The Limits of Model-Based Regulation

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ABSTRACT

Using loan-level data from Germany, we investigate how the introduction of model-based capital regulation affected banks' ability to absorb shocks. The objective of this regulation was to enhance financial stability by making capital requirements responsive to asset risk. Our evidence suggests that banks 'optimized' model-based regulation to lower their capital requirements. Banks systematically underreported risk, with underreporting being more pronounced for banks with higher gains from it. Moreover, large banks benefitted from the regulation at the expense of smaller banks. Overall, our results suggest that sophisticated rules may have undesired effects if strategic misbehavior is difficult to detect.

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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. The design of bank capital regulation has been at the core of this debate.[1] Capital regulation is meant to address distortions in the banking sector which are due to the existence of safety nets such as deposit insurance, central bank support, or implicit bailout guarantees. While such safety nets help prevent inefficient runs they also create incentives for banks to take on more risk and leverage than socially optimal, with potentially negative effects for financial stability. Capital regulation aims at addressing these issues by increasing 'skin in the game' and forcing banks to internalize the social costs of bank failures on the broader economy. In this paper, we examine how the introduction of model-based capital regulation under the Basel II standard of 2007 affected banks' ability to absorb shocks.

Prior to the introduction of model-based regulation, the regulatory environment was considered to be too coarse, leading to excessive distortions in lending. Bank assets were bucketed into broad risk categories and each category was subject to a flat capital charge (a flat tax). In contrast, model-based regulation is based on the economic principle "He who pollutes should be taxed": The higher the risk on a specific asset position, the higher the capital charge. To determine asset-specific risk, model-based regulation relies on credit risk estimates produced by a complex array of risk models, designed and calibrated by banks themselves and subsequently approved by the supervisor. As a consequence, many banks have more than 100 different risk models with thousands of parameters in place, all of which require constant validation and re-calibration by the bank's risk management team and surveillance by the supervisor.[2] By tying capital charges to predicted asset risk, model-based regulation avoids penalizing banks for holding safe assets on their balance sheets, so that the distortion in the allocation of credit that accompanied the simple flat tax feature of

[1]With *capital regulation* we refer to minimum requirements on the amount of equity financing used by a bank. The terms *capital* and *equity* are used interchangeably throughout the paper.

[2]The latest revision of the regulatory framework, Basel III, retains the most important features of Basel II – most prominently the feature of model-based capital regulation – but introduces some corrective measures that are meant to address the most obvious problems with the previous framework (see Section VI.F for further details).

Basel I is eliminated.

In a world with no information and enforcement problems, such a sophisticated regulation should unambiguously improve welfare. The conclusion, however, becomes murkier in a world with information and incentive constraints. As argued by Glaeser and Shleifer (2001), coarser regulation can be the optimal regulatory choice and may dominate more sophisticated forms of regulation in the presence of enforcement constraints. Applied to bank regulation, Kashyap, Rajan, and Stein (2008) note that "clearly, a system of risk-based capital works well only insofar as the model used by the bank [...] yields accurate and not-easily-manipulated estimates of the underlying economic risks."[3]

To examine the accuracy of reported credit risk estimates, we exploit the institutional details of the Basel II introduction in Germany in 2007, as well as the high granularity of our loan-level data set obtained from Deutsche Bundesbank. Following the reform, banks were allowed to choose between two broad approaches: (i) the model-based approach (referred to as the *internal ratings-based approach*, shortened to *IRB*), in which bank internal credit risk parameters such as the estimated borrower *probability of default (PD)* crucially determine *risk weights* and hence capital requirements for individual loans;[4] and (ii) the traditional approach that does not rely on internal risk parameters (referred to as the *standard approach*, shortened to *SA*). The model-based approach required the existence of a costly and extensive risk management system that had to be certified by the regulator. Thus, it was introduced only by the largest banks, while smaller regional banks remained under SA.

The introduction of model-based regulation was staggered across portfolios over time. Banks that opted for IRB (referred to as *IRB banks*) needed to eventually apply the new

[3]In the context of lending, it is now well understood that the quality of a loan is not only a function of 'hard' and verifiable information, but also a function of 'subjective' and non-verifiable information. Model-based regulation may change the incentives of banks to capture negative 'soft' information in their credit risk estimates, as they strive to reduce capital charges (see also Holmström and Milgrom (1991), Rajan, Seru, and Vig (2015)). The inherent complexity of the model-based approach makes it very difficult – if not impossible – for the regulator to detect such behavior.

[4]In the Basel framework, capital regulation is based on the concept of *risk-weighted assets (RWAs)*, where each bank asset receives a specific *risk weight* that in turn determines the capital requirement for the asset. For the model-based approach, banks are required to estimate the borrower-specific PD, and loans to borrowers with higher PDs receive higher risk weights and are thus subject to higher capital requirements.

approach to all loan portfolios. While banks wanted to transfer all portfolios to the new approach as soon as possible, they needed certification from the supervisor for the underlying risk models (calibrated at portfolio level). Supervisors delayed the approval of each model until they felt comfortable about its reliability. In many cases, this meant waiting for more data before a specific portfolio of loans could be transferred to IRB. Importantly, the staggered introduction of the new approach among IRB banks implied that, at a given point in time, the loan pool of the *same* bank included both IRB and SA loans. This feature of the implementation process allows us to examine the effects of model-based regulation within the group of IRB banks only, distinguishing between loans under model-based regulation and loans that have not yet been transferred to the new approach.[5]

We find that, on an *absolute* basis, estimated credit risk parameters for loans under the model-based approach significantly underestimate actual asset risk. This implies that the resulting capital requirements for these loan portfolios are lower than intended by the regulator. According to a back-of-the-envelope calculation, the required amount of capital for IRB exposures would increase by € 34.7 billion (or 76 % of the current amount) if actual default rates instead of reported PDs were used to calculate capital requirements. Interestingly, within the group of IRB banks, credit risk parameters for loans under the more traditional standard approach (which do not have an impact on capital requirements) do not exhibit the same downward bias. In fact, we further show that – due to the underreporting of PDs – IRB loans have significantly lower capital requirements *relative* to SA loans, while observed loan losses tend to be higher among the former set of loans. Moreover, interest rates in the IRB loan pool are significantly higher than in the SA loan pool, suggesting that banks were aware of the inherent riskiness of these loan portfolios, even though reported PDs and risk weights did not reflect this.[6] Putting it differently, interest rates seem to do a better job of predicting defaults and measuring risk than reported PDs (see, e.g., Meiselman, Nagel, and Purnanandam (2018) for a similar argument). Importantly, all these results are

[5] We further describe the IRB implementation process in Section I, and address potential concerns related to the selection of IRB portfolios within a bank in Section III.

[6] Since interest rates are not reported, we obtain them by matching the credit register data with detailed firm income statement data from Bundesbank (see Section II.A and Internet Appendix A for details).

present in every year until the end of our sample period in 2012 and are quite stable over the business cycle (during the period of our study the German economy underwent both a downturn and a recovery).

While aggregate results are striking, one could be concerned about borrower- or bank-specific factors differently impacting the level of reported PDs, default rates, or interest rates in SA and IRB portfolios. To address such concerns, our main empirical strategy makes use of variation in the regulatory approach *within the same firm* and *within the same bank*, arising from the staggered introduction of Basel II. The following example illustrates our strategy: Consider a firm that has two loans, both from IRB banks. For one bank, the loan is in a portfolio that has already been shifted to the new approach (IRB pool), while for the other bank the loan is in a portfolio that is awaiting approval from the regulator (SA pool). While both banks estimate the same variable – the firm's PD within the next year – capital requirements depend on the estimated PD for loans in the IRB pool, but not for loans in the SA pool.[7] Comparing estimated parameters for loans to the *same* firm in the *same* year allows us to causally identify the effects of model-based regulation on the level of reported PDs. In particular, this *within firm* analysis mitigates concerns related to omitted variables (such as macro factors) which may differentially affect SA and IRB loans. Moreover, we are able to exploit *within bank* variation in the regulatory approach (since the *same* bank has both IRB and SA loans), which allows us to systematically control for bank-specific heterogeneity.

The loan-level analysis yields very similar insights as the analysis on an aggregate level. For the *same* firm in the *same* year, reported PDs for IRB loans are 22 to 29 % lower than reported PDs for SA loans, meaning that model-based capital requirements are 12.5 to 17.5 % lower than the benchmark implied for SA loans.[8] This significant difference in implied capital requirements persists when looking at risk weights that control for loan

[7]Importantly, PDs are intended to measure the probability of a specific firm defaulting within the subsequent year. They are independent of the specific loan terms, and all banks are estimating the same variable.

[8]As we explain below, the mapping from PDs into risk weights is concave, so that the percentage increase in capital requirements associated with an increase in PD depends on the level of the PD. The numbers presented here correspond to an assessment at the median PD. If the median PD (0.38 %) is increased by 22 [29] %, capital requirements increase by 12.5 [17.5] %.

terms and credit risk mitigants such as collateral, while the observed loan losses and interest rates for IRB loans tend to be similar or higher than for loans under SA. Moreover, all of the results are robust to the inclusion of bank interacted with year fixed effects that control for bank-specific heterogeneity.

The results of the *within firm* analysis and the incongruence between reported PDs and interest rates suggest that the underestimation of default rates in IRB portfolios relative to SA portfolios was not driven by unanticipated events on the part of the bank. To further strengthen our analysis, we exploit variation in the incentives to underreport PDs *within the pool of IRB loans*. Specifically, we test whether underestimation of actual default rates is particularly pronounced (i) for loans to firms with relatively low PDs, for which small reductions in the PD imply large reductions in the associated capital requirements (due to concavity of the mapping from PDs to capital requirements), (ii) for loans from more capital-constrained banks that enjoy higher marginal benefits of relaxing regulatory requirements, and (iii) for loans from banks for which the loan book makes up a large part of the balance sheet, so that capital requirements for credit risk are particularly important for them. Importantly, these tests systematically control for time-varying omitted factors that might explain the selection of loans into the IRB pool within a specific bank. The tests illustrate that the underestimation of actual default rates is most pronounced in cases where the incentives to underreport are greatest. PDs in the IRB portfolio are underreported across the entire PD band, but the degree of underreporting is largest for firms with low PDs. Furthermore, reported PDs tend to be lower for more capital-constrained banks and for banks for which the loan book is particularly important, even for the same firm in the same period.

To better understand the underlying drivers behind our findings, we examine whether the underestimation of actual default rates *within a bank's IRB loan pool* depends on the time at which the respective loan was issued. We find that PDs for IRB loans that were originated in the 12 months after the reform underestimate actual default rates by about 0.8 percentage points more in 2009 and by about 1 percentage point more in 2010, compared with IRB loans that were originated in the 12 months before the reform. Furthermore, we find no significant change in PD once the classification for an *existing* relationship changes from SA to IRB. This indicates that our findings are not driven by explicit downward adjustments in PDs following the introduction of model-based regulation. Instead, it seems that the introduction of model-based regulation changed banks' incentives and in turn affected the performance of the models that are used to measure credit risk, akin to Goodhart's law.

Building on the above, we also analyze whether the reform generated any differential effects on lending. The high compliance costs associated with the model-based approach meant that only the largest banks adopted it. We show that these large banks benefited from the reduction in capital requirements associated with the new approach and consequently expanded their lending at the expense of smaller banks, which seems paradoxical given the negative externalities that such banks may exert on the financial system. Specifically, we find that banks that opted for the introduction of the model-based approach increased their lending by about 9 % relative to banks that remained under the traditional approach. The relative increase in lending of IRB banks was particularly pronounced for firms with relatively low PDs (and hence lower capital requirements), as intended by the regulation. However, the underestimation of actual default rates was most severe for loans to these firms, and in particular for loans that were newly issued after the reform had been implemented. Thus, the reform's objective of steering banks towards safer borrowers was undermined by the tendency to underreport actual asset risk. In sum, newly issued loans under IRB were at least as risky as the loans under SA but had significantly lower capital requirements.

In our view, the most natural interpretation for our findings is that banks 'optimized' capital requirements, exploiting the discretion they had under the model-based approach. This interpretation is further supported by additional findings which show that the disconnect in the relationship between capital requirements and actual loan losses is more severe when more discretion is given to the bank.[9] While a number of alternative interpretations

[9]There are two versions of the model-based approach, the foundation approach (F-IRB) and the advanced approach (A-IRB). Under F-IRB, banks estimate only the PD while standard values are assumed for other parameters such as loss given default (LGD) or exposure at default (EAD). Under A-IRB, banks estimate also LGD and EAD. While the same patterns are present for both F-IRB and A-IRB loans, our results are much more pronounced for loans under A-IRB, which is clearly more complex and accords more autonomy to the bank.

for our findings are possible, all of them have in common that model-based regulation led to unintended outcomes and compromised IRB banks' ability to absorb shocks (see Section VI for an extensive discussion). A welfare analysis would have to weigh these costs against potential benefits of the reform that could for example be associated with the increase in lending by IRB banks and/or potential improvements in the allocation of credit. Such welfare analysis is, however, beyond the scope of this paper.

Our paper connects several strands of the literature. The literature on financial regulation is an obvious starting point. A small but growing number of papers analyze how ratings used for regulatory purposes affect financial stability. As shown by Rajan, Seru, and Vig (2015) in the context of securitization, risk depends on the behavior of the parties involved, may change over time, and tracking it for regulatory purposes may be near-impossible.[10] Hellwig (2010) argues that model-based capital regulation suffers from the fact that many of the risks involved are endogenously determined and not exogenously given. Further, Acharya, Engle, and Pierret (2014) question the predictive abilities of risk weights, as they are based on accounting data, can only be updated ex-post, and can easily be gamed by banks (see also Hoenig (2013)). Our identification strategy combined with the richness of our data set allows us to identify the effect of the shift towards model-based regulation on the reported credit risk estimates and the associated capital requirements. To the best of our knowledge, our paper is the first to demonstrate how banks exploited complex regulation to economize on regulatory capital.[11]

We also add to the literature on regulatory complexity. Some argue that complex and sophisticated rules are often dominated by simpler regulation that is easier to enforce (Glaeser and Shleifer (2001)). Complex regulation imposes a significant enforcement cost

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

[11]Three recent papers, Plosser and Santos (2014), Begley, Purnanandam, and Zheng (2017), and Berg and Koziol (2017) confirm our findings in different settings.

on society and provides incentives to regulated entities to find ways around the regulation.[12] Recent empirical evidence on the impact of complex regulation in the insurance sector is provided by Koijen and Yogo (2015, 2016). We add to this literature by highlighting how complex rules that are difficult to monitor may threaten the efficacy of financial regulation.

Importantly, our paper is not about explicit manipulation, outright fraud, or the complexity of models per se. Rather, we think that our findings illustrate that banks will always try to circumvent regulation, optimizing from a private perspective, and that sophisticated model-based regulation can be accompanied by considerable enforcement challenges. Our findings imply that banks respond to the way in which the regulation is designed and that complex rules can be exploited to reduce the amount of regulatory requirements imposed by the regulator. As such, our findings support recent efforts in the regulatory community (i.e., Basel III) to constrain discretion in banks' modelling choices and limit the amount by which they can reduce capital requirements under the IRB approach. The evidence presented in this paper provides support for the view that simpler and more transparent rules that provide less discretion to banks could be more effective in addressing distortions leading to excessive leverage in the banking sector (see, e.g., Glaeser and Shleifer (2001), Hellwig (2010), Admati and Hellwig (2013), Haldane (2013), and Acharya, Engle, and Pierret (2014)).

