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**Conference Paper**

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2014: Evidenzbasierte Wirtschaftspolitik  
- Session: Banking - Empirical Evidence, No. A08-V3

**Provided in Cooperation with:**

Verein für Socialpolitik / German Economic Association

*Suggested Citation:* Behn, Markus; Haselmann, Rainer; Vig, Vikrant (2014) : Risk weights, lending, and financial stability: Limits to model-based capital regulation, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2014: Evidenzbasierte Wirtschaftspolitik - Session: Banking - Empirical Evidence, No. A08-V3, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

This Version is available at:

<https://hdl.handle.net/10419/100430>

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# Risk weights, lending, and financial stability: Limits to model-based capital regulation

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February 21, 2014

## ABSTRACT

Model-based capital regulation is considered to be one of the key innovations of Basel II. The objective of this innovation was to make capital charges more sensitive to risk. Using data from the German credit register, and employing a difference-in-difference identification strategy, we empirically investigate how the introduction of this regulation affected the quantity and the composition of bank lending. We find that credit supplied by banks that introduced the model-based approach exhibits a higher sensitivity to model-based PDs as compared with credit supplied by banks that remained under the traditional approach. Interestingly, however, we find that risk models used for regulatory purposes tend to underpredict actual default rates. There is no such prediction error in PDs for loans under the traditional approach.

**Keywords:** capital regulation, internal ratings, Basel III

**JEL Classification:** G01, G21, G28

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Acknowledgements: We would like to thank Tobias Berg, Jörg Breitung, Joaco Cocco, Hans Degryse, Hans-Martin von Gaudecker, Charles Goodhart, Reint Gropp, Anil Kashyap, Fred Malherbe, John Moore, Steven Ongena, Rafael Repullo, Jean-Charles Rochet, Stephen Schaefer, Henri Servaes, Andrei Shleifer, Vania Stavrakeva, Javier Suarez and Harald Uhlig as well as seminar participants at Deutsche Bundesbank for 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 and deep insights regarding the German banking sector. Birgit Maletzke and Patricia Müller provided us with valuable insights regarding the institutional details surrounding the introduction of asset-specific risk weights by German banks. Financial support from the German Research Foundation (Priority Program 1578) is acknowledged. The usual disclaimer on errors applies here as well.

# 1. Introduction

Following the financial crisis of 2008, policy makers around the world have concentrated their efforts on designing a regulatory framework that increases the safety of individual institutions as well as the stability of the financial system as a whole. Most prominently, the Basel III framework aims to enhance both the level and the quality of banks' regulatory capital (Basel Committee on Banking Supervision 2011). While there is relatively wide agreement on the necessity of such measures, a deeper debate has evolved on whether capital levels are appropriately measured in the current framework. Specifically, capital requirements in Basel III are defined in terms of risk-weighted assets (RWA), a measure that crucially depends on estimates from banks' internal risk models.

Proponents of risk-weighted regulation argue that it leads to a better allocation of resources, as banks are no longer penalized for having low-risk positions on their balance sheets. As model-based regulation sought to achieve a better alignment between regulatory capital and actual asset risk, the scope for regulatory arbitrage was meant to be reduced. However, although well-intended, critics argue that by now the regulatory system is much too complex, making it difficult for regulators to keep track of all the bank internal estimations required for the determination of regulatory capital ratios. Additionally, as it has become evident that RWA tend to vary across banks, regulators, investors, and even the banks themselves increasingly distrust this measure, preferring to rely on un-weighted capital ratios instead.<sup>1</sup> Overall, the calls for simpler capital rules seem to become louder.<sup>2</sup>

In this paper, we analyze how the introduction of risk-weighted capital charges affected banks' lending behavior towards the German corporate sector. The main thesis of the paper is that regulation based on models tends to reward "hard" information at the expense of "soft" information (or other information that is not included in the model). To the extent that the quality of a loan is a function of both soft and hard variables, this overweighting

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<sup>1</sup>See, e.g., Basel Committee on Banking Supervision (2013), European Banking Federation (2012), and the studies by individual banks cited in these publications.

<sup>2</sup>See, e.g., Acharya et al. (2013), Admati and Hellwig (2013), Haldane (2013), Hoenig (2013), Hellwig (2010), or Hoenig (2010).

of hard information alters the relative mix of “soft” and “hard” information, thus changing the very quality of the loan pool.<sup>3</sup> Further, linking capital charges to model-based risk estimates creates a preferential treatment of loans to firms that score high on the dimensions used as inputs in the risk model. Consequently, we expect that loans to firms with low model-based risk estimates are expanded relatively more following the introduction of risk-weighted capital charges.

It is likely that shifts in the loan portfolio have a direct impact on the accuracy of banks’ risk models. These models have been calibrated under a regime in which their outputs did not affect capital charges for loans. However, with risk-weighted regulation, the overreliance on hard information could induce a worsening of the borrower pool, so that model-based risk estimates would systematically underestimate the true riskiness of the borrowers. We present a model based on the theory of multitasking proposed by Holmström and Milgrom (1991) that delivers the following trade-off as a response to the reform: First, since banks shift their lending towards borrowers with low model-based risk estimates, we expect average probabilities of default (PDs) for loan portfolios that apply the new regulatory approach to be lower. Second, as model-based regulation induces a change in the borrower pool, we expect risk estimates for these loans to be less accurate than risk estimates for loans under the old regime. While the first effect is likely to have a positive impact on financial stability, the second effect is likely to have a negative impact on financial stability.

To test these hypotheses, we exploit the institutional details of the German Basel II introduction in 2007. Following the reform, banks were allowed to choose between a new regulatory approach (referred to as the internal ratings-based approach, short IRB) and a more traditional approach that did not rely on internal risk parameters (referred to as the standard approach, short SA). The introduction of IRB required an extensive risk management system that had to be certified by the regulator. Consequently, only very large banks introduced the new regulatory approach, while smaller regional banks opted for the standard approach to determine capital charges. In the first part of the paper, we analyze how banks that introduced the new regulatory approach adjusted their lending following the reform, as

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<sup>3</sup>This resonates with the theory of multitasking proposed by Holmström and Milgrom (1991). In the context of securitization, this argument has been used in Rajan et al. (2012).

compared with banks that did not introduce the new approach. As we are trying to identify a supply side effect, we focus on firms that borrow from both types of banks. Identifying our coefficients from variation within the same firm allows us to control for credit demand (see Khwaja and Mian 2008).

Importantly, the introduction of IRB in German banks was staggered over time. As risk models need to be certified by the regulator on a portfolio basis, banks did not shift all their loan portfolios to the new approach at the same time.<sup>4</sup> While IRB banks report model-based risk estimates (i.e., PDs) for most of their loans, some of these loans are still subject to the standard approach, while others have already been shifted to IRB. Exploiting this setup, we are able to test for systematic differences in the prediction error (i.e., the difference between a dummy for actual default and the PD of the loan) between IRB loans and SA loans. As we have relationship-level data, we can systematically control for bank as well as firm heterogeneity.

The following findings emerge from our analysis. First, we show that indeed the reform changed both the quantity and the composition of bank lending. Risk weights are calibrated in a way that ensures that capital charges under IRB are on average lower than under SA.<sup>5</sup> Consequently, as the reform meant a reduction in capital charges for banks that introduced IRB, these banks increased their lending by about 9 percent as compared with banks that remained under the standard approach. Further, controlling for firm heterogeneity, we find that IRB banks increase lending to the same firm relatively more if model-based PDs for the firm are relatively low, but not if they are relatively high. For example, an increase of one standard deviation in firm PD induces a 1.2 percent smaller increase in loans from IRB banks. These estimation results are robust to the inclusion of bank fixed effects that control for heterogeneity across banks. Hence, credit supplied by banks that introduced IRB exhibits a higher sensitivity to model-based PDs than credit supplied by banks that remained under SA.

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<sup>4</sup>The implementation of IRB happened on a portfolio basis: Banks had to shift whole portfolios of loans to the new approach. They were not allowed to pick individual loans for IRB. Furthermore, they were not allowed to move IRB portfolios back to SA.

<sup>5</sup>Regulators wanted banks to introduce the new approach and hence provided incentives for the costly implementation of IRB.

Second, we evaluate how these changes in the lending decision process affected banks' evaluation of credit risk. In 2008, IRB banks had transferred only a portion of their loan portfolios to the new approach. Exploiting this within bank variation, we analyze whether the predictive abilities of banks' PDs depend on the regulatory approach used for a specific loan. We observe that the average PD is always lower in IRB portfolios as compared with SA portfolios. This is consistent with the documented shift in lending towards firms with low model-based PDs. However, there seems to be no difference in the average default rate between the two types of loans. Risk estimates for IRB loans underpredict actual default rates, while there is no such effect in PDs for SA loans. Finally, the result is also robust to the inclusion of bank fixed effects that control for bank heterogeneity. While the effect is particularly strong directly after the reform, it is also present in later periods and persistent until the end of the sample period in 2011.

Our results could be biased if the order in which banks transfer their loan portfolios to IRB is driven by factors that explain differences in the predictive abilities of PDs for SA loans and IRB loans. Given the institutional details of the Basel II introduction in Germany, such a scenario is very unlikely. Nevertheless, to remove any remaining doubts, we focus on variation over time within the portfolio of IRB loans. For loans originated in 2005 or 2006, the average PD is similar to the actual default rate. In contrast, for loans originated after the Basel II reform, in 2007 or 2008, the actual default rate is higher than the average PD, indicating an underestimation of credit risk for this set of loans. The fact that the underestimation effect is much stronger for IRB loans that were originated after the reform as compared with IRB loans originated before the reform indicates that our findings are not driven by the selection of IRB loan portfolios. While these loans differ in the time of origination, they find themselves within the same portfolios within IRB banks, i.e., within those portfolios for which the new approach has already been implemented.

It is important to note that our findings do not imply that banks manipulate PDs for IRB loans. If this would be the case, we should observe an underprediction of actual default rates that is independent of the issuance date of IRB loans. Rather, we believe that the most likely explanation is a change in incentives induced by an overreliance on information

included in banks' risk models (i.e., a change in the borrower pool after the reform). While the underestimation effect is particularly pronounced right after the introduction, it does not seem as if the model validation process within IRB banks is able to solve the problem. A validated risk model again provides incentives to bankers to expand lending to those borrowers that score particularly well in the modified risk model. Since risk models do not include the entire information set available to the banker (including the soft information that is costly to collect for the banker), the bias is likely to be persistent.

When assessing the impact of our results on financial stability, one potential caveat has to be taken into account: Apart from the PD, risk-weights in the model-based approach also depend on loan-specific factors such as the loss given default (LGD), exposure at default (EAD), and the maturity (M) of the loan. Risk-weights in the advanced IRB approach will be lower the better the estimate on any of these parameters. Hence, the reform provides additional incentives for banks to invest into the quality of these parameters, for example by increasing the level of collateralization for IRB loans. Consequently, overall loan quality might have improved, despite the fact that default rates are higher than PDs for IRB loans. An assessment of the reform on overall credit risk and bank stability needs to take all loan-specific factors into account. Nevertheless, we believe that the underestimation of actual default rates that we document is interesting in itself.

Our paper also has important policy implications regarding the design of the new regulatory framework, Basel III. Although the framework introduces a leverage ratio, its currently discussed level is rather low, so that risk-based requirements as in Basel II would remain the binding ones for most banks. Our findings highlight important deficiencies of such an approach. To be clear, this paper does not make the point that a leverage ratio is better able to regulate a bank's capital. But clearly, more research is required to evaluate the pros and cons of different approaches to capital regulation in a systematic manner.

