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Abstract

This paper investigates the incentives for banks to bias their internally generated risk estimates. We are able to estimate bank biases at the credit level by comparing bank-generated risk estimates within loan syndicates. The biases are positively correlated with measures of regulatory capital, even in the presence of bank fixed effects, consistent with an effort by low-capital banks to improve regulatory ratios. At the portfolio level, the difference in borrower probability of default is as large as 100 basis points, which can improve the typical loan portfolio's Tier 1 capital ratio by as much as 33 percent. Congruent with a regulatory motive, the sensitivity to capital is greater for larger, riskier, and more opaque credits. In addition, we find that low-capital banks' risk estimates have less explanatory power than those of high-capital banks with regard to the prices set on loans, indicating that low-capital banks not only have downward-biased risk estimates but that they also incorporate less information.

Key words: banks, incentives, default models, capital regulation, Basel II

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1 Introduction

The regulation and supervision of the financial industry is increasingly reliant on information produced by regulated entities. This is particularly true in banking, where internally generated risk estimates are now being used to determine capital requirements. However, the quality of this information may not be invariant to its use. The logic follows in a similar vein as Goodhart's Law or the Lucas Critique (Lucas, 1976) – econometric models are not independent from their policy use. In this paper, we investigate the quality of information banks disclose to regulators. Specifically, we investigate how capital standards can induce banks to bias reported risk estimates. Capital standards make reported risk costly for institutions, encouraging them to seek relief via downward-biased risk estimates.

When the Basel I Accord was introduced in 1998, it was praised for strengthening the regulation on bank capital and for creating a level playing field for "internationally active banks." However, soon after its introduction the Accord was questioned because, among other things, it took a simplistic approach to credit risk. Under Basel I, on-balance sheet assets were bucketed into broad risk categories and each category was assigned a fixed risk weight that would determine the amount of capital banks would need to set aside.

Pursuant to advances in risk-modeling, the Basel Committee proposed a new capital adequacy framework in 2004, Basel II, that sought to address these criticisms. An important novelty of Basel II was that it allowed banks to use an internal ratings-based approach to determine their required capital levels, provided they met a set of specified conditions. Under this approach, the risk-weight of the loan is a function of the bank's internally generated estimates for the borrower's probability of default (PD), the bank's loss given default (LGD), and the bank's exposure at default (EAD).

The internal ratings-based approach was praised because it built on banks' own information, thereby making capital standards more risk sensitive and more aligned with banks' own risk management models. This conclusion ignores the wisdom of Goodhart and Lucas – it assumes banks will produce accurate risk estimates by incorporating the private information they gather on borrowers without regard for the policy-induced outcome. However, the disclosure of this information is costly as it defines the amount of capital banks must set aside for credit risk purposes.[1] While these banks are supervised, there is discretion in the use of these models and there is no specified penalty for poor model performance. This incentive operates at the level of the firm as well as at the department level given capital is internally allocated within the bank. As a result, the bank is motivated to exploit its discretion and optimize the reported inputs to these models.

We exploit the unique features of the Shared National Credit (SNC) program to identify whether there are systemic differences in banks' reported risk metrics under the internal ratings-based approach. This program collects the risk estimates of banks that own the same syndicated loan. Therefore, we observe different banks' estimates for the *same* credit at the *same* point in time. Banks are required to report their risk metrics both before and after risk mitigants that can reduce the risk exposure. This information allows us to compare the information that two or more banks report at a given point in time for a given credit before credit enhancements modify their estimates.

For many years, the Shared National Credit (SNC) program collected annual information on syndicated loans that are equal or larger than $20 million and are held by three or more federally supervised financial institutions. Agent banks report detailed data on the loan and syndicate, including the composition of the syndicate and the loan share of each syndicate member. Beginning in 2009, the SNC program was expanded to gather additional information on credits at a greater frequency. Banks adopting Basel II were designated as "expanded" reporters and are required to report their participations in these credits quarterly. Expanded reporters using the internal ratings-based approach are required to report their Basel II risk metrics, including the PD, LGD, and EAD for each credit exposure.

We focus on differences in probability of default, as loss given default and exposure at default

[1] This cost is one reason why the "unraveling result", that firms disclose their private information to maximize their value, does not hold in this context (Grossman and Hart (1980), Grossman (1981), Milgrom (1981) and Milgrom and Roberts (1986)). For models that rationalize partial disclosure of private information see, for example, Verrecchia (1983), Dye (1985), Jung and Kwon (1988), Hughes and Pae (2004), and Kahn and Santos (2006).

can depend on bank-specific factors. In addition, banks can modify losses to account for credit enhancements that may reduce their credit exposure. We focus on the before-enhancement risk metrics as these arrangements alone can generate differences in risk metrics. We nonetheless use LGD, EAD and the after-enhancements risk metrics to gauge the ultimate effect of differences in PD on expected loss and capital standards.

We find that credit risk metrics disclosed by banks vary considerably across syndicate-member banks. Further, by using the median value of expanded reporters in a syndicate as a benchmark, we discover some banks report risk metrics systematically above the median of the syndicate and others systematically report risk metrics below the median. These differences exist across the set of risk metrics we consider and continue to hold when we account for both credit- and bank-specific factors. These findings indicate that some banks hold less capital for a given credit by reporting lower credit risk.

More importantly, the banks reporting less credit risk tend to be the least well capitalized from a regulatory perspective. We find that on average banks with lower Tier 1 capital ratios report lower estimates of risk. The downward bias in risk metrics by low capital banks persists when we consider after-credit-enhancement measures and when we aggregate loans into portfolios. The magnitude of these differences is significant. The difference in PD across bank quarters is as large as 100bps between a low and high capital bank. For a typical loan this could vary risk-weighted assets by 33%, with a corresponding result on required capital. Therefore, the size of the bias is meaningful with respect to the capital held against the portfolio of loans and it is correlated with the overall riskiness of the bank.

We find that the sensitivity of bias to bank capital is greater for certain types of credits – consistent with constrained banks' desire to lower required regulatory capital. Risk-weighted assets are concave in probability of default according to Basel calculations, therefore riskier credits require larger changes in PD for a desired reduction in RWA. In addition, larger credits have a larger impact on the overall RWA of a loan portfolio. Indeed, we show that the downward bias for low capital banks is greater for loans to riskier borrowers and loans that comprise a larger portion of their overall portfolio. We also discover that the relation between bias and capital is concentrated in private credits where there is greater scope for discretionary reporting.

These results are consistent with a regulatory arbitrage motive where constrained banks seek to reduce their required capital via selective reporting. However, the relation between bias and capital is also consistent with low-capital banks being less conservative. In other words, these institutions may report lower risk metrics and hold less capital, because they are less risk averse relative to other banks in the same syndicate. To account for persistent bank characteristics, including the risk-attitudes of banks, we repeat the analysis in the presence of bank fixed effects. We find that the positive relation between PD bias and bank capital is robust to this alternative specification. This fact, along with the findings that the risk discount is larger for privately held borrowers and when the bank has a larger exposure, are not easily explained by the risk-attitude hypothesis.

To further disentangle these two explanations, we investigate the pricing of loans using internal risk estimates. In this analysis, we restrict the sample to agent banks because they play a central role in setting the interest rates on loans. The results show that the risk metrics that low-capital banks report, in particular the probability of default of the borrower, have less explanatory power than high-capital banks with respect to loan spreads. In sum, we show that low-capital banks report both lower risk estimates as well as risk estimates that incorporate less information than their peers. These two findings are consistent with the regulatory incentive rather than the "risk-perception" hypothesis, for in the latter there is no reason to expect a cross-sectional difference in the explanatory power of reported risk metrics on loan interest rates.

Regardless of the underlying motive, our results illustrate that it is crucial to add mechanisms that entice banks to report unbiased risk metrics and to control for their quality. To this end, the insight of Kaplow and Shavell (1994) could be useful. They show that in models of self-reported behavior the expected punishment must be larger than the cost of reporting the behavior. In designing these mechanisms, it is also important to take into account how formal comparisons between banks may influence their risk estimates. Analogous to the incentives described in the Keynesian "beauty contest"[2] or Scharfstein and Stein (1990), banks may choose to disclose information not based on what they think the risk of the loan is, but rather on what they believe the other banks that also own the loan believe the risk is.

Our paper underscores the emerging literature on the inconsistencies of internal risk models across banks. Carey (2002) and Jacobson et al. (2006), for example, show that internal risk metrics are not consistent across banks by comparing the ratings different banks assign to loans of a given borrower. Financial Services Authority (2012) observes bank-level differences between risk metrics, PD and LGD, of a hypothetical common portfolio of credits. RMA Capital Working Group (2000) and Firestone and Rezende (2013) document similar heterogeneity by banks participating in syndicated loans. Our study is similar to these in that we rely on risk metrics different banks report on the same credit. In contrast to these studies, which rely on a cross-section alone, our data forms a panel from the information banks report quarterly over a three-year period. Unlike earlier work, our focus is not limited to identifying inconsistencies across banks – we are also interested in understanding the source of these inconsistencies.

Hence, our paper contributes to the literature on the role incentives play in the production of risk estimates (e.g. Rajan et al. (2010)). Prior work has documented the role incentives played in distorting estimated risks in the mortgage securitization market (Rajan et al., 2014), noting that the nature of the information (soft vs. hard) is important. Our paper documents evidence of this behavior in the context of banking regulation. Indeed, we uncover both an increased sensitivity to capital incentives for softer information loans (i.e. non-public firms) and a disconnect between pricing and reported risk estimates, consistent with less informed risk metrics. Begley et al. (2014) also investigate banks' under-reporting of risk by examining the frequency of Value-at-Risk violations in bank trading books.

More closely related work, Behn et al. (2014), demonstrate that in Germany banks eligible to

[2]See Keynes (1936), Chapter 12, for a presentation of the general idea. Entrants are asked to choose the six prettiest faces from a hundred photographs, with the contestant choosing the most popular face receiving a prize. "We have reached the third degree where we devote our intelligences to anticipating what average opinion expects the average opinion to be."

use their internal models systematically report lower PDs for loans whose capital charges were set under the bank's internal model than for the loans whose capital charge was set under the standardized approach and yet the former were more likely to default than the latter.[3] Whereas this analysis is essentially a within-firm analysis of changing PDs under different regulatory regimes, our work complements these findings by comparing the incentive for bias across banks.

The remainder of our paper is organized as follows. The next section presents background details on the data and characterizes our sample. Section 3 tests whether there are systematic discrepancies in the risk metrics banks report. Section 4 investigates whether these discrepancies are related to regulatory capital. Section 5 concludes the paper.

