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Risk-based pricing in competitive lending markets*

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Abstract

We use unique data on banks' private risk assessments of corporate borrowers to quantify how competition among banks affect the risk sensitivity of interest rates in the Norwegian credit market. We show that an increase in competition makes corporate lending rates less sensitive to banks' own assessment of borrower risk and this is more pronounced in market segments with higher degree of asymmetric information. Our results are driven by banks with low franchise values, outlining a novel channel of how the competition-fragility nexus can operate.

JEL Classification: G11, G21, G28.

Keywords: Banking competition, market power, risk pricing, financial stability.

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1 Introduction

Banks' first line of defence against losses is their operating income. Adequate pricing of credit risk can therefore be important for bank solvency and ultimately financial stability. Yet, financial institutions price risks in competitive markets and their risk-pricing is likely to be affected by market and macroeconomic factors as well as bank-specific policies. The Great Financial Crisis highlighted that banks do not always price risks adequately due to competitive pressures that resulted in less screening (Dell'Ariccia, Igan, and Laeven, 2012; Müller and Noth, 2018), disregard of risks (Rajan, Seru, and Vig, 2015), or predatory lending practices (Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff, 2014). More broadly, the competition-fragility view (Keeley, 1990; Besanko and Thakor, 1993; Suarez, 1994; Matutes and Vives, 2000; Hellmann, Murdock, and Stiglitz, 2000; Repullo, 2004; Martinez-Miera and Repullo, 2010) argues that increased competition can lower banks' franchise values and thereby induce banks to take more risk. In principle, this could materialize in less risk-sensitive prices. The impact of competition on bank risk is not unambigous, however. For instance, more competition can lead to lower rates, which in turns induces borrower to take less risk and improved financial stability (Boyd and De Nicolo, 2005; Boyd, De Nicolò, and Jalal, 2006).

Investigating the relationship between competition and bank risk-pricing is challenging due to data requirements. First, detailed data on bank portfolios and bank's subjective risk assessment are needed to understand whether competition leads to changes in how banks price risk. Observing for instance how the interest rate to firms with some objectively defined measure of risk is affected by a change in competition is not sufficient, as banks, due to screening, can potentially have a different risk assessment than what is observable from an outsiders perspective. Second, it is likely that different types of banks are present in areas with different competitive pressures, potentially leading to a correlation between competition and risk-pricing which is ultimately driven by some, unobserved bank characteristic.

In this paper we investigate how competition affects the risk sensitivity of lending rates, using a novel supervisory database on all outstanding corporate loans in Norway. A key advantage with the data is that it contains banks' own risk assessment, which allow us to compare riskiness according to a risk measure plausibly accounting for both hard (observable to outsiders) information and soft information acquired by the bank in the screening process. Due to the granularity of the data, we also have substantial variation within banks, firms and markets, allowing us to investigate within-bank variation in risk-pricing across different market segments. Our main contribution is to document that increases in competition, proxied by several alternative and complementary measures, reduces the sensitivity of interest rates to banks' own assesement of borrowers probability of default. We show that this effect is driven by banks that have low franchise values, consistent with the models commonly used to analyze the competition-fragility nexus.

Our empirical analysis consists of three main steps. First, we use supervisory data on all outstanding corporate loans in Norway to document that borrower risk has a sizeable and significant impact on the interest rate of loans. In our data, banks report borrower-specific credit risk exposures along with loan-level information including interest rates, loan volumes, guarantees, and lines of credit. These data further include a bank-internal risk assessment of the borrower in the form of an estimated probability of default (PD). We complement this by bank-level information and firm-level information to account for bank and borrower characteristics that determine loan terms. We document that higher risk is associated with higher interest rates. This also holds when controlling for credit ratings, suggesting that a component of the PDs consist of banks' soft information.[1] According to our baseline estimation, a 1 percent increase in the PD estimate increase the interest rate by 13 basis points within firms of the same rating class.

Second, we exploit the granularity of our data to establish the causal effect of competition on the sensitivity of interest rates with respect to banks own PD estimate. We refer to this sensitivity as banks' "risk-pricing". We use three different measures of competition; Herfindahl-Hirshcman indicies (HHI), number of competitors in a local market, as well as an event study framework where we investigate the risk-pricing of incumbents when a new bank enters their market. A key challenge in identifying the effect of competition on risk pricing is selection between banks with different risk management strategies and competitive settings. For instance, if banks with a risk management strategy that entails that interest rates have a low risk-sensitivity select on competitive markets, we would estimate a negative relationship between competition and risk pricing. To overcome this empirical challenge, we exploit within bank-year variation to assess how risk-pricing varies across different markets with different competitive pressures, but for the same bank.