This paper adds to a small but growing literature on the appropriateness and consistency of Basel risk weights for bank regulation. Most recently, the Basel Committee on Banking Supervision (2013) published an extensive study, documenting that risk weights for credit risk in the banking book vary substantially across banks. While the bulk of this

variation is driven by differences in the underlying risk of banks' asset composition—and hence in line with the greater risk sensitivity of the Basel framework—the study also finds considerable practice-based drivers, among them differences in banks' modeling choices. Conducting a hypothetical portfolio exercise among 32 major international banks, the paper documents a notable dispersion in the estimation of probabilities of defaults and loss given defaults by different banks for the same exposure. This is in line with studies conducted at the International Monetary Fund (IMF): Le Leslé and Avramova (2012) find that credit risk measurement varies greatly across banks, as regulatory formulas are complex and leave room for interpretation. Das and Sy (2012) find that stocks of banks with lower ratios of risk-weighted assets to total assets performed better in the crisis, but less so in Europe where banks could use the internal-ratings based approach. They interpret this as evidence that market participants have less faith in risk-weighted assets when these are based on banks' internal risk models.<sup>6</sup> Similarly, Hagendorff and Vallasca (2013) show for an international sample of large banks that risk-weighted assets are only loosely connected to market-based measures of bank risk.

According to Hellwig (2010) risk-weighted capital regulation suffers from the fact that many of the risks involved are not exogenously given, but endogenously determined. As they depend on the behavior of the parties involved, they may change over time, and tracking them for regulatory purposes may be close to impossible. As an example, Acharya (2011) argues that the reliance on regulatory risk weights distorted banks' incentives to lend: Low risk weights for residential mortgage-backed securities made investment in that asset class attractive, which increased mortgage lending and endogenously turned residential housing into a systemically important asset class. Moreover, as Acharya et al. (2013) point out, risk weights can only be updated ex-post, as they are derived from accounting data. Consequently, they have no predictive power. Nevertheless, banks game risk-weighted assets by shifting their portfolios towards assets with lower risk weights, which does not necessarily mean lower risk. In this way—Acharya et al. (2013) argue—false and underestimated risk weights automatically lead to excessive leverage (see also Hoenig 2013).

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<sup>6</sup>On this point, see also Demirgüç-Kunt et al. (2013) and Haldane (2013).



Several authors have discussed potential problems with model-based capital regulation. Mariathasan and Merrouche (2012) find that during crisis times the unweighted leverage ratio is a much better predictor of bank failure than the risk-weighted ratio.<sup>7</sup> Moreover, they document a strong decline in the ratio of risk-weighted assets to total assets prior to the crisis, and interpret their findings as evidence for a strategic use of internal risk models under Basel II. Firestone and Rezende (2013) examine the consistency of estimated probabilities of default in the U.S. market for syndicated loans and find substantial dispersion in these parameters across banks. According to Haldane (2012), the primary source of complexity in the Basel framework is the granular, model-based risk weighting.<sup>8</sup> Compared to Basel I with its five different risk weights, the number of estimated Basel II parameters within a large bank run into the tens of thousands, thus increasing opacity. To reduce both complexity and opacity, Haldane (2011) proposes to disregard risk weights and focus on much simpler market-based metrics instead.

## **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.<sup>9</sup> In 1988, the Basel I agreement introduced risk-based capital charges by assigning bank assets into different risk groups (or buckets) with pre-assigned risk-weights (Basel Committee on Banking Supervision 1988). Risk-weighted assets were calculated by multiplying these risk-weights (0, 20, 50, or 100 percent) with actual asset values, and capital requirements were defined in terms of risk-weighted assets.

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<sup>7</sup>Using U.S. data, Berger and Bouwman (2013) find that both measures are able to predict bank distress.

<sup>8</sup>Haldane (2012) also points out that the length of regulatory documents itself is revealing: While the text of the original Basel agreement in 1988 comprised only 30 pages, Basel II came in at 347 pages, and the Basel III agreement contains 616 pages, reflecting an ever-increasing degree of complexity.

<sup>9</sup>The introduction of risk-weighted capital charges and potential problems related to them have been discussed in several papers, e.g. Behn et al. (2013), Brun et al. (2013), Hellwig (2010), Kashyap and Stein (2004), Danielsson et al. (2001), Jones (2000), Brinkmann and Horvitz (1995). For an assessment from the side of the regulator see Basel Committee on Banking Supervision (1999).

The next revision of this regulatory framework, referred to as Basel II, tried to establish a more granular link between capital charges and individual asset risk. The new framework, introduced in Germany in 2007, allowed banks to use their own internal risk models to determine capital charges for credit risk (Basel Committee on Banking Supervision 2006). Under the internal ratings-based (IRB) approach, each exposure gets assigned an individual risk weight that crucially depends on the bank's estimated probability of default (PD) for a specific borrower.<sup>10</sup> Risk-weighted assets are calculated by multiplying the—loan-specific—risk-weights with actual assets values, and capital requirements are defined in terms of risk-weighted assets as under Basel I.

In Germany, Basel II was implemented by revision of the Solvabilitätsverordnung (2006), which provides the foundation for national bank regulation. This code allows banks to choose between two broad methodologies for calculating their capital charges: The internal ratings-based approach described above and the so-called standard approach, that is basically equivalent to the old Basel I framework with fixed risk weights for corporate loans (100 percent of the loan amount net of collateral).<sup>11</sup>

The Solvabilitätsverordnung (2006) provides a comprehensive set of rules and guidelines for banks that want to use internal risk models for calculating their capital charges: PD models used for regulatory purposes should estimate creditors' one-year probability of default.<sup>12</sup> As the bank could have incentives to report low PDs in order to economize on regulatory capital, internal risk models are subject to a strong supervisory review—including on-site audit (see also Bundesbank 2004). In particular, the regulator requires a precise and consistent estimation of credit risk, and proof that the model has been used for internal risk management and credit decisions for at least three years before it may be used for regula-

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<sup>10</sup>In the foundation IRB approach the bank estimates only the PD, while standard values are assumed for loss given default (LGD), exposure at default (EAD), and maturity of the loan. In the advanced IRB approach, the bank has to estimate all four parameters. As risk weights depend on the PD—our parameter of interest—in both approaches, we do not distinguish between the two in the empirical analysis.

<sup>11</sup>Exceptions are cases where borrowers have external credit ratings, as the SA allows banks to use these ratings to determine capital requirements. However, the German market for corporate bonds is very small; hence, very few companies have an external rating.

<sup>12</sup>According to § 125 of the Solvabilitätsverordnung (2006), a creditor is in default if (a) the bank has valid indications that the creditor will not be able to fulfill his obligations, or (b) the creditor is more than 90 days past due on his obligations.

tory purposes. Furthermore, the bank has to constantly validate its models and adjust them if their estimates are inconsistent with realized default rates. The supervisor certifies rating systems, continuously monitors compliance with minimum standards, and assesses banks' internal validation procedures (see also Bundesbank 2003).

PD models are estimated on a portfolio basis. For corporate loans, their most important determinant is accounting information from firms' financial statements (see, e.g., Initiative für den Finanzstandort Deutschland 2006; Krahen and Weber 2001). For loans to small and medium enterprises (SMEs), where there is often a significant publication lag for accounting information, also target financial ratios or industry characteristics may be used. Besides these quantitative factors, also qualitative information such as a firm's management quality or its competitive situation can be included in the models. However, since such information is by definition hard to quantify its impact on the rating is rather limited. A prominent PD model used for the estimation of corporate credit risk is Moody's RiskCalc<sup>TM</sup> model (Moody's Analytics 2013). To obtain predicted probabilities of default for a given portfolio, historical information on corporate defaults is regressed on accounting information such as the equity ratio, capital structure, net debt ratio, sales growth, net profit ratio, personnel cost ratio, payables payment period, or cash flow per liabilities. In a second step, estimates from this model are used to attribute predicted PDs to current and new borrowers. In cases where loan officers consider model outputs to be unreasonable they have the option to overwrite the predicted PD. However, if such overwrites occur to frequently, the regulator may ask the bank to revise its model. Furthermore, a bank has to revise its model if the annual validation process reveals a considerable discrepancy between predicted PDs and actual default rates.

Besides loan-specific variables such as the loss given default, the exposure at default and the maturity of a loan, the firm-specific PD estimate is the key ingredient for the calculation of risk-weighted assets. Figure 1 shows the relationship between estimated PDs and corresponding risk-weights, assuming standard values for the remaining parameters. Risk-weight curves are relatively steep for the lowest PDs and become flatter for higher PDs. This is in line with the objectives of the new agreement: To provide banks with incentives to introduce IRB, risk-weight curves were calibrated in a way that ensured that capital re-

quirements would be substantially lower under IRB than under SA (Basel Committee on Banking Supervision 2006, p. 12).

To be eligible for the model-based approach to capital regulation, banks need to fulfill certain conditions and minimum disclosure requirements. Since the organizational efforts as well as the administrative expenses for the introduction of the new approach are high, only large banks opted for its introduction (of our sample of 1,603 German banks, only 45 banks applied for an IRB license; nevertheless these banks account for about 50 percent of the loans in our sample). The introduction of new rating models is a complex process, so that banks did not apply the new approach to all loans at once; rather, they agreed on a gradual implementation plan with the regulator.<sup>13</sup> The plan specified an order according to which different business units (loan portfolios) had to be 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. The phased roll-out of IRB means that during the transition, which typically lasts for several years, banks have both IRB and SA loans in their portfolios. We exploit this feature of the implementation process in our empirical section, where we compare PD estimations with actual default rates for loans that are subject to different regulatory approaches.

### 3. Data

Our principal source of data is the German credit register compiled by Deutsche Bundesbank. As part of its supervisory role, the central bank collects data each quarter on all outstanding loans of at least € 1.5 million.<sup>14</sup> The data set starts in 1993 and includes information on the lender's and the borrower's identity, the amount of the loan outstanding and several other loan characteristics. As a response to the Basel II reform, reporting requirements for the credit register have been expanded considerably from 2008 onwards.

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<sup>13</sup>See Solvabilitätsverordnung (2006), §§ 64-67 for details on the implementation plan.

<sup>14</sup>Since we focus on corporate lending, this cut-off does not constitute a big issue for our analysis. When matching firm balance sheet information from the Bundesbank USTAN database to the credit register, we find that—in the matched sample—lending recorded in the credit register makes up about 80-90 percent of firms' overall bank debt on average.

In addition to the previous information, banks now also report exposure-level information on the regulatory approach (SA or IRB) and the estimated probability of default (PD). For loans under the IRB approach, the reported PD is the one that is used to determine regulatory capital charges. For loans under SA, banks also have to report PDs if they are estimated internally. As IRB banks aim to transfer all eligible loan portfolios to the new approach once the respective model is certified by the regulator, they report PDs for both IRB loans and SA loans. We use PDs for SA loans as a benchmark against which we evaluate the performance of PDs for IRB loans. Further, the database contains information on risk-weighted assets and loan loss provisions in case a loan defaults. The provisioning rules for loan losses are specified in the Solvabilitätsverordnung (2006). Banks have to make provisions that correspond to the expected loss as soon as there is information about repayment problems or default of a specific borrower (see § 125 of Solvabilitätsverordnung (2006)). We combine this exposure-level data with annual bank balance sheet information from Bundesbank's BAKIS database and annual firm balance sheet information from Bundesbank's USTAN database.

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

Descriptive statistics on the loan level are presented in Panel B of Table 1 and grouped by the regulatory approach used for the determination of capital charges. There are about twice as many SA loans (80,961) as compared with IRB loans (45,246) right after the introduction of the new regulatory approach. The first line of the table shows the average change in the amount of loans outstanding around the introduction of Basel II.<sup>15</sup> The average IRB

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<sup>15</sup>The sample includes all loans in the credit register that have an observation both before and after the reform. We calculate the change in lending around the reform by collapsing all quarterly data for a given exposure into single pre-event and post-event periods by taking the average of the two years before and the two years after the Basel II introduction. The change in lending is defined as the difference in the logarithm of these averages, so that there is one observation per loan.

loan in our sample was increased by about 6.5 percent over the Basel II introduction, while the average SA loan was increased by about 1.4 percent. Information on PDs becomes available in the credit register from 2008 onwards. The average PD in 2008Q1 is slightly higher for SA loans (2.6 percent) as compared with IRB loans (1.4 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.<sup>16</sup> Overall, this translates into an average risk weight of 68.5 percent for SA loans, which is considerably higher than the average risk weight for IRB loans (47.8 percent). Furthermore, banks are required to report loan loss provisions for loans in default. Since certain loans are backed by collateral or guarantees, the consequences of a borrower's default may vary. For both SA loans and IRB loans, loan loss provisions in case of a default are around 45 percent. Since the German credit register does not contain information on interest rates, we follow a procedure developed by Haselmann et al. (2013) to back out interest rates from the data that is available in the credit register. Specifically, we infer the repayment structure of the loan contract (e.g., whether it is repaid at the end of the contract period, linearly, or de-/progressively) from the quarterly data on loan amounts. We match this contract-level information with firm-level data on aggregate interest payments obtained from Bundesbank's USTAN database. This procedure allows us to back out effective annual interest rates on the loan contract level.<sup>17</sup> As displayed in the last line of Panel B, interest rates for loans under the standard approach are on average slightly lower (6.8 percent) than interest rates for loans under IRB (7.5 percent).