2 Data and Sample Summary

In this section we provide background information on our primary data source, the Expanded Shared National Credit Program, and we describe the role for internally-generated risk metrics under Basel II. The final portion of this section describes our sample characteristics.

2.1 Expanded Shared National Credit Program

Our primary analysis exploits syndicated loan data from the Shared National Credit (SNC) Program. The Program is an interagency initiative to evaluate large syndicated credits administered by The Federal Reserve System (FRS), the Office of the Comptroller of the Currency (OCC), and the Federal Deposit Insurance Corporation (FDIC). A core objective of the program is to provide uniformity in the approach to credit ratings determinations. Toward this end, the program collects data on an annual basis from syndicated loan agents on any loan commitment for which the aggregate commitment is $20 million or more and which is shared by, or sold to, two or more federally supervised institutions that are unaffiliated with the agent bank. Agents report detailed data on the loan and syndicate, including the composition of the syndicate, the

[3] The authors rely on firms that have at least two loans at the same bank: one where a borrower's loan is in an internal-ratings based portfolio and one where a borrower's loan is still under the standardized approach.

type of loan, and the borrower.[4]

Beginning in 2009, the Program was expanded to further enable the benchmarking of credits to common borrowers. Banks adopting Basel II were designated as "expanded" reporters and are required to report their participations in these credits quarterly.[5] Expanded reporters must also provide their internal risk metrics for these credits. If the reporter is using or preparing to use the Advanced Internal Ratings-Based Approach (AIRB) to determine Basel II capital adequacy, they should report the risk metrics necessary to calculate their Basel II risk weights.

2.2 Basel II – Advanced Internal Ratings-Based Approach

Since Basel I, risk-weighted assets (RWA) have been a key component of bank regulatory ratios. The most prominent example is the Tier 1 capital ratio which is the ratio of a bank's core equity capital to RWA. Under Basel I, assets are prescribed a risk-weighting based on five distinct risk buckets: 0%, 10%, 20%, 50%, and 100%. Corporate loans in good standing, for example, receive a risk-weight of 100%. The weighted sum of exposures results in a bank's total RWA which can then be used to calculate various regulatory ratios, including the Tier 1 capital ratio.

A drawback of this approach is that assets with different risks are assigned the same risk-weight. Basel II regulations seek to mitigate this problem by introducing an alternative capital adequacy framework. Basel II allows banks to use either the standard approach or the Advanced Internal Ratings-Based Approach (AIRB). The standard approach made capital requirements on corporate loans dependent on the rating of the borrower where unrated borrowers were assigned a fixed risk-weight of 100%. In contrast the AIRB approach allows banks to estimate risk components such as Probability of Default (PD), Loss Given Default (LGD) and Exposure at Default (EAD) using internal models. These risk components are then used to calculate the risk-weighted value of the asset.

[4] The SNC data was processed solely within the Federal Reserve for the analysis presented in this paper. For other studies that use data from the SNC program see Bord and Santos (2012), Bord and Santos (Forthcoming), and Santos (2013).

[5] Basel II adoption is mandatory for large, internationally active banking organizations (so-called core banking organizations with at least $250 billion in total assets or at least $10 billion in foreign exposure) and optional for others.

The transition to the AIRB approach has varied across regulatory jurisdictions. In order to be approved for this approach, banks must enter a "parallel-run" period during which they remain subject to general-risk based capital rules until the appropriate regulator approves their transition to using AIRB to calculate RWA. Our sample includes banks that have already been approved to use AIRB for capital purposes as well as as those undergoing a parallel run.

2.3 Sample Summary

Using the SNC program expanded reporters, we construct a panel of credit-bank-quarters, where a credit is a syndicated loan. In order to understand the types of credits and banks in the sample, we construct two summary tables. The first, Table 1, summarizes the properties of the credit-quarters for which at least one bank reports a PD. Credits are limited to term loans and revolvers and exclude facilities designated as held for sale since banks are not required to report risk metrics for the latter. The sample consists of 14,870 distinct credit facilities, representing 7,569 unique borrowers ranging over the fourteen quarters from 2010Q2 to 2013Q3.

Credit-quarter sample averages are skewed by larger credits. The average commitment size for facilities is \$359m with eighteen participating banks while the median is \$150m with eight participating banks. Approximately 22% of the credit-quarters are term loans with the complement being revolvers. On average we observe 2.4 expanded reporters per facility. 30% of the facilities are with public borrowers. 8.5% are "new" loans originated in the current quarter. The average credit in the sample is 2.5 years old.

Table 1 also summarizes the median risk metrics for these credits. In addition to PD, banks must report several other risk characteristics, including percent LGD and dollar EAD. In the AIRB approach, banks report LGDs before and after credit-risk mitigants (CRM) which consist of collateral, guarantees and credit derivatives. EAD is reported in dollars, which can result in noisier credit metrics as the relevant scaling dollar amount will vary across institution.[6] For much of the analysis we concentrate on PDs, as these are *borrower* specific and therefore a

[6]For example some firms report EAD relative to the global commitment value of the facility, others to the participants allocation. Other times the units are in millions or thousands. While we adjust these as best we can, the metrics dependent on EAD are inevitably noisier than those based on LGD and PD.

bank independent measure of credit risk. In contrast LGD and EAD can be a product of a bank-specific capabilities or experiences. Nevertheless, we also generate the percent loss on the credit, $E(L)$, by taking the product of PD, LGD and EAD relative to commitment size.

PDs are skewed by riskier credits as the median assigned PD for a credit-quarter is 70bps and the average is 2.5%. The average LGD before CRM is 33.8% and the average expected dollar loss scaled by the commitment size is 0.6%. After accounting for risk mitigants the average loss is roughly the same, but we can see the median is slightly lower at 0.1%. Throughout the paper risk metrics will be reported in percentages.

The second summary table, Table 2, outlines the relevant sample of bank-quarters. For confidentiality purposes we cannot reveal which banks are in the sample. There are fifteen banks that report PDs. However, institutions are not observed in every quarter as the sample of reporting banks increases over time. In the initial quarter nine banks report and over time more are added with the final bank entering the sample in the first quarter of 2013.

If the high-holder is a U.S. Bank Holding Company (BHC), bank financial data is sourced from the FR Y-9C regulatory reports. If the high-holder is a foreign bank, Tier 1 capital and assets are from the FR Y-7Q regulatory filing with remaining data derived from public filings with adjustments made to account for differences in accounting standards.[7] From these results we can see that these are extremely large banks with average assets of almost $2 trillion. Although some of these banks are more active than others in syndicated lending – the average number of credits exceeds 1,000 and the median is 561.

3 Biases in Reported Risk Metrics

We begin our investigation by testing for the presence of bank biases in internal risk metrics. In the next Section we test for the relation between these biases and characteristics of the bank, specifically measures of capital constraints. To estimate bank-level biases, we calculate the deviation in a banks' risk metrics from the median of reporting banks in the same syndicate

[7]For derivatives, IASB standards permit less balance sheet offsetting than FASB, resulting in larger balance sheets all else equal.

during that quarter, $\Delta PD_{i,j,t}$.[8] For example, the deviation in PD for bank i in credit j at time t is:

$$\Delta PD_{i,j,t} = PD_{i,j,t} - PD_{j,t}^{Median}$$

We also calculate the percent deviation from the median, denoted $\%\Delta$. To minimize the role of extreme deviations in our analysis we trim the top and bottom 1% of these realizations for each quarter. By comparing risk estimates for a given credit at a specific point in time, we eliminate alternative sources of variation and focus our analysis on differences in risk estimates all else equal.

We then regress these deviations on bank fixed effects, $\gamma_{\mathbf{i}}$, and time fixed effects, $\tau_{\mathbf{t}}$,

$$\Delta PD_{i,j,t} = \gamma_{\mathbf{i}} + \tau_{\mathbf{t}} + \epsilon_{i,j,t}. \tag{3.1}$$

To test for the significance of these fixed effects, we conduct an F-test that each bank fixed-effect is jointly equal. We exclude credit-quarters where only one bank reports risk metrics since we cannot calculate the deviation. Standard errors are robust to heteroskedasticity and clustered by borrower and quarter.

The results point to significant bank biases in internally generated risk metrics, Table 3. In Columns (1) and (2), we can reject the null hypothesis that bank fixed effects are equal to zero for PDs and LGDs before CRM (LGD_{Bef}) as the reported F-statistics are well in excess of relevant critical values (~ 2.1). This is true for percent deviation from the median, Panel A, and raw deviation from the median, Panel B. Note that there are more positive biased banks than negative. If all banks appeared with equal frequency there would need to be equal numbers of positive and negative biased banks. However, some banks appear more frequently than others, therefore the average bank bias need not correspond to the number of positive or negative deviations in the sample.

We combine PD and LGD and find that the two metrics are not offsetting, the product also

[8] We use the median as opposed to the mean to reduce the risk of these biases being driven by outliers.

varies significantly. The product of PD and LGD_{Bef} or LGD after CRM (LGD_{Aft}) generally has the same biases as PD, Columns (3) and (5), as does expected loss relative to commitment size, Columns (4) and (6). The presence of fixed effects indicates that for the same credit, internal risk metrics are significantly different across banks and that these differences are correlated with institutions to a degree that is not random.

Beyond the statistical significance, the magnitude of the coefficients is quite meaningful. For example the PD percent deviations in (A.1) range from -25% to 69%, meaning that on average one bank report PDs that are 25% lower than the median and another on average reports PDs that are 69% higher. In Panel B we can get a sense of these quantities in terms of default probabilities. In (B.1) the largest negative bias is -32bps and the highest is 47bps. While seemingly small, we will show that these magnitudes are economically meaningful when calculating RWA and the Tier 1 capital ratios.

We repeat the test for bank biases in the presence of additional control variables, Table 4. In this specification we suppress the reporting of bank fixed-effects but continue to report the statistic of interest, the F-test statistic. We add several bank-credit level controls, including a dummy variable indicating whether the reporting bank is the agent for the credit, the median credit PD, the share of the commitment held by the reporting bank, a dummy indicating whether the borrower is public, a dummy indicating whether the loan is a revolver, the log of commitment size, and the age of the credit in quarters. We also include the number of reporting banks in the syndicate to control for potential bias introduced by variation in the number of reporters. For this specification we focus on raw deviations, rather than the percent deviation, as the gains from a raw deviation are easier to interpret going forward at the bank-level.[9] Again, for each specification we can easily reject that bank fixed-effects are equal.