Our main empirical finding is that an increase in competition makes corporate lending rates less sensitive to banks' own assessment of borrower risk. We further find this result to be more pronounced in market segments that potentially feature a higher degree of asymmetric information, such as high-risk borrowers or small and medium sized firms (SMEs). Overall, our results therefore suggest that competition can affect financial fragility and that the pricing of loans is an important margin of adjustment.

Third and finally, we investigate the mechanism behind our main result. We consider two potential explanations. The first explanation is motivated by the large literature focusing on the role of bank franchise values and how competition erodes franchise values, ultimately leading banks to take more risk. In line with this literature, we investigate whether banks with low franchise values are driving our results.[2] We focus on net interest margins (Repullo, 2004) and bank equity (Demsetz, Saidenberg, and Strahan, 1996) as proxies for bank franchise value. We find that, across all three competition measures, banks with low net interest margins and low equity to total assets are driving our results. This is consistent with the view that competition affects bank franchise value, which in turn affects bank risk-taking. A second potential mechanism is that higher competition leads to lower screening, which in turn make banks' own PD estimates less informative about actual risk and thereby also observed interest rates. To check this hypothesis, we test whether the predictive abilities of bank PD estimates for actual defaults depends on the competitive situation. We do not

[1] PD also has considerable explanatory power to predict firm defaults.

[2] Franchise value refers to the value a bank can derive from continuing its business. It is often described as the NPV of future cashflows, hence market value, or simply positive profits.

find conclusive evidence that more competition leads to worse PD estimates. As such, our results are mostly consistent with a mechanism focused on the impact of competition on bank franchise values.

Related literature Our paper relates to several strands of the literature. The first strand of the literature relates to microlevel evidence on banks' risk-pricing. Edelberg (2006) studies the impact of increased use of risk-based pricing for consumer loans in the US since the mid 1990s due to the development of scoring-techniques. She shows that risk premia increased, spreads between high- and low-risk borrowers widened, and more high-risk households got access to credit in response. Other studies confirm that risk-based pricing and screening can improve access to credit, especially for riskier market segments at higher costs (Berger, Frame, and Miller, 2005; Magri and Pico, 2011; Walke, Fullerton Jr, and Tokle, 2018). Strahan (1999) shows that riskier borrowers pay higher rates and face worse loan terms. He also documents that banks use other loan terms than just the price and quantity, such as collateral requirements or maturities, to deal with risky borrowers. Furthermore, several authors provide evidence of the importance of the degree of asymmetric information between the bank and the borrower for the pricing decision of banks (Cerqueiro, Degryse, and Ongena, 2011; Gambacorta and Mistrulli, 2014). Einav, Jenkins, and Levin (2012) and Einav, Jenkins, and Levin (2013) demonstrate how lenders in the market for auto loans were able to increase profits through risk-based pricing. Our primary contribution to this literature is to document how competition affect banks' risk-pricing.

As such, our paper also relates to the broader literature on the nexus between competition and financial fragility. A large theoretical and empirical literature argues that competition, by decreasing bank franchise value, increases financial fragility by inducing banks to take more risk (Keeley, 1990; Besanko and Thakor, 1993; Suarez, 1994; Matutes and Vives, 2000; Hellmann et al., 2000; Repullo, 2004). Consistent with this view, Beck, Demirgüç-Kunt, and Levine (2006) document that across a broad range of countries, financial crises tend to occur more frequently in concentrated banking sectors. On the other hand, Boyd and De Nicolo (2005) and Boyd et al. (2006) argues theoretically and empirically that higher competition can - by lowering interest rates - induce borrower to self-select into having lower default risk, thereby potentially reducing financial fragility. Martinez-Miera and Repullo (2010) builds on this, and shows that the link between competition and fragility can be non-monotone. Our finding provides a novel channel through which competition can affect financial fragility. Importantly, the channel operate primarily through banks with low franchise values.

2 Description of the data, sample, and main variables

2.1 The data

We use data from three different sources for the period from 2012 to 2019. Our main source is a relationship-level supervisory dataset containing information on all firm-bank relationships in Norway within a given year. The data includes credit risk exposures to corporates which are totalled over one year, a borrower-specific probability of default (PD) that is estimated by the bank, and a borrower-specific interest rate. The reported total credit risk exposure includes credit lines (drawn as well as the total credit limit) and guarantees and might sum-up several loans given to the same borrower within a year. The interest rate then should be interpreted as an average rate for all credit products. The PD captures the banks' own assessment of the probability of default of the borrower, conditional on their information set which may include both hard information and soft information. In Subsection 2.3, we provide additional tests regarding the information content of the variable *PD*.