Finally, Panel C of Table 1 contains descriptives for several firm-level variables. First, we calculate a PD variable on the firm level by taking the average of all PDs assigned to the firm (by different banks) in the first quarter of 2008. The average for this firm-level variable is 2.2 percent and lies between the average PD for SA loans and the average PD

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<sup>16</sup>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.

<sup>17</sup>See Haselmann et al. (2013) for further details.

for IRB loans. Second, several accounting variables are obtained by a hand-match of the Bundesbank USTAN database with the credit register.<sup>18</sup> The match was conducted based on company name, location, and industry segment that are available in both data sources. The matched dataset contains detailed information on lending relationships and balance sheet items for 5,961 distinct firms. We report summary statistics on total assets, debt to assets and return on assets (ROA) for this sample. The average size of our sample firms is 154 million euros, the average debt to asset ratio is 34.3 percent, and the average return on assets is 7.9 percent.

## 4. Model

In this section, we develop a simple model in order to motivate our empirical strategy. The main argument of our paper is that the introduction of model-based regulation induced a change in the composition of borrowers, leading to an underestimation of credit risk in the model-based approach.

To illustrate this idea, let the true quality  $q$  of a loan be a function of noisily measured hard information  $h$  and soft information  $s$ :

$$\begin{aligned} h &= a_1 + \varepsilon_1 \\ s &= a_2 + \varepsilon_2, \end{aligned} \quad \text{where } \varepsilon \sim N\left(0, \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix}\right)$$

Now assume that  $q = h + s$ , but the regulator only observes  $h$ . This captures the idea that soft information  $s$  is not observable and therefore not contractible. For simplicity, capital charges are modeled as a tax imposed only on hard information. Under this assumption, the value of originating a loan for a bank can be written as follows:

$$V = (1 - t)a_1 + a_2 - c(a_1, a_2),$$

where  $c(a_1, a_2)$  indicates the effort cost for collecting hard and soft information. Assuming

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<sup>18</sup>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 database see Bachmann and Bayer (2013).

that effort is a substitute, i.e., exerting more effort on one task raises the marginal cost of effort for the second task, the cost function for collecting information can be specified as:

$$C(a_1, a_2) = \frac{1}{2}a_1^2 + \frac{1}{2}a_2^2 + Ka_1a_2, \quad \text{with } 1 > K > 0$$

Defining  $\beta = 1 - t$ , this implies the following optimization problem for the bank:

$$\max_{a_1, a_2} \beta a_1 + a_2 - \frac{1}{2}a_1^2 - \frac{1}{2}a_2^2 - Ka_1a_2$$

Solving this problem yields:

$$\text{FOC: } \beta - a_1 - Ka_2 = 0$$

$$1 - a_2 - Ka_1 = 0$$

$$\Rightarrow a_1^* = \frac{\beta - K}{1 - K^2} \quad \text{and} \quad a_2^* = \frac{1 - \beta K}{1 - K^2},$$

where  $a_1^*$  is the effort exerted on collecting hard information and  $a_2^*$  is the effort exerted on collecting soft information. Looking at the partial derivatives illustrates how  $\beta$ —a tax/reward on hard information—affects the relative effort exerted on the two types of information:

$$\frac{\partial a_1^*}{\partial \beta} > 0 \Rightarrow \text{Increase effort on collection of hard information}$$

$$\frac{\partial a_2^*}{\partial \beta} < 0 \Rightarrow \text{Decrease effort on collection of soft information}$$

Thus, the model illustrates that rewarding the collection of hard information may incentivize banks to exert less effort on the collection of soft information. The impact on overall loan quality depends on the relative importance of soft information:

$$\frac{dq^*}{d\beta} = \phi \frac{da_1^*}{d\beta} + \frac{da_2^*}{d\beta}$$

$$\Leftrightarrow \frac{dq^*}{d\beta} = \frac{\phi^2 - \phi\kappa}{1 - \kappa^2} = \frac{\phi(\phi - \kappa)}{1 - \kappa^2} \geq 0 \quad \text{if } \phi \geq \kappa$$

The equation illustrates that overall loan quality may decline if the collection of soft information is very important. In this case, the loss in soft information dominates the positive



effect that comes from the additional effort exerted on the collection of hard information. Keeping this in mind, we try to evaluate the overall impact of the reform on loan quality in the empirical part of the paper.

## **5. Banks' lending reaction to the introduction of IRB**

In this section we document banks' lending reaction to the introduction of model-based capital regulation, i.e. the internal ratings-based approach. We expect three effects: First, as capital requirements are lower under IRB than under SA, we expect that banks that introduced the new approach expand their lending relative to banks that did not. Second, as the reduction in capital requirements is greatest for firms with relatively good hard information (i.e., firms with relatively low PDs), we expect that IRB banks' expansion in lending is greatest for these firms. Third, firms with relatively bad soft information are subsidized the most if IRB banks rely more on hard information following the reform. Therefore, we expect lending to these firms to increase relatively more than lending to firms with relatively good soft information.

### **5.1. Bank level lending**

Acknowledging high organizational and administrative efforts for the introduction of IRB, the regulator provided banks with incentives to introduce the new approach by calibrating it in a way that ensured that requirements were lower under IRB than under SA (Basel Committee on Banking Supervision 2006, p. 12). Consequently, when banks introduced IRB in 2007Q1 they experienced a reduction in capital requirements for loans—both in absolute terms and relative to SA banks that did not introduce the new approach. Figure 2 shows that following this reform IRB banks expanded their lending to corporate borrowers in Germany. 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. Prior to the introduction the development of aggregate loans was relatively similar for the two groups of banks. Following the reform,

however, we see a sharp increase in aggregate loans for IRB banks, while the loans of SA banks remain relatively constant or even decline.

We formally test whether IRB banks expanded lending relative to SA banks following the reform by running simple, cross-sectional ordinary least squares (OLS) regressions. To avoid problems of autocorrelation we collapse quarterly bank-level loans into single pre-event and post-event time periods by taking the average of the two years before and the two years after the reform (Bertrand et al. 2004). The change in the logarithm of these averages serves as dependent variable in the following regression:

$$\Delta \log(\text{bank loans}) = D(\text{IRB bank}) \times \beta_1 + B' \beta_2 + \varepsilon, \quad (1)$$

where  $D(\text{IRB bank})$  is a dummy that indicates whether the respective bank introduced the IRB approach during our sample period and  $B'$  is a vector of bank control variables that includes the pre-event values of the logarithm of assets, the ratio of equity to assets, the ROA, and a set of dummies that indicate the bank's type. To be clear, the regression includes one observation for each bank, measuring the change in aggregate loans over the Basel II introduction in 2007Q1.

Estimation results are presented in Table 2. The first column includes only the IRB bank dummy as an explanatory variable. Following the reform, IRB banks increased their lending by about 9 percent as compared with SA banks.<sup>19</sup> In column 2 we add several bank-level control variables, and find that smaller banks, better capitalized banks, and more profitable banks increased their lending relatively more following the reform. The coefficient for the IRB bank dummy doubles in magnitude as compared with column 1, and also becomes more significant. Finally, in column 3, we add bank type dummies and find that state banks reduced their lending relative to commercial banks and cooperative banks. The coefficient for the IRB bank dummy remains significantly positive. Overall, the findings in this section document that—as expected—those banks that opted for the introduction of the Basel II internal ratings-based approach, and hence experienced a reduction in capital

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<sup>19</sup>According to Halvorsen and Palmquist (1980), the effect of dummy variables in semi-logarithmic equations is equal to  $\exp(\beta) - 1$ .

charges for the average loan, increased their lending relative to banks that remained under the standard approach. In the next section, we check whether this increase in lending is particularly strong for loans to firms with relatively good hard information.

## 5.2. Loan level lending and hard information

Under IRB, the capital charge for a specific loan depends on the estimated PD for that loan (see Section 2 for details). The PD is determined by the bank's internal risk model and depends on several hard information criteria. The better the hard information for a specific firm, the lower the PD for that firm, and the lower the capital charge for loans to that firm. Hence, we expect that IRB banks increase lending particularly to those firms where hard information is relatively good.

We test this assertion using loan level data from the German credit register. In particular, we assess how the change in lending for a particular bank-firm relationship depends on the regulatory approach adopted by the bank as well as on the goodness of hard information provided by the firm. As on the bank level, we collapse the quarterly loan 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. The change in the logarithm of loans from bank  $i$  to firm  $j$  serves as dependent variable in the following regression:

$$\Delta \log(\text{loans})_{ij} = \alpha_i + \alpha_j + D(\text{IRB bank})_i \times \text{Firm PD (2008Q1)}_j \times \gamma + \varepsilon_{ij}, \quad (2)$$

where  $i$  denotes the individual bank, and  $j$  denotes the individual firm. As a proxy for the goodness of hard information for a specific firm, we use the average PD banks report for that firm in 2008Q1, the first quarter in which this information is available (see Section 3). The lower this PD, the better the hard information the firm able to provide to its banks. The variable is interacted with the dummy 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. We do this by including firm fixed effects,  $\alpha_i$ , into our regression, hence ensuring that identification for the coefficient of interest comes only from

variation within the same firm.<sup>20</sup> That is, we test whether—following the reform—the same firm obtains relatively more loans from IRB banks as compared with SA banks, and whether this effect depends on the hard information the firm is able to provide. In the most stringent specification we additionally include bank fixed effects,  $\alpha_j$ , that allow us to systematically control for heterogeneity across banks. That is, we test whether the same bank increases its lending relatively more to firms with good hard information, and whether this effect depends on whether the bank is an IRB bank or not. Finally, to allow for potential correlation among changes in lending from the same bank we cluster standard errors at the bank level in all loan-level regressions.

Results for these regressions are presented in Panel A of Table 3. We start with a specification without any fixed effects that includes only the IRB bank dummy. As on the aggregate level, we find that following the reform loans by IRB banks are increased significantly more than loans by SA banks. In column 2 we add firm fixed effects in order to control for credit demand. The coefficient remains remarkably stable, indicating that changes in credit demand are not a big concern for our analysis. Economically, the two coefficients indicate that loans from IRB banks are increased by about 4.5 percent relative to loans from SA banks.<sup>21</sup> We proceed by splitting the sample based on the goodness of hard information firms are able to provide. Column 3 includes only firms with a lower-than-median average PD in 2008Q1, while column 4 includes only firms with a higher than median PD.<sup>22</sup> 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 (i.e., when hard

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<sup>20</sup>Consequently, the sample is constrained to firms that have at least one loan from an IRB bank and at least one loan from an SA bank.

<sup>21</sup>The magnitude is somewhat smaller than on the bank level, for which we have the following most likely explanations: (a) Our test shows the effect on the percentage change for the average loan. The effect will be relatively larger on the bank level if IRB banks increase larger loans relatively more compared with smaller loans; (b) our test focuses on changes in lending on the intensive margin, i.e. for loans that already existed prior to the reform. It could be that IRB banks also increase lending more on the extensive margin, i.e. they create more new loans following the reform as compared with SA banks. This would also magnify the effect on the bank level.