The rest of the paper is organized as follows. In the next section we describe the institutional setup, before we introduce our data set in Section II. We explain our empirical strategy in Section III and present our main findings in Section IV. Afterwards we analyze how the reform affected banks' lending decisions and the structure of financing in Section V. Section VI includes a comprehensive discussion on possible interpretations of our findings, and Section VII concludes.

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

I. The introduction of model-based regulation in Germany

A. *From Basel I to Basel II*

One of the main advances in bank regulation in recent decades was the introduction of risk-based capital regulation, aimed at ensuring higher capital requirements for riskier assets while at the same time promoting the adoption of stronger risk management practices by the banking industry.[13] In 1988, the Basel I agreement first introduced risk-based capital requirements for credit risk by assigning bank assets into different risk groups (or buckets) with pre-assigned risk-weights (Basel Committee on Banking Supervision (1988)). Risk-weighted assets were calculated by multiplying these risk weights (0, 10, 20, 50, or 100 %) with actual asset values, and capital requirements were defined in terms of risk-weighted assets. This rather simple approach was soon criticized for providing incentives to risk shift, since riskier assets in the same bucket provided higher returns while requiring the same amount of equity financing.

The Basel II agreement was introduced in 2007 and aimed at addressing these concerns. It allowed banks to choose between two broad methodologies for calculating capital charges for credit risk: (i) the so-called standard approach (SA) which is essentially equivalent to the old Basel I framework with fixed risk-weights for corporate loans (100 % of the unsecured loan amount);[14] and (ii) the model- or internal ratings-based (IRB) approach – with an additional distinction between Foundation IRB (F-IRB) and Advanced IRB (A-IRB) – that tries to establish a more granular link between capital requirements and individual asset risk. Risk weights under IRB crucially depend on bank-internal estimates of four pa-

[13]The introduction of risk-weighted capital charges and the potential problems related to them have been discussed in several papers, for example Brinkmann and Horvitz (1995), Jones (2000), Daníelsson, Embrechts, Goodhart, Keating, Muennich, Renault, and Shin (2001), Kashyap and Stein (2004), Hellwig (2010), and Behn, Haselmann, and Wachtel (2016).

[14]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 (only 0.1 % of those in our sample). In unreported regressions we find that our results are less pronounced in the small subsample of firms with external credit ratings. Since external ratings may serve as a useful benchmark for regulators assessing the bank's internal risk models banks could be reluctant to underreport risk estimates for firms with external credit ratings, as misreporting would be more likely to be detected by the supervisor.

rameters: the borrower-specific probability of default (PD), and the loan-specific loss given default (LGD), exposure at default (EAD), and maturity. All four of these parameters need to be estimated under A-IRB, while only the PD is estimated and standard values are assumed for the other parameters under F-IRB.[15] Under both SA and IRB, risk mitigation instruments such as eligible collateral can be used to decrease risk weights for the secured part of an exposure (see Section II.B for further detail on this). Aggregate risk-weighted assets are calculated by first multiplying and then summing loan-specific risk weights and loan amounts, and capital requirements are defined in terms of aggregate risk-weighted assets as under Basel I (Basel Committee on Banking Supervision (2006)).

B. The IRB implementation process

The introduction of the IRB approach imposed sizeable organizational efforts and administrative expenses and also required a certain degree of sophistication, so that it was implemented only by the largest banks.[16] To compensate for the costs of adopting the new approach, the regulation was calibrated in a way that ensured that capital requirements were, on average, slightly lower under IRB than under SA.[17] Of our sample of 1,603 German banks, 45 banks applied for an IRB license, accounting for about 50 % of the loans in our sample. Of the 45 banks that introduced the IRB approach, 17 introduced F-IRB, 18 introduced A-IRB, and 10 use F-IRB for some portfolios and A-IRB for other portfolios. Large parts of our analysis (in particular the entire analysis on the performance of internal risk models) rely exclusively on information reported by the 45 IRB banks in our sample.

The implementation of the IRB approach among German banks was a closely moni-

[15]We do not distinguish between F-IRB and A-IRB in large parts of the analysis, since our main variable of interest, the firm-specific PD, needs to be estimated in both versions. Differences between the two versions of the IRB approach are investigated in Section VI.D.

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

[17]Specifically, the average risk weight for SA loans in our sample is 61.6 %, while the average risk weight determined with the IRB formula (i.e., the IRB-implied risk weight) would have been 59 % (see Table 1, Panel B).

tored process, comprising the following main elements (for details, see Bundesbank (2005)):

- Banks that opted for the IRB approach submitted a so-called ‘implementation plan’ to the supervisor. This plan clarified the nature of the portfolios to be transferred and the exact timeline of the transfer process (which could not exceed five years). Loan portfolios were typically defined in terms of the bank’s business units and contained all loans that were evaluated under the same set of internal risk models.[18]

- Banks had incentives and generally wanted to transfer all portfolios as soon as possible, to save on regulatory capital requirements. However, before transferring a specific portfolio they needed to obtain supervisory approval of the underlying risk models. To obtain approval, banks had to demonstrate that the respective models had been used internally for at least three years and were suitable instruments for credit risk measurement and management. For this reason, banks had to start the implementation process with well-performing models for which they had a sufficient amount of data on past loan performance.[19]

- Supervisors granted permission to transfer a specific portfolio to IRB once they had concluded their suitability examinations of the underlying models and were satisfied with the outcome. This process resulted in a staggered implementation of the new approach, since supervisors delayed the shifting of portfolios that did not yet have a suitable model or for which the submitted model produced unsatisfactory outcomes. In addition, resource constraints prevented the supervisor from examining all risk models at the same time, leading to further delay in the approval of some models and

[18]Internal risk models comprised PD models for loans under F-IRB, and PD, LGD, EAD, and maturity models for loans under A-IRB. Portfolios were defined up to different levels of granularity. On a high level, banks would typically distinguish between retail portfolios and corporate loan portfolios. Within the retail sector, they would have portfolios for mortgage loans, consumer loans, student loans, etc. Similarly, for the corporate sector they would have portfolios for loans to small and medium enterprises (SMEs), loans to larger corporations, loans to firms in a specific industry, etc. The exact classification of loan portfolios varied across banks and was specified in the implementation plan.

[19]Section III further discusses banks’ incentives and describes how we address possible selection concerns on the order of IRB implementation. Section VI.A discusses interpretations of our findings that relate to strategic early adoption for specific portfolios.

additional staggering of the implementation process.[20]

- Once a set of risk models was approved, all existing and new loans in the corresponding portfolio were irrevocably shifted to the new approach. From that moment on, risk weights for these loans were determined by the estimates produced by the underlying risk models. Importantly, banks could not add or remove individual loans from a specific portfolio that had been shifted, since portfolio classifications were defined in the implementation plan and could not be adjusted ex post. Approved models needed to be validated annually, and banks needed to adjust the model if their estimates were inconsistent with realized defaults or losses.
- By the end of the implementation period (typically after five years), all of the bank's loan portfolios needed to be shifted to the IRB approach.[21] , it was not possible for banks to strategically select individual portfolios for the new approach, while keeping other portfolios under the standard approach.

The phased roll-out of IRB meant that during the transition the same bank had both IRB loans and SA loans in its loan book. Moreover, in order to obtain model approval banks needed to provide PD estimates not only for the IRB but also for the SA portfolios in our sample. We exploit this feature of the implementation process in our empirical section, where we compare PD estimates with actual default rates for loans provided by IRB banks that are subject to different regulatory approaches.

[20]As specified in Bundesbank (2005), suitability examinations were generally handled on a first-come, first-served basis. Although supervisors were concerned to give all institutions *"the opportunity to use the IRB approach to calculate their minimum capital requirements in due time"*, it was necessary to stagger the approval process during the implementation period due to *"the large number of pending suitability examinations"* (see pp. 8 and 12-13).

[21]There were exemptions from this rule. For example, sovereign exposures were allowed to remain permanently under the standard approach. The same applied to exposures in maturing business lines, where it was considered unreasonable to require the bank to develop a rating system given that the business was anyway expiring. Since our focus is on corporate loan portfolios with existing risk models, our analysis is not affected by these exemptions.

C. PD models as key component of the IRB approach

The focus of the paper is on PD models, which form a vital part of rating systems and affect risk weights under both F-IRB and A-IRB approaches. According to the regulation, these models are required to estimate the probability that a specific borrower defaults within the next year. Figure 1 illustrates that higher PDs imply higher risk weights (using the standard F-IRB values for the other parameters), where the mapping between PDs and risk weights is relatively steep for the lowest PDs and becomes flatter for higher PDs. This is in contrast to SA loans, where risk weights are fixed at 100 % and do not depend on estimated PDs. Importantly, PDs are firm-specific estimates – meaning that all banks should arrive at similar estimates – while loan-specific risk mitigation instruments are taken into account in other parts of the risk weight formula.[22] Although models are calibrated on a portfolio basis, PDs are meant to be portfolio invariant in the sense that the capital required for a given loan should depend only on the risk associated with the borrower and not on the portfolio it is added to.[23] For corporate loans, the most important determinant of the PD is accounting information from firms' financial statements. For loans to small and medium enterprises (SMEs), where there is often a significant publication lag for accounting information, target financial ratios or industry characteristics may also be used. Besides these quantitative factors, models can also rely on qualitative information such as a firm's management quality or its competitive situation.[24] In cases where loan officers consider model outputs to be unreasonable they have the option of overwriting the predicted PD. However,

[22]The reason why the PD is a firm-specific variable is the presence of cross-default clauses. Cross-default clauses are prevalent around the world (including in Germany) and essentially trigger a default on all loan obligations (i.e., put the borrower into default) in case of a default on any individual loan. This applies not only to actual defaults, but also to technical defaults (i.e., defaults that are triggered by a covenant violation).

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

[24]A prominent PD model used for the estimation of corporate credit risk is Moody's RiskCalc^{TM} model (Moody's Analytics (2013)). To obtain predicted probabilities of default for a given portfolio, historical information on corporate defaults is regressed on accounting information such as the equity ratio, capital structure, net debt ratio, sales growth, net profit ratio, personnel cost ratio, payables payment period, or cash flow per liabilities. In a second step, estimates from this model are used to attribute predicted PDs to current and new borrowers.

if such overwrites occur too frequently, the regulator may ask the bank to revise its model.

[Figure 1 about here]

II. Data and descriptive analysis

A. Loan information from the German credit register

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 exposures of at least € 1.5 million.[25] For reporting purposes, all of a bank's loans to a specific firm are consolidated into a single data point, so that there is one observation (i.e., one 'loan') per bank-firm relationship.[26] The data set starts in 1993 and includes information on the lender's and the borrower's identity, the outstanding exposure amount and several other loan characteristics. In response to the Basel II reform, reporting requirements for the credit register have been expanded considerably from 2008 onwards. In addition to the previous information, banks now also report loan-level information on the regulatory approach (SA or IRB), the estimated PD, the risk weight, the amount of collateral, and loan losses. We combine this loan-level data with annual bank balance sheet information from Bundesbank's BAKIS database and information on loan pool loss rates (SA vs. IRB, at the bank $\times$ year level) from SREP reporting templates. Further, since the German credit register does not contain direct information on interest rates, we follow Haselmann, Schoenherr, and Vig (2018) and back out effective interest rates as described in detail in the Internet Appendix A. Specifically, the simple structure of most German loan contracts allows us to infer the repayment schedules from the quarterly data on loan amounts. We match this contract-level information with firm-level data on aggregate interest payments

[25]The credit register also contains observations with exposure values lower than € 1.5 million, as banks have to report smaller exposures if the aggregate exposure to a connected group of clients is larger than the reporting threshold. We eliminate these observations in order to obtain a consistent sample and avoid possible selection issues. In any case, our results are robust to the inclusion of the loans smaller than € 1.5 million that are reported in the credit register.

[26]In practice the same observation may comprise several loans from the same bank to the same firm. However, all of these loans are placed in the same loan pool (i.e., SA vs. IRB) and exhibit the same firm-specific PD. Moreover, risk weights and loss rates refer to the bank's aggregate exposure vis-à-vis the firm.

obtained from Bundesbank's USTAN database and back out effective annual interest rates on the loan contract level.[27]

Our sample includes 1,603 German banks, 45 of which opted for IRB following the introduction of Basel II (we will refer to these 45 banks as 'IRB banks'). Panel A of Table I shows that the average IRB bank is larger and less capitalized than the average SA bank, whereas average ROA is similar in the two groups of banks. As mentioned before, only large and internationally active banks introduced IRB, while smaller regional banks remained under the standard approach.

[Table I about here]

At the loan level, our data set contains three types of loans: (1) loans provided by SA banks; (2) loans provided by IRB banks that are still subject to SA; and (3) loans provided by IRB banks that are already subject to the new approach. Although information in the credit register is available on a quarterly basis, reported PDs tend to be sticky and are adjusted only infrequently, except for cases where a new loan is granted to the firm and the bank has to reassess the firm's credit risk. Thus, to avoid the duplication of observations, we include only the fourth quarter of each year in large parts of the empirical analysis (while the results for the remaining quarters are very similar). Furthermore, we classify loans that are transferred from SA to IRB during our sample period according to the regulatory approach under which the reported PD was generated. To understand this better, imagine a portfolio that was shifted to the IRB approach in 2009. At that time, the submitted PDs (which were also used in the process of approving the IRB model) were generated under the SA regime, and correspondingly the loans are still classified as SA loans. A given bank-firm relationship is then reclassified as IRB once (i) the portfolio in which the loan is located has been shifted to the IRB approach, and (ii) the bank has issued a new loan to the firm,

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

that is, a loan that was generated under the IRB regime and triggered a reassessment of the firm's credit risk.[28] For the entire analysis on PDs and capital requirements, we use only loans provided by the 45 IRB banks in our sample (i.e., types (2) and (3) from above). In particular, as IRB banks 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 IRB banks' SA loans as a benchmark against which we evaluate the performance of PDs for IRB loans. For the lending analysis in Section V we consider also loans provided by SA banks.

B. Calculating IRB implied risk weights for SA loans

To estimate the impact of a potential underestimation of PDs on capital requirements for credit risk, we calculate risk weights implied by the IRB formula for loans that are still under SA. While comparing PDs and actual default rates is sufficient to examine whether capital requirements are lower than intended by the regulator, looking also at risk weights can provide additional insights. The reason is that risk weights are meant to capture also loan-specific factors that may affect losses given default (such as the amount of collateralization), whereas PDs are estimated at the firm level and do not depend on such factors.