The results we have reported thus far extend the findings of existing studies that find systematic differences in LGDs across banks using a common portfolio of credits (Firestone and Rezende, 2013). Additionally, we find significant dispersion in the PDs assigned to a given bor-

[9]We obtain similar qualitative conclusions using alternative measures including percent deviation and log differences.

rower and the dependent loss estimates. Whereas some might argue LGDs differ across banks with different loss recovery capabilities, PDs are borrower specific calculations, independent of bank factors. What might explain these systematic differences? In the remainder of this paper we explore potential motives for this behavior by comparing risk metric deviations to measures of capital and other bank characteristics.

4 Incentives and Biases in Risk Metrics

To investigate potential reasons for these biases, we relate deviations in risk metrics to banks' Tier 1 capital ratio conditional on other bank characteristics. Tier 1 capital is a key regulatory ratio that is dependent on risk-weighted assets. The lower the Tier 1 capital ratio the closer a bank is to regulatory constraints and the greater the potential incentive to lower RWA to improve the ratio. This holds for lines of business as well – a lower ratio means less capital available for various lines of business and a greater incentive to maximize returns relative to this capital constraint via lower RWA. Even though "parallel-run" banks are not officially calculating RWA using the internally generated risk metrics, they are still incentivized to use statistical models and methods that will ultimately result in a more favorable level of RWA.

The pooled cross-sectional regression takes the form,

$$\Delta PD_{i,j,t} = \beta_0 Tier1_{j,t} + \beta_1' \mathbf{BankControls_{j,t}} + \beta_2 Agent_{i,j,t} + \tau_{\mathbf{t}} + \varepsilon_{i,j,t} \tag{4.1}$$

where the coefficient of interest is the relation between Tier 1 and risk metric deviations, β_0. We condition on several other bank characteristics, including the log of total bank assets, the ROE of the bank, a dummy indicating a foreign bank, and a dummy indicating whether the bank is the agent for the credit facility, *Agent*. The regression also includes time fixed-effects, $\tau_{\mathbf{t}}$ and the number of reporting banks in the syndicate. Standard errors are robust to heteroskedasticity and clustered by bank and quarter to account for auto-correlation within banks and common unobserved shocks at a point in time.

We find that the PD deviations are positively related to the Tier 1 ratio at statistically significant levels, Table 5 Column (A.1), consistent with the more capital constrained banks reporting lower risk estimates. Note that this is not a statement about accuracy of PDs in predicting default, but on the bias relative to other banks. A 1% lower Tier 1 ratio implies average reported PDs decline by 7bps. In contrast LGDs are not related to Tier 1, (A.2). LGDs dampen the magnitude of the PD effect on expected loss measures (before and after risk mitigants) but do not deter the statistical significance, (A.3)-(A.6). As discussed in Section 2, the loss metrics become noisier and more bank dependent when they include EAD. In addition, banks with lower PDs may hedge less, thereby saving money and capital on these efforts, but resulting in expected losses after CRM closer to their more highly capitalized peers.

Across all specifications ROE also exhibits a positive and statistically significant relation with risk deviations, i.e. the more profitable a bank the higher the reported PD vis-a-vis their peers. Publicly traded banks typically target ROE as a benchmark for management compensation. By biasing RWA downward, a bank can reduce required equity holdings to achieve a Tier 1 capital ratio target, thereby raising ROE.

We calculate an alternative measure of bank regulatory constraints meant to estimate the distance of a bank from their target Tier 1 ratio where the target is a function of bank characteristics and aggregate conditions, *Tier 1 Gap*. This is formed by taking the residuals from a regression of Tier 1 capital on log assets, ROE, leverage, date fixed effects, and a foreign bank dummy. The residuals are estimated quarterly for every bank in our sample for the full period 2009Q3-2013Q3, therefore more information is used to calculate the Tier 1 Gap than is included the regressions with bank characteristics, i.e. Table 5 Panel A.[10] Estimating Eq. 4.1 using *Tier 1 Gap* in place of the bank controls yields similar results, both in magnitudes and statistical significance, Panel B.

Why might PD be more correlated with the regulatory constraint than LGDs? Statistical default models are based on a larger universe of firms and therefore there is greater scope for

[10]This metric has the additional benefit of further anonymizing banks in our sample. Toward that end, we do not report the estimated coefficients.

selecting what information to use in the model, whereas LGDs are estimated conditional on default, reducing the potential set of inputs. Also, a small magnitude change in PD, from 150bps to 50bps is arguably less salient than a large change in LGD which would need to fall from 36% to 12% to achieve a similar effect.

4.1 Magnitudes

To understand the importance of these magnitudes for the loan portfolio as a whole, we aggregate the measured deviations in PD and its dependents to the bank-quarter level, weighting by the utilized value of the loan.[11] Figure 1 illustrates the positive relationship between weighted PD deviations and Tier 1 Gap for each bank-quarter. We can see a spread in weighted PD of approximately 100bps between banks with a negative versus a positive Tier 1 Gap.

We test the statistical significance by regressing weighted-deviations on bank characteristics in the presence of time fixed effects, similar to Table 5. The results reported in Table 6 confirm that banks with a lower Tier 1 ratio (Panel A) or a lower Tier 1 Gap (Panel B) have downward biased PDs. If Tier 1 Gap increases by 10% the weighted PD bias increases by 73bps. The sign and significance extends to most of the estimated loss metrics albeit at smaller magnitudes, (2)-(5). Bank characteristics and time fixed-effects explain a significant amount of the variation in weighted risk metrics, particularly for PD. In (A.1) and (B.1), the R-squared is 34% and 32%, respectively. The R-squared falls as we consider combinations of risk metrics that are dependent on noisier measures (See Section 2).

Within a syndicate, the risk metric that is most comparable across participating banks is the probability of default. By definition, the reported PD should only reflect the borrowers' characteristics, whereas LGD can vary across banks due to differences in institutional expertise. Similarly, specifications that consider risk metrics after risk mitigants will differ across banks. Therefore, in the remainder of the paper we focus on PDs. It suffices to say that the pattern of declining magnitude and statistical significance for the more bank-specific measures are repeated

[11] The utilized value is the drawn portion for revolving credit facilities and the outstanding principal for term loans.

in the specifications that follow.

The observed PD deviations can have a meaningful impact on the capital allocated to corporate loan portfolios. Figure 2 illustrates the sensitivity of RWA to PD at varying levels of PD using average facility characteristics.[12] A 70bps change from 150bps PD to 80bps can decrease RWA from 90% to 75% reducing the necessary capital for corporate loans by 20%.

4.1.1 Identification

A key concern when interpreting these results is that the Tier 1 ratio is endogenous and the nature of the endogeneity can take several forms. One form is reverse causality between the Tier 1 ratio and PD bias. However, the direct effect of lower PDs is a lower RWA and a higher Tier 1 ratio. Therefore, lower PD banks should have higher Tier 1 all else equal. A second form of endogeneity, learning, is also easily dismissed. If banks suffer a loss and learn their portfolio is riskier, they should exhibit a lower Tier 1 ratio and *increase* their PDs. A third form is that the Tier 1 ratio summarizes the bank's competency and that their inaccurate PDs and low Tier 1 ratio are signs of poor skill. But, incompetency predicts inaccurate PDs, not biased PDs.

A fourth form is less easily dismissed. The Tier 1 capital ratio might capture a bank's attitude toward risk. A low Tier 1 ratio indicates a bank with higher risk-weighted leverage. Assuming this is the banks preferred capital structure, higher leverage is consistent with a greater tolerance for risk. In order to account for persistent bank characteristics, like risk-attitudes, we repeat the regression specification from Table 6 with bank fixed-effects. Within bank variation in PD bias is positively related to Tier 1 capital ratios, see Column (1) of Table 7. This is true for Tier 1 (Panel A) and Tier 1 Gap (Panel B).

An additional proxy for a bank's risk attitude is the average riskiness of the portfolio. To gauge riskiness, we use the syndicate median PD to measure the riskiness of a credit and for each bank we take the average of these PDs weighted by utilization. The resulting weighted average PD summarizes the average riskiness of a bank's loan portfolio. In (2) we report that

[12]Maturity of 3 years, LGD of 35% and an EAD of 100%. Formulas for calculating RWA under AIRB can be found in Basel Committee on Banking Supervision (2006).

the riskiness of a bank's portfolio, as determined by the median, is *positively* correlated with the weighted average deviation – banks with riskier portfolios report more conservative PDs. In addition, both Tier 1 measures remain positive and statistically significant. Hence, the correlation between bias and Tier 1 capital is robust to persistent bank specific factors as well as a measure of a bank's portfolio risk. These two facts are difficult to reconcile with a pure risk-attitude explanation.

Yet another alternative explanation is that low-capital banks are "pickier," choosing to concentrate their holdings in credits where they believe they earn the highest spread relative to their view of PD. This would result in banks retaining credits where their internal estimates are low relative to other banks and avoiding credits where their estimates are higher. If selectivity is a persistent bank trait, it will be captured in the bank fixed-effects specification in Column (1). Nevertheless, we construct two tests to address this line of thought. The first explicitly controls for a bank's level of selectivity. The second will be discussed in the next section and focuses on a sub-sample of credit-quarters that banks are unlikely to select on PD.

We control for bank selectivity by constructing a measure of participation in the marketplace. If banks are simply being more selective, participation should be positively related to PD deviations. We regress PD deviations on the Tier 1 measures and the percentage of credits a bank participates in for a given quarter, (3). Market participation is positively related to PD bias, meaning that the less selective banks have upward biased PDs. However, the coefficients on the Tier 1 ratio and Tier 1 Gap remain positive and statistically significant at the 1% and 5% levels. Therefore, selectivity may be one determinant of heterogeneity in observed PD's, however it does not appear to be correlated with measures of capital. Indeed, the high R-squared's in Table 7 suggest that persistent, bank-level characteristics are important to understanding the degree of cross-sectional variation in risk estimates. While outside the scope of this investigation, the results suggest there is scope for further research into bank-level heterogeneity in risk estimates.

The final two columns consider independent sub-samples to verify that the estimates are not the result of any single bank outlier. Column (4) considers non-U.S. domiciled banks and (5) domestic banks. In Panel A, the relation between weighted PD deviation and Tier 1 is positive and statistically significant at the 1% level for both foreign and domestic samples. In Panel B, the relation with Tier 1 Gap is positive for both samples, but only statistically significant for foreign banks. Nevertheless the magnitudes in the domestic sample are similar to those observed in other specifications. In unreported tables we have also verified the broader sample results are robust to excluding any single bank.