<sup>22</sup>Ideally, we would have used the average PD in 2006Q4 in this test, i.e. a pre-reform value. Unfortunately, information on PDs becomes available in the credit register only in 2008Q1, which is why we have to rely on the assumption that these PDs are relatively sticky in most cases. Additionally, we use alternative criteria for the goodness of hard information in a smaller matched sample for which we have firm balance sheet information (see Panel B of Table 3).

information is relatively good and capital charges are relatively low), but not when the firm's PD is relatively high (i.e., when hard information is relatively bad and capital charges are relatively high). In column 5 we interact the IRB bank dummy with the firm PD variable and find the same effect: IRB banks increase lending to the same firm relatively more, but less so when the firm's PD is higher. This effect is robust to the inclusion of bank fixed effects in column 6 and the inclusion of firm and bank fixed effects in column 7. Economically, the coefficient indicates that an increase of one standard deviation in *Firm PD (2008Q1)* (0.031, see Table 1, Panel B) induces a 1.2 percent smaller increase in loans from IRB banks, which corresponds to roughly one quarter of the overall effect identified in columns 1-2.

Unfortunately the PD data in the credit register becomes available only in 2008Q1, one year after the Basel II introduction. Ideally, we would like to have a proxy for the goodness of a firm's hard information prior to the event. In the previous analysis we had to rely on the assumption that the PD data is relatively sticky, so that firm PDs in 2006Q4 are similar to those in 2008Q1. Alternatively, we can use different proxies for hard information from a matched sample that contains firm balance sheet information. While this sample is smaller than the original one, it has the advantage that balance sheet information is also available for 2006, the year before the reform. We now provide additional tests, using the matched sample, in order to validate the results from above.

Results for these tests are presented in Panel B of Table 3. As balance sheet variables that proxy for the goodness of a firm's hard information we use the firm's pre-event leverage, size, and profitability. The PD for a specific loan will typically be lower the lower the firm's leverage, the larger its size, and the higher its profitability. The matched sample contains up to 8,748 loans to 1,712 distinct firms and hence corresponds to roughly one fifth of the original sample. In columns 1 and 2 we assess how a firm's leverage affects IRB banks lending decision. We find that an increase of one standard deviation in the firm debt to asset ratio (0.209, see Table 1, Panel B) induces a 6.1 to 8.5 percent smaller increase in lending from IRB banks. Similarly, an increase of one standard deviation in the logarithm of firm assets (1.775, see Table 1, Panel B) induces an increase in loans from IRB banks that is about 7 percent larger. Finally, also a firm's profitability affects IRB banks lending reaction: An

increase in one standard deviation of pre-event ROA (5.876, see Table 1, Panel B) results in an increase in loans from IRB banks that is about 2 to 3.5 percent larger. All these estimation results are robust to the inclusion of both firm and bank fixed effects. Overall, the results presented in this section provide strong evidence that—following the reform—IRB banks expanded loans in particular to those firms that have relatively good hard information, i.e., those firms for which estimated PDs and hence capital charges are relatively low.

### **5.3. Loan level lending and soft information**

So far we have shown that IRB banks expanded their lending following the Basel II reform, as they faced lower capital charges for loans, and that this effect was strongest for firms with relatively good hard information, i.e., firms for which the reduction in capital charges was the greatest. We claim, however, that the reform changed IRB banks incentives to lend, in the sense that it increased their reliance on hard information that goes into their internal risk models. Before the reform, IRB banks relied on both hard and soft information when making their lending decisions. After the reform, as capital charges started to depend on the hard information in the PD models, a bias towards greater reliance on this hard information was created. As a consequence, we expect that firms with relatively good hard information (i.e., firms with relatively low PDs), but relatively bad soft information experienced greater increases in loans from IRB banks, as IRB adjusted their lending decision behavior in a way that was favorable for these firms.

In order to test our claim we need a proxy for the non-quantifiable soft information of a certain firm that does not go into banks' internal risk models, which is per definition a difficult task. We try to circumvent this problem in the following way: To the extent that current accounting numbers reflect the hard information that goes into banks' internal risk models, changes in these numbers can be used as a proxy for the soft information that is not yet incorporated into the model estimates. In particular, we assume that the soft information for firms that experience, e.g., a positive change in ROA, has been better than the soft information for firms that experience a negative change in ROA. To be clear, we do not assume that future changes in ROA should be seen as soft information. We only

require that there is some positive correlation between these changes and the goodness of information on the firm that cannot be quantified for banks' internal models, which is, in our view, a relatively mild assumption.

Using the change in a firm's ROA from 2006 to 2007 as a proxy for the firm's soft information, we are able to estimate the following equation:

$$\Delta \log(\text{loans})_{ij} = \alpha_j + D(\text{IRB bank})_i \times \delta_1 + D(\text{IRB bank})_i \times \text{ROA Change}_j \times \delta_2 + \varepsilon_{ij}, \quad (3)$$

where  $i$  denotes the individual bank, and  $j$  denotes the individual firm. The dependent variable is, as in the previous section, the change in the logarithm of loans from bank  $i$  to firm  $j$  over the Basel II introduction. To control for a firm's demand for credit, the equation includes firm fixed effects,  $\alpha_j$ , that ensure that the coefficient of interest are identified only from variation within the same firm. As before, standard errors are clustered at the bank level to account for potential correlation among changes in loans from the same bank.

Results for these regressions are reported in Table 4. In the first four columns we apply a sample split based on our criteria for hard information (i.e., lower than median PD versus higher than median PD), and soft information (i.e., a negative change in ROA versus a positive change in ROA). The table shows that IRB banks increase lending relatively more to firms with relatively good hard information and relatively bad soft information, i.e. those firms that benefit the most from changed incentives in banks' lending decision processes. Compared with SA banks, IRB banks increase loans to these firms by about 11 percent more over the reform. Coefficients in the remaining columns are insignificant, indicating that IRB banks' expansion of loans is indeed driven by the group of firms identified above. Interestingly, however, the magnitude of the remaining coefficient is the one we would expect given our argumentation: For firms with good hard information and good soft information we get a positive but insignificant coefficient (column 2), i.e., these firms receive on average more loans following the reform, but not as much as firms benefitting from changes in banks' decision processes. The group of firms with relatively bad hard information receives relatively less loans from IRB banks following the reform (columns 3 and 4), but among these firms, those that benefit from changes in the lending decision process—i.e., firms with bad soft

information (column 3)—are relatively better off. In column 5 we interact the IRB bank dummy with a variable that gives the change in the firm’s ROA from 2006 to 2007 (*ROA Change*). The negative and significant coefficient is in line with the findings in column 1 to 4. An increase of one standard deviation in the change in ROA (4.077, see Table 1, Panel B) implies a 2.4 percent smaller increase in lending from IRB banks. Overall, results in this section provide strong evidence that IRB banks increased lending in particular to those firms that had relatively good hard information, but relatively bad soft information, i.e., those that benefitted the most from changes in the lending decision process that followed the Basel II reform. As IRB banks relied on their internal models for the calculation of capital requirements for loans, they started to neglect soft information—or, put differently, information that could not be quantified for the use in banks’ internal models—when making their lending decision. Instead, they increasingly relied on the hard information they used in their internal risk models. In the remainder of the paper, we will investigate the implication of this change in the lending decision process of IRB banks for goodness of banks’ evaluation of credit risk.

## **6. The impact of changed lending incentives on the quality of PD estimates in banks’ internal models**

In this section we evaluate how the changes in the lending decision process documented in the previous section affected banks’ evaluation of credit risk. In particular, we investigate whether actual defaults deviate from the numbers implied by PD estimates, and whether this deviation depends on the regulatory approach used for a specific loan. Further, we examine whether the deviation depends on the timing of loan origination, that is, we check whether the pattern is different for loans that were originated under Basel II as compared with loans that were originated under Basel I. Finally, we provide several robustness checks.



## 6.1. Empirical strategy

We now explain the empirical strategy employed in order to validate the main argument of our paper: That the introduction of model-based capital regulation induced a change in lending behavior that affected the estimations derived from banks' internal risk models. For each quarter, we estimate the following equation in order to test the relationship between PDs and actual default rates:

$$y_{ijk} = \alpha + \delta \cdot 1_{(k \in T)} + \varepsilon_{ijk}, \quad (4)$$

where  $j$  denotes the individual bank,  $i$  denotes the individual firm, and  $k$  indicates whether the loan belongs to an SA or to an IRB portfolio within the bank. The dependent variable  $y_{ijk}$  is defined as the difference between a dummy that indicates actual default and the PD that bank  $j$  attributes to loans to firm  $i$ . As PDs for loans vary between 0 and 1,  $y_{ijk}$  is positive for loans that actually default and negative for loans that do not default. The indicator variable  $1_{(k \in T)}$  takes a value of 1 if loans to firm  $i$  belong to the IRB portfolio of bank  $j$ , and 0 if they belong to the SA portfolio. Further, the equation includes a constant  $\alpha$  and a random error term  $\varepsilon_{ijk}$ . In order to allow for potential correlation among default events for loans to the same firm, standard errors are clustered at the firm level in all regressions.

If we want to interpret the coefficient of interest,  $\delta$ , as the causal impact of the regulatory approach on the prediction error  $y_{ijk}$  for a specific loan, the covariance between  $1_{(k \in T)}$  and  $\varepsilon_{ijk}$  should be equal to zero ( $Cov(\varepsilon_{ijk}, 1_{(k \in T)}) = 0$ ). As banks that introduced the model-based approach tend to be larger, internationally more active and more sophisticated than banks that remained under the traditional approach, an estimation based on loans from both types of banks could have biased our coefficients. Fortunately, the institutional details of the German Basel II introduction described in Section 2 allow us to circumvent this concern by using within-bank variation in the regulatory approach. IRB institutions did not shift all their portfolios to the new approach at the same time, so that we can use variation between loans that have already been shifted to IRB and loans that are still under SA to identify  $\delta$  in Equation (4).

Although the approach described above addresses many concerns, coefficients could be biased if there are omitted factors that determine whether firms are assigned to SA or IRB portfolios within IRB banks. To address this issue, we focus on firms that borrow from at least two banks, 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. Depending on the quarter, our sample contains up to 19,864 loans to 4,971 distinct firms that fulfill this criterion. For each quarter, we estimate:

$$y_{ijk} = \alpha_i + \alpha_j + \delta \cdot 1_{(k \in T)} + \varepsilon_{ijk}, \quad (5)$$

where  $\alpha_i$  and  $\alpha_j$  denote firm and bank fixed effects, respectively, and the remaining variables are defined as in Equation (4). By adding  $\alpha_i$  and  $\alpha_j$  we are able to systematically control for heterogeneity across banks and across firms. That is, we can check whether the prediction error for loans to the same firm is greater when IRB instead of SA is used by the bank, and—similarly—whether the estimation error for loans from the same bank is greater when IRB instead of SA is used for loans to a specific firm.

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

We argue that model-based regulation induced an overreliance on hard information, thus giving rise to underestimation of actual default rates. If this argumentation holds true, the effect should be particularly pronounced for loans that were originated after the introduction of model-based regulation. For those loans, capital charges depended on PD estimates

at the time of loan origination, while they did not for loans that were originated before the reform and consequently shifted to IRB. We exploit this time series variation in the loan issuance date to circumvent the selection concern. Specifically, we restrict ourselves to loans that actually use the IRB approach and check whether the underestimation of actual default rates is greater for loans that were originated after the reform as compared with loans that were originated before the reform. We estimate the following equation:

$$y_{ij} = \alpha_j + \delta \cdot 1_{(c \in B)} + \varepsilon_{ij}, \quad (6)$$

where  $1_{(c \in B)}$  is an indicator variable that takes a value of 1 if the the IRB loan was issued after the implementation of Basel II (in the year 2007) and 0 otherwise. Note that this specification is not prone to selection concerns and therefore allows for an unbiased estimate of the effect of the regulatory approach on the functioning of PD models.<sup>23</sup>

## 6.2. Descriptive analysis

We start the analysis by assessing how PD estimates from banks' internal risk models compare with actual default rates for a respective set of loans. The information on PDs—and with it the information on actual defaults—becomes available in the credit register in 2008Q1. As described above, the analysis in this section focuses on IRB and SA loans from IRB banks only. Although the information is available on a quarterly basis, we evaluate loan portfolios once per year—at the end of each year—for reasons of presentability.<sup>24</sup> As stated in Section 2, PDs should estimate one-year default rates and a loan is considered to be in default if the borrower is 90 days past due on his obligations. Accordingly, the dummy variable *Actual Default* captures whether a loan is in default in at least one of the four quarters following the one in which the PD is evaluated. Importantly, all loans that are already in default in a respective quarter are excluded from the analysis.