To obtain a risk weight variable that is not affected by the relative calibration of SA and IRB approaches, we calculate IRB-implied risk weights for SA loans, proceeding in several steps. First, we calculate loan-specific risk weights for loans from bank j to firm i at time t according to the following Basel II formula:

$$RW_{ijt} = \frac{C_{ijt}}{L_{ijt}} \times RW(C)_{ijt} + \frac{L_{ijt} - C_{ijt}}{L_{ijt}} \times RW(B)_{ijt} \tag{1}$$

with $RW(C)_{ijt}$ being the risk weight attached to the collateral and $RW(B)_{ijt}$ the firm-specific

[28]We assume that a new loan is granted for a given bank-firm relationship in cases where the total loan amount increases by at least 50 %. By applying this threshold we ensure that quarterly variations in the firm's current account are not counted as new loan issuances. Our results do not depend on the exact definition of the threshold and are very similar for other cutoff values (e.g., 33 %).

risk weight attached to the borrower.[29] The loan amount is indicated by L_{ijt} and the value of the collateral is indicated by C_{ijt}. Second, we obtain information on the loan amount, the reported value of the collateral, and the actual loan-specific risk weight under SA from the credit register. Using the information that the firm-specific risk weight for corporate borrowers under the Basel II SA is set to 100 %, we can back out the risk weight of the collateral for each SA loan by simply rearranging the terms in Equation (1):

$$RW(C)_{ijt} = \frac{RW_{ijt} \times L_{ijt} - (L_{ijt} - C_{ijt})}{C_{ijt}} \tag{2}$$

Third, we plug the reported PDs for SA loans into the standard Basel function determining the link between borrower-specific PDs and risk weights. Under the Foundation IRB (F-IRB) approach, the PD is the only input to this formula, while standard values are assumed for other parameters such as loss-given-default (LGD), exposure at default (EAD), and maturity. Using the F-IRB formula, we determine the *borrower-specific* risk weight $RW(B)_{ijt}^{imp}$ implied by the PDs for SA loans (see Figure 1 for an illustration of the mapping from PDs to risk weights under F-IRB). Finally, we plug the implied borrower-specific risk weight and the risk weight for the collateral (as obtained from Equation (2)) into Equation (1), to obtain the *loan-specific* IRB implied risk weight for SA loans.

C. Descriptive statistics for our main data set

Descriptive statistics for SA and IRB loans provided by IRB banks during our sample period from 2008 to 2012 are presented in Panel B of Table I. The first line of the panel shows that the average PD is higher for SA loans (2.6 %) compared with IRB loans (1.8 %). As explained in Section I.C, the PD is a firm-specific (rather than loan-specific) measure, so that all banks are estimating the same variable and, in an ideal world, should come up with

[29] The weight for the collateralized part of the exposure is capped at 1, that is, it cannot be larger than 1 for overcollateralized exposures. The formula reflects the so-called ‘simple approach’ for the recognition of collateral, which we assume to be applicable for all loans. In practice, banks can also use the ‘comprehensive approach’, according to which the LGD (and thus the risk weight) of the loan is adjusted to reflect the value of the collateral, subject to an appropriate haircut.

very similar for it. 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. In stark contrast to estimated PDs, actual default rates are higher for IRB loans when compared with SA loans. Importantly, all loans that are already in default in a respective quarter are excluded from the analysis. Risk weights for a specific loan also incorporate loan-specific information (in particular the collateralization of the loan, see previous subsection). The average *RISK WEIGHT* for SA loans (61.6 %) as well as the average IRB implied *RISK WEIGHT* for SA loans (59.0 %) are both considerably higher than the average *RISK WEIGHT* for IRB loans (49.0 %). This contrasts with the actual average loan *LOSS RATE*, which is 0.49 % for SA and 0.51 % for IRB loans. To note, the loan losses reported in the credit register are the write-offs conducted in the moment in which a loan exposure becomes non-performing (i.e., when the PD jumps to one). In practice, it often takes many years until final loan loss rates on a non-performing exposure are known, and recent evidence suggests that banks have been underreporting as well as delaying the recognition of loan losses since the financial crisis of 2008 (see, e.g., Blattner, Farinha, and Rebelo (2019)).[30] To account for discrepancies between initially estimated and eventually realized loss rates, it is common for banks to apply provisioning overlays and corrections at the portfolio level. Thus, it is likely that the loan-level losses reported during our sample period constitute a lower bound for the eventual losses on the exposures.[31] In Section IV.A, we further examine final loss rates for SA and IRB loans by making use of loan pool level data that also includes information on ex post adjustments to the losses recorded at loan level.

Panel B further shows that interest rates for loans under the standard approach are on average lower (7.9 %) than interest rates for loans under IRB (8.8 %). Moreover, it reports descriptives for a number of controls that we use in the empirical analysis: IRB loans are

[30]The ECB conducted in 2013 (one year after the end of our sample period) an Asset Quality Review (AQR) for 25 German banks whose exposures constitute the majority of observations in our sample. Following this review, banks had to increase the loss provisions for the corporate loan portfolio by about € 3 billion, corresponding to an adjustment of 0.5 % of their entire exposures to the corporate sector. Furthermore, we find that the AQR adjustment in the banks' loss provisions is correlated with their share of IRB and SA exposures – the correlation between the IRB share and the adjustment in loan loss provisions is 0.33.

[31]Moreover, the *LOSS RATE* information is unfortunately missing for roughly one third of the defaulted exposures in our sample, which constitutes another source of downward bias.

slightly larger than SA loans, about equally well collateralized, and somewhat less likely to make up a large share of the firm's aggregate loans reported in the credit register (the dummy *D(RELA)* is equal to 1 whenever a bank's loans to a specific firm make up more than 75 % of the firm's aggregate loans). The last line of Panel B shows the average change in the amount of loans outstanding around the introduction of Basel II.[32] The average IRB loan in our sample was increased by about 6.4 % over the Basel II introduction, while the average SA loan was increased by about 1.6 %.

Finally, Panel C of Table I contains descriptives for firm-level variables, obtained by a hand-match of the Bundesbank USTAN database with the credit register. The match was conducted based on company name, location, and industry segment, which are available in both data sources. The matched dataset contains detailed information on lending relationships and balance sheet items for 5,961 distinct firms. The average firm in this sample has total assets of € 154 million, the average debt to asset ratio is 34.3 %, and the average return on assets is 7.9 %.

III. Estimation strategy

A. Main tests

Our empirical analysis assesses whether reported PDs under the IRB approach adequately reflect the credit risk of the underlying corporate loan portfolios, both in absolute and in relative terms. A first step is to compare reported PDs for IRB loans with realized default rates throughout our sample period. This absolute comparison allows assessing whether capital requirements for IRB loans reach their intended level, since these requirements are directly tied to the level of reported PDs and calibrated under the assumption that

[32]The sample includes all loans in the credit register that have an observation both before and after the reform. We calculate the change in lending around the reform by collapsing all quarterly data for a given exposure into single pre-event and post-event periods by taking the average of the two years before and the seven quarters after the Basel II introduction (the eighth quarter is not considered because it coincided with the collapse of Lehman Brothers and hence the onset of the global financial crisis). The change in lending is defined as the difference in the logarithm of these averages, so that there is one observation per bank-firm relationship.

PDs match realized default rates on average.

While comparing reported PDs and actual default rates at an aggregate level provides important insights, one could be concerned that such aggregate findings are driven by borrower- or bank-specific factors. To address such concerns, our main empirical strategy makes use of variation in the regulatory approach *within the same firm* and *within the same bank*. Focusing on firms that borrow from at least two banks at the same time – one bank where loans to the firm belong to a portfolio that has already been shifted to IRB and one bank where they are still under SA – we estimate the following equation:

$$y_{ijt} = \alpha_{it} + \alpha_{jt} + \delta \cdot \mathbb{1}_{jpt} + C'_{ijt}\gamma + \varepsilon_{ijt}, \tag{3}$$

where i denotes the individual firm, j denotes the individual bank, p denotes the loan pool within the bank (IRB or SA), and t denotes time. The dependent variable y_{ijt} is either the logarithm of the loan-specific PD reported at time t by the bank to the supervisor (*LOG(PD)*)[33], the *(IMPLIED) RISK WEIGHT*, the actual *LOSS RATE*, or the *INTEREST RATE* for the loan. The dummy $\mathbb{1}_{jpt}$ takes on a value of 1 if the PD for the respective loan of bank j at time t was generated under IRB and 0 if it was generated under SA (see Section II.A), and C_{ijt} is a vector of loan-specific control variables, including the loan size, collateralization, and a dummy indicating relationship lending. By adding firm × year interactions, α_{it}, we are able to systematically control for time-varying heterogeneity across firms. That is, we can check whether the PD reported by different banks for the *same* firm in the *same* year is lower if a loan is part of the IRB pool as compared with the SA pool. The inclusion of bank × year interactions, α_{jt}, allows us to control for time-varying heterogeneity across banks; that is, we can rule out that time-varying differences between banks are driving the results. Finally, the equation includes a random error term ε_{ijt}. In order to allow for potential correlation among default events for loans from the same bank or in the same year, standard errors are clustered at the bank × year level in all regressions.

[33]The distribution of PDs in logarithms looks more Gaussian and is less prone to outliers, thus improving the properties of the OLS estimation. We also used the PD in levels as a dependent variable and obtained very similar results, controlling for outliers by winsorizing or trimming the data.

While Equation (3) controls for bank-specific heterogeneity (α_{jt}), it is unable to control for time-varying omitted factors that might influence the selection of loans into the IRB pool within a bank. If PD models for IRB loans produced systematically different estimates than PD models for SA loans – for reasons unrelated to the attached capital requirements – this would be an identification concern for our empirical estimates. As explained in Section I.B, the main reason for the staggered implementation of IRB was that supervisors needed to approve the underlying risk models before a specific portfolio of loans could be shifted to the new approach. For this reason, banks started the IRB implementation process with those loan portfolios for which they had sufficient modelling experience and data, while supervisors delayed the approval of less advanced models.[34] Indeed, the results in Internet Appendix B clearly show that IRB models are better able to differentiate between defaulting and non-defaulting borrowers than SA models, that is, they have higher discriminatory power. As better performing models with higher discriminatory power should be better able to predict actual default rates, any potential bias stemming from the order of IRB adoption should in principle work against finding a stronger underestimation of PDs for IRB loans. Nevertheless, the next subsection further refines the identification strategy to address any remaining selection concerns.

[34]Banks might have had incentives to start the implementation process with portfolios in which PDs were most favourable, since they would generate the largest reduction in capital requirements relative to the standard approach. This could have been (i) low-default portfolios in which estimated PDs were (correctly) very low, or (ii) portfolios with optimistically-biased models in which PDs were (incorrectly) very low. As noted, the institutional nature of the implementation process with its strong focus on model performance made selective early adoption of IRB very difficult in practice. Moreover, neither of the two cases referenced above are of concern for our identification strategy: our main specification systematically addresses any possible selection concerns arising from case (i), as we are comparing PDs provided by different banks for the same borrower at the same time (and in any case, default rates for IRB loans are higher than default rates of SA loans and lower than reported PDs for IRB loans, both of which is inconsistent with this type of selection); and case (ii) constitutes an alternative mechanism that we will further discuss in Section VI.A, rather than a selection concern that could undermine the validity of our estimates.

B. Additional tests and refinement of the identification strategy

B1. Exploiting cross-sectional variation in the incentives to underreport

A refinement of our identification strategy exploits cross-sectional variation in the incentives to underreport along several dimensions: (1) the concave shape of the mapping from PDs into regulatory risk weights implies higher incentives to underreport PDs for loans to low PD firms (recall Figure 1); (2) banks with a higher buffer on top of minimum regulatory capital requirements have less incentives to economize on regulatory capital – and hence less incentives to underreport PDs – compared with banks that are closer to the regulatory threshold; and (3) banks for which the loan book makes up a large part of the balance sheet have higher incentives to underreport, since capital requirements for credit risk are particularly important for them. Exploiting these cross-sectional differences, we develop several additional tests that rely exclusively on variation *within the IRB loan pool* in order to identify the coefficients of interest. By construction, these tests are not prone to possible selection concerns with respect to the order in which portfolios were shifted to the new regulatory approach.

The first test – referred to as the 'curvature test' – makes use of the observation that the incentives to underreport PDs are particularly pronounced for firms with relatively low PDs, since a small increase in the PD leads to large increase in the capital requirements for loans to these firms. Assuming that the cost of underreporting is the same across the PD spectrum (stronger assumption), or does not change at the same rate as the benefit of underreporting (weaker assumption), we estimate the following specification:

$$y_{ijpt} = \alpha_{it} + \alpha_{jpt} + \delta \cdot \left[\mathbb{1}_{jpt} \times FIRM\ PD_i \right] + \varepsilon_{ijpt}, \qquad (4)$$

where α_{jpt} denote bank $\times$ year $\times$ loan pool interactions that control for time varying omitted factors that could potentially influence the selection of loans into the IRB pool within a specific bank. The variable $FIRM\ PD_i$ is the average PD for loans to firm i in the first quarter where this information is available.[35] By including an interaction between *FIRM* PD_i and $\mathbb{1}_{jpt}$, we can test whether underreporting is indeed more pronounced for firms with relatively low PDs. Using *LOG(PD)* as a dependent variable, a positive coefficient for the interaction term would indicate that, within a bank's IRB loan pool in a given period, the relative underreporting of PDs for IRB loans is less pronounced for firms with relatively high PDs.

The second *within IRB* test relies on differences in bank capitalization. Generally speaking, better capitalized banks are less constrained by regulatory requirements and thus have fewer incentives to underreport PDs. To test this conjecture, we restrict the sample to include only IRB loans provided by IRB banks, and estimate the following equation:

$$y_{ijpt} = \alpha_{it} + \delta \cdot CAPITAL_{jt} + \varepsilon_{ijpt}, \tag{5}$$

where the bank's capitalization is captured by its total capital ratio. The specification includes firm × year interaction as before; in contrast to the 'curvature test', we cannot include bank × year interactions, since they would absorb the coefficient of interest. Using *LOG(PD)* as a dependent variable, a positive coefficient for δ would imply that better capitalized banks tend to assign higher PDs to the same firm in the same period for loans under IRB. In addition to capitalization, we also use differences in the importance of the loan book and bank size as distinguishing features.

B2. Mechanism behind the underestimation of PDs

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

[35] The test examines whether there are differences in underreporting across firms; hence, the distinguishing variable needs to be at the firm level. The average PD we calculate considers both SA and IRB loans. We expect the incentives to underreport to be greater for firms with relatively low values of *FIRM* PD_i.

capital).

Similar to the tests under (ii), the 'cohort test' is not prone to selection concerns with respect to the order of IRB implementation, since the coefficient of interest is estimated *within the sample of IRB loans* only. For this test, we restrict ourselves to loans using the IRB approach that were granted in the 12 months before and after the reform in 2007. That is, we include bank-firm relationships under the IRB approach (a) that newly appear in our dataset in either 2006 or 2007, or (b) that already existed before but exhibit a new loan issuance in either 2006 or 2007. Using this subsample, we check whether the underestimation of actual default rates at a given point in time is greater for loans that were originated after the reform as compared with loans that were originated before the reform. Specifically, we estimate the following equation:

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

where $\mathbb{1}_{(l \in B)}$ is an indicator variable that takes a value of 1 if the IRB loan was issued in the 12 months following the implementation of Basel II (i.e., in 2007) and 0 if it was issued in the year prior to the reform (i.e., in 2006), and α_j are bank fixed effects. 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 in the 12 month both before and after the reform. For this reason and since the interpretation of regression results with the PD as a dependent variable is not straightforward without firm fixed effects, we use a variable called *ESTIMATION BIAS* (defined as the difference between a dummy for actual default and the reported PD for the loan) as a dependent variable in the 'cohort test'. We evaluate the *ESTIMATION BIAS* for the loans in our subsample in 2009 and 2010 (we could also do that in the years 2011 and 2012 – however given that some loans mature before, the number of observations is decreasing with every year we move forward). We also run the same specification for the sample of SA loans, which serve as a control group.

