contract 2 is 0.04, and the interest rate for Contract 3 is 0.07. This leads to annual interest rates of 0.0700 in 1999, 0.0853 in 2000, and 0.0804 in 2001 for Bank A, and 0.0800 in 2001 and 2002 for Bank B.

Step 4: To verify the validity of the computed interest rates we apply the algorithm to a sample of contracts for which we collect information on actual interest rates. We obtain actual interest rates from the Center for Financial Studies (CFS) Loan Data Set used in Brunner and Krahnen (2008, 2013).[46] The dataset comprises, for a randomly drawn set of medium-sized firms, bank-borrower

[46] We thank Jan-Pieter Krahnen for providing us with the data.

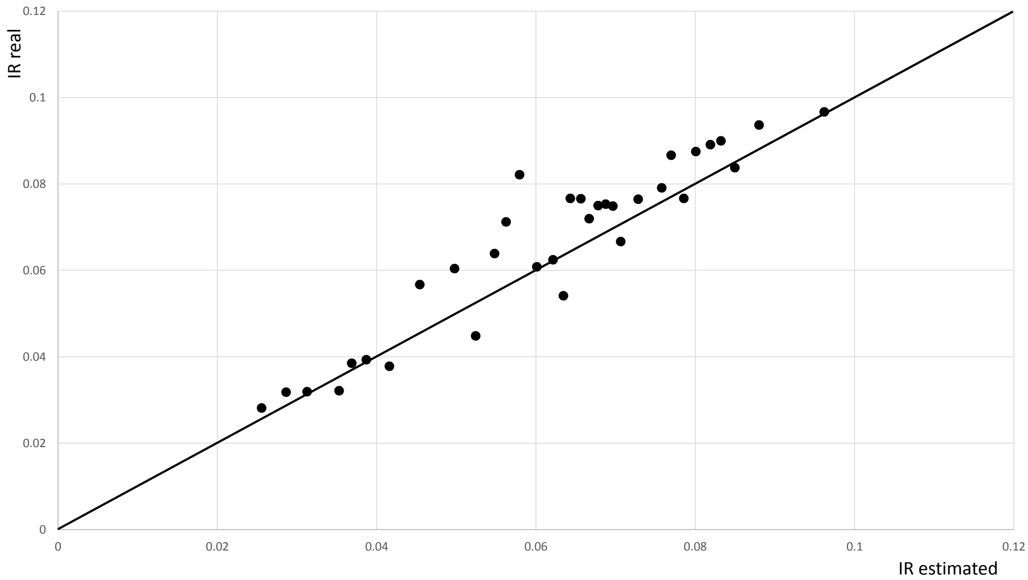
relationship level interest rates collected from five major banks (three private banks, one public sector bank, and one cooperative bank) from 1992 to 1996. We additionally update the data for the 2011-2012 period for one bank. In total, 93 of the firms with balance sheet and loan data at Deutsche Bundesbank could be matched. For 87 out of the 93 firms balance sheet and loan data overlaps (is available for the same year), allowing us to estimate interest rates. For 72 of the firms such information is available in at least one year for which we obtained actual interest rates. We start with 164 firm-year observations for which real and balance sheet level interest rates are available. For 167 of the 725 annual firm-bank relationships that exist for those 164 firm-year observations, we know the actual interest rate. After applying the algorithm we obtain 100 estimated relationship-level interest rates for 50 firms. Since Bundesbank rules require each reported data point to comprise at least three individual observations, we summarize three adjacent estimated interest rates into 33 buckets (the last bucket contains four observations) for the graphical analysis. Figure A.1 plots the average actual interest rates against the average estimated interest rates for those 33 buckets including a 45 degree line. The correlation between the actual and estimated interest rates is 0.9429. When we regress the actual interest rate on estimated interest rates, the slope is close to one with 0.9929 (Table A.3) and the constant term is insignificant with 0.44 percentage points. The comparison with actual interest rates shows that the algorithm to compute relationship-level interest rates provides a reasonable proxy for actual interest rates.