4.2 Additional Evidence of Incentives

To further investigate the role of regulatory incentives, we test to see if the sensitivity to capital is greater for those credits with the largest capital benefit. In order to test for these conditional biases we regress the deviations in PD on a credit characteristic term, $X_{i,t}$, the Tier 1 Gap, and interactions between the two,

$$\Delta PD_{i,j,t} = \beta_0 Tier1Gap_{j,t} + \beta_X X_{i,t} + \beta_{0,X}(Tier1Gap_{j,t} * X_{i,t}) + \beta_2 Agent_{i,j,t} + \tau_{\mathbf{t}} + \varepsilon_{i,j,t}. \tag{4.2}$$

The coefficient of interest is on the interaction term, $\beta_{0,X}$. We condition on the credit characteristic, a dummy indicating whether the bank is the agent for the credit facility, and time fixed-effects. Standard errors are robust to heteroskedasticity and clustered by bank and date.[13]

We find that the sensitivity of PD bias to Tier 1 Gap is positively related to several characteristics that increase the potential benefit of a downward bias, Table 8. The first characteristic is riskiness. The impact of a change in PD on RWA declines as credits get riskier, see Figure 2; therefore, the higher the level of PD the greater a change is necessary to achieve a similar impact on RWA. We test this by by interacting Tier 1 Gap with a dummy variable indicating a loan is in the top tercile on median PD. We find riskier loans are more sensitive to Tier 1 Gap and the interaction is statistically significant at the 1% level, Column (1).

The second characteristic is utilization. Utilized loans will typically have greater exposure

[13]We obtain similar conclusions when repeating the analysis with the Tier 1 ratio conditional on bank controls (Appendix Table 10) or in specifications including bank fixed-effects.

at default, therefore the benefit from a lower PD is greater. We interact the Tier 1 Gap with a dummy equal to one if a loan is utilized, (2). The estimates imply that the relation between Tier 1 Gap and bias is significantly larger for utilized credits at the 1% significance level.

The third characteristic is loan size relative to a bank's loan portfolio. A downward bias in a large credit is more beneficial to RWA than a bias in a small credits. For each bank at each point in time, we rank their loans based on the outstanding principal of the loan and create a size dummy equal to one if a loan is in the top tercile, (3). The relation between Tier 1 Gap and PD deviations is larger for loans that are relatively big and the difference is significant at the 1% level.

An alternative interpretation of this result is that banks participate more in syndicates in which they have a differentially optimistic outlook, hence they are larger in credits for which they have a positive view relative to other participants. To test this view we estimate the interaction with a syndicate share dummy indicating a top tercile participation, (4), and then simultaneously with the relative size term, (5). While low capital banks' downward biased credits are correlated with syndicate participation, the correlation does not diminish the interaction between Tier 1 Gap and relative size.

We also consider the degree to which firm opacity correlates with the biasing behavior. Public companies are typically publicly rated and have more "hard" information, therefore banks have less discretion in their estimation of PDs. Indeed, when we estimate Tier 1 Gap interacted with a public borrower dummy, we find that Tier 1 Gap is positively related to PD deviations, but that this is significantly smaller for public firms, (6).

Recall, one competing hypothesis is that low-capital banks are selecting credits for which they have a low PD relative to the market. In Column (7) we consider a sub-sample where the participation choice is mitigated by the type of credit. Participation is less optional for banks that are agents, these banks are leads in the syndication deal and their incentive to participate includes a relationship with the borrower as well as origination fees. In addition, recent studies, including Sufi (2007), Ivashina (2009), and Focarelli et al. (2008), document that lead banks in loan syndicates use the retained share to align their incentives to those of syndicate participants. Hence, agent banks are unlikely to be "cherry-picking" credits based on differential PD estimates. In a sample of agent banks in the first reporting quarter after origination, we find an even larger relation between PD and Tier 1 Gap, with a coefficient of .11 that is statistically significant at the 5% level.

4.3 Evidence from Loan Spreads

In this section we turn to banks' pricing of loans to better understand the behavior of low capital banks relative to their peers. Loan prices provide an alternative benchmark by which to gauge the information content of risk estimates. We estimate loan pricing models for banks by relating the spreads on loan originations to loan characteristics and the borrowers' probability of default. If PDs are biased proportional to their level, the estimated pricing model will find the coefficient on PD is higher for banks with downward biased PDs – they charge *more* per unit of risk because the spread is high relative to the PD.

A second dimension on which PDs can be compared is how well they explain loan pricing decisions. A key concern with internal estimates is that bank's exert discretion over the information they use to produce risk estimates and that this information is less complete than it otherwise could be. To test this we compare the explanatory power of PD-based loan pricing models across banks. Low explanatory power relative to other banks implies that spreads are chosen using information that is not reflected in risk estimates, consistent with low quality estimates that incorporate less relevant information.

We obtain loan pricing information from Loan Pricing Corporations (LPC) *Dealscan* database. We measure the loan price using the all-in-drawn spread over LIBOR.[14] We match to the SNC data using fuzzy matching on borrower name, origination date, maturity date, commitment type, commitment size, and agent bank. Marginal results are hand-matched. We focus the analysis on agent banks in the first quarter after the LPC origination date.[15] Agent banks' PDs

[14]For other studies that investigate loan pricing using LPC data see Santos and Winton (2008), Hale and Santos (2009), and Santos (2011).

[15]An alternative is to use the SNC origination date as in Table 8 Column (7), however the SNC origination

should be particularly informative for pricing as the lead banks typically set the initial price of the loan, only modifying it if the market demands. Recall, we demonstrate the relation between bias and capital is robust to a sub-sample of agent banks in the quarter following origination (Table 8, Column (7)).

The resulting sample consists of 4,683 loans. However seven banks have fewer than 50 loans, limiting our ability to estimate a robust pricing model. For the remaining eight banks we estimate the following regression for all first quarter, agent banks with a reported PD less than 10%.[16]

$$Spread_{i,t} = \alpha + \beta_{PD} PD_{i,t} + \beta_{PD^2} PD_{i,t}^2 + \beta_{\mathbf{LC}} \mathbf{LoanControls_{i,t}} + \tau_{\mathbf{t}} + \varepsilon_{i,t} \tag{4.3}$$

There is a distinct non-linearity between PD and spread over this range, therefore it is important to include a non-linear term, PD^2. We control for the following loan characteristics: type (revolver vs. term loan), maturity, log commitment size, the number of participants and other loan features including whether the loan is secured and whether the loan contains dividend covenants. We also include time fixed-effects to account for macroeconomic factors. Standard errors are robust to heteroskedasticity and clustered by borrower. The detailed results of these regressions can be found in Appendix Table 11.

The coefficient on PDs will be higher for banks with downward biased PD. Given the relation between bias and capital documented earlier, we expect higher betas for those banks with lower capital. Due to the non-linearity, the sensitivity of spread to PD varies over the realized distribution of PDs. We calculate the average sensitivity at two PD levels, 25bps and 200bps, roughly the interquartile range of the relevant distribution.[17] A plot of these sensitivities shows a downward relation with the average Tier 1 Gap, the more constrained a bank the higher the implied spread per unit of PD, Figure 3 (a) and (b). In addition, we expect banks with

date is not updated as frequently as LPC resulting in fewer observations.

[16]The PD restriction leaves out 113 credits. We exclude these so that unusually high PDs do not impact our pricing model estimates.

[17]i.e. $\beta_{PD}^{Lo} = \frac{\beta_{PD}*.25+\beta_{PD^2}*.25^2}{.25}$ and $\beta_{PD}^{Hi} = \frac{\beta_{PD}*2+\beta_{PD^2}*2^2}{2}$.

less informative PDs to have a lower R-squared. Figure 3c (c) demonstrates a positive slope between the R-squared of the pricing equation and Tier 1 Gap, i.e. lower capital banks have less informative PDs.

We assess the statistical significance of these patterns by regressing pricing estimates on Tier 1 Gap and the Tier 1 ratio. Given that these are estimated regressors, we bootstrap the standard errors and cluster them by bank. Indeed, we find that for a given PD, banks with less capital have higher spreads and lower R-squareds, see Table 9 Panel A. Lower capital banks charge less per unit of PD, consistent with a downward biased PD. For Tier 1 Gap, (A.1) and (A.2), the coefficient is statistically significant at the 5% level for both levels of PD; for the Tier 1 ratio, (A.4) and (A.5) it is statistically significant at the 5% level at the 200bps PD specification. The R-squareds are positively related to both Tier 1 Gap and the Tier 1 Ratio at the 10% and 5% significance levels, respectively.

One drawback of estimating pricing coefficients at the bank level is that the pricing coefficients are premised on different sample sizes. As a robustness check, we repeat the estimation by forming roughly equally sized portfolios of credit-quarters based on deciles of Tier 1 Gap and the Tier 1 ratio. Using these deciles, we estimate ten sets of coefficients and R-squareds from Equation 4.3.[18] We repeat the regression analysis using the alternative set of regressors, Table 9 Panel B. Given the natural pooling that occurs, the results are attenuated in this sample. However the coefficients on implied spread are consistently negative and statistically significant at the 10% level in (B.4). The coefficients on R-squared are positive and statistically significant at the 10% level using Tier 1 Gap and the Tier 1 ratio.

While the pattern between the "price" of risk and Tier 1 measures is a natural result of the observed correlations between deviations and capital ratios, the R-squared results are novel. The R-squared characterizes the ability of the PD and other observables to explain the variation in loan pricing. They are particularly important when evaluating the information content of PDs relative to the bank's unobserved information which goes into determining loan prices. Higher

[18]See Appendix Table 12 for the pricing estimates and Appendix Figure 4 for the illustrative relation with Tier 1 Gap.

Tier 1 capital banks, on average, report PDs that are more informative for loan prices relative to low Tier 1 banks, consistent with more information being incorporated in the reported risk metric. These results are difficult to reconcile with alternative hypotheses based on the optimism levels of these banks or their risk attitudes.

5 Conclusions

Using a novel data set of syndicated loan participants and their Basel II risk metrics, we identify significant cross-sectional variation in how banks rate common borrowers. We find that the variation in probability of default is strongly correlated with measures of a bank's Tier 1 capital ratio. On average, banks with lower capital report downward biased estimates relative to the median reporting bank in the syndicate. The magnitude of these biases are meaningful at the loan portfolio level and can result in differences in risk-weighted assets as large as 30%.