In a second test, we examine how the PD of existing relationships changes once our classification switches from SA to IRB (i.e., once the PD of a loan whose portfolio switched from SA to IRB has been updated, see Section II.A). In other words, we estimate our main specification on the sample of loans for which the classification switches from SA to IRB throughout our sample period, adding bank $\times$ firm interactions that ensure that the coefficient of interest is identified from within-relationship variation.

IV. Empirical results

A. *Results at an aggregate level*

We start the empirical analysis by assessing how PD estimates from banks' internal risk models compare with actual default rates for loans under SA and IRB. Generally, since PDs are based on past data, one would expect an underestimation of default rates during downswings, and an overestimation during upswings. During our sample period, the German economy underwent a slowdown and a recovery. As documented in Figure 2, GDP decreased and aggregate default rates increased until the first quarter of 2009; thereafter GDP recovered and the default rate constantly declined.

[Figure 2 about here]

Table II and Figure 3 show average values of PDs and actual default rates between 2008 and 2012 for SA and IRB loans from the 45 banks that adopted the IRB approach (IRB banks). There are 66,045 lending relationships in 2008, 14,713 under SA and 51,332 under IRB. Additional portfolios are shifted to IRB throughout our sample period, which is why the number of SA loans declines to 8,907 in 2012. For each of our five sample years, we find that model-based PDs for IRB loans are lower than actual default rates. This implies that capital requirements for IRB loans are lower than intended by the regulator, who calibrated the mapping between PDs and risk weights based on the assumption that estimated PDs match realized default rates on average. In contrast, for SA loans we observe a close match of PDs and default rates in the first year and a slight overprediction of default rates in the remaining years, in line with expectations given economic developments. Panel C of Table II also shows that average PDs for IRB loans are always lower than average PDs for SA loans (the difference between the two groups lies between 0.7 and 1.1 percentage points and is highly significant), while the reverse is true for actual default rates (which fluctuate between 1.9 and 2.6 % for SA loans, and between 2.1 and 3.0 % for IRB loans). Moreover, Figure 3 shows the *ESTIMATION BIAS*, that is, the difference between a dummy for actual default and the reported PD for the loan. The *ESTIMATION BIAS* is larger for IRB loans (meaning that PDs for these loans underestimate actual default rates relatively more), and the difference is relatively stable over the business cycle: it is 1.6 percentage points (PP) in 2008; 1.4 PP in 2009; 1.2 PP in 2010; 1.3 PP in 2011, and 1.0 PP in 2012. Taken together, these results illustrate that reported PDs for IRB loans significantly underestimate actual default rates, both in absolute terms and relative to the control group of SA loans. This is a striking result, in particular when considering that IRB models tend to have a slightly higher discriminatory power than SA models (recall Internet Appendix B).

[Table II and Figure 3 about here]

Apart from the firm-specific PD, risk weights and actual loan losses also depend on loan-specific factors such as the loss given default (LGD), exposure at default (EAD), and the maturity (M) of the loan. The data from the credit register allows us to take this into account. Average values for the *(IMPLIED) RISK WEIGHT* and the actual *LOSS RATE* are displayed in Table II and Figure 3. Risk weights for IRB loans are 3 to 15 percentage points lower than IRB implied risk weights for SA loans, which means that banks have significantly lower capital requirements for IRB exposures. Importantly, by using the IRB implied (rather than the actual) risk weight for SA loans, we control for any intended downward calibration of capital requirements under the IRB approach, so that the documented effect is purely due to underreporting of PDs (see Section II.B for details). In contrast, actual loss rates are similar among both groups of loans; if anything, they tend to be slightly higher for loans under IRB in most years. As we show in Internet Appendix C, this difference in loss rates between SA and IRB loan pools becomes significantly more pronounced when accounting for provisioning overlays and corrections at the aggregate portfolio level that banks apply in order to account for discrepancies between initially estimated and eventually realised loss rates (see Section II.C). Final loss rates on IRB portfolios are, on average, 64 to 78 basis points higher than final loss rates on SA portfolios, suggesting considerably higher risk for the former set of loans.

Finally, Table II and Figure 3 also show average interest rates in SA and IRB portfolios. The level of interest rates in a competitive market may be seen as an indicator for the riskiness of the underlying loan portfolios. Thus, by comparing interest rates for SA and IRB portfolios we can analyze whether our findings are driven by pure misjudgment or conscious underreporting of credit risk. We find that, in stark contrast to PDs and risk weights, interest rates for loans under IRB are higher than interest rates for loans under SA. This suggests that banks were aware of the actual risk involved with loans under the model-based approach, but did not report this information to the supervisor in order to avoid higher capital requirements. While higher interest income for IRB loans may compensate the higher risk of these loans from a short-term perspective, Meiselman, Nagel, and Purnanandam (2018) show that in the cross-section of banks high accounting profitability is associated with high systematic tail risk, and most strongly so if profits are paid out as dividends. Indeed, during our sample period IRB banks paid out 40.0 % of their profits to shareholders, while SA banks exhibited an aggregate payout ratio of -6.2 % (i.e., they retained all their earnings and additionally raised external capital). Taken together, this illustrates that high short-term profitability should not be seen as a substitute for the loss absorbing capacity that capital requirements intend to create, as profits can be paid out to shareholders instead of being retained on the balance sheet as a buffer against shocks.

B. Main results at the loan level

Albeit illustrative, the findings in the previous section could be explained by borrower- or bank-specific differences between SA and IRB portfolios. To address this concern, we move the analysis to the loan level and apply the identification strategy described in Section III. We start by showing regression results for Equation (3). Results using the logarithm of the loan-specific PD as a dependent variable are presented in Table III, Panel A. As already noted, PDs are firm-specific and do not capture recovery rates that might vary from bank to bank. Thus, all banks that are providing loans to a specific firm should arrive at similar PD estimates, even though they may have very different financial contracts with the firm. However, column 1 shows that banks assign significantly lower PDs to the *same* borrower if the loan is part of an IRB portfolio as compared with an SA portfolio. In column 2, we include firm $\times$ year interactions. In this test, the sample is constrained to firm-year observations where the respective firm has at least one IRB loan and at least one SA loan from an IRB bank. The negative coefficient implies that PDs for IRB loans are significantly lower than PDs for SA loans to the *same firm in the same year*. Finally, the result is also robust to the inclusion of bank $\times$ year interactions in column 3: PDs from the *same bank in the same year* are significantly lower for loans under IRB. The magnitudes are large: PDs for IRB loans are 22 to 29 % smaller than PDs for SA loans.[36] A back-of-the-envelope calculation using the standard F-IRB formula indicates that increasing the median PD of 0.38 % by 22 [29] % would increase capital requirements from 5.19 to 5.85 [6.09] % of the unsecured loan amount (i.e., a 12.5 [17.5] % increase).[37] In the next section, we will further assess what the underreporting implies in terms of aggregate capital amounts and illustrate that the true effect is significantly underestimated when looking only at the median PD, due to the non-linear shape of the PD-risk weight correspondence.

[Table III about here]

Applying the same estimation strategy as before, we find that the actual risk weights for IRB loans are about 6.5 percentage points lower than the implied risk weights for SA loans,

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

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

while standard errors can be obtained as

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

[37] If we assume that the median PD of 0.38 % is 22 [29] % too low the correct PD should be 0.49 [0.54] %. Under the F-IRB approach, this corresponds to an increase in risk weights from 65 to 73 [76] % of the loan amount. Applying a standard capital requirement of 8 % of risk weighted-assets, the required amount of capital would increase from 5.19 to 5.85 [6.09] % of the loan amount.

even for loans to the same firm in the same year (Table III, Panel B). These risk weights account for loan terms and credit risk mitigants such as collateral that would reduce losses in the case of default. In contrast, as already documented in the previous sections, the initial loan-level write-offs recorded in the credit register are similar in the two groups of loans. If anything, they are higher for loans under IRB, which is indicated by the significantly positive coefficients for *D(IRB LOAN)* in columns 1 and 2 of Table III, Panel C. Finally, in sharp contrast to PDs and (implied) risk weights, interest rates for IRB loans are significantly higher than interest rates for loans under SA, even for the same firm in the same period (Table III, Panel D).[38] In a competitive market, differences in interest rates are likely to reflect differences in the underlying risk of a loan, which is consistent with the higher ex post loss rates for IRB portfolios that we documented in Section IV.A.

Overall, our results show that banks have substantially lower capital requirements for IRB loan portfolios that are – according to the observed loan losses – at least as risky as the SA loan portfolios. The lower than intended amount of required equity financing reduces banks' ability to absorb shocks, thus undermining the objective of capital regulation itself.

C. Differences in the incentives to underreport within IRB loan pools

C1. 'Curvature test'

In this section we address concerns about possible differences between SA and IRB portfolios that could have an impact on the results in the previous section, that is, possible selection concerns arising from the order in which IRB banks shifted their loan portfolios from SA to IRB. The first test relying on variation in the incentives to underreport *within the IRB loan pool* is the 'curvature test', which exploits the non-linear shape of the mapping from PDs into regulatory risk-weights. This non-linear shape implies stronger incentives to underreport for loans to firms with relatively low PDs, since small reductions in the PD are

[38]Interest rates are obtained for a small subset of firms, which explains the drop in the number of observations (see Internet Appendix A for the procedure by which we obtain interest rates). Importantly, we have re-estimated all specifications on the subset of loans for which we have the interest rates, and the patterns we find are very similar to those seen in the full sample.

associated with relatively large reductions in capital requirements for loans to such firms (see Figure 1 and discussion in Section III.B).

Table IV provides regression results for Equation (4) in columns 1-4, using the PD as a dependent variable. First, we include only the IRB loan dummy and run separate regressions for firms where the initial average *FIRM PD* is below or above the median, using the restricted sample of firms that have both IRB and SA loans from IRB banks. The results confirm that PDs for loans under IRB are lower than PDs for loans under SA, particularly for firms with below median PDs (more negative coefficient). In column 3 we interact the firm's average PD with the IRB loan dummy and find a significant effect for the interaction term. The magnitude of the coefficient implies that underreporting of PDs for loans under the model-based approach as compared with loans under the traditional approach is about 6.8 % larger for firms at the 25^{th} percentile compared with firms at the 75^{th} percentile of *FIRM PD*. We then add bank $\times$ year $\times$ loan pool interactions that control for any differences between SA and IRB portfolios of a specific bank; results are unaffected (column 4). These findings show that underreporting of PDs is strongest for precisely those loans where small reductions in the PD translate into large reductions in risk-weighted assets.

[Table IV about here]

The specification with bank $\times$ year $\times$ loan pool interactions in column 4 of Table IV addresses potential concerns about selection of loan portfolios into the IRB pool. An alternative way of addressing such concerns is to constrain the analysis to the 237,985 IRB loans in our sample, and check whether the underestimation of PDs *relative to the other loans in this sample* depends on the initial level of the firm's average PD. Results for this test are shown in columns 5 and 6 of Table IV. As a dependent variable for this test we have to use the *ESTIMATION BIAS*, that is, the difference between a dummy variable indicating default within the next four quarters and the reported PD for the loan.[39] The negative coefficient for *FIRM PD* in column 5 implies that the underreporting of PDs *within the portfolio of IRB loans* is smaller for loans to firms with higher PDs, that is, loans for which the incentives to underreport are smaller. The result is robust to the inclusion of bank × year interactions that control for time-varying heterogeneity across banks (see column 6).

To illustrate the results graphically, we split the 237,985 IRB loans into four equal-sized buckets, according to the level of the reported PD. The first bucket contains the loans with PDs up to a level of 0.001, the second bucket the loans with PDs between 0.001 and 0.004, the third bucket the loans with PDs between 0.004 and 0.011, and the fourth bucket the loans with PDs larger than 0.011. As can be seen from the bucket allocation, three quarters of PDs are lower than or close to 1 % and thus lie in the rather steep area of the PD-risk weight correspondence. The left chart in Figure 4, Panel A shows that the underestimation of actual default rates is most pronounced in the first bucket where the incentives to underreport are greatest. The average reported PD in the first bucket is 0.0006, which is almost 10 times smaller than the average actual default rate in this bucket (which is equal to 0.0053).[40] The factor of underestimation is 4.5 in the second bucket, 2.7 in the third bucket, and 1.2 in the fourth bucket. Hence, PDs in the IRB portfolio are underreported across the entire PD band, but the degree of underreporting is largest for the very safest loans with the lowest PDs.

[Figure 4 about here]

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[39] The reason for this is that using the PD as in previous regressions would require the inclusion of firm fixed effects or firm × year interactions in order to get a reasonable interpretation. This is, however, not possible since firm fixed effects or firm × year interactions would absorb the variable of interest, *FIRM PD*. Including firm fixed effects or firm × year interactions is possible in columns 1-4, since the variables of interest in these regression exhibit variation within the same firm, in contrast to the *FIRM PD* variable. As explained below, we also use variation in bank capitalization as a proxy for differences in the incentives to underreport. In that cross-section, it is possible to include firm × year interactions also in regressions using only the sample of IRB loans (since the variable of interest is at the bank × year level).

[40] To illustrate what such an underestimation means from an investor perspective, we compare reported PDs and actual default rates with corporate default rates in different rating classes of the Moody's rating scale. In an annual report, Moody's publishes one-year default rates by rating class for corporate bonds since 1983 (Moody's (2015)). Looking at mean default rates over the period from 1983 to 2015, the average reported PD in the lowest bucket of Figure 4 corresponds to a Moody's rating of Aa3. In contrast, the average default rate in the same bucket corresponds to a rating of Ba1, which constitutes a downgrade of seven notches on Moody's alphanumeric scale relative to the reported PDs.

Deflating PDs at the lower end of the PD end has a particularly pronounced effect on aggregate banking sector capitalization, since a marginal reduction in PDs reduces capital requirements much more for low PD loans compared with high PD loans. The right chart in Figure 4, Panel A illustrates this point. Making use of the standard formula for converting PDs into risk weights and multiplying the resulting risk-weighted assets with a capital requirement of 8 %, the figure shows that capital requirements for the unsecured part of the loan exposure in the first PD bucket would be on average 3.25 times higher if actual default rates rather than reported PDs were used to calculate them. That is, for a unsecured loan amount of 100, banks would have to use equity financing of 6.1 rather than 1.9. The requirement would be 7.8 instead of 3.9 % in the second bucket, 9.4 instead of 6.7 % in the third bucket, and 14.3 instead of 13.5 % in the fourth bucket.