The second data source is supervisory data on the bank balance sheets and income statements of Norwegian banks. The third data source is a firm-level dataset from a credit rating agency (Bisnode), containing information on balance sheet and income statement items, in addition to a firm-specific credit rating and location. As we discuss in the following subsection, this data is on average only available for larger corporations - effectively ensuring that we restrict attention to limited liability companies.[3] We use the firm location to construct regional banking markets.

2.2 The sample

In the regressions, we restrict our attention to the first year a firm-bank relationship is observed to avoid double counting of persisting pricing decisions and to exclude changes in borrower quality driven by moral hazard, i.e. increased ex-post risk taking. The merged data then includes roughly 755k observations on a relationship-year level for the period 2012 to 2019. However, we use the full data including the pre-existing relationships to construct proxies for competition, such as market shares and number of competitors across different markets.

In the main analysis, the sample is further reduced due to data availability. First, there is no reporting threshold, implying that exposures are reported for very small firms and sole-proprietorships, as well as large corporations. Given that the firm data we merge is only for limited liability firms, we miss firm information on 57% of observations. Note, however, that this only corresponds to 22% of total new credit volume. These missing observations are typically small exposures and the reported interest rates do not differ much between borrowers with and without information. Reported PDs are on average higher for borrowers with missing information. Therefore, by restricting us to firms with available accounting information, we sample on average larger exposures to larger firms which are on average less likely to default.

Second, banks report interest rates and PDs only on a subset of around 18% of observations. These missing reporting details occur for exposures of various sizes and characteristics.

With these two restrictions in mind, our final sample includes 125,399 observations, i.e. about 17k bank-borrower relationships per year. The final sample covers on average about 30% of total newly formed credit exposures. Further, smaller deviations from this sample appear in the estimations due to missing covariates. We report detailed summary statistics on the variables we use in Table 1.

[3] Limited liability companies account for roughly 95 % of total private sector employment throughout most of the years in our sample.

Table 1: Summary statistics of variables.

	(1) N	(2) Mean	(3) SD	(4) Min	(5) p(5)	(6) p(50)	(7) p(95)	(8) Max
Dependent variable								
Interest Rate	106,910	5.15	2.48	-23.24	2.14	4.85	9.15	29.98
Variable of interest at the bank-firm-level								
PD	106,910	3.19	8.43	0	0.15	1.19	10.94	100
Bank-firm-level controls								
Collateralized	106,910	0.46	0.50	0.00	0.00	0.00	1.00	1.00
Loan-Assets Ratio	106,910	34.45	43.50	0.00	0.13	18.60	101.46	295.78
Log(Loan Amount)	106,910	-0.61	2.16	-20.72	-3.84	-0.85	2.99	8.59
Firm-level controls								
A-Rating	99,764	0.67	0.47	0.00	0.00	1.00	1.00	1.00
B-Rating	99,764	0.16	0.37	0.00	0.00	0.00	1.00	1.00
C-Rating	99,764	0.03	0.16	0.00	0.00	0.00	0.00	1.00
Fixed Assets Ratio	99,764	43.77	34.23	0.00	0.12	37.10	98.00	99.94
Intangible Assets Ratio	99,764	2.23	6.67	0.00	0.00	0.00	13.27	45.24
Debt Ratio	99,764	80.96	44.80	3.50	29.88	78.40	132.85	500.00
ROA	99,764	4.02	24.42	-132.89	-34.14	4.54	37.71	76.38
Firm Age	99,764	10.86	12.70	0.00	0.00	7.00	32.00	167
Log(Assets)	99,764	8.54	1.79	0.00	5.91	8.43	11.70	20.49
Market-level controls - municipalities								
Log(Total Credit)	1,597	6.90	1.62	2.05	4.57	6.80	9.61	13.20
Bank-level controls								
CIR	372	58.99	13.37	2.41	44.22	57.37	76.06	205.05
Deposit Ratio	372	64.03	14.99	0.00	29.99	67.01	78.73	86.64
Equity Ratio	372	10.59	2.54	0.45	7.69	10.41	14.14	23.66
Liquidity Ratio	372	6.10	4.34	0.06	2.09	5.23	14.95	30.37
LLP Ratio	372	0.17	0.24	-0.28	-0.03	0.11	0.56	1.38
NIM	372	2.00	0.77	0.92	1.41	1.89	2.71	7.42
ROE	372	12.45	15.52	-9.98	5.61	10.42	16.32	137.37
Log(Assets)	372	15.95	1.44	13.34	14.26	15.53	18.68	21.74
Assets (in mil. NOK)	372	61.63	325.67	0.56	1.45	5.45	130.09	2777.26