These findings, as well as evidence that banks bias PDs more for risky and large credits, are consistent with a regulatory arbitrage motive; however, they could also result from heterogeneity in banks' risk attitudes – more risk averse banks maintain higher Tier 1 capital ratios and report higher PDs while more risk tolerant banks maintain less capital and report lower PDs. In either case, banks demonstrate agency to systematically bias risk estimates. Whether it is preferences or a concerted effort to reduce regulatory capital, the fact that banks produce systematically disparate risk estimates presents a distinct challenge to an equitable regulatory regime.

Further analysis suggests that downward biased risk estimates are not solely explained by variation in risk attitudes, as the quality of this information is also lower. Low capital banks concentrate this biasing behavior on private firms where they are more likely to have proprietary information and greater discretion as to the inputs to their risk models. More importantly, banks with low capital set spreads on loans that are less consistent with their reported PD, a fact that is not easily dismissed by heterogeneity in risk tolerance.

Our results present supporting evidence for the adverse effects suggested by the Lucas Critique. Given the increasing reliance on bank-generated information, we highlight the critical role of incentives on the quality of these disclosures. To ensure the integrity of internally generated risk estimates, new programs should include mechanisms that incentivize the production of unbiased, accurate risk metrics.

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Figure 1: Weighted Average PD Deviations Relative to Tier 1 Gap

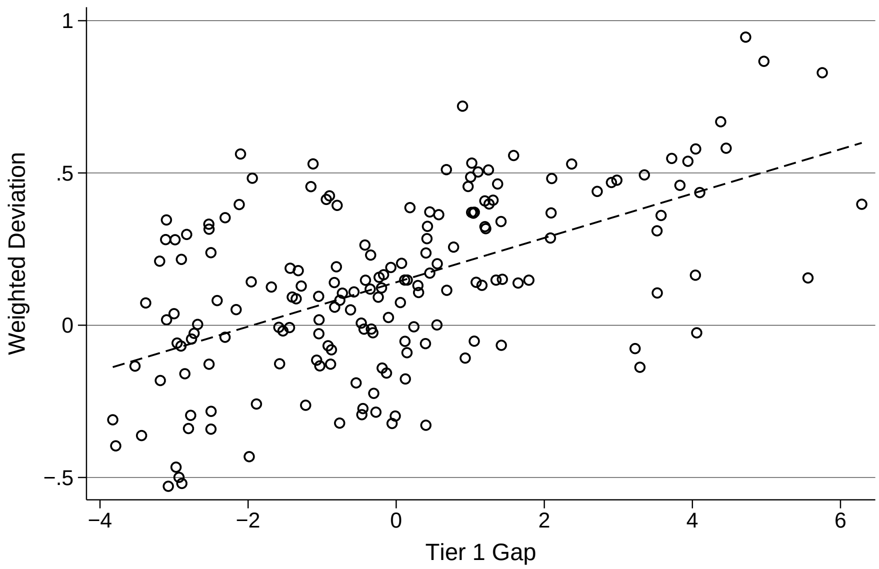


Figure 1 plots the average deviation from median PD by bank quarter versus the Tier 1 Gap. The average is weighted by the share of utilized funds for that bank-quarter. Tier 1 Gap is the estimated residual from a regression of sample banks on size, leverage, profitability and time-fixed effects. We obtain similar patterns with Tier 1 capital, however for confidentiality reasons we do not present that illustration.

Figure 2: Variation in Probability of Default Impact on Risk Weighted Assets

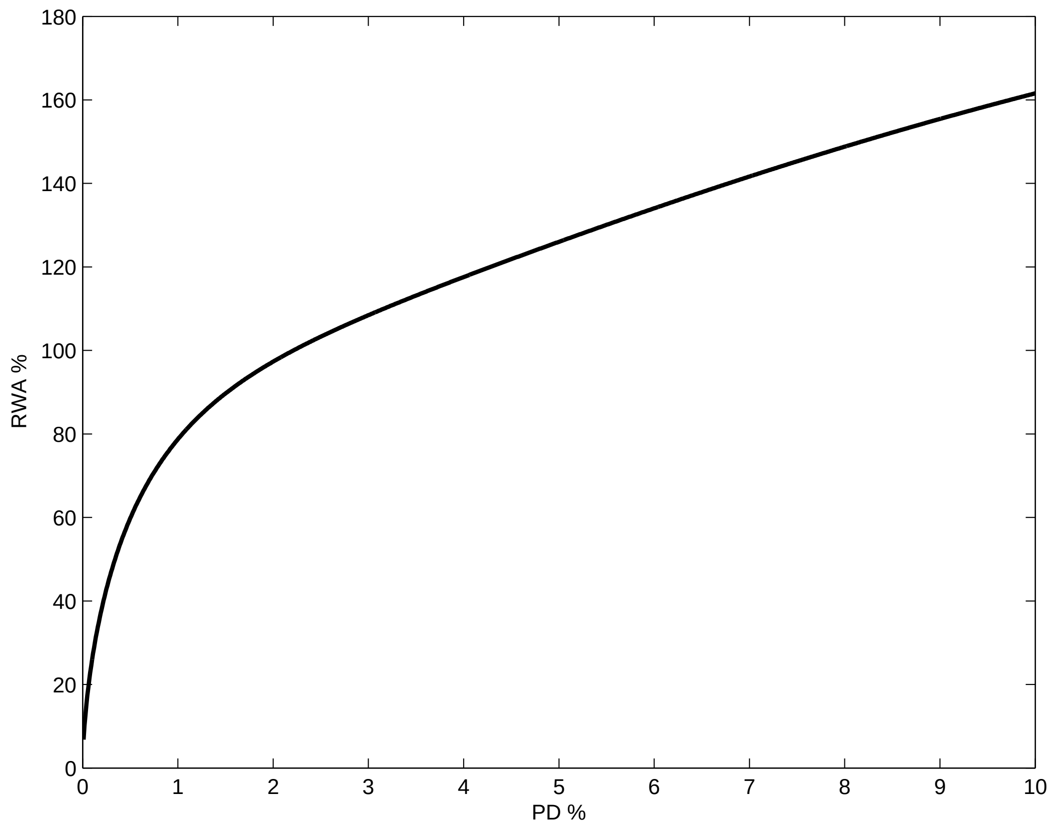
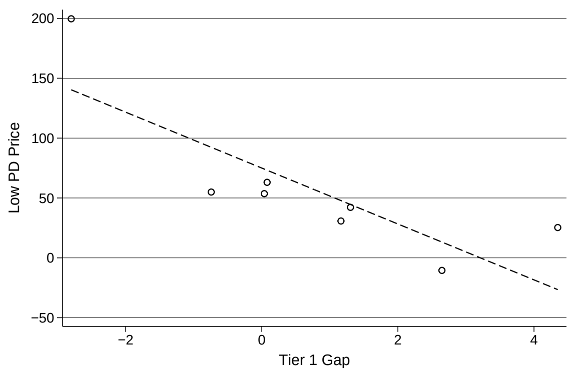
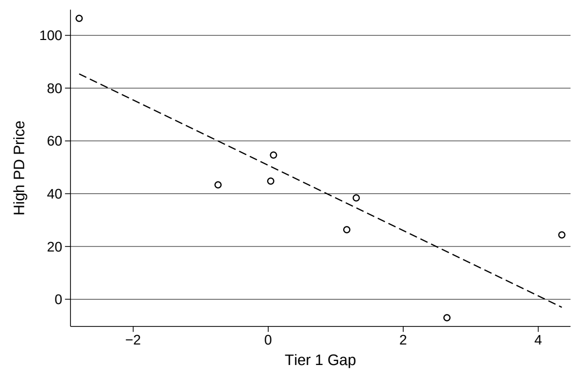


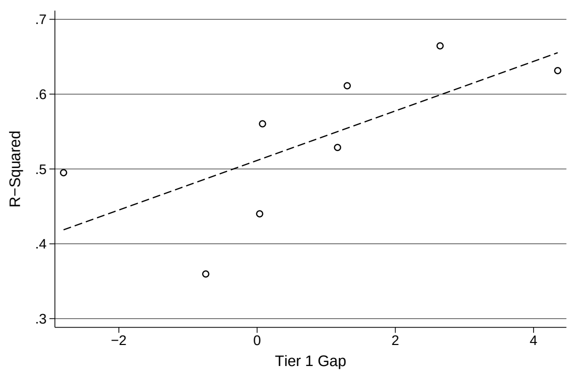
Figure 2 plots the RWA as a function of PD under the Basel II AIRB. This relation is based on average sample values for maturity (3 years) and LGD (35%).



(a) Spread/PD: PD=25bps



(b) Spread/PD: PD=200bps



(c) R-Squared

Figure 3: Bank Pricing Estimates vs. Tier 1 Gap

Figure 3 plots estimates from eight bank pricing regressions versus their average Tier 1 Gap. The pricing regressions regress credit spread on credit characteristics and PD for each bank. (a) and (b) illustrate the relation between the average spread per unit of PD based on estimated coefficients for each bank. (c) illustrates the R-squared of each bank's pricing regression.

Table 1: Summary of Credits

Table 1 summarizes the characteristics of credits in the sample. One observation is a credit-quarter between 2010Q1 and 2013Q3. Sample restricted to term loan or revolver credits with at least two banks reporting a PD.

	N	Mean	Median	Std. Dev.
Commitment Size ($ mm's)	78,160	359.1	150.0	683.4
Utilized ($ mm's)	78,160	114.7	37.4	263.2
Participants	78,146	17.52	8.0	50.1
Reporting Participants	78,160	2.4	2.0	1.8
% Utilized	78,160	47.0%	41.8%	40.8%
Term Loan Dummy	78,160	22.3%	0.0%	41.6%
Public	78,160	30.6%	0.0%	46.1%
Age (Quarters)	78,160	9.4	6.0	9.9
New	78,160	8.5%	0.0%	27.9%
Median:				
PD	78,160	2.5%	0.7%	5.0%
LGD_{Bef}	73,513	33.8%	35.0%	11.0%
$E(L_{Bef})$	73,513	0.6%	0.2%	1.5%
$E(L_{Aft})$	78,160	0.6%	0.1%	1.6%

Table 2: Summary of Banks

Table 2 summarizes the properties of banks in the sample. One observation is one bank-quarter between 2010Q1 and 2013Q3.