Table V further illustrates what the underreporting implies in economic terms. As illustrated in column 2, the uncollateralized loan volume is largest in the bucket with the lowest PDs, since these loans are larger and less collateralized on average when compared with loans in the other buckets. Column 3 shows an estimate for the required amount of capital in each bucket, obtained by multiplying the exposure values in column 2 with the requirements based on reported PDs (1.9, 3.9, 6.7 and 13.5 %, respectively); column 4 shows the same estimate using the required amount of capital based on actual default rates (6.1, 7.8, 9.4 and 14.3 % respectively), and columns 5 and 6 display the resulting increase in capital requirements. According to this approximation, banks would have to raise an additional amount of € 34.7 billion in equity if actual default rates instead of reported PDs were used for the IRB portfolios in our sample, constituting about 76 % of current capital requirements for the unsecured part of these portfolios (see last row). The bulk of the increase is due to the first bucket with the low PD loans, for which capital requirements increase by € 24.4 billion or 226 %. The reason for this disproportionate increase in the first bucket is threefold: (i) the underestimation of default rates is strongest at the lower end of the PD band, (ii) any underestimation of PDs has a stronger impact on capital requirements for lower values of PDs (recall Figure 1), and (iii) the uncollateralized loan volume in the bucket with the lowest

PDs is greatest.

[Table V about here]

C2. Differences in bank capitalization

Besides the level of the PD, also the level of bank capitalization affects the incentives to underreport. Banks that are sufficiently capitalized have less incentives to economize on regulatory capital, since the marginal benefit of relaxing regulatory constraints is smaller. To test whether such cross-sectional variation affects the degree of underreporting, we check whether the reported PD for IRB loans depends on the level of bank capitalization. Estimation results for Equation (5) are shown in columns 1 and 2 of Table VI. The sample is restricted to the 237,985 IRB loans, and since the variable of interest in this test is at the bank $\times$ year level we can include also firm $\times$ year interactions that control for any heterogeneity across firms (in contrast to the tests in columns 5-6 of Table IV). The coefficient of interest implies that reported PDs for IRB loans *to the same firm in the same period* are significantly lower if the loan is granted by a less capitalized bank. Again, underreporting of PDs is more pronounced the higher the bank's incentives to underreport, and the effect is identified *within the IRB loan pool*.

[Table VI about here]

To illustrate the findings graphically, Panel B of Figure 4 employs the same technique as Panel A but uses the level of bank capitalization to split the loans into buckets. The first bucket contains loans from banks with a capital ratio up to 9.9 %, the second bucket the loans from banks with capital ratios between 9.9 and 13.2 %, the third bucket the loans from banks with capital ratios between 13.2 and 16.7 %, and the last bucket the loans from banks with capital ratios larger than 16.7 %. Results are similar to those in Panel A. PDs in the first bucket (where bank capitalization is low) significantly underestimate actual default rates (left chart), and consequently banks achieve a material reduction in capital requirements for these loans (right chart). The effects are less pronounced in the other buckets and reverse in the fourth one.

C3. Differences in the importance of the loan book

The incentives for banks to underreport credit risk estimates should also depend on the overall importance of the loan book for the respective bank. That is, incentives to underreport PDs for corporate loans should be higher for banks for which the loan book constitutes a larger part of the balance sheet or generates a larger share of the income. To test this assertion, we introduce a measure labelled 'investment banking intensity', which is defined as the ratio of non-interest income to total income. We re-estimate Equation (5), using the investment banking intensity variable instead of the capital ratio as a distinguishing feature among banks.

The results are shown in Table VI, columns 3 and 4. There are no pure investment banks in our sample, since these are very scarce in Germany and the few of them that exist do not use the IRB approach in case they have credit risk. Therefore, the comparison rests on the large German universal banks with their investment banking sections. While banks with more investment banking activity might be more aggressive in risk taking, their incentives to underreport credit risk could be lower since their total income is less dependent on interest income. Put differently, if a bank's income consists mostly of non-interest income, the loan book is of less importance and the bank might be less willing to risk regulatory scrutiny. Indeed, we find that banks with a higher investment banking intensity tend to assign higher PDs to IRB loans to the same firm in the same period, compared with banks for which investment banking intensity is low (i.e., banks for which the loan book is relatively more important), which again suggests stronger underreporting when the incentives to underreport are stronger.

C4. Differences in bank size

In a final cross-sectional test we also look at differences in bank size, although we do not have a strong prior on its interaction with the incentives to underreport. On the one hand, larger banks may be able to put in a lot of effort and spend a lot of resources on 'risk weight optimization', which could imply a higher degree of underreporting. On the other hand, larger banks may have other means of 'optimizing' risk weights. For example, they could focus on other parameters under the Advanced IRB approach (see Section VI.D) or on capital requirements under the market risk framework, both of which may be easier to manipulate. Results are reported in columns 5 and 6 of Table VI and show that larger banks tend to assign higher PDs to the same firm (in the same period), meaning that underreporting of PDs is less pronounced for these banks.

D. Origin of the underestimation of default rates

Underestimation of actual default rates for IRB loans can either originate from direct manipulation of PDs of existing loans, after the portfolios have been shifted to the IRB approach, or from new loans that are granted by the bank. While IRB models themselves cannot be adjusted (without permission from the regulator), it is perhaps possible to manipulate the inputs that go into these models to the extent that the inputs require some degree of subjectivity, that is, contain what is often referred to as 'soft' information. Model-based regulation may change the incentives of banks to capture negative 'soft' information in their credit risk estimates. Ignoring this type of information helps to reduce capital requirements, while at the same time affecting the performance of the models that have been approved by the regulator.

Table VII provides regression results for Equation (6). Restricting ourselves to loans using the IRB approach that were granted in the 12 months before and after the reform in 2007, we find a significant difference in *ESTIMATION BIAS* between the two subsets of IRB loans both in 2009 (columns 1-2) and 2010 (columns 5-6). That is, PDs for IRB loans *originated* under Basel II are significantly more likely to underestimate actual default rates than PDs for IRB loans *originated* before the reform. Columns 2 and 6 show that this result is robust to the inclusion of bank fixed effects. Compared with IRB loans originated before the reform, IRB loans originated after the reform underestimate actual default rates by about 0.8 percentage points more in 2009 and by about 1 percentage point more in 2010.

This indicates that the introduction of model-based regulation changed banks' incentives and in turn affected the performance of the models that are used to measure credit risk. As a placebo test, we replicate Equation (6) using SA loans only. Here, we find no statistical difference between loans issued in 2006 and 2007.

[Table VII about here]

In the second test, we examine how the PD of existing relationships changes once our classification switches from SA to IRB; we do not find a significant change in PD (see Table VIII). This is perhaps not very surprising, as a systematic downward correction in PDs after a portfolio is transferred to IRB would attract the attention of the supervisors. In sum, the degree of underreporting is greater for loan exposures where the underreporting is less likely to be detected.

[Table VIII about here]

V. Effects on lending and the structure of financing

In this section, we examine how the reform affected banks' incentives to lend. Banks that introduced IRB experienced a significant reduction in capital requirements for loans – both in absolute terms and relative to SA banks that did not introduce the new approach. It may be that these banks exploited a possible cost advantage arising from the lower amount of required equity financing by expanding loans. To analyze whether the reform's differential impact on capital requirements had consequences for banks' lending behavior, we first test whether IRB banks indeed expanded their lending relative to SA banks. We then analyze whether this effect was stronger for firms with low PDs, for which the reduction in capital requirements was most pronounced, and finally exploit variation in the regulatory approach within the group of IRB banks – similar to before – to improve identification.

A. Bank-level evidence

The left-hand panel of Figure 5 illustrates that the aggregate supply of credit to domestic non-banks by all German banks increased considerably around the Basel II reform in 2007. Interestingly, specifically those banks that introduced the model-based approach expanded their lending to corporate borrowers in Germany following the reform (right-hand panel of Figure 5).[41] Prior to the reform, the development of loan growth was relatively similar for the two groups of banks. Following the reform, however, we see a sharp increase in aggregate loans for IRB banks, while the loans of SA banks remain relatively constant or even decline. To formalize the analysis, we collapse quarterly bank-level loans into single pre-event and post-event time periods by taking the average of the two years before and the two years after the reform, and regress the change in this variable on a dummy that indicates whether the bank introduced the model-based approach. Table IX, columns 1 and 2, show that IRB banks increased their lending by about 9 % as compared with SA banks.[42] As noted before, the IRB approach was implemented by larger banks, since these banks had the ability to spread the compliance costs associated with the implementation of the model-based approach over a large portfolio of loans. Smaller banks, on the other hand, were unable to bear the cost and did not introduce the new approach. Thus, larger banks drastically expanded their lending relative to smaller banks following the reform, resulting in a concentration of market shares in the corporate loan market.

[Table IX and Figure 5 about here]

B. Loan-level evidence

Next, we test whether the increase in lending from IRB banks was particularly pronounced for firms with relatively low PDs, that is, firms for which the decrease in capital

[41]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.

[42]In column 2 we add several bank-level control variables (i.e., the pre-event logarithm of assets, ratio of equity to assets, ROA and bank ownership dummies). The coefficient for the IRB bank dummy remains significantly positive.

requirements was largest. To do this, we collapse the quarterly loan-level data into single pre-event and post-event time periods by taking the averages of the two years before and the seven quarters after the reform, and regress the change in this variable on an interaction between an IRB bank dummy and the *FIRM PD* variable from above.[43] Formally, we run the following regression:

$$\Delta LOG(LOANS)_{ij} = \alpha_i + \alpha_j + \gamma \cdot \left[\mathbb{1}_j \times FIRM\ PD_i \right] + \varepsilon_{ij}, \tag{7}$$

where i denotes the individual firm, and j denotes the individual bank. Firm fixed effects, α_i, systemically control for heterogeneity across firms (see Khwaja and Mian (2008)), and bank fixed effects, α_j, systematically control for heterogeneity across banks.

Estimation results for Equation (7) are presented in Table IX, columns 3 to 6. The coefficient for the interaction between the IRB bank dummy and the *FIRM PD* variable is significantly negative. Together with the other coefficients this indicates that IRB banks increased lending to the same firm relatively more, but less so when the firm's PD is higher (column 3). This effect is robust to the inclusion of firm fixed effects in column 4, bank fixed effects in column 5, and both firm and bank fixed effects in column 6. Economically, the coefficients indicate that an increase of one standard deviation in *FIRM PD* induces a 1.2 to 2.5 % smaller increase in loans from IRB banks.

In line with the reform's objectives, IRB banks expanded their loans in particular to borrowers with relatively low PDs. However, as illustrated in Section IV.C, the underestimation of actual default rates was most severe for loans to these firms. Hence, the reform's objective of steering banks towards safer borrowers was undermined by the tendency to underreport actual asset risk. In sum, loans under IRB were at least as risky as the loans under SA, but had significantly lower capital requirements.

[43]We do not include the last quarter of 2008 in the post-event period, since average PDs considerably increased in Germany following the Lehman collapse, which resulted in a considerable increase of capital requirements for IRB loans (see Behn, Haselmann, and Wachtel (2016), and the right-hand panel of Figure 5, which shows that IRB banks reduced their lending more than SA banks following the Lehman collapse).

C. Within-IRB results

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

$$\Delta LOG(LOANS)_{ij} = \alpha_i + \alpha_j + \delta \cdot \mathbb{1}_{jp} + X'_{ij}\gamma + \varepsilon_{ij}, \tag{8}$$

where $\mathbb{1}_{jp}$ takes the value of one if the respective loan is in the IRB pool and zero if it is in the SA pool of bank j.

Regression results for Equation (8) are shown in Table X, columns 1-3. Recall that risk weights for IRB loans are on average 12 percentage points lower than risk weights for SA loans (Table I), which translates into a reduction in capital requirements of about 1 percentage point (since capital requirements are 8 % of RWA: $0.08 \times 0.12 = 0.0096$). In response, loans in the IRB portfolios are increased by about 8 % more than loans in the SA portfolios of IRB banks (column 1). Results are robust to the inclusion of bank fixed effects in column 2 and firm fixed effects in column 3.[44] To test whether IRB banks also extended more new loans in the IRB portfolios, we construct a dummy variable (NEW LOAN) that takes the value of one if – either for an existing or a new bank-firm relationship – a new loan was issued during the post-event period. Re-estimating Equation (8), results in columns 4-6 of Table X illustrate that the issuance of a new loan for a given borrower is 5 to 12 % more likely if the firm finds itself in a portfolio that has already been shifted to IRB.

[Table X about here]

Overall, the lending results suggests that the reform caused an increase in loan supply on both the intensive and the extensive margin. At the same time, PD results show that the

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

capital requirements for these loans were significantly lower than intended by the regulator, particularly for loans that were newly issued after the reform. A welfare analysis would have to trade off the (potential) benefits arising from additional lending activity against the costs that could, for example, relate to a (potentially) less stable banking system. Such an analysis is, however, beyond the scope of this paper.

VI. Interpretation of results and alternative explanations

There are a number of possible interpretations for our findings, all of which are related to how model-based regulation may lead to unintended outcomes. The most obvious interpretation is that banks exploited the discretion they had under the model-based approach in order to reduce capital requirements. This was possible because the regulation established a direct link between internal risk estimates and the amount of equity financing required for a specific exposure. Several of our findings support this interpretation. Most notably, underreporting of credit risk estimates is most pronounced in cases where the incentives to underreport are greatest. Moreover, interest rates suggest that banks were aware of the higher risks associated with IRB loans, while reported PDs and capital requirements did not reflect these risks.

In this section, we discuss a number of alternative explanations for our findings, related to selective early adoption of IRB, endogenous failure of risk models, self-reporting of risks, regulatory rigidity, and regulatory capture, or regulatory anticipation of underreporting. What all of the alternative explanations have in common is that they relate to some type of incentive problem that leads to an underestimation of actual default rates; the end result is the same in all cases: the underestimation of PDs reduces regulatory requirements and thus undermines the basic objectives of capital regulation.

A. Selective early adoption of IRB for optimistically-biased portfolios

A variant of the interpretation outlined above would be that banks successfully lobbied for early IRB adoption for portfolios with optimistically biased models, potentially by capturing the supervisor (see Section VI.E on the latter). Given the institutional setup around the IRB implementation described in Section I.B, we think that such selective early adoption was difficult in practice. Moreover, our analysis in Section IV.D indicates that the underestimation of default rates for IRB loans is mainly driven by new loans that were originated after the reform, rather than loans that existed already before a specific portfolio was shifted to IRB. This result seems inconsistent with selective early adoption for portfolios with optimistically biased models.

There is, however, a slightly more subtle form of selective early adoption that is more consistent with our overall findings. As illustrated in Section IV.C, the non-linear mapping from PDs into risk weights implies that a small reduction in PDs at the lower end of the spectrum implies a much larger reduction in capital requirements than the same absolute reduction in PDs at the higher end of the spectrum. Since PD models are usually evaluated by comparing estimated PDs and average default rates at the portfolio level, banks might have pushed models that are optimistically biased at the low end of the PD spectrum and pessimistically biased at the high end of the spectrum, generating on average correct default rates while at the same time minimizing regulatory capital requirements. Results for the 'curvature test' are consistent with this type of model selection, as the results are particularly pronounced at the low PD end. However, it can only be part of the explanation, since we do not find that PDs for IRB loans are 'correct on average'.