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<sup>23</sup>In contrast to previous estimations it is difficult to include also firm fixed effects in these regressions, as there are relatively few firms that obtained new loans both before and after the reform.

<sup>24</sup>Results for the remaining quarters are similar to the results we report, and available from the authors upon request. See also Figure A.1 in the appendix for an overview of average PDs and actual default rates for all quarters.

Panel A of Table 5 shows descriptive statistics for lending relationships under IRB. There are 50,163 lending relationships in our sample that had already been shifted to IRB in 2008. During the sample period from 2008 to 2011, additional portfolios are shifted to IRB. Relationships that were under SA in 2008 but are moved to IRB before 2011 are constantly classified as SA loans, since this was the regulatory regime under which they were originated. New relationships are classified according to the regulatory approach under which they were issued. When comparing model based PDs with actual default rates, we observe that PDs for IRB loans underestimate actual defaults in 2008, 2009, and 2011. Only in 2010, the estimated PDs and actual defaults of IRB loans match.

In Panel B of Table 5 we repeat the analysis presented in Panel A for those loans that were still subject to the standard approach in 2008. These portfolios will be transferred to IRB once the respective model is certified by the regulator. While the underlying PD models should hence be similar for IRB loans and SA loans, capital charges under IRB depend on the estimated PDs while capital charges under SA do not. Interestingly, while PDs for IRB loans underestimated actual defaults on average, we do not find a similar pattern for IRB banks' SA loans. In 2008, the actual default rate almost matches the average PD, and in the remaining years it is even lower than the average PD (especially in 2010, a year with a very low actual default rate).

Figure 3 plots average PDs and actual default rates for IRB loans and SA loans over time.<sup>25</sup> In line with our expectation, average PDs for IRB loans are always lower than average PDs for SA loans. As shown in Section 5, IRB banks have shifted their lending more towards firms with low model-based PDs as capital charges under IRB are particularly low for loans to these firms. Kernel density plots for PDs further illustrate this point (see Figure 4). Clearly, the distribution for IRB loans is to the left of the distribution for SA loans in all years. This is confirmed in a Kolmogorov-Smirnov test for equality of distributions: The hypothesis that the distributions for SA loans and IRB loans are equal can be rejected at the 1 percent level in all cases.

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<sup>25</sup>Again, for reasons of presentability, we evaluate loan portfolios only once a year. Results for the remaining quarters are very similar (see Figure A.1 in the Appendix).

Panel C of Table 5 and the lower part of Figure 3 further present corresponding actual default rates for the two sets of loans. In stark contrast to PDs, actual default rates are similar for both portfolios in 2008 and 2009, and, are somewhat higher for IRB loans in 2010 and 2011 as compared with SA loans.

Finally, Panel C of Table 5 also reports differences in the difference between actual default rates and average PDs. In all years, this difference is larger for IRB loans: Compared to PDs for SA loans, PDs for IRB loans underestimate actual default. Albeit illustrative, the latter findings might be explained by borrower or bank specific factors. We therefore proceed by testing our assertions more formally in a regression framework.

### **6.3. Regression framework: IRB versus SA loans**

Results for Equation (5) are presented in Table 6. We start with the specification without any fixed effects in the first four columns and estimate the equation separately for each quarter in order to ensure that each loan turns up only once in each regression.<sup>26</sup> In line with the findings in the previous section, the regressions show that the estimation error is significantly greater for IRB loans as compared with SA loans, i.e.—compared to PDs for SA loans—PDs for IRB loans significantly underpredict actual default rates.<sup>27</sup> Next, we add firm fixed effects in columns 5 to 8. In these tests, the sample is constrained to firms that have at least one IRB loan and at least one SA loan from an IRB bank. The coefficient for the IRB loan dummy remains significantly positive in all cases PDs are more likely to underpredict actual default if IRB instead of SA is used for a specific loan.

As a final test, we complete the specification by adding bank fixed effects in columns 9 to 12 of Table 6. The coefficient for the IRB loan dummy remains significantly positive, which means that—within the same bank—underprediction of actual default is more likely if IRB instead of SA is used for a particular loan. Overall, empirical results provide strong

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<sup>26</sup>Again, we constrain ourselves to 2008Q4, 2009Q4, 2010Q4, and 2011Q4 for reasons of presentability. Results for the remaining quarters are very similar and available from the authors upon request.

<sup>27</sup>The coefficients for the IRB loan dummy in columns 1-4 correspond to the differences in differences in Panel C of Table 5.

support for our assertion that PDs for loans under the IRB approach tend to underpredict actual default rates.

#### **6.4. Regression framework: IRB loans issued before and after the event**

In this section, we revisit potential selection concerns arising from the order in which IRB banks shift their loan portfolios from SA to IRB. As discussed in detail in Section 6.1, 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, we exploit time series variation in the date of loan issuance to remove any remaining doubts. To do so, we restrict ourselves to loans that actually use the IRB approach, and check whether the underestimation of actual default rates is greater for loans that were originated after the reform as compared with loans that were originated before the reform. In other words, we circumvent the selection concern by focusing on variation over time within the portfolio of IRB loans.

Specifically, we evaluate the performance of a sample of loans that were originated between 2005 and 2008, within two years before and after the reform. As our data is on the bank-firm level (and not on the contract level), we define the year of a loan issuance as follows: First, if a new bank-firm relationship is formed in a given year, it is clear that a new loan was originated in that year. Second, for existing bank-firm relationships, we assume that a new loan was granted if we see an increase of at least € 1.5 million (the lower bound for being reported in the credit register) and of at least 30 percent of the amount already outstanding in a given quarter.<sup>28</sup> Panel A of Figure 5 shows actual default rates and PD averages for these loans in 2009Q4. Loans originated in 2005 or 2006 (pre-reform) exhibit average PDs that are relatively close to actual default rates. In contrast, the actual default rate is considerably higher than the average PD for loans originated after the Basel II reform in 2007 or 2008 (post-reform), indicating an underestimation of credit risk for this set of

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<sup>28</sup>We focus on large increases in the outstanding loan amount of a given bank-firm relationship since most firms keep a checking account with their banks whose balances keep varying around a certain level quarter by quarter. Importantly, our results do not depend on the exact definition of a new loan issuance, i.e., we have tried different cutoff values and obtained similar results.

loans.

Panel A of Figure 5 evaluates loan performance in 2009, which means that loans originated in different years differ in the time elapsed since their origination.<sup>29</sup> To rule out that the length of a specific relationship explains part of our findings in Panel A, we repeat the analysis using a different evaluation horizon. In particular, we evaluate loan performance four years after origination. That is, loans originated in 2005 are evaluated in 2009Q4, loans originated in 2006 are evaluated in 2010Q4, and so on. Hence, Panel B of Figure 5 evaluates the performance of all loans that still exist four years after their origination.<sup>30</sup> Average PDs are slightly higher than actual default rates for loans originated before the reform, and considerably lower than actual default rates for loans originated after the reform.

Table 7 provides regression results for Equation (6). As before, we use the estimation error as a dependent variable and start with a specification without any fixed effects for the set of loans introduced in Figure 5, Panel A. We find a significant difference between the two regimes, i.e., PDs for loans originated under Basel II are significantly more likely to underestimate actual default rates than PDs for loans originated before the reform. Column 2 shows that this result is robust to the inclusion of bank fixed effects, which means that the same bank more often underestimates the actual default rate for loans that were originated under Basel II. Finally, columns 3 and 4 repeat the estimations from the first two columns, using the set of loans with a four-year evaluation horizon from Figure 5, Panel B. Results are very similar.

Results in this section confirm that our findings in the previous section are not driven by the selection of IRB loan portfolios. We find a stronger underestimation effect for IRB loans that were originated after the reform as compared with IRB loans that were originated before the reform. While these loans differ in the time of origination, they find themselves within the same loan portfolios within IRB banks, i.e., those portfolios for which the new

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<sup>29</sup>Evaluating loans in 2009 allows us to include loans that were originated within a two-year window around the reform, with the sample being relatively balanced between loans that were originated before and after the reform. The same test in 2010 yields similar results, but is less balanced since the share of loans originated before the reform is considerably lower.

<sup>30</sup>We also tried alternative evaluation horizons (three years, five years) and obtained similar results.

approach has already been implemented.

## 6.5. Further results

We further report some robustness tests to our main specification in Equation (5). Previously, we have given equal weight to all observations. However, one might argue that it is more important that IRB banks get PDs for larger loans right, as these loans are more important for the determination of overall required capital. If the underestimation effect is less severe for larger loans, it could be that on aggregate banks get required capital right. To test this, we report results for weighted regressions in columns 1 to 4 of Table 8, where we weight each observation by its loan size. Coefficients are somewhat smaller in these regressions as compared with the coefficients in the unweighted regressions (Table 6, columns 5 to 8). Nevertheless, they are still significant in most cases, indicating that the underestimation effect for IRB loans is also present if one considers the size of each loan.

Next, we use two alternative definitions for the dependent variable in the remaining columns of Table 8. First, in columns 5 to 8, we take the absolute value of the difference between the actual default dummy and the estimated PD for each loan as a left-hand-side variable. The coefficient for the IRB loan dummy is positive and significant in all cases. In previous regressions we investigated whether PDs for IRB loans are more likely to understate actual credit risk. By focusing on the absolute value of the estimation error, we treat an overestimation of actual default risk in the same way as an underestimation. Still, the regressions show that PD estimates for IRB loans are less precise than PD estimates for SA loans on average. Second, we focus only on loans that actually defaulted, i.e., on loans for which the difference between the actual default dummy and the PD is greater than 0, and set the difference for the remaining loans equal to 0. In this way, we check whether default risk for loans that actually defaulted was underestimated more by PDs for IRB loans. The positive and significant coefficients for the IRB loan dummy in columns 9 to 12 show that this is indeed the case. PDs for loans that defaulted were on average lower if the IRB instead of the standard approach was used for the loan.



## 7. Conclusion

The regulation of bank capital requirements is one of the most controversial topics in today's world of banking. Most recently, Basel-type model-based regulation has come under pressure as there seems to be growing distrust among investors on the validity of regulatory risk weights. In this paper, we use data from the German credit register to show that the introduction of the Basel II internal ratings-based (IRB) approach affected both the quantity and the composition of bank lending. Specifically, banks that introduced the IRB approach increased their lending following the reform, in particular to firms with relatively low model-based PDs. In the second part of the paper we examine how this change in the composition of borrowers affected the validity of internal risk estimates. We find that risk estimates for IRB loans tend to underestimate actual default rates for IRB loans, while there is no such effect for SA loans. Moreover, the underestimation effect is worse for those IRB loans that were originated after the reform.

While we cannot—and also do not want to—rule out additional problems associated with model-based regulation, our empirical findings strongly suggest that overreliance on borrowers with favorable value parameters for the PD models plays a crucial role in explaining the underestimation of actual default rates. An alternative explanation for problems with model-based regulation would be a pure manipulation story: It could be that banks simply shift existing PDs downwards in order to economize on regulatory capital. Our time-series tests (i.e., the comparison of estimation errors for loans issued before and after the reform) can be seen as evidence against such an explanation: If banks simply manipulated PDs of existing borrowers after the reform, the estimation error should be high for all IRB loans, irrespective of the date of loan origination. We have shown, however, that the estimation error is considerably larger for loans that were issued after the reform, where banks had incentives to lend to firms that score well on the dimensions used in the risk models.