	N	Mean	Median	Std. Dev.
Tier 1 Ratio	188	13.3%	12.7%	2.4%
Log(Assets)	188	21.0	21.3	0.8
ROE	188	7.3%	7.2%	5.6%
Leverage	188	92.9%	94.0%	2.7%
Foreign	188	60.1%	100.0%	49.1%
Tier 1 Gap	188	0.0%	-0.3%	2.2%
Credits	188	1033	561	974
Participation	188	19.3%	11.2%	18.1%

Table 3: Regression of Percent Deviation in Risk Metric on Bank Fixed Effects

Table 3 regresses the deviation of risk metrics on bank fixed effects. Deviations are calculated each quarter relative to the median risk metric in the syndicate. In Panel A the dependent variable is percent deviation from the median; in Panel B it is raw deviation. The sample consists of all bank-credit-quarters with more than one reporting bank from 2010Q1 to 2013Q3. PD is probability of default in percent. LGD is loss given default in percent. $\mathbf{E}(L)$ is the expected loss calculated as the product of PD, LGD, and $EAD/Commitment$. LGD and its dependent variables are reported before (Bef) and after (Aft) CRM. Regressions include year-quarter fixed effects. The F-stat tests the hypothesis that bank fixed effects are equal. Standard errors are clustered by borrower and date. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A %Δ:	(1) PD	(2) LGD_{Bef}	(3) $PD * LGD_{Bef}$	(4) $E(L_{Bef})$	(5) $PD * LGD_{Aft}$	(6) $E(L_{Aft})$
Bank FE:						
1	0.18***	0.13***	0.28***	0.41***	0.22***	0.38***
2	0.69***	0.068***	0.69***	0.45***	0.53***	0.51***
3	-0.15***	-0.11***	-0.26***	-0.14***	-0.16***	-0.18**
4	0.11***	0.027	0.085***	0.19***	-0.014	0.37
5	0.026				0.058**	0.29***
6	0.10***	-0.052***	0.0084	0.30***	-0.049**	0.43***
7	-0.092**	-0.072***	-0.19***	-0.16***	-0.24***	-0.12***
8	0.18***	-0.14***	-0.00076	0.045	-0.056	0.012
9	0.24***	-0.052**	0.13***	-0.37***	0.075***	-0.080
10	0.20***	-0.083***	0.28***	0.44***	0.24***	0.041
11	0.16***	0.042**	0.18***	0.24***	0.16***	0.31***
12	0.20***	0.025***	0.17***	0.35***	0.077***	0.34***
13	0.58***	-0.13***	0.37***	0.56***	0.30***	0.38***
14	-0.25***	0.054***	-0.22***	-0.039	-0.29***	-0.013
15	0.24***	0.13***	0.36***	0.37***	0.29***	0.56***
Observations	151,871	129,530	129,498	133,938	132,363	151,855
R-squared	0.144	0.178	0.153	0.136	0.106	0.079
F-Stat	90.6	120	152	97.0	78.9	46.7

Panel B Δ:	(1) PD	(2) LGD_{Bef}	(3) $PD * LGD_{Bef}$	(4) $E(L_{Bef})$	(5) $PD * LGD_{Aft}$	(6) $E(L_{Aft})$
1	0.13***	4.04***	0.088***	0.080***	0.075***	0.056***
2	0.47***	2.91***	0.15***	-0.0071***	0.11***	-0.013***
3	-0.22***	-3.64***	-0.11***	-0.061***	-0.12***	-0.061***
4	0.0067	0.36	0.012	0.026***	-0.026***	0.058
5	0.058***				0.033***	0.042***
6	0.010	-2.66***	-0.028**	-0.0036	-0.051***	0.010
7	-0.034	-1.84***	-0.026**	-0.010	-0.056***	-0.000037
8	0.24***	-5.26***	0.029**	0.019*	-0.0016	0.0049
9	0.29***	-1.54**	0.010	-0.11***	-0.013	-0.044***
10	0.37***	-2.55***	0.12***	0.12***	0.091**	0.042**
11	0.36***	1.78***	0.14***	0.076***	0.14***	0.13***
12	0.15***	0.48	0.061***	0.077***	0.020*	0.058***
13	0.42***	-5.26***	0.12***	0.11***	0.10***	0.072***
14	-0.32***	1.20***	-0.083***	-0.037***	-0.11***	-0.027
15	0.083***	4.55***	0.038***	0.021***	0.023***	0.033***
Observations	151,859	129,529	129,497	133,940	132,362	151,852
R-squared	0.050	0.207	0.058	0.053	0.047	0.053
F-Stat	62.1	193	78.7	49.7	51.6	40.0

Table 4: Regression of Percent Deviation in Risk Metric on Bank Fixed Effects w/Controls

Table 4 regresses the percent deviation of risk metrics on bank fixed effects. Deviations are calculated each quarter relative to the median risk metric in the syndicate. The dependent variable is the deviation from the median. The sample consists of all bank-credit-quarters with more than one reporting bank from 2010Q1 to 2013Q3. PD is probability of default in percent. LGD is loss given default in percent. $\mathbf{E}(L)$ is the expected loss calculated as the product of PD, LGD, and $EAD/Commitment$. LGD and its dependent variables are reported before (Bef) and after (Aft) CRM. $Agent$ is a dummy variable equal to one if the bank is an agent. $MedianPD$ is the median probability of default for a credit. $Share$ is the share of the commitment held by the bank. $Public$ is a dummy equal to one for public firms. $Revolver$ is a dummy equal to one for revolving credit facilities. $log(Commit.)$ is the log of the total commitment size. Age is the number of quarters since the origination date. $Participants$ is the number of participants in the credit-quarter. $Reporters$ is the number of reporting banks in the credit-quarter. Bank FE are suppressed for brevity, however F-stats are reported for the null that they are equal. Regressions include year-quarter fixed effects. Standard errors are clustered by borrower and date. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Δ:	PD	LGD_{Bef}	$PD*LGD_{Bef}$	$E(L_{Bef})$	$PD*LGD_{Aft}$	$E(L_{Aft})$
Bank FE:	+	+	+	+	+	+
F-Stat	57.1	195	74.7	45.7	48.4	40.5
Agent	-0.059***	-0.35**	-0.015*	-0.080***	0.0016	-0.016**
	(0.022)	(0.18)	(0.0077)	(0.018)	(0.0083)	(0.0067)
Median PD	0.044***	0.038**	0.021***	0.020***	0.022***	0.013***
	(0.0074)	(0.015)	(0.0039)	(0.0042)	(0.0039)	(0.0029)
Share	-0.25***	-1.49***	-0.11***	-0.080***	-0.094***	-0.084***
	(0.068)	(0.42)	(0.030)	(0.026)	(0.027)	(0.024)
Public	-0.010	-0.15**	-0.0072**	-0.0080***	-0.0068**	-0.0044*
	(0.0068)	(0.064)	(0.0034)	(0.0029)	(0.0033)	(0.0024)
Revolver	-0.019**	-0.058	-0.0086**	-0.014***	-0.016***	-0.012**
	(0.0083)	(0.083)	(0.0036)	(0.0033)	(0.0033)	(0.0047)
log(Commitment)	-0.012***	-0.16***	-0.0068***	-0.0035**	-0.0043**	-0.0050***
	(0.0043)	(0.042)	(0.0017)	(0.0016)	(0.0020)	(0.00099)
Age	0.0014***	-0.0025	0.00017	0.00038***	0.00019	0.00018**
	(0.00043)	(0.0047)	(0.00019)	(0.00012)	(0.00020)	(0.000073)
Participants	-5.7e-06	-0.0017*	-0.00011*	-0.00011***	-0.00011**	-0.000061
	(0.00019)	(0.00095)	(0.000059)	(0.000031)	(0.000054)	(0.000052)
Reporters	-0.012***	0.025	-0.00073	-0.00029	0.0019	-0.00089
	(0.0022)	(0.024)	(0.0010)	(0.00063)	(0.0012)	(0.00091)
Observations	151,817	129,491	129,460	133,901	132,330	151,810
R-squared	0.064	0.208	0.079	0.090	0.069	0.068
R-squared w/out Bank FE	0.025	0.002	0.031	0.044	0.032	0.035

Table 5: Regression: Deviation in Risk Metrics on Bank Characteristics

Table 5 regresses the deviation of risk metrics on bank controls. Deviations are calculated each quarter relative to the median risk metric in the syndicate. The dependent variable is the deviation from the median. The sample consists of all bank-credit-quarters with more than one reporting bank from 2010Q1 to 2013Q3. PD is probability of default in percent. LGD is loss given default in percent. $\mathbf{E}(L)$ is the expected loss calculated as the product of PD, LGD, and $EAD/Commitment$. LGD and its dependent variables are reported before (Bef) and after (Aft) CRM. Panel A considers *Tier 1*, the most recent reported Tier 1 Capital ratio; *log*($Assets$) is the log of total assets; ROE is the most recent ROE; $Foreign$ is a dummy for non-US banks; $Agent$ a dummy variable equal to one if the bank is the agent bank. Panel B, considers *Tier 1 Gap*, the estimated residual from a regression of sample banks on size, leverage, profitability and year-quarter fixed effects. Regressions include year-quarter fixed effects and the number of reporting banks for that credit-quarter. Standard errors reported in parentheses are clustered by bank and date. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A	(1) PD	(2) LGD_{Bef}	(3) $PD * LGD_{Bef}$	(4) $E(L_{Bef})$	(5) $PD * LGD_{Aft}$	(6) $E(L_{Aft})$
Tier 1	0.073***	-0.17	0.024***	0.015***	0.028***	0.011***
	(0.016)	(0.40)	(0.0036)	(0.0032)	(0.0035)	(0.0025)
log(Assets)	0.031	0.16	0.022	0.035***	0.028*	-0.0013
	(0.039)	(1.54)	(0.018)	(0.013)	(0.015)	(0.013)
ROE	1.77**	33.5*	1.04***	0.79***	0.90***	0.60***
	(0.69)	(17.2)	(0.28)	(0.24)	(0.27)	(0.19)
Foreign	-0.022	0.12	-0.023	-0.056	-0.044	-0.0070
	(0.11)	(1.91)	(0.040)	(0.039)	(0.035)	(0.024)
Agent	-0.082**	0.33	-0.018	-0.084***	0.0022	-0.019*
	(0.033)	(0.25)	(0.012)	(0.019)	(0.016)	(0.011)
Observations	151,865	129,534	129,502	133,945	132,367	151,858
R-squared	0.020	0.054	0.023	0.027	0.020	0.025