B. Endogenous adjustments of bank behaviour and 'winner's curse'

A slightly less nefarious interpretation of the results in the previous sections is that following the Basel implementation banks were more likely to attract additional lending business with borrowers for which their risk model was unusually optimistic. Indeed our lending results in Section V illustrated that IRB banks expanded loans in particular to those firms that score relatively well on their risk models. This could lead to endogenous failure of the model, for the following reason: if the most optimistic bank wins new lending business, newly assigned PDs will be lower than the average PD for the borrower (since only the winning bank will report the PD in the credit register), giving rise to a winner's curse problem. Thus, instead of conscious underreporting of PDs in order to save on regulatory capital, the failure to accurately predict actual default rates could be due to unconscious adjustments of bank behavior following the implementation of model-based regulation. While we cannot exclude that such unconscious adjustments also occur, the interest rate results suggest that banks were aware of their underreporting. Irrespectively of whether the underreporting of PDs occurred consciously or unconsciously, it clearly reduced banks' loss absorbing capacity and thus undermined the objectives of capital regulation.

C. Self-regulation vs. model-based regulation per se

One could argue that the problems we document were not caused by model-based regulation in itself, but rather by the manner in which it was implemented (reliance on banks' *internal* risk models). Following this logic, problems could have been avoided or at least mitigated if risk models had been provided by supervisors rather than banks themselves. Certainly, one would expect less of a downward bias in this case, although such an approach could be subject to other problems. However, also under the current regulation banks only propose models, while the final decision on model approval rests with the supervisors. In other words, supervisors are already heavily involved in the process, and still we observe the patterns documented above. In interpreting our findings, one should keep in mind Goodhart's Law: once the rules are in place, banks have incentives to change their behavior, which will adversely affect the performance also of models implemented by the supervisor. Thus, we have doubts whether the problems documented in our paper would be solved if models were implemented by supervisors instead of the banks themselves.

D. Regulatory rigidity

It could also be that the model failure was caused by the need to comply with rigid regulatory standards, rather than by misaligned incentives. Regulators required banks to stick to the models that were approved and this took away some discretion from the banks and reduced their ability to adapt. While banks had the flexibility to adjust the PDs and other parameters if they deemed them to be incorrect, a large amount of such 'overwrites' would raise the attention of the supervisor. Thus, it could be the lack of discretion that came with the regulation which led to the failure of the models. It could further be that interest rates did a better job at predicting defaults because banks had the freedom to adjust them flexibly in the face of new information.

To assess whether our findings are driven by regulatory rigidity we analyze whether effects are more or less pronounced with higher discretion on the side of banks. As explained in Section I, banks that opted for the new regulatory approach could choose between two alternatives to determine capital charges for their loan portfolios: the Foundation IRB (F-IRB) approach and the Advanced IRB (A-IRB) approach. Compared to the F-IRB approach, the A-IRB approach gives banks more flexibility in determining capital charges since it requires them to estimate not only the borrower's PD, but also loan-specific factors such as loss given default (LGD) and exposure at default (EAD). Under the F-IRB approach these loan-specific parameters are provided by the regulator and hard-wired into the calculation of risk-weights. Consequently, the PD is the only parameter that banks can adjust in the F-IRB approach, whereas under A-IRB they can adjust also the other parameters.

For the years from 2008 to 2012, our sample includes 100,616 loans under F-IRB and 132,171 loans under A-IRB.[45] Average values of estimated PDs, actual defaults, the estimation bias, risk weights, loan losses, and interest rates for these loans are shown in Figure 6. Compared with the F-IRB approach, both reported PDs and actual defaults are

[45] As mentioned in Section I, of the 45 banks that introduced the IRB approach, 17 introduced F-IRB, 18 introduced A-IRB, and 10 use F-IRB for some portfolios and A-IRB for other portfolios. Moreover, 5,198 IRB loans are classified as retail IRB loans and attributed neither to the F-IRB nor to the A-IRB approach (loans to small businesses can be classified as retail loans, subject to certain size threshold).

higher for loans under the A-IRB approach. Moreover, the *ESTIMATION BIAS* is larger for A-IRB loans in the first year, similar in the second, and larger for F-IRB loans in the last three years of the sample period. The latter may reflect that incentives to underreport PDs could be higher under F-IRB, since it could be preferable for banks to underreport LGDs or other risk parameters rather than PDs under the more complex A-IRB approach (e.g., in case deviations of reported and actual PD are easier to detect than deviations of reported and actual LGDs). In line with this story, we find that risk weights tend be lower while actual loss rates are higher for loans under A-IRB, compared with loans under F-IRB. Moreover, interest rates charged on A-IRB loans are higher than those for loans under F-IRB, suggesting that banks were aware of the higher risks associated with these loans.[46] In sum, more discretion on the side of banks implies a higher degree of incongruence between reported risk weights and actual loan losses, making it unlikely that more discretion and flexibility on the side of banks would help to mitigate the underreporting problem.

[Figure 6 about here]

E. Naïve supervisor versus regulatory capture

The economic magnitudes of the effects we document are quite large (see in particular Section IV.C), which raises the natural question of why the supervisors did not detect the underreporting. While a fully-fledged analysis of the political economy of capital regulation is outside the scope of this paper, we briefly discuss the two most common explanations for this type of failure, namely that supervisors were either naïve or captured by the banks.

To start with, our lending results (comparing SA and IRB banks) illustrate that the large IRB banks clearly benefitted from the regulation and became even more dominant in the corporate loan market. Within IRB banks, the evidence on the effects bank size is mixed: on the one hand, results in the previous subsection illustrated that banks using the A-IRB approach (which tend to be the larger ones) benefitted more on aggregate; on the other

[46]Unfortunately, power issues prevent us from doing a fully-fledged regression analysis, as coefficients tend to be insignificant in saturated specifications with bank $\times$ year and firm $\times$ year interactions (although the magnitudes of coefficients are quite sizable).

hand, results in Section IV.C suggested that the underreporting of PDs is less pronounced for loans from larger IRB banks. Except for the latter, this evidence seems to be consistent with a story of regulatory capture.

However, the results are also consistent with a naïve regulator story. Large banks tend to spend a lot of resources to hire consultants and lawyers who can help them navigate the complexity associated with the model-based regulation in a way that is optimal for them. Moreover, underestimation may be more difficult to detect in practice, since the models are assessed one at a time (and not all at once, as in our paper), which reduces the number of observations being assessed at the time and thus makes statistical inference more difficult. It should also be kept in mind that supervisors had to check hundreds of models at different banks at the same time, and that 'optimization' seemed to be happening in rather subtle ways. For instance, our results tell us that the underestimation of default rates is particularly pronounced for loans that were newly issued after the reform (cohort analysis), rather than existing loans (for which downward corrections in PDs would be easy to detect). While statistical learning may seem easy, it does require a long time series of data to make reasonable conclusions about the source of the issue. Research has shown that parameter learning is very slow and requires years of high frequency data (Collin-Dufresne, Johannes, and Lochstoer (2016)). Finally, it is important to note that supervisors do not observe the interest rate on loan contracts, which prevents them from conducting some of the tests included in our paper. In sum, robustly concluding and proving that a previously approved model produces systematically wrong estimates is far from straightforward.

F. Regulatory or supervisory anticipation

Still an alternative explanation is that the supervisor was well aware of the underreporting but did not act because it wanted to provide some additional capital relief to banks in order to foster the transition to IRB and promote lending. However, looking at speeches and the regulatory agenda of recent years, it seems that the type of underreporting of risk estimates that we uncover was both surprising and undesirable (for an overview of relevant quotes, see Internet Appendix D). To give a few examples, Janet Yellen stated in 2013 that *"key Basel Committee work in the years ahead will include [...] increasing the comparability of risk-based capital requirements across banks and across countries."* In a similar vein, Jens Weidmann proposed in 2014 that *"the flaws of the risk-based approach need to be addressed. To improve the comparability of the methods used to calculate the capital requirements, the Basel Committee is aiming to curtail banks' leeway in weighting risk. For example, it is hard to assess the probability of default for low-default portfolios."*

To address the problems with the model-based approach, regulators have taken decisive action and adjusted the regulatory framework in recent years. Addressing unwarranted variability in risk-weighted assets is one of the main objectives of the recently agreed Basel III finalization package (see Basel Committee on Banking Supervision (2017)). The package (i) adopts a more stringent 'input floor' for PDs to ensure a minimum level of conservatism of model parameters for asset classes where the IRB approaches remain available; (ii) provides greater specification of parameter estimation practices to reduce variability; and (iii) introduces an 'output floor' that limits the amount by which capital requirements can be lower under the IRB approach, relative to the standard approach. The reforms still need to be implemented in major jurisdictions around the globe and face significant pushback from bank lobby groups. In parallel, supervisors have started carrying out dedicated on-site reviews to ensure that approved internal models comply with currently applicable regulatory standards (for example, the European Central Bank that now supervises many of the banks in our sample launched the 'Targeted Review of Internal Models' in 2017, comprising more than 200 dedicated on-site examination and involving around 100 staff members).

G. Correlation of defaults

While higher interest rates in a competitive market are suggestive evidence that banks knowingly underreported PDs for IRB loans, it is possible that differences in interest rates reflect other factors than differences in the idiosyncratic risk of the loans. For example, differences in the price of loans could be driven by differences in the correlation of default probabilities in IRB and SA portfolios that we would miss by conducting loan-level analysis. While theoretically this is an interesting point, we do not think it is really a first order concern for our analysis. First, IRB banks are the largest 45 banks that command approximately 55 % of the loan market (average total assets are 133 billion euro). In other words, these are well-diversified banks – the contribution of any individual loan to the banks' portfolio risk is going to be miniscule. Second, our sample comprises an upswing as well as a downswing period. We can exploit this fact to test whether there are any systemic differences in default correlation structures between SA and IRB portfolios. To see how, consider the following example: assume that there are two loan portfolios, A and B, and that both have an average PD of 2 %. The correlation of defaults in portfolio A is 0, while in portfolio B it is 0.2. While both portfolios should on average witness a 2 % default rate, defaults will be distributed uniformly over time in portfolio A, and clustered in portfolio B. In other words, there will be boom periods in which portfolio B will have much less defaults than portfolio A, and there will be bust periods where default rates in portfolio B will be much higher than in portfolio A. On average of course, both portfolios should have the same average default rate of 2 % (see Feldhütter and Schaefer (2018) for an illustration of this point). In stark contrast, we find that IRB loans default more than SA loans in both upswing and downswing periods, with relatively constant differences in default rates. This suggests that differences in interest rates are unlikely to be driven by differences in diversification between IRB and SA portfolios.

VII. Conclusion

Using data from the German credit register, we investigate how the introduction of model-based capital regulation affected banks' ability to absorb shocks. While reported PDs and risk-weights are significantly lower, observed loan losses tend to be higher for loans under the new regulatory approach. Furthermore, there is an incongruence between the reported probabilities of default/risk-weights and interest rates charged for loans under model-based regulation, suggesting that banks were aware of the inherent riskiness of these loan portfolios. We also find that results are stronger in cases where banks have higher incentives to underreport or greater discretion to use internal risk parameters. Finally, we show that the large banks that introduced the model-based approach benefitted from the resulting reduction in capital requirements and consequently expanded their lending at the expense of smaller banks, leading to further concentration in the German market for corporate loans.

A few points are worth highlighting. First and foremost, our paper provides a positive assessment of the model-based regulation and not a normative evaluation of it. In other words, our paper does not make any welfare statements about model-based regulation. While we observe that banks underestimate the level of risk and thus reduce aggregate capital requirements, it could be that the reform lowered distortions in the cross-section as the capital charge was more tied to individual loan risk. Moreover, as documented, lower capital charges for loans under model-based regulation promoted lending by large banks, with potentially beneficial effects for certain borrowers. The objective of this paper is to provide a detailed assessment of model-based regulation against the stated objectives of the reform (i.e., a better alignment between banks' asset risk and their capital requirements) and of capital regulation more broadly (i.e., a sufficient ability of the banking sector to withstand unexpected shocks). In this respect, we believe that we uncover several important unintended consequences of the regulation, which is what we refer to as 'the limits of model-based regulation'.

Our results suggest that the objectives of the reform have not been fully achieved, since banks 'optimized' model-based regulation. This 'optimizing' behavior resulted in lower than intended capital requirements for loans that were at least as risky as before and thus undermined the objectives of capital regulation itself. Furthermore, the fixed costs associated with the implementation of the model-based approach implied that it was introduced only by the largest banks. These large banks benefitted from the reduction in capital requirements associated with the new regulation and consequently became even more dominant in the market for corporate loans. This is rather counterintuitive, since a lot of discussions on financial stability and regulation revolve around the 'too-big-to-fail' issue. Our results indicate that model-based regulation imparted a subsidy to size and thereby could have exacerbated the 'too-big-to-fail' problem.

One could argue that self-reporting of risks by banks or a lack of trained supervisory manpower caused the problems we document. That is, models provided by supervisors or a higher amount of supervisors could help to make this complex regulation work well. In line with this view, several central banks and other supervisory authorities have considerably expanded their supervisory workforce in recent years. We have reservations against this view and would like to echo Goodhart's Law (or the Lucas critique): "When a measure becomes a target, it ceases to be a good measure;" or, applied to our case: once the rules are in place, banks have incentives to change their behavior, which will adversely affect the performance also of models implemented by the supervisor. Thus, we have doubts whether the problems documented in our paper would be solved if complex models were implemented or enforced by supervisors instead of the banks themselves.

It should be noted that we are not suggesting that banks committed outright fraud. Furthermore, we are not providing any evidence on regulatory capture. While our results are consistent with a regulatory capture mechanism, they are also consistent with a naïve regulator. Our results, however, suggest that there might be limits of complex regulation and that simplifying regulation might be more effective (Haldane (2013)). Our findings raise important questions about political economy factors that might play a role in the introduction of complex capital regulation. The political economy of complex financial regulation remains an important topic for further research.

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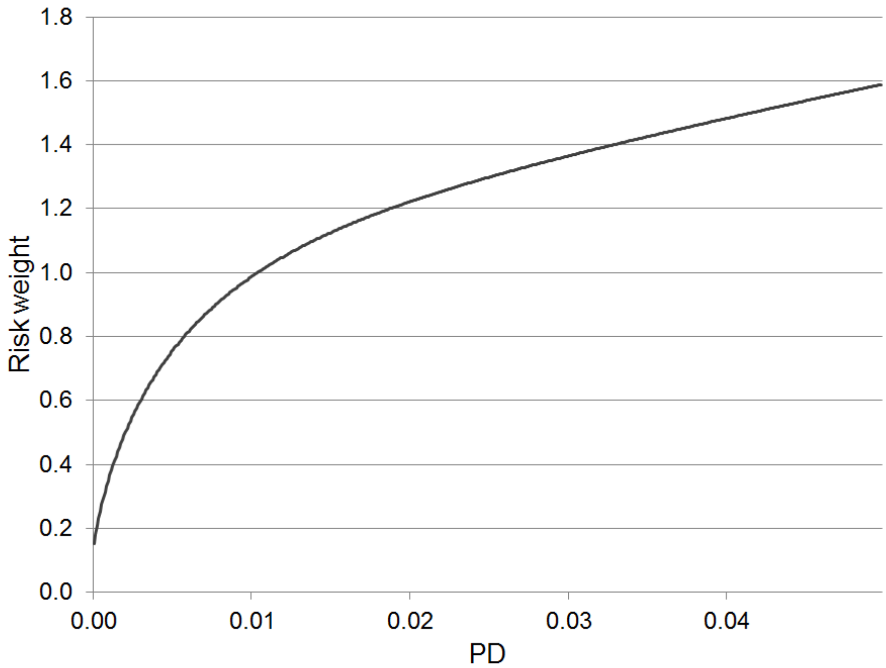

Figure 1. PDs and regulatory risk-weights

This figure shows how estimated PDs map into regulatory risk-weights for loans in the corporate sector, assuming standard values for loss given default (45 %) 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.