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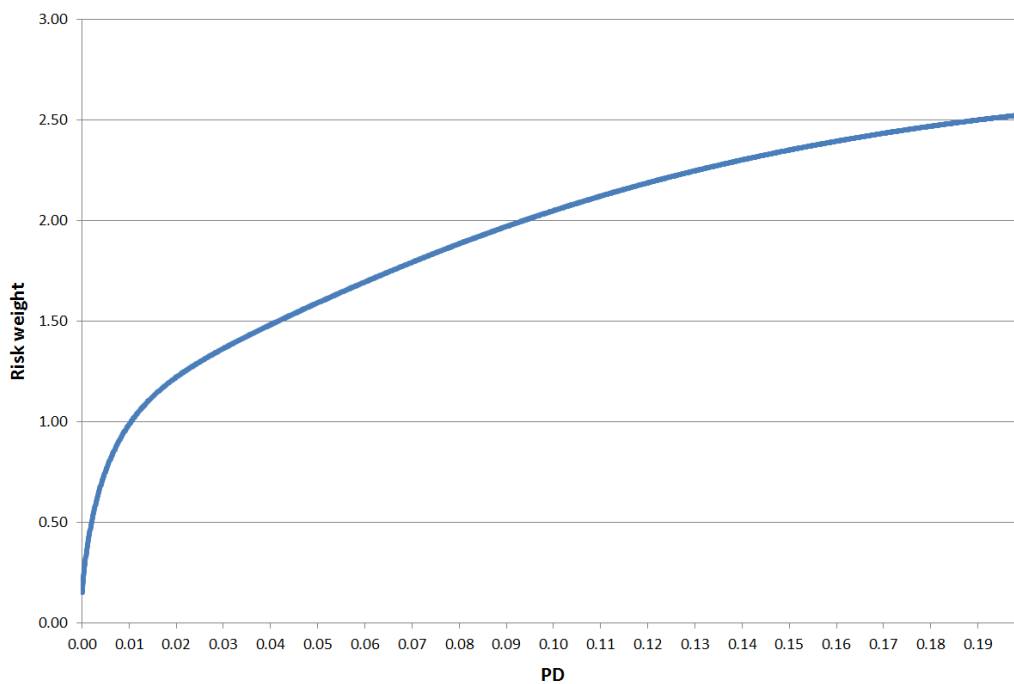


Figure 1: PDs and regulatory risk weights

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

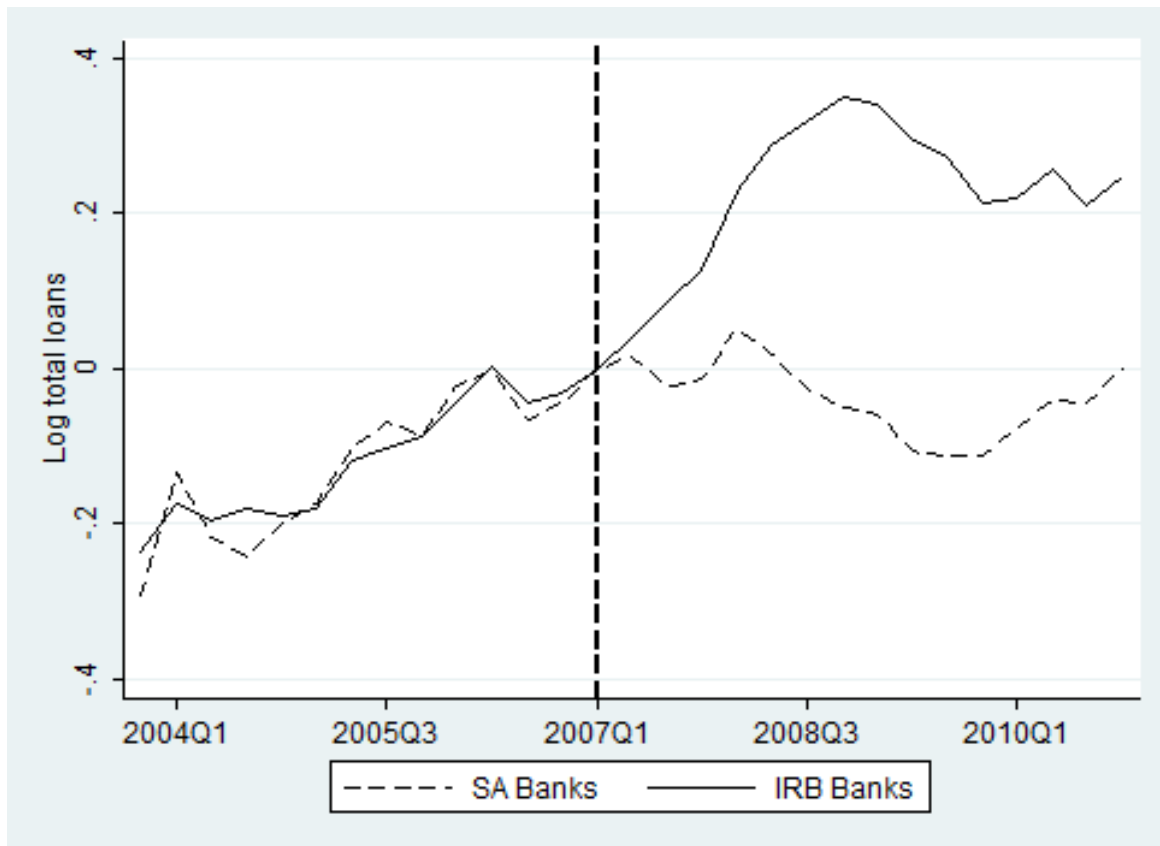


Figure 2: Aggregate lending around the Basel II introduction

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

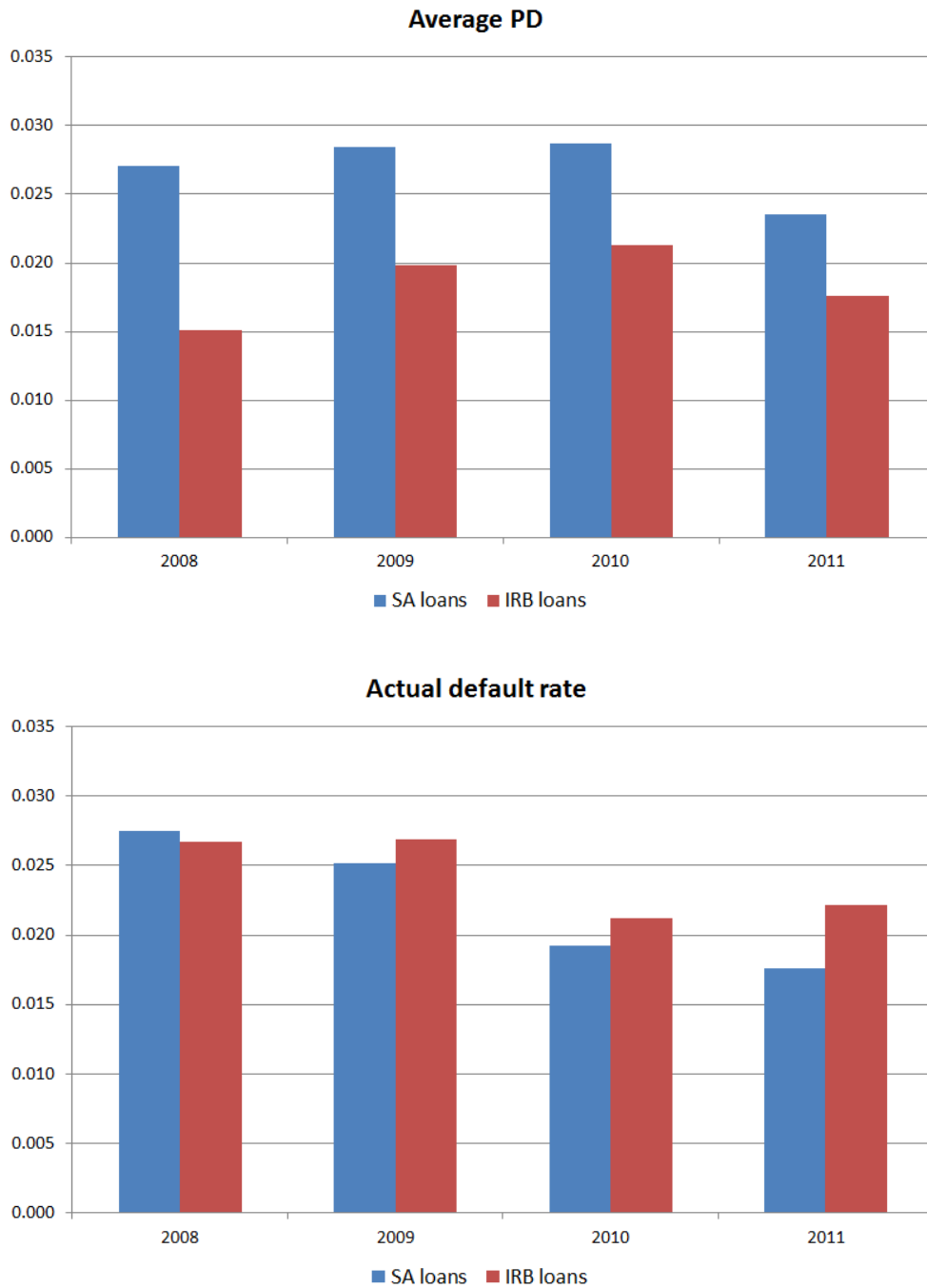


Figure 3: Average PDs and actual default rates

The figure shows average PDs and actual default rates for SA loans and IRB loans during the period from 2008Q1 to 2012Q2. For reasons of presentability we evaluate loan portfolios only once per year, at the end of each year (see Figure A.1 in the Appendix for the remaining quarters). The sample includes all loans that are not in default at the respective point in time. For the top panel, we calculate the averages of reported PDs for the respective portfolios of loans. For the bottom panel, we create a dummy that equals 1 for loans that default in the year following the respective quarter, and calculate the average of this dummy variable for the respective portfolios of loans.



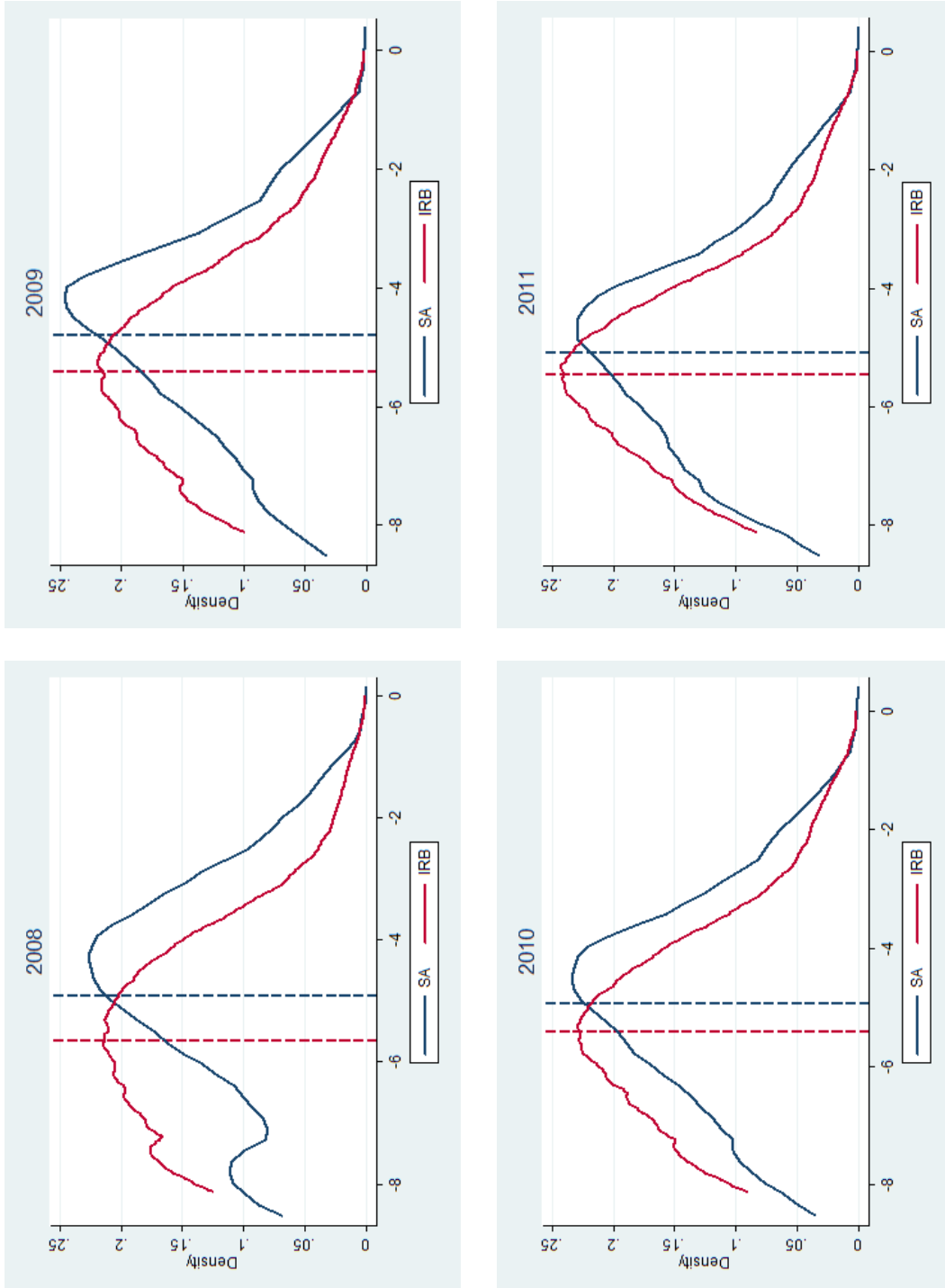


Figure 4: PD kernel densities

The figure shows Epanechnikov kernel densities for PDs at 2008Q4, 2009Q4, 2010Q4, and 2011Q4, respectively. PDs are reported in logarithms for reasons of presentability. The smoothing parameter in the density estimation is set to 0.4. The blue line corresponds to PDs for SA loans of IRB banks, the red line corresponds to IRB loans of IRB banks. Dashed vertical lines represent the respective mean of the distribution.