Panel B	(1) PD	(2) LGD_{Bef}	(3) $PD * LGD_{Bef}$	(4) $E(L_{Bef})$	(5) $PD * LGD_{Aft}$	(6) $E(L_{Aft})$
Tier 1 Gap	0.061***	-0.33	0.018***	0.013**	0.022***	0.0064
	(0.015)	(0.33)	(0.0063)	(0.0052)	(0.0055)	(0.0051)
Agent	-0.13***	0.21	-0.029	-0.075***	-0.0020	-0.029*
	(0.036)	(1.10)	(0.020)	(0.018)	(0.011)	(0.015)
Observations	151,865	129,534	129,502	133,945	132,367	151,858
R-squared	0.013	0.006	0.007	0.015	0.010	0.013

Table 6: Regression of Weighted Average Deviation on Tier 1 Measures

Table 6 regresses the weighted deviation of risk metrics on Tier 1 measures. Deviations are calculated each quarter relative to the median risk metric in the syndicate. Deviations are weighted by facility utilization for a given bank-quarter and then summed to the bank level. The sample consists of bank-quarters from 2010Q1 to 2013Q3. PD is probability of default in percent. LGD is loss given default in percent. $\mathbf{E}(L)$ is the expected loss calculated as the product of PD, LGD, and $EAD/Commitment$. Panel A considers *Tier 1*, the most recent reported Tier 1 Capital ratio; $log(Assets)$ is the log of total assets; ROE is the most recent reported ROE; $Foreign$ is a dummy for non-US banks. Panel B, considers *Tier 1 Gap*, the estimated residual from a regression of sample banks on size, leverage, profitability and year-quarter effects. Regressions include year-quarter fixed effects. Standard errors reported in parentheses are clustered by bank and date. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A Δ:	(1) PD	(2) $PD * LGD_{Bef}$	(3) $E(L_{Bef})$	(4) $PD * LGD_{Aft}$	(5) $E(L_{Aft})$
Tier 1	0.075***	0.016***	0.012***	0.019***	0.0072**
	(0.022)	(0.0036)	(0.0032)	(0.0042)	(0.0028)
ROE	0.57	0.36*	0.25	0.47**	0.31*
	(0.77)	(0.21)	(0.21)	(0.20)	(0.18)
log(Assets)	0.072*	0.023	0.023	0.030*	0.012
	(0.042)	(0.017)	(0.016)	(0.016)	(0.016)
Foreign	-0.11	-0.062	-0.055	-0.076**	-0.045
	(0.13)	(0.041)	(0.039)	(0.038)	(0.028)
Year FE	+	+	+	+	+
Observations	174	169	169	174	174
R-Squared	0.333	0.232	0.171	0.307	0.137

Panel B Δ:	(1) PD	(2) $PD * LGD_{Bef}$	(3) $E(L_{Bef})$	(4) $PD * LGD_{Aft}$	(5) $E(L_{Aft})$
Tier 1 Gap	0.073***	0.015***	0.012***	0.018***	0.0063
	(0.021)	(0.0046)	(0.0038)	(0.0058)	(0.0044)
Year FE	+	+	+	+	+
Observations	174	169	169	174	174
R-Squared	0.321	0.167	0.119	0.210	0.055

Table 7: Regression of PD Weighted Average Deviation on Tier 1 Measures and Bank Fixed-Effects

Table 7 regresses the weighted deviation of PD on the Tier 1 Gap. Deviations are calculated each quarter relative to the median observed PD for that credit. Deviations are weighted by facility utilization for a given bank-quarter and then summed to the bank level. The sample consists of bank-quarters from 2010Q1 to 2013Q3. *PD* is probability of default in percent. Panel A considers *Tier 1*, the most recent reported Tier 1 Capital ratio; *log*(*Assets*) is the log of total assets; *ROE* is the most recent reported ROE; *Foreign* is a dummy for non-US banks. Panel B, considers *Tier 1 Gap*, the estimated residual from a regression of sample banks on size, leverage, ROE and year-quarter effects. *Portfolio PD* is the average median PD for all credits in the bank's portfolio with more than one reporter, weighted by utilization. *Activity* is the percentage of outstanding credits the bank participated in that quarter. Regressions include year-quarter fixed effects. Standard errors reported in parentheses are clustered by bank and date. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A Δ:	(1) *PD*	(2) *PD*	(3) *PD*	(4) *PD*	(5) *PD*
Tier 1	0.046***	0.044**	0.049***	0.052***	0.077***
	(0.018)	(0.017)	(0.017)	(0.018)	(0.028)
ROE	-0.95	-0.64	-0.89	-0.16	-2.25**
	(0.74)	(0.81)	(0.74)	(0.80)	(0.90)
log(Assets)	0.030	0.023	0.020	0.025	-0.22*
	(0.31)	(0.31)	(0.28)	(0.68)	(0.13)
Foreign	-0.97*	-0.90	-0.72		
	(0.55)	(0.56)	(0.61)		
Portfolio PD		0.061**			
		(0.026)			
Activity			1.49**		
			(0.68)		
Foreign Only				+	
U.S. Only					+
Year FE	+	+	+	+	+
Bank FE	+	+	+	+	+
Observations	174	174	174	101	73
R-Squared	0.783	0.792	0.790	0.778	0.891

Panel B Δ:	(1) *PD*	(2) *PD*	(3) *PD*	(4) *PD*	(5) *PD*
Tier 1 Gap	0.044*	0.041**	0.047**	0.051**	0.048
	(0.023)	(0.020)	(0.022)	(0.020)	(0.030)
Portfolio PD		0.074***			
		(0.027)			
Activity			1.60**		
			(0.79)		
Foreign Only				+	
U.S. Only					+
Year FE	+	+	+	+	+
Bank FE	+	+	+	+	+
Observations	174	174	174	101	73
R-Squared	0.771	0.787	0.779	0.776	0.873

Table 8: Regression: Deviation in Risk Metrics and Interactions with Tier 1 Gap

Table 8 regresses the deviation of PD on the Tier 1 Gap and various interactions. Deviations are calculated each quarter relative to the median observed PD for that credit. In (1)-(6), the sample consists of all bank-credit-quarters with more than one reporting bank from 2010Q1 to 2013Q3. In (7), the sample is restricted to agent banks and credits in the first quarter following origination. *Tier 1 Gap*, the estimated residual from a regression of sample banks on size, leverage, profitability and time-fixed effects. Non-interaction terms are suppressed for brevity. *Risky* is a dummy equal to one if a credits has a PD in the top tercile of all credits in the quarter. *Utilized* is a dummy equal to one if the credit is drawn. *Large* is a dummy equal to one if the credits current utilization is in the top tercile for a given bank-quarter. *Share* is a dummy equal to one if the commitment share held by the bank is in the top tercile for the bank-quarter. *Public* is a dummy equal to one for public firms. Regressions include year-quarter fixed effects and the number of reporting banks for that credit-quarter. Standard errors reported in parentheses are clustered by bank and date. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

							Agents 1^{st} Q
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Δ:	PD	PD	PD	PD	PD	PD	PD
Tier 1 Gap	0.017*	0.023**	0.049***	0.049***	0.038**	0.081***	0.11**
	(0.0094)	(0.012)	(0.015)	(0.015)	(0.015)	(0.017)	(0.046)
T1G∗ Risky	0.13***						
	(0.022)						
Risky	0.12						
	(0.13)						
T1G∗ Utilized		0.055***					
		(0.0100)					
Utilized		0.063*					
		(0.038)					
T1G∗ Large			0.038***		0.035***		
			(0.0057)		(0.0058)		
Large			0.059***		0.061***		
			(0.014)		(0.013)		
T1G∗ Share				0.045***	0.044***		
				(0.0086)	(0.0090)		
Share				0.047	0.046		
				(0.041)	(0.040)		
T1G∗ Public						-0.039***	
						(0.0081)	
Public						-0.040**	
						(0.019)	
Observations	151,865	151,865	151,865	151,865	151,865	151,865	3,139
R-squared	0.026	0.015	0.014	0.014	0.015	0.014	0.037

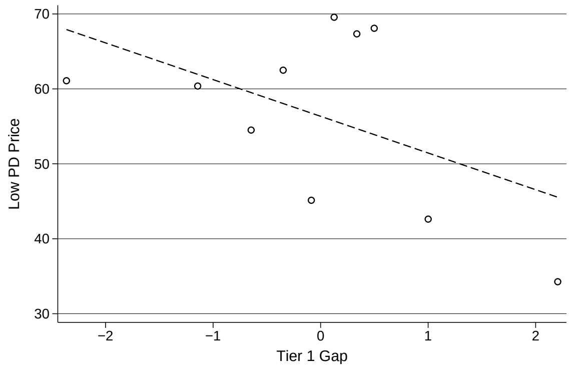
Table 9: Regression of Pricing Coefficients and R^2's on Tier 1 Measures

Table 9 regresses the estimates from the pricing regressions on Tier 1 ratio and Tier 1 Gap. β_{PD}^{Lo} and β_{PD}^{Hi} are the average sensitivity of spreads to a 1% change in PD at PDs of 25bps and 200bps. R^2 is the percent of explained variance from the pricing regression. Panel A estimates the PD coefficients and R^2 using individual banks. Panel B sorts credits into deciles based on Tier 1 Gap (1-3) or Tier 1 ratio (4-6). Standard errors reported in parentheses are bootstrapped. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

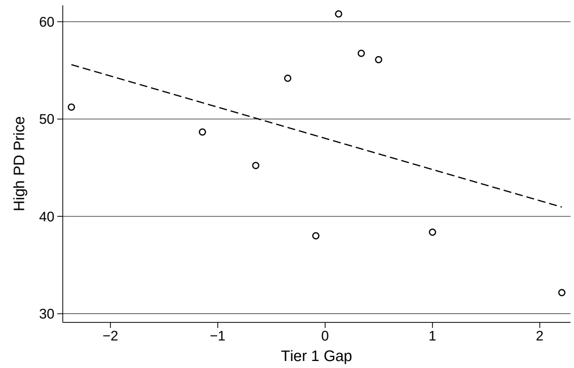
Panel A Bank Estimates	(1) β_{PD}^{Lo}	(2) β_{PD}^{Hi}	(3) R^2	(4) β_{PD}^{Lo}	(5) β_{PD}^{Hi}	(6) R^2
Tier 1 Gap	-23.3**	-12.4**	0.033*			
	(10.4)	(4.91)	(0.018)			
Tier 1				-15.7	-9.20**	0.027**
				(9.59)	(4.44)	(0.012)
Observations	8	8	8	8	8	8
R-Squared	0.666	0.689	0.487	0.465	0.589	0.516