Table A.3: Actual and Estimated Interest Rate

Dep. Var.: $IR\ real_{ijt}$	
$IR\ estimated_{ijt}$	0.9929***
	[15.19]
$Constant$	0.0044
	[1.03]
Observations	100
R-squared	0.702

This table shows the results from regressing actual firm-bank relationship interest rates ($IR\ real_{ijt}$) on estimated interest rates ($IR\ estimated_{ijt}$) and a constant. We report t-statistics in parentheses.

Figure A.1: **Actual and Estimated Interest Rate**



This figure plots actual interest rates (y-axis) against estimated interest rates (x-axis) around a 45 degree line. Individual firm-bank relationship observations are aggregated into buckets comprising three individual observations to comply with Bundesbank reporting regulations. The plot shows the average actual interest rates and average estimated interest rates for the 33 buckets. (Source: CFS Loan Data Set and Deutsche Bundesbank).

Appendix B: Rank ordering of riskiness in IRB models

In validating internal rating systems regulators differentiate between the model's discriminatory power and the model's calibration (Deutsche Bundesbank 2003). More specifically, the discriminatory power of a model denotes its ability to differentiate between defaulting and non-defaulting borrowers. The accuracy of calibration corresponds to the mapping from estimated PD to the realized ex-post probabilities of default. In order to determine a bank's capital requirements under the model-based approach only the level of calibration matters. Therefore banks are incentivized to understate the level of calibration and not the discriminatory power of the risk models.

A priori it is not clear whether one would expect the discriminatory power of IRB models to be higher or lower compared with SA models. On the one hand, IRB models are first introduced for those portfolios that have a long history and sufficient data and should therefore have relatively high discriminatory power. On the other hand, we have documented that underreporting of PDs is more pronounced for low PD borrowers, and such differences in the incentives to underreport might also affect the overall discriminatory power of IRB models.

The most common statistical measure to test the discriminatory power of rating systems is the cumulative accuracy profile (CAP; see, e.g., Deutsche Bundesbank 2003, Satchell and Xia 2007). First, all observations are ordered by their respective PDs, from riskiest to safest (i.e., the loans with the highest PDs come first). Then, for a given fraction x of the total number of observations, the CAP is constructed by calculating the percentage d(x) of the defaulters whose PDs are equal to or higher than the minimum PD within the fraction x (compare with Satchell and Xia 2007, p. 5-6). We plot CAPs for IRB and SA models over our sample period in Figure B.1. The yellow line corresponds to a perfectly performing model, which would assign the highest PDs to the defaulters, thus increase linearly between zero and the fraction of defaulters among all observations, and remain at one afterwards.[47] The blue line corresponds to a random model, for which the fraction x of observations with the highest PDs will contain x percent of all defaults (and so on). The CAPs for IRB models (orange line) and SA models (grey line) are close to each other, but IRB models tend to slightly outperform SA models. This is confirmed when looking at accuracy ratios, which are defined as the area between the respective CAP and the CAP of the random model divided by the area between the CAP of the perfectly performing model and the CAP of the random model. For

[47] CAPs are calculated in percentile steps of the PD distribution. Using narrower or broader steps generates almost identical graphs and accuracy ratios.

IRB models, this accuracy ratio equals 0.55 while for SA models the value is 0.46.

Higher discriminatory power of IRB models is in line with the expectations of the regulator since only rating systems with sufficient explanatory power are approved for regulatory usage. Importantly, the discriminatory power of the rating system says nothing about the level of regulatory capital which the bank has to hold. The fact that banks systematically underreport PDs for those models that have on average a better or at least a similar discriminatory power lends further support to a manipulation motive.