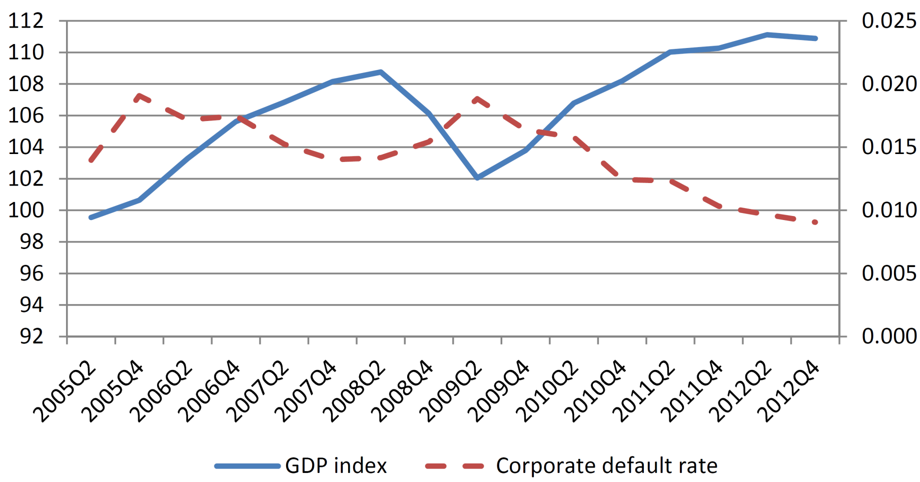

Figure 2. Business cycle

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

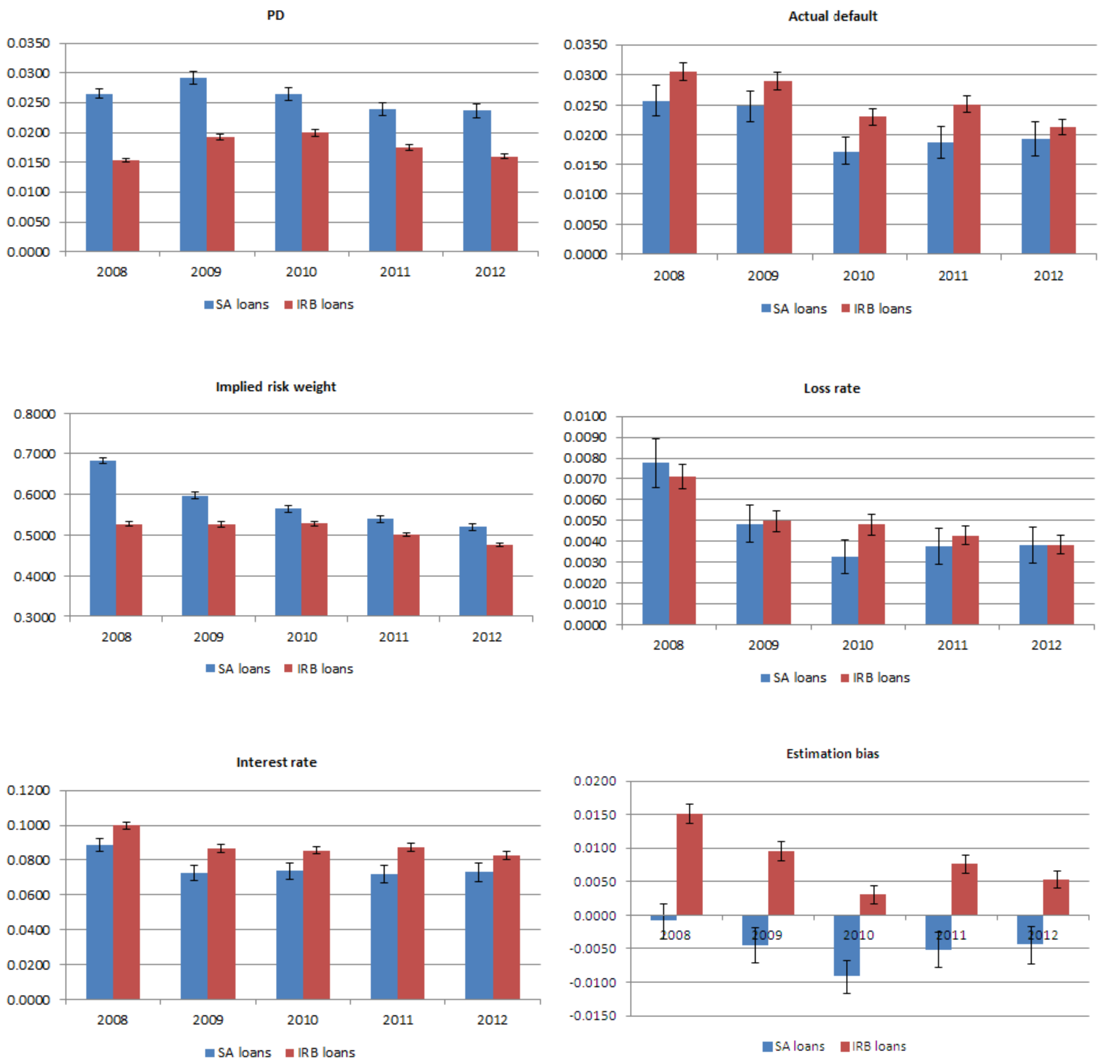

Figure 3. Main variables in SA and IRB loan pools.

The figure shows average values for PDs, actual default rates, (implied) risk weights, loan loss rates, and interest rates for SA and IRB loans during the period from 2008 to 2012. The sample includes all loans that are not in default in the respective year. Confidence intervals are at the 95 %-level.

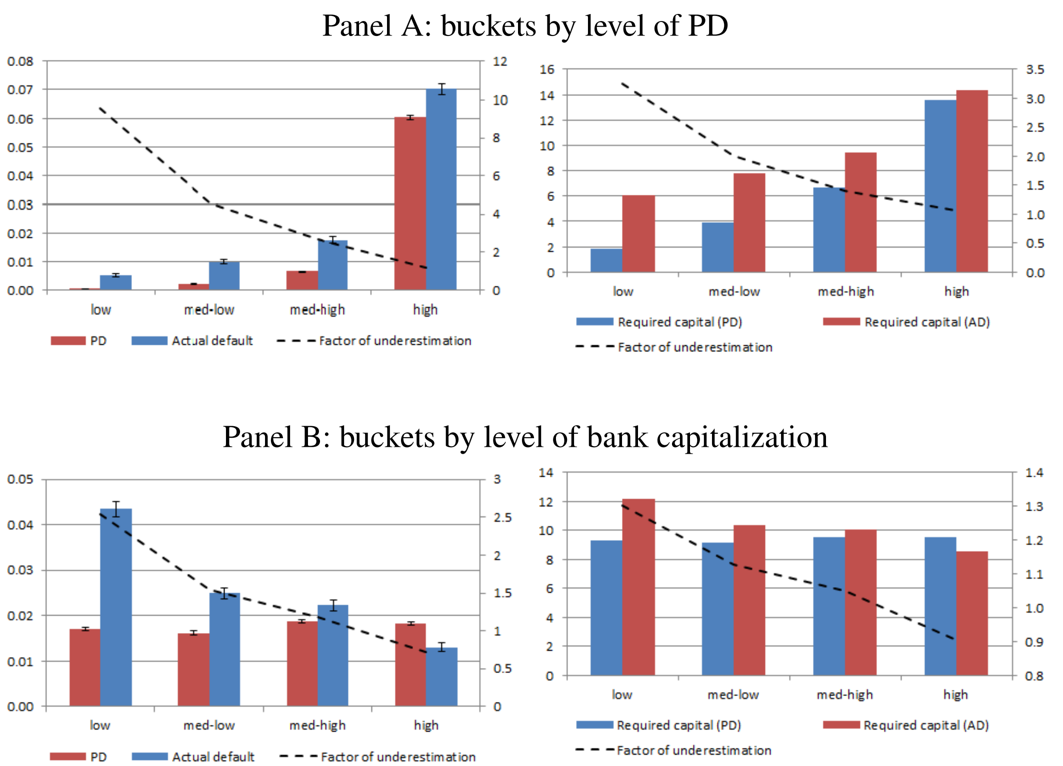

Figure 4. Underreporting in IRB portfolios split by level of PD or bank capitalization.

We split all IRB loans into four equal sized buckets, sorted by the level of the PD (Panel A), or the level of bank capitalization (Panel B). In Panel A, the first bucket contains the loans with PDs up to a level of 0.00116, the second bucket the loans with PDs between 0.00116 and 0.0039, the third bucket the loans with PDs between 0.0039 and 0.0114, and the fourth bucket the loans with PDs larger than 0.0114. In Panel B, the first bucket contains loans from banks with a capital ratio up to 9.9 %, the second bucket the loans from banks with capital ratios between 9.9 and 13.2 %, the third bucket the loans from banks with capital ratios between 13.2 and 16.7 %, and the last bucket the loans from banks with capital ratios larger than 16.7 %. In both panels, the left chart shows average reported PDs (red bars) and actual default rates (blue bars) on the left hand scale, and the factor of underreporting – obtained by dividing average actual default rates by average reported PDs – on the right hand scale. The left-hand scale of the right chart in both panels shows the amount of required capital for a loan amount of 100, calculated by plugging either reported PDs (red bars) or actual default rates (blue bars) into the PD-RWA correspondence plotted in Figure 1 and multiplying the resulting risk-weighted assets with a capital requirement of 8 %. The right-hand scale shows the factor by which required capital is lower due to reported PDs underestimating actual default rates.

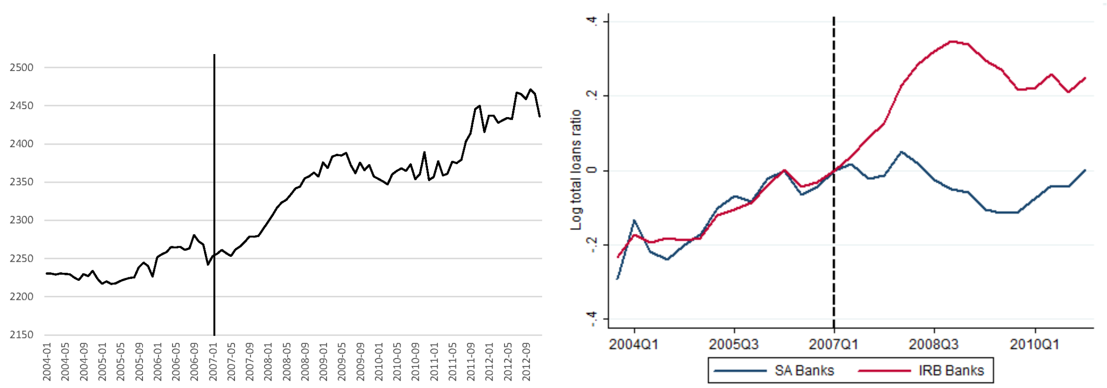

Figure 5. Aggregate lending around the Basel II introduction.

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

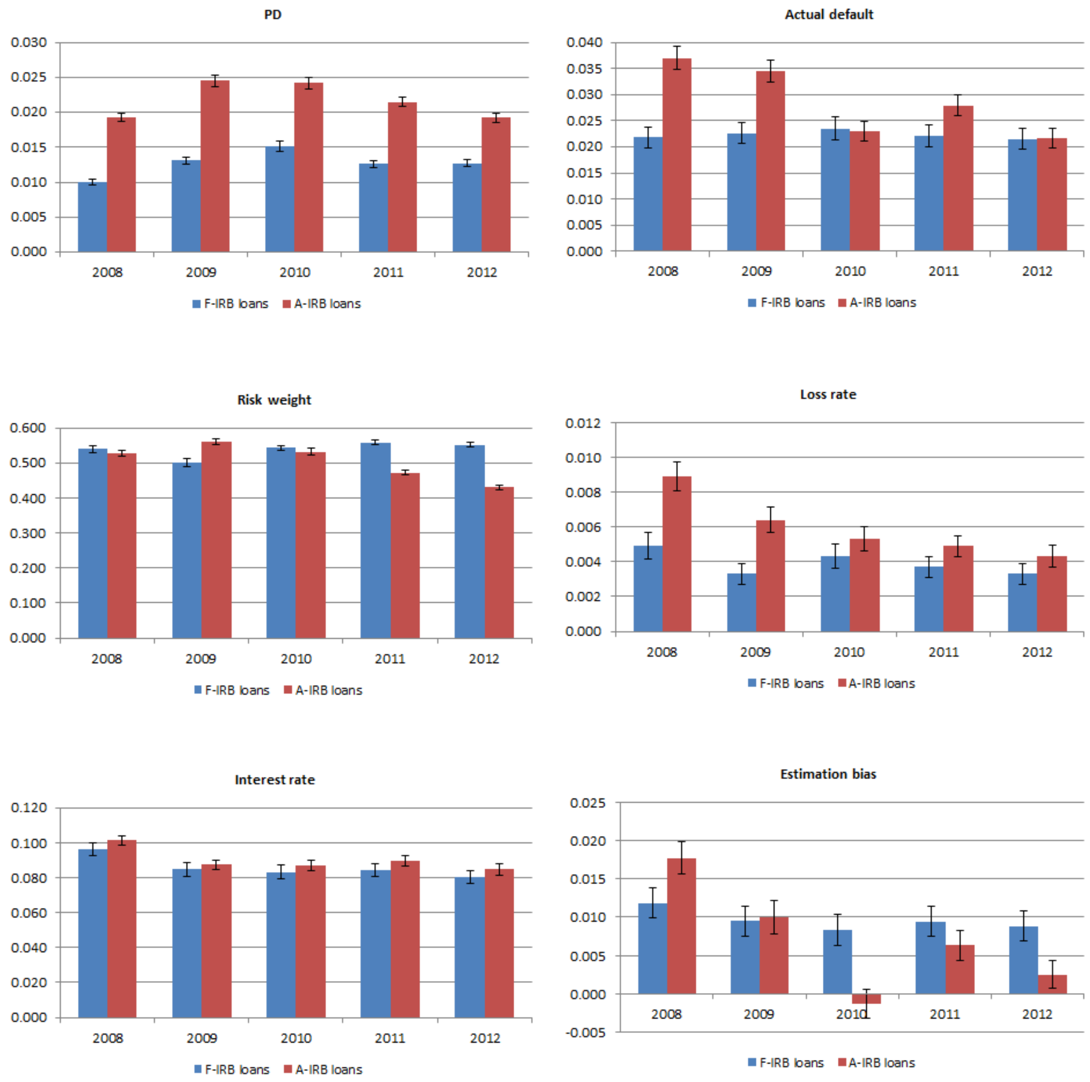

Figure 6. Foundation vs. Advanced IRB approach.