Panel B T1 Decile	(1) β_{PD}^{Lo}	(2) β_{PD}^{Hi}	(3) R^2	(4) β_{PD}^{Lo}	(5) β_{PD}^{Hi}	(6) R^2
Tier 1 Gap	-4.90	-3.20	0.035*			
	(3.64)	(2.90)	(0.019)			
Tier 1				-7.16*	-4.74	0.023*
				(4.13)	(3.20)	(0.013)
Observations	10	10	10	10	10	10
R-Squared	0.249	0.174	0.483	0.401	0.352	0.441

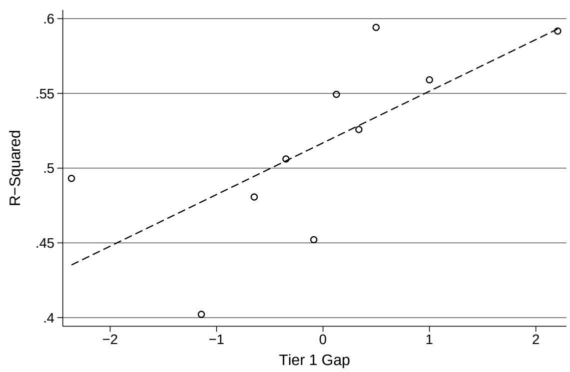
A Results Appendix



(a) Spread/PD: PD=25bps



(b) Spread/PD: PD=200bps



(c) R-Squared

Figure 4: Tier 1 Gap Decile Pricing Estimates vs. Tier 1 Gap

Figure 4 plots estimates from ten portfolios pricing regressions versus the average Tier 1 Gap of the portfolios. The pricing regressions regress credit spread on credit characteristics and PD for each portfolio. Portfolios are formed by choosing breaking the observed credits into deciles based on the agent banks Tier 1 Gap. (a) and (b) illustrate the relation between the average spread per unit of PD based on estimated coefficients for each bank. (c) illustrates the R-squared of each bank's pricing regression.

Table 10: Regression: Deviation in Risk Metrics and Interactions with Tier 1 Ratio

Table 10 regresses the deviation of PD on the Tier 1 ratio and various interactions. Deviations are calculated each quarter relative to the median observed PD for that credit. In (1)-(6), the sample consists of all bank-credit-quarters with more than one reporting bank from 2010Q1 to 2013Q3. In (7), the sample is restricted to agent banks and credits in the first quarter following origination. *Tier 1*, is the Tier 1 ratio. *Risky* is a dummy equal to one if a credits has a PD in the top tercile of all credits in the quarter. *Utilized* is a dummy equal to one if the credit is drawn. *Large* is a dummy equal to one if the credits current utilization is in the top tercile for a given bank-quarter. *Share* is a dummy equal to one if the commitment share held by the bank is in the top tercile for the bank-quarter. *Public* is a dummy equal to one for public firms. Regressions include year-quarter fixed effects and the number of reporting banks for that credit-quarter. Several other non-interaction terms are suppressed for brevity: ROE, log(Assets), and a foreign bank dummy. Standard errors reported in parentheses are clustered by bank and date. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

							Agents 1^{st} Q
Δ:	(1) PD	(2) PD	(3) PD	(4) PD	(5) PD	(6) PD	(7) PD
Tier 1	0.030**	0.033**	0.062***	0.062***	0.053***	0.090***	0.13**
	(0.015)	(0.014)	(0.017)	(0.016)	(0.017)	(0.016)	(0.052)
T1∗ Risky	0.12***						
	(0.027)						
Risky	-1.48***						
	(0.45)						
T1∗ Utilized		0.059***					
		(0.0090)					
Utilized		-0.70***					
		(0.13)					
T1∗ Large			0.032***		0.030***		
			(0.0066)		(0.0064)		
Large			-0.36***		-0.33***		
			(0.091)		(0.088)		
T1∗ Share				0.037***	0.036***		
				(0.011)	(0.011)		
Share				-0.45***	-0.44***		
				(0.14)	(0.14)		
T1 ∗ Public						-0.036***	
						(0.0080)	
Public						0.42***	
						(0.11)	
Observations	151,865	151,865	151,865	151,865	151,865	151,865	3,139
R-squared	0.034	0.024	0.022	0.021	0.023	0.022	0.055

Table 11: Regression of Spreads on Loan Characteristics by Bank

Table 11 regresses the all-in spreads on bank risk metrics and loan characteristics. Sample consists of the agent banks reporting for the first time after a loan was originated. Column (1) pools all observations. Columns (2)-(9) reflect individual banks. Standard errors reported in parentheses are clustered by borrower. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank No.:	All	1	2	3	4	5	6	7	8
	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread
PD	51.8***	64.3***	54.9***	213***	56.6***	31.4	25.4	-11.0	42.7***
	(3.43)	(5.60)	(4.88)	(26.4)	(14.4)	(21.2)	(38.6)	(17.9)	(12.1)
PD^2	-3.72***	-4.82***	-5.05***	-53.3***	-6.63**	-2.52	-0.53	2.00	-2.16
	(0.49)	(0.80)	(0.65)	(7.22)	(2.64)	(2.53)	(4.23)	(1.62)	(1.49)
Revolver	-34.1***	-37.3***	-22.0***	-51.2	57.3***	21.3	-68.6	-73.9*	-71.1***
	(3.88)	(5.37)	(4.37)	(42.9)	(12.1)	(37.5)	(42.4)	(39.8)	(20.5)
Maturity	-0.61	-0.073	-2.18	5.55	-3.27	4.74	95.6***	-9.48	-1.56
	(1.39)	(2.71)	(2.25)	(4.30)	(3.75)	(14.1)	(17.5)	(15.5)	(5.23)
Public	-22.7***	-9.21***	-30.5***	-39.3***	-38.7***	-42.7***	-25.7	-77.3***	-9.11*
	(1.50)	(2.05)	(2.79)	(9.03)	(4.93)	(15.5)	(17.2)	(12.3)	(5.26)
log(Comm.)	-22.7***	-9.21***	-30.5***	-39.3***	-38.7***	-42.7***	-25.7	-77.3***	-9.11*
	(1.50)	(2.05)	(2.79)	(9.03)	(4.93)	(15.5)	(17.2)	(12.3)	(5.26)
Div Cov	-18.3***	-12.2***	-13.6***	-18.4	-14.6	1.99	-51.4	36.6	-19.3*
	(3.10)	(4.47)	(5.09)	(17.5)	(9.72)	(27.4)	(44.8)	(37.0)	(11.2)
Secured	6.55	9.66	0.81	-30.5	22.8	36.4	424***	81.6*	8.86
	(4.61)	(6.82)	(7.26)	(21.3)	(15.2)	(43.6)	(99.9)	(43.2)	(20.8)
Participants	0.21***	0.14***	1.09***	3.19*	1.41***	0.28**	-0.60**	0.068	-0.055
	(0.040)	(0.050)	(0.20)	(1.80)	(0.42)	(0.13)	(0.27)	(0.11)	(0.14)
Observations	4,683	1,695	1,627	225	416	80	61	82	323
R-Squared	0.482	0.560	0.440	0.495	0.360	0.529	0.631	0.665	0.611

Table 12: Regression of Spreads on Loan Characteristics by Tier 1 Gap Decile

Table 12 regresses the all-in spreads on bank risk metrics and loan characteristics. Sample consists of the agent banks reporting for the first time after a loan was originated. Column (1) pools all observations. Columns (2)-(11) reflect different credit samples based on the Tier 1 Gap decile of the agent bank. Standard errors reported in parentheses are clustered by borrower. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Decile	1	2	3	4	5	6	7	8	9	10
	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread
PD	62.5***	62.1***	55.8***	63.7***	46.2***	70.8***	68.9***	69.8***	43.2***	34.6***
	(11.6)	(10.7)	(9.12)	(11.0)	(8.53)	(12.6)	(9.08)	(9.44)	(8.76)	(10.6)
PD^2	-5.64**	-6.69***	-5.30***	-4.75***	-4.08***	-5.01***	-6.05***	-6.85***	-2.42*	-1.20
	(2.34)	(1.35)	(1.25)	(1.26)	(1.21)	(1.85)	(0.98)	(1.53)	(1.34)	(1.15)
Revolver	-30.5***	-27.2**	-36.7***	-4.57	-12.2	-38.3***	-38.0***	-33.6***	-31.0***	-86.2***
	(10.9)	(11.1)	(8.30)	(7.08)	(8.86)	(8.71)	(10.8)	(9.75)	(10.3)	(17.6)
Maturity	2.58	-2.41	2.43	1.47	-7.08**	-12.2*	-1.67	6.36	3.99	12.3*
	(3.55)	(3.52)	(3.83)	(3.71)	(3.47)	(6.78)	(4.45)	(4.14)	(3.90)	(6.39)
log(Comm.)	-42.2***	-33.2***	-17.4***	-15.4***	-30.2***	-13.4***	-18.6***	-5.59	-20.0***	-34.5***
	(6.41)	(5.25)	(4.22)	(3.81)	(3.95)	(4.22)	(4.08)	(3.60)	(4.06)	(5.64)
Public	-24.8**	-16.2*	-6.91	-22.0***	-8.85	-17.0*	-24.8***	-7.66	-14.1	-24.0*
	(10.2)	(9.18)	(7.88)	(7.71)	(7.21)	(9.08)	(8.44)	(7.76)	(9.64)	(13.0)
Div. Cov	-25.5	10.5	8.70	2.22	2.82	1.91	4.99	3.92	5.63	15.8
	(17.0)	(16.3)	(10.3)	(10.9)	(11.1)	(16.8)	(11.6)	(10.0)	(13.2)	(21.5)
Secured	36.1***	30.8**	30.9***	31.0***	23.1**	24.7*	8.01	15.6	20.0	15.3
	(13.5)	(13.8)	(11.5)	(11.8)	(10.5)	(13.2)	(12.2)	(10.3)	(14.0)	(20.4)
Participants	3.14**	1.46***	0.23*	0.45***	0.22***	0.35***	0.16*	0.17*	0.14	0.072
	(1.43)	(0.54)	(0.14)	(0.12)	(0.079)	(0.13)	(0.094)	(0.091)	(0.093)	(0.12)
Observations	472	483	513	381	584	391	477	421	404	439
R-Squared	0.493	0.402	0.481	0.506	0.452	0.549	0.526	0.594	0.559	0.592