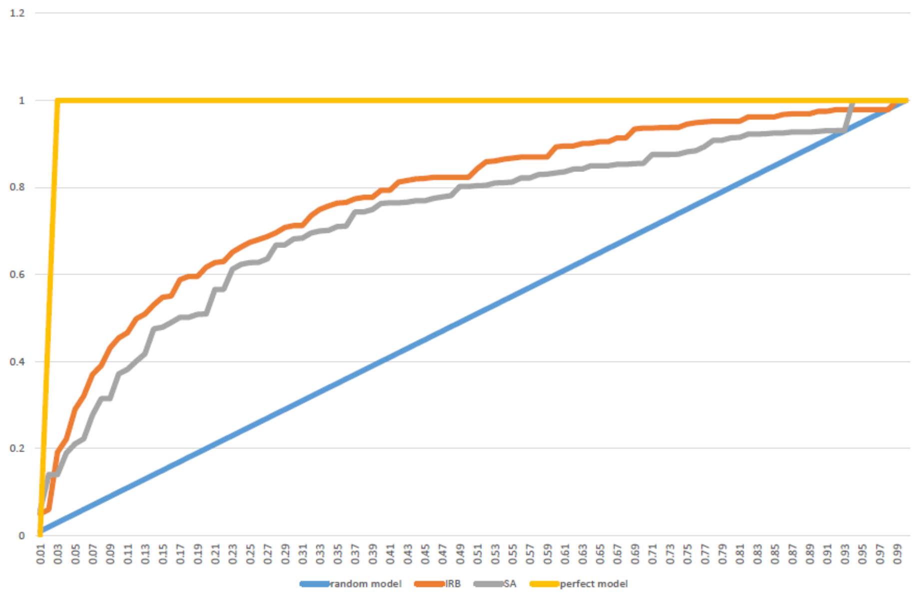


Figure B.1: Cumulative accuracy profile

The figure plots cumulative accuracy profiles (CAPs) that are used to assess the discriminatory power of rating systems. Observations are ordered by their respective PDs, from riskiest to safest. Then, for a given fraction x of the total number of observations, the CAP is constructed by calculating the percentage d(x) of the defaulters whose PDs are equal to or higher than the minimum PD within the fraction x. CAPs are calculated in percentile steps of the PD distribution. The yellow line corresponds to a perfectly performing model, the blue line corresponds to a random model, the orange line corresponds to IRB models, and the grey line corresponds to SA models. (Source: Deutsche Bundesbank).

Acknowledgements
We would like to thank Daron Acemoglu, Tobias Berg, Dion Bongaerts, Jörg Breitung, Joao Cocco, Jean-Edouard Colliard, Hans Degryse, Charles Goodhart, Matrin Hellwig, Victoria Ivashina, Anil Kashyap, Randy Kroszner, Fred Malherbe, John Moore, Steven Ongena, Rafael Repullo, Jean-Charles Rochet, Stephen Schaefer, Henri Servaes, Andrei Shleifer, Kelly Shue, Vania Stavrakeva, Sascha Steffen, Jeremy Stein, Rene Stulz, Johannes Stroebel (discussant NBER corproate finance), Javier Suarez, Anjan Thakor, Harald Uhlig and Luigi Zingales, as well as seminar participants at Adam Smith Workshop London, Becker Friedman Institute University of Chicago, Bonn University, Cass Business School, CEMFI Madrid, CEPR Summer Symposium Gerzensee, Deutsche Bundesbank, European Central Bank, German Economic Association Annual Meeting Hamburg, Hanken School of Economics, IMFS Conference Frankfurt, London Business School, London School of Economics, Max Planck Institute Bonn, NBER Summer Institute (CF/RISK, ME and CRA), Northwestern University, Rotterdam RSM, Stanford University, Tilburg University, University of Frankfurt, University of Leuven, and University of Zurich for their useful comments and discussions. We are grateful to the Deutsche Bundesbank, in particular to Klaus Düllmann and Thomas Kick, for their generous support with the construction of the data set. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the European Central Bank or its staff. Financial support from the German Research Foundation (Priority Program 1578) and the RAMD grant from LBS is acknowledged. The usual disclaimer on errors applies also applies here.

Markus Behn
European Central Bank, Frankfurt am Main, Germany; email: markus.behn@ecb.int

Rainer Haselmann
Goethe University Frankfurt and SAFE, Frankfurt am Main, Germany; email: haselmann@safe.uni-frankfurt.de

Vikrant Vig
London Business School, London, United Kingdom; email: vvig@london.edu

Postal address	60640 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Website	www.ecb.europa.eu

ISSN	1725-2806 (online)
ISBN	978-92-899-2176-3
DOI	10.2866/906624
EU catalogue No	QB-AR-16-045-EN-N