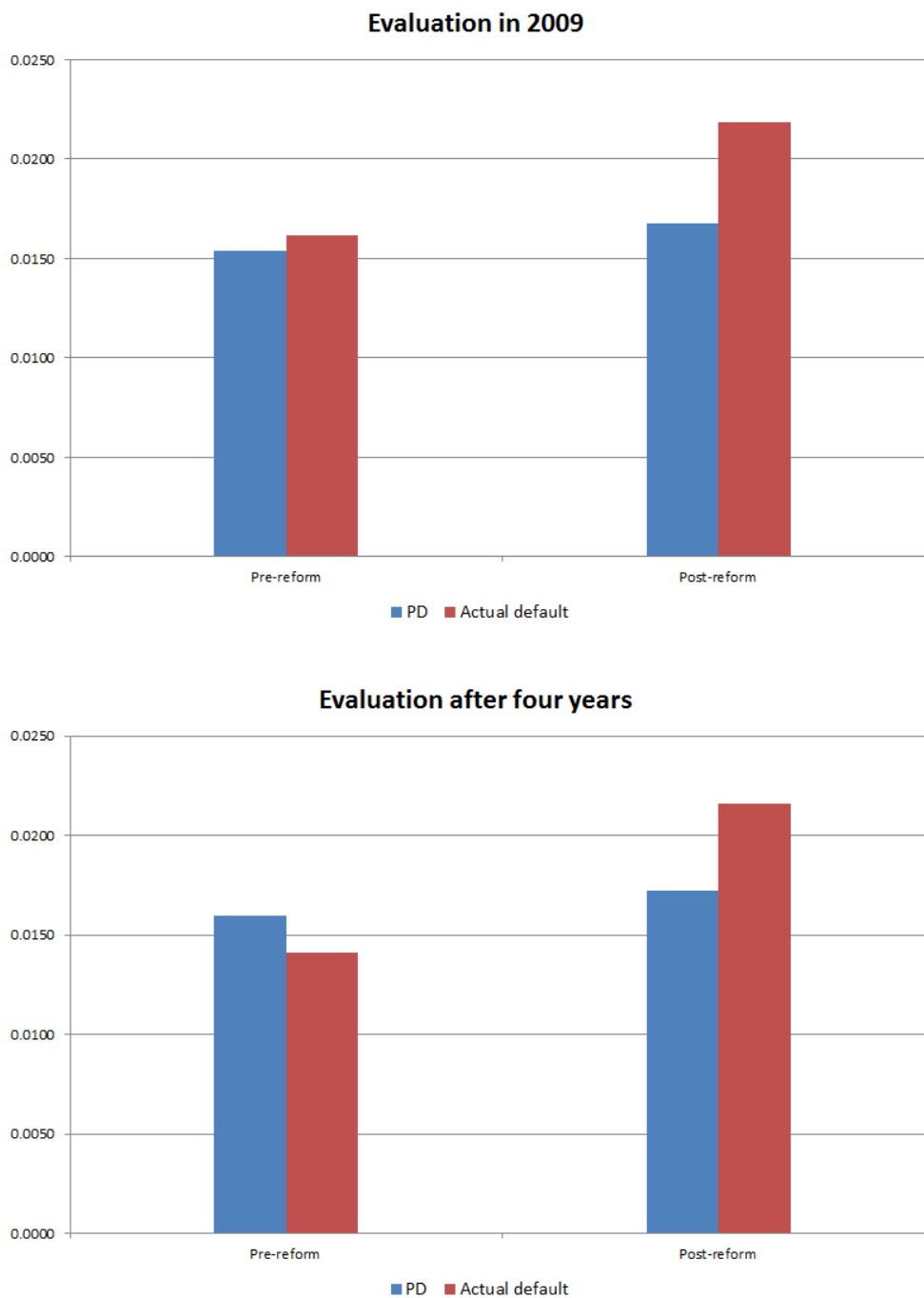


Figure 5: Average PDs and actual default rates by loan cohorts

The figure shows average PDs and actual default rates for loans under IRB that were originated in the years around the Basel II introduction, i.e., for bank-firm-relationships that did not exist before or that display a large increase (i.e., at least €1.5 million and at least 30 % of existing loan amount) in 2005 or 2006 (pre-reform), 2007 or 2008 (post-reform). In Panel A, all loans are evaluated in 2009Q4, whereas Panel B evaluates loans four years after their origination, i.e., loans originated in 2005 are evaluated in 2009Q4, loans originated in 2006 are evaluated in 2010Q4, and so on.

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
Bank type				
... commercial	14.0	–	54.3	–
... state	29.4	–	34.3	–
... cooperative	56.7	–	11.4	–
Panel B: Loan descriptives				
	SA loans (81,961 loans)		IRB loans (45,246 loans)	
	Mean	S.D.	Mean	S.D.
$\Delta$ log(loans)	0.016	0.358	0.064	0.570
PD	0.026	0.060	0.018	0.061
RWA to loans	0.685	0.375	0.422	0.436
LLP to loans	0.438	0.286	0.478	0.305
Interest rate	0.068	0.040	0.075	0.042
Panel C: Firm descriptives				
	(5,961 firms)			
	Mean	S.D.		
Firm PD	0.022	0.031		
Firm assets (2006, in mn €)	154	817		
Firm debt / 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 (c) loans that have an observation both before and after the introduction of Basel II in 2007. Besides information on changes in lending around the reform the panel also includes information on loan interest rates, on the loan-specific ratio of risk-weighted assets to loans, of loan loss provisions to loans, and on the PD in 2008Q1, the first quarter for which this information is available. Panel C contains information on the firm level for a matched sample of 5,961 firms. Firm balance sheet information is obtained from Bundesbank's USTAN database.

Table 2: Bank level lending

	Dependent variable: $\Delta \log(\text{bank loans})$		
	(1)	(2)	(3)
D(IRB bank)	0.0867** (0.0346)	0.1754*** (0.0465)	0.1115** (0.0505)
Log bank assets (2006)		-0.0147* (0.0077)	0.0073 (0.0086)
Bank equity ratio (2006)		0.0067* (0.0036)	0.0067* (0.0039)
Bank ROA (2006)		0.0448* (0.0235)	0.0498** (0.0239)
D(state bank)			-0.0772** (0.0355)
D(cooperative bank)			0.0461 (0.0345)
Constant	0.1901*** (0.0096)	0.4076** (0.1673)	-0.0411 (0.1856)
Observations	1,603	1,547	1,547
R-squared	0.0015	0.0168	0.0336

The table shows results for simple OLS regressions, where the dependent variable is the change in the logarithm of aggregate bank lending over the Basel II introduction in 2007Q1. For each bank, we calculate aggregate lending by summing all loans in a respective period. We then collapse all quarterly data for a given bank into single pre-event and post-event periods by taking the average of the two years before and the two years after the Basel II introduction. The dependent variable in the regressions above is the difference in the logarithm of these averages, so that there is one observation per bank. The dummy variable  $D(\text{IRB bank})$  indicates whether the respective bank adopted the Basel II internal ratings-based approach during our sample period. Robust standard errors are reported in parentheses. Note: \* indicates statistical significance at the 10 % level, \*\* at the 5 % level and \*\*\* at the 1 % level.

Table 3: Loan level lending

Panel A: Firm PD (2008Q1)							
	Dependent variable: $\Delta \log(\text{loans})$						
	(1) All	(2) All	(3) Low PD	(4) High PD	(5) All	(6) All	(7) All
D(IRB bank)	0.0486*** (0.0173)	0.0445** (0.0180)	0.0759*** (0.0245)	0.0150 (0.0142)	0.0511*** (0.0193)		
D(IRB bank) $\times$ Firm PD (2008Q1)					-0.5519*** (0.1580)	-0.4529*** (0.1434)	-0.3951** (0.1573)
Firm PD (2008Q1)						-0.2990*** (0.0890)	
Constant	0.0286*** (0.0068)						
Firm FE	NO	YES	YES	YES	YES	NO	YES
Bank FE	NO	NO	NO	NO	NO	YES	YES
Observations	44,784	44,784	22,391	22,393	44,784	44,784	44,784
R-squared	0.0024	0.2268	0.1818	0.2890	0.2271	0.0402	0.2626

Panel B: Additional firm variables							
	Dependent variable: $\Delta \log(\text{loans})$						
	(1)	(2)	(3)	(4)	(5)	(6)	
D(IRB bank) $\times$ Firm debt / assets (2006)	-0.4276*** (0.0759)	-0.3020*** (0.0683)					
D(IRB bank) $\times$ Log firm assets (2006)			0.0391*** (0.0101)	0.0374*** (0.0117)			
D(IRB bank) $\times$ Firm ROA (2006)					0.0060*** (0.0021)	0.0034* (0.0018)	
D(IRB bank)		0.1609*** (0.0299)		-0.4580*** (0.1132)		-0.0239 (0.0304)	
FIRM FE		YES	YES	YES	YES	YES	YES
BANK FE		NO	YES	NO	YES	NO	YES
Observations		8,411	8,411	8,735	8,735	8,748	8,748
R-squared		0.3015	0.3659	0.3245	0.3880	0.3138	0.3784

The table shows how loan level lending changed over the Basel II introduction. For each bank-firm relationship, we collapse all quarterly data for into single pre-event and post-event periods by taking the average of the two years before and the two years after the Basel II introduction. The dependent variable in the regressions above is the difference in the logarithm of these averages, so that there is one observation per bank-firm relationship. Data are restricted to (a) loans that are larger than € 1.5 million (b) loans from commercial, state, or cooperative banks that are subject to the Basel II capital regulation (c) loans that have an observation in both the pre- and the post-event period (d) loans to firms that have at least one loan from an SA bank and one loan from an IRB bank. Panel A uses only data from the credit register, Panel B uses a matched sample that includes firm balance sheet information from Bundesbank's USTAN database. 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.

Table 4: Loan level lending—change in ROA

	Dependent variable: $\Delta \log(\text{loans})$				
	(1)	(2)	(3)	(4)	(5)
	PD low ROA down	PD low ROA up	PD high ROA down	PD high ROA up	All
IRB Bank	0.1034** (0.0406)	0.0135 (0.0392)	0.0003 (0.0186)	-0.0278 (0.0223)	0.0146 (0.0225)
IRB Bank $\times$ ROA Change					-0.0057** (0.0023)
Firm FE	YES	YES	YES	YES	YES
Observations	1,551	1,701	2,494	2,661	8,407
R-squared	0.2842	0.3063	0.3580	0.2891	0.3120

The table shows how loan level lending changed over the Basel II introduction. As before, we collapse our sample into single pre- and post-event time periods and use the change in  $\log(\text{loans})$  for a bank-firm relationship as the dependent variable. The sample is split into firms with below/above median PD and firms where the change in ROA from 2006 to 2007 was negative/positive. The variable *ROA change* denotes the change in the firm's ROA from 2006 to 2007. 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.