The figure shows average values for PDs, actual default rates, loan loss rates, risk weights, and interest rates for loans under the Foundation and the Advanced IRB approach during the period from 2008 to 2012. The sample includes all loans that are not in default in the respective year. Confidence intervals are at the 95 %-level.

Table I. Descriptives

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

Panel B: Loan descriptives of IRB banks				
	SA loans (59,000 loans)		IRB loans (237,985 loans)	
	Mean	S.D.	Mean	S.D.
PD	0.0262	(0.0564)	0.0176	(0.0506)
ACTUAL DEFAULT	0.0217	(0.1447)	0.0259	(0.1590)
RISK WEIGHT	0.6155	(0.7558)	0.4900	(0.5374)
IMPLIED RISK WEIGHT	0.5902	(0.5528)	—	—
LOSS RATE	0.0049	(0.0542)	0.0051	(0.0546)
INTEREST RATE	0.0792	(0.0560)	0.0876	(0.0589)
LOG(LOANS)	8.8335	(1.1652)	9.1280	(1.2714)
COLLATERAL	0.5017	(0.4538)	0.4871	(0.4472)
D(RELA)	0.7026	(0.4571)	0.6156	(0.4865)
Δ *LOG(LOANS)*	0.0159	(0.3582)	0.0644	(0.5697)

Panel C: Firm descriptives		
	(5,961 firms)	
	Mean	S.D.
FIRM ASSETS (2006, in mn €)	154	(817)
LOG FIRM ASSETS (2006)	10.363	(1.428)
FIRM DEBT TO ASSETS (2006)	0.343	(0.202)
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 of the IRB banks. 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. *D(RELA)* is a dummy variable that is equal to 1 whenever a bank's loans to a specific firm make up more than 75 % of the firm's aggregate loans reported in the credit register. Δ *LOG(LOANS)* refers to the change in the log of loans around the Basel II reform (average of seven quarters after minus average of two years before the reform). The remaining variables include observations from 2008 to 2012. Panel C contains information on the firm level for a matched sample of 5,961 firms. Firm balance sheet information is obtained from Bundesbank's USTAN database.

Table II. Characteristics of SA and IRB loans within IRB banks

	Observations	PD		*ACTUAL DEFAULT*		*(IMPLIED) RISK WEIGHT*		*LOSS RATE*		*INTEREST RATE*	
Panel A: SA loans		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2008	14,713	0.0265	(0.0504)	0.0257	(0.1582)	0.6919	(0.5608)	0.0078	(0.0725)	0.0876	(0.0527)
2009	13,734	0.0292	(0.0647)	0.0248	(0.1554)	0.5905	(0.5622)	0.0048	(0.0530)	0.0786	(0.0587)
2010	11,154	0.0264	(0.0572)	0.0173	(0.1304)	0.5700	(0.5511)	0.0033	(0.0433)	0.0750	(0.0557)
2011	10,492	0.0239	(0.0518)	0.0188	(0.1357)	0.5346	(0.5312)	0.0038	(0.0442)	0.0749	(0.0556)
2012	8,907	0.0237	(0.0560)	0.0193	(0.1376)	0.5124	(0.5268)	0.0038	(0.0422)	0.0748	(0.0577)
Panel B: IRB loans		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
2008	51,332	0.0153	(0.0443)	0.0305	(0.1720)	0.5269	(0.6971)	0.0071	(0.0668)	0.0968	(0.0571)
2009	48,816	0.0193	(0.0552)	0.0289	(0.1675)	0.5259	(0.7614)	0.0050	(0.0549)	0.0858	(0.0596)
2010	45,078	0.0199	(0.0596)	0.0230	(0.1500)	0.5278	(0.6740)	0.0048	(0.0530)	0.0857	(0.0597)
2011	47,592	0.0174	(0.0482)	0.0251	(0.1564)	0.5008	(0.5148)	0.0043	(0.0470)	0.0862	(0.0588)
2012	45,167	0.0160	(0.0441)	0.0213	(0.1445)	0.4750	(0.4743)	0.0039	(0.0477)	0.0832	(0.0585)
Panel C: Difference		Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat	Difference	t-stat
2008	66,045	0.0112	(26.1907)	-0.0048	(-3.0368)	0.1564	(25.7114)	0.0006	(1.0990)	-0.0092	(-3.1929)
2009	62,550	0.0099	(17.8498)	-0.0041	(-3.0368)	0.0714	(10.494)	-0.0001	(-0.3800)	-0.0072	(-2.1869)
2010	56,232	0.0065	(10.3944)	-0.0057	(-3.6836)	0.0362	(5.4004)	-0.0015	(-2.7691)	-0.0107	(-3.1220)
2011	58,084	0.0065	(12.3322)	-0.0063	(-3.8211)	0.0388	(7.2040)	-0.0005	(-0.9968)	-0.0113	(-2.9616)
2012	54,074	0.0077	(14.3537)	-0.0020	(-1.2031)	0.0444	(8.2243)	0.0000	(-0.1842)	-0.0084	(-2.1039)

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

Table III. Main results

Dependent variable:	Panel A: *LOG(PD)*			Panel B: *(IMPLIED) RISK WEIGHT*		
	(1)	(2)	(3)	(1)	(2)	(3)
D(IRB LOAN)	-0.3341***	-0.3446***	-0.2478***	-0.0676***	-0.0542***	-0.0665***
	(0.0434)	(0.0359)	(0.0347)	(0.0175)	(0.0161)	(0.0133)
LOG(LOANS)	-0.0557***	-0.0248**	-0.0526***	-0.0536***	-0.0378***	-0.0405***
	(0.0080)	(0.0105)	(0.0096)	(0.0076)	(0.0059)	(0.0058)
COLLATERAL	0.1726***	0.1703***	0.1425***	-0.2826***	-0.2711***	-0.2251***
	(0.0489)	(0.0404)	(0.0311)	(0.0411)	(0.0185)	(0.0166)
D(RELA)	0.0465*	-0.1230***	-0.0473	0.0224**	0.0367**	0.0197
	(0.0249)	(0.0369)	(0.0331)	(0.0100)	(0.0186)	(0.0165)
Firm FE	YES	—	—	YES	—	—
Firm × year FE	NO	YES	YES	NO	YES	YES
Bank × year FE	NO	NO	YES	NO	NO	YES
Observations	296,985	50,798	50,798	284,845	48,569	48,569
R-squared	0.7289	0.7128	0.7519	0.6315	0.5534	0.5944
Kennedy estimator	-0.2847	-0.2920	-0.2200	—	—	—
Standard error	(0.0310)	(0.0254)	(0.0271)	—	—	—
Dependent variable:	Panel C: *LOSS RATE*			Panel D: *INTEREST RATE*		
	(1)	(2)	(3)	(1)	(2)	(3)
D(IRB LOAN)	0.0013*	0.0012**	0.0009	0.0055**	0.0098***	0.0200***
	(0.0007)	(0.0005)	(0.0006)	(0.0026)	(0.0026)	(0.0053)
LOG(LOANS)	0.0002	0.0001	-0.0001	-0.0019*	-0.0039	-0.0046
	(0.0001)	(0.0001)	(0.0001)	(0.0012)	(0.0028)	(0.0033)
COLLATERAL	-0.0002	-0.0015***	-0.0019***	-0.0067***	0.0009	0.0016
	(0.0006)	(0.0005)	(0.0006)	(0.0016)	(0.0045)	(0.0061)
D(RELA)	0.0008	0.0005	0.0007	-0.0017	0.0089	0.0122
	(0.0009)	(0.0008)	(0.0009)	(0.0017)	(0.0092)	(0.0105)
Firm FE	YES	—	—	YES	—	—
Firm × year FE	NO	YES	YES	NO	YES	YES
Bank × year FE	NO	NO	YES	NO	NO	YES
Observations	294,592	50,543	50,543	11,759	1,677	1,677
R-squared	0.5830	0.7051	0.7078	0.6935	0.8045	0.8289

The sample includes loans from IRB banks in 2008, 2009, 2010, 2011, and 2012. The dependent variable is logarithm of the PD in Panel A, the *(IMPLIED) RISK WEIGHT* in Panel B, the *LOSS RATE* in Panel C, and the *INTEREST RATE* in Panel D. In columns 2 and 3 of each panel, the sample is restricted to firm-year observations in which the respective firm has at least one IRB loan and at least one SA loan. *D(IRB LOAN)* indicates the regulatory approach under which the PD for the respective loan was generated and is equal to 1 if the PD was generated under IRB. The last two lines of Panel A include adjusted coefficients and estimates for the standard errors, following the reasoning of Halvorsen and Palmquist (1980), Kennedy (1981), and van Garderen and Shah (2002) (see footnote 36). Robust standard errors adjusted for clustering at the bank × year level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table IV. Heterogeneity in underreporting – curvature test

Dependent variable:	*LOG(PD)*				*ESTIMATION BIAS*	
	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	LOW PD	HIGH PD	ALL	ALL	IRB LOANS	IRB LOANS
D(IRB LOAN)	-0.3552***	-0.1232**	-0.3573***			
	(0.0430)	(0.0495)	(0.0327)			
D(IRB LOAN) × *FIRM PD*			8.4063***	8.0937***		
			(1.3610)	(1.3548)		
FIRM PD					-0.3013***	-0.2965***
					(0.0398)	(0.0397)
Bank FE	—	—	—	—	YES	—
Bank × year FE	YES	YES	YES	—	NO	YES
Firm × year FE	YES	YES	YES	YES	NO	NO
Bank × year × loan pool FE	NO	NO	NO	YES	NO	NO
Observations	25,414	25,384	50,798	50,798	237,985	237,985
R-squared	0.6848	0.7053	0.7546	0.7603	0.0311	0.0392

The sample includes loans from IRB banks in 2008, 2009, 2010, 2011, and 2012. The dependent variable is the logarithm of the PD in columns 1-4 and the *ESTIMATION BIAS* (defined as the difference between an *ACTUAL DEFAULT* dummy and the PD) in columns 5-6. *D(IRB LOAN)* indicates the regulatory approach under which the PD for the respective loan was generated and is equal to 1 if the PD was generated under IRB. *FIRM PD* is the firm's average PD in the first quarter in which this information is available. In columns 1-4, the sample is restricted to firm-year observations in which the respective firm has at least one IRB loan and at least one SA loan. In columns 5-6, the sample includes only IRB loans. Robust standard errors adjusted for clustering at the bank × year level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table V. Impact of correcting underestimation of PDs on the required amount of capital

(1)	(2)	(3)	(4)	(5)	(6)
PD bucket	Uncollateralized loan volume (bn)	Regulatory capital reported PDs (bn)	Regulatory capital actual default (bn)	Increase in requirement (bn)	Increase in requirement (%)
$[< 0.001]$	580	10.8	35.1	24.4	226 %
$[0.001 - 0.004]$	147	5.8	11.5	5.7	100 %
$[0.004 - 0.011]$	121	8.0	11.4	3.4	42 %
$[> 0.011]$	156	21.1	22.3	1.2	6 %
ALL	1,003	45.6	80.3	34.7	76 %

We split all IRB loans into four equal sized buckets, sorted by the level of the PD (column 1). The first bucket contains the loans with PDs up to a level of 0.00116, the second bucket the loans with PDs between 0.00116 and 0.0039, the third bucket the loans with PDs between 0.0039 and 0.0114, and the fourth bucket the loans with PDs larger than 0.0114. Column 2 shows aggregate uncollateralized loan volumes in each of the four buckets. Column 3 shows the amount of required capital for these exposures, calculated by plugging the average PD in the bucket into the PD-RWA correspondence plotted in Figure 1 and multiplying the resulting risk weight with the exposure value in column 2 and a capital requirement of 8 %. Column 4 shows the required amount of capital when following the same procedure but using the average default rate instead of the average PD, and columns 5 and 6 display the resulting increase in capital requirements in each bucket.

Table VI. Heterogeneity in underreporting – bank cross-section

Dependent variable:	*LOG(PD)*					
	(1)	(2)	(3)	(4)	(5)	(6)
CAPITAL RATIO	0.0218***	0.0192***				
	(0.0050)	(0.0048)				
INVESTMENT BANK INTENSITY			0.0106***	0.0080***		
			(0.0034)	(0.0029)		
LOG(ASSETS)					0.0311*	0.0303**
					(0.0181)	(0.0154)
Firm FE	YES	—	YES	—	YES	—
Firm × year FE	NO	YES	NO	YES	NO	YES
Bank × year FE	NO	NO	NO	NO	NO	NO
Observations	221,636	89,666	221,636	89,666	221,636	89,666
R-squared	0.7274	0.7558	0.7259	0.7545	0.7254	0.7542

The table investigates how the the level of reported PDs for IRB loans depends on bank characteristics. In all columns, the sample includes only IRB loans and is restricted to observations with at least two IRB loans within the same firm (columns 1, 3, 5) or firm-period (columns 2, 4, 6). *CAPITAL RATIO* refers to the bank's total regulatory capital ratio, *INVESTMENT BANKING INTENSITY* is defined as the ratio on non-interest income in total income, and *LOG(ASSETS)* refers to the logarithm of total assets. Robust standard errors adjusted for clustering at the bank × year level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table VII. Cohort analysis

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

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

Table VIII. Switching portfolios

Dependent variable:	*LOG(PD)*			
	(1)	(2)	(3)	(4)
D(IRB LOAN)	-0.1292	-0.0057	-0.0245	0.0460
	(0.0906)	(0.0749)	(0.0492)	(0.0491)
Constant	-5.2827***			
	(0.0878)			
Year FE	NO	YES	YES	YES
Bank × firm FE	NO	NO	YES	YES
Bank × year FE	NO	NO	NO	YES
Observations	7,685	7,685	7,685	7,685
R-squared	0.0015	0.0049	0.7459	0.7595

The sample for these tests is restricted to bank-firm relationships for which the classification switches from SA to IRB throughout our sample period (i.e., relationships that were classified as SA at the beginning of our sample period for which the PD was updated after the portfolio had been transferred to IRB). *D(IRB LOAN)* is the usual IRB loan indicator from our main specifications. Robust standard errors adjusted for clustering at the bank × year level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table IX. Lending around the reform – SA versus IRB institutions

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

The dependent variable in columns 1 and 2 is the change in the logarithm of aggregate bank lending over the Basel II introduction in 2007Q1, where all quarterly data for a given bank is collapsed into single pre-event and post-event periods by taking the average of the two years before and the two years after the Basel II introduction. The dummy variable *D(IRB BANK)* indicates whether the respective bank adopted the internal ratings-based approach during our sample period. Columns 3-6 show results on the loan level, where the dependent variable is the difference in the logarithm of the loan amount. For each bank-firm relationship, we collapse all quarterly data into single pre-event and post-event periods by taking the average of the two years before and the seven quarters after the Basel II introduction. Data are restricted to loans to firms that have at least one loan from an SA bank and one loan from an IRB bank. *FIRM PD* is the firm's average PD in the first quarter for which this information is available. Robust standard errors adjusted for clustering at bank level are reported in parentheses. Note: * indicates statistical significance at the 10 % level, ** at the 5 % level and *** at the 1 % level.

Table X. Lending around the reform – within IRB institutions

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

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