Table 5: Estimation error—descriptives

Panel A: IRB banks, IRB loans				
	Observations	Actual default	PD	Actual default – PD
2008	50,163	0.0267	0.0151	0.0116
2009	47,167	0.0269	0.0198	0.0071
2010	47,019	0.0212	0.0213	-0.0001
2011	46,357	0.0222	0.0176	0.0046

Panel B: IRB banks, SA loans				
	Observations	Actual default	PD	Actual default – PD
2008	22,751	0.0275	0.0270	0.0004
2009	23,426	0.0251	0.0284	-0.0033
2010	21,130	0.0192	0.0287	-0.0095
2011	18,894	0.0176	0.0235	-0.0059

Panel C: IRB vs. SA			
	Difference in actual default	Difference in PD	Difference in difference
2008	-0.0008 [-0.6170]	-0.0120 [-31.7598]	0.0112 [8.5746]
2009	0.0018 [1.3766]	-0.0086 [-18.2768]	0.0103 [7.9694]
2010	0.0020 [1.7269]	-0.0074 [-14.2997]	0.0094 [7.8497]
2011	0.0046 [3.7342]	-0.0060 [-13.7121]	0.0106 [8.5387]

The table compares actual default rates with banks' estimated PDs in 2008Q4, 2009Q4, 2010Q4, and 2011Q4, respectively. Panel A includes all loans by IRB banks that were subject to the IRB approach in 2008Q1, the first period where this information is available. The column *Actual default* displays the mean of a dummy variable that is equal to 1 if the loan defaults in the year following the respective quarter. Loans that are already in default in the respective quarter are excluded. The column *PD* displays the average estimated one-year default rate for the same set of loans, and the column *Actual default - PD* displays the difference between the two. Panel B repeats the same analysis for all loans by IRB banks that were subject to the standard approach in 2008Q1. Panel C compares the two panels with each other by calculating—for each quarter—the difference between the values for IRB loans and for SA loans. The numbers in brackets are t-statistics.

Table 6: Estimation error—regressions

		Dependent variable: Estimation error (actual default – PD)											
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		2008	2009	2010	2011	2008	2009	2010	2011	2008	2009	2010	2011
D(IRB loan)	0.0112*** (0.0014)	0.0103*** (0.0013)	0.0094*** (0.0013)	0.0106*** (0.0012)	0.0113*** (0.0021)	0.0079*** (0.0020)	0.0073*** (0.0019)	0.0096*** (0.0019)	0.0076*** (0.0028)	0.0074*** (0.0024)	0.0071*** (0.0025)	0.0090*** (0.0025)	
Constant	0.0004 (0.0011)	-0.0033*** (0.0011)	-0.0095*** (0.0010)	-0.0059*** (0.0010)									
Firm FE	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	
Bank FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	
Observations	72,914	70,593	68,149	65,251	19,864	19,182	17,650	15,431	19,864	19,182	17,650	15,431	
R-squared	0.0010	0.0009	0.0009	0.0011	0.6248	0.5910	0.5973	0.5861	0.6297	0.5989	0.6065	0.5914	

The table shows loan-level regression results for 2008Q4, 2009Q4, 2010Q4, and 2011Q4, respectively. The dependent variable in all regressions is the difference between a dummy that indicates whether the respective loan defaults in the year following the respective period and the estimated PD of the loan. The sample includes all loans from IRB banks, where columns 5-12 are restricted to firms that have at least one IRB loan and at least one SA loan from an IRB bank. As we evaluate loans periodwise, there is one observation per bank-firm relationship in each regression. The dummy *D(IRB loan)* indicates the regulatory approach under which a specific loan was originated and is equal to 1 if the loan was issued under IRB. Columns 5-8 include firm fixed effects to control for heterogeneity across borrowers and columns 9-12 additionally includes bank fixed effects that control for heterogeneity across banks. Robust standard errors adjusted for clustering at the firm level are reported in parentheses. Note: \* indicates statistical significance at the 10 % level, \*\* at the 5 % level and \*\*\* at the 1 % level.



Table 7: Estimation error by cohorts

	Dependent variable: Estimation error (actual default – PD)			
	Evaluation in 2009		Evaluation after four years	
	(1)	(2)	(3)	(4)
Basel II	0.0043*** (0.0010)	0.0045*** (0.0010)	0.0062*** (0.0013)	0.0067*** (0.0013)
Constant	0.0008 (0.0010)		-0.0018** (0.0009)	
BANK FE	NO	YES	NO	YES
Observations	67,015	67,015	49,382	49,382
R-squared	0.0002	0.0213	0.0005	0.0291

The table evaluates how the estimation error depends on the year of the loan origination. We include only loans that were originated in the years around the Basel II introduction, i.e., bank-firm-relationships that did not exist before or that display a large increase (i.e., at least €1.5 million and at least 30 % of existing loan amount) in the respective year. The dependent variable in all regressions is the difference between the dummy for actual default and the estimated PD for the loan. The dummy *Basel II* is equal to 1 if the loan was originated after the Basel II introduction (i.e., in 2007 or 2008) and equal to 0 if it was originated before (i.e., in 2005 or 2006). In columns 1 and 2, loans are evaluated in 2009Q4. In columns 3 and 4, loans are evaluated four years after their origination, i.e., loans originated in 2005 are evaluated in 2009Q4, loans originated in 2006 are evaluated in 2010Q4, and so on. Robust standard errors adjusted for clustering at the firm level are reported in parentheses. Note: \* indicates statistical significance at the 10 % level, \*\* at the 5 % level and \*\*\* at the 1 % level.

Table 8: Estimation error—further results

	Value weighted			Absolute error			Positive error					
	(1) 2008	(2) 2009	(3) 2010	(4) 2011	(5) 2008	(6) 2009	(7) 2010	(8) 2011	(9) 2008	(10) 2009	(11) 2010	(12) 2011
D(IRB loan)	0.0087** (0.0036)	0.0053*** (0.0019)	0.0045*** (0.0017)	0.0068*** (0.0020)	0.0040** (0.0021)	0.0030* (0.0018)	0.0043** (0.0017)	0.0098*** (0.0018)	0.0077*** (0.0019)	0.0054*** (0.0017)	0.0058*** (0.0015)	0.0097*** (0.0017)
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	19,864	19,182	17,650	15,431	19,864	19,182	17,650	15,431	19,864	19,182	17,650	15,431
R-squared	0.6332	0.6583	0.5594	0.6543	0.6540	0.6463	0.6586	0.6334	0.6598	0.6379	0.6406	0.6142

The table shows further loan-level regression results for 2008Q4, 2009Q4, 2010Q4, and 2011Q4, respectively. Columns 1-4 provide weighted regression results, where the dependent variable is the same as in Table 6 and observations are weighted by the size of the respective loan. In columns 5-8 the dependent variable is equal to the absolute value of the difference between the dummy for actual default and the estimated PD for the loan. In columns 9-12 the dependent variable is equal to the difference between the dummy for actual default and the estimated PD for the loan for positive values of this difference and set to 0 for negative values. As before, the sample includes all loans from IRB banks to firms that have at least one IRB loan and at least one SA loan from an IRB bank. Loans are evaluated periodwise, so that there is one observation per bank-firm relationship in each regression. The dummy *D(IRB loan)* indicates the regulatory approach under which a specific loan was originated and is equal to 1 if the loan was issued under IRB. All columns include firm fixed effects to control for heterogeneity across borrowers. Robust standard errors adjusted for clustering at the firm level are reported in parentheses. Note: \* indicates statistical significance at the 10 % level, \*\* at the 5 % level and \*\*\* at the 1 % level.

## **Appendix**

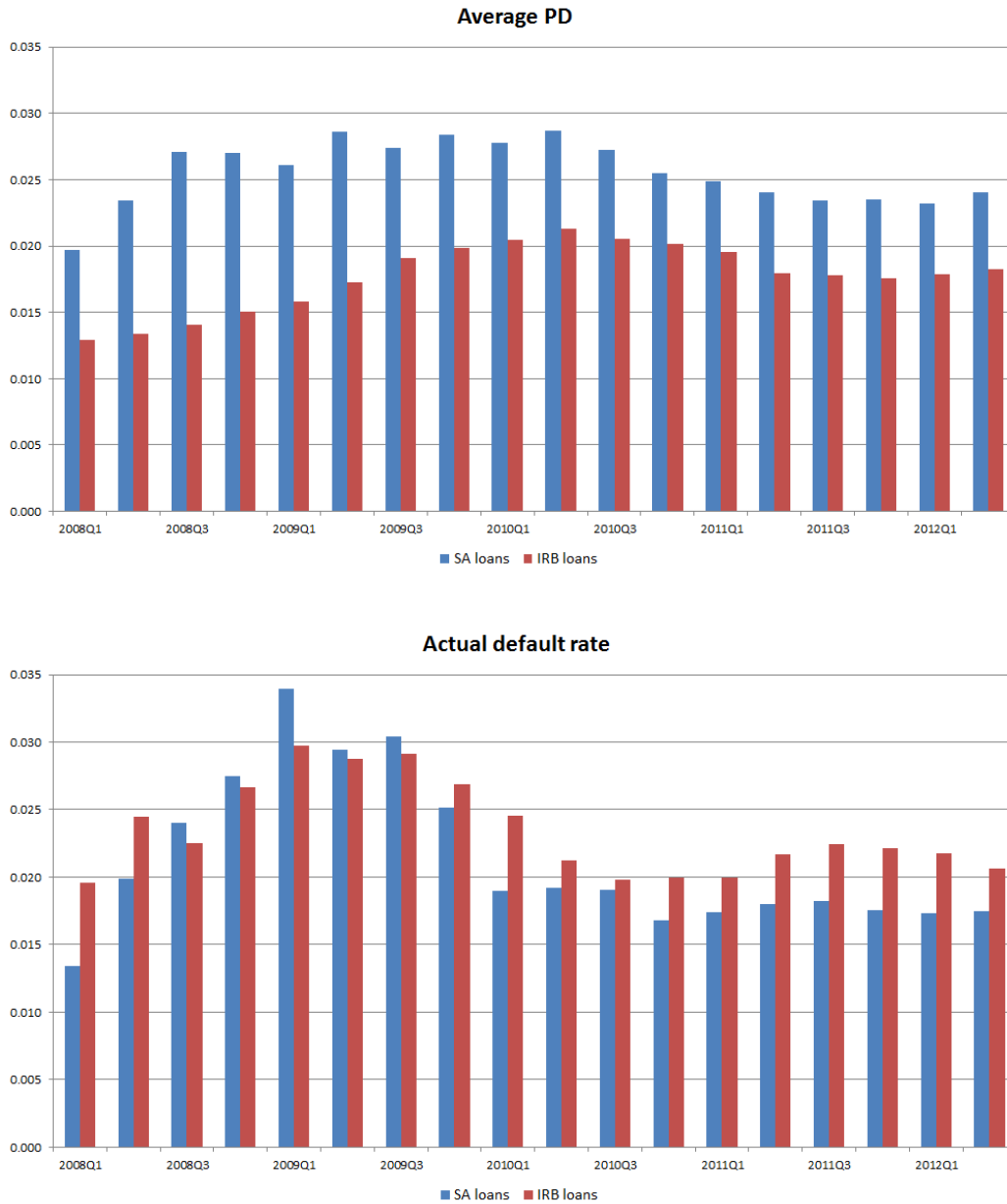


Figure A.1: Average PDs and actual default rates

The figure shows average PDs and actual default rates for SA loans and IRB loans during the period from 2008Q1 to 2012Q2. The sample includes all loans that are not in default at the respective point in time. For the top panel, we calculate the averages of reported PDs for the respective portfolios of loans. For the bottom panel, we create a dummy that equals 1 for loans that default in the year following the respective quarter, and calculate the average of this dummy variable for the respective portfolios of loans.