Notes: The table shows the number of observations (column 1), mean (column 2), standard deviation (column 3), minimum (column 4), 5th percentile (column 5), median (column 6), 95th percentile (column 7), and maximum (column 8) of the indicated variable. The variables *Loan-Assets Ratio*, *Fixed Assets Ratio*, *Intangible Assets Ratio*, *Debt Ratio*, and *ROA* are winsorized at the 1st and 99th percentile to avoid outliers to influence our results. There are two observations with negative interest rates to which our results are not sensitive. A PD of 100 is reported upon default of a borrower. *Collateralized* is a dummy equal to one if the collateral value fully covers (100 percent or more) the exposure value. We provide further summary statistics on *PD* and *Interest Rate* within each rating class in Table C1 in the Appendix.

Banks In Norway, 128 banks were operating between 2012 and 2019 of which we have 114 banks in our sample. The remaining 14 banks are small and drop out as they do not report PDs. Norway's banking market is concentrated (for a detailed description see Norges Bank (2020)). The top 2

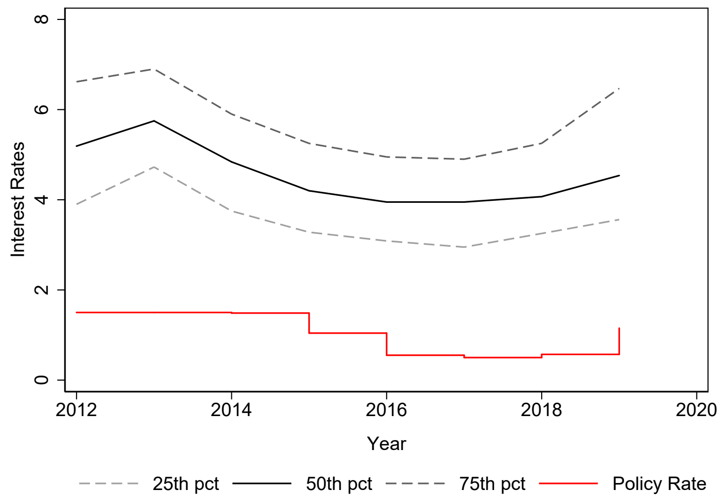


Figure 1: Median interest rate and policy rate over time.

Notes: The upper lines shows the evolution of median interest rates (solid) and its interquartile range (dashed) over the observation period. The lower line shows the Norwegian policy rate (red) which is calculated as the daily weighted average for each year.

banks (DNB and Nordea) account for 44 percent of lending in the corporate market and the top 10 banks account for over 42 percent of the observations in our sample. Most of the remaining banks are small, regionally focused savings banks. The differences between banks are reflected in the standard deviation in total asset size of banks which is reported in the last row of the lowest panel in Table 1.

Firms There are 81,663 firms in our sample. We have credit ratings for 84 percent of these firms. According to NACE industry classification codes, banks lend to a variety of different firms. The most represented industries, in which we observe 60 percent of firms, are construction, wholesale and retail, as well as real estate. However, average exposures to construction or wholesale and retail firms are below the sample average while exposures to real estate firms, agriculture, mining, and facilities are on average much larger. A particular outlier in this respect is the oil industry. While the average exposure to borrowers is about 7 mil. NOK,[4]. exposures to firms in the oil industry are on average 123 mil. NOK, 17 times as high, although there are only about 150 oil firms in our sample. Our data covers SMEs as well as large Norwegian corporations. The average (median) firm in our sample has 82k NOK (4k NOK) in total assets.

Bank-borrower relationships We observe 106,910 new credit relationships, where 24 percent of borrowers have relationships with more than one bank. The average (median) loan volume is 7 mil NOK (421k NOK). Collateral is reported on 85 percent of credit relationships and we observe that almost half of the lending is fully collateralized. We observe 4,204 defaults of those newly created

[4] 1 USD $\approx$ 9 NOK, december 2021

credit relationships during our sample period which translates into a default rate of 3.96 percent. PDs vary from 0 to 100, where loans with a PD of 100 captures loan that are in default. Most interest rates range between 2 and 9 percent with an average of 5.13 percent during our sample period. This corresponds to an average mark-up above the policy rate of around 4 percent. Figure 1 shows the evolution of lending rates and the reference policy rate over the years of our sample.

Markets and regions Administratively, Norway (at the end of our sample) is divided into 20 counties ("fylker"). The counties are divided into 357 smaller municipalities ("kommuner"). We use firms' location to define regional banking markets. Our analysis uses municipalities as the level for observing banking competition. We provide details and robustness on this choice in Appendix A. Credit relationships in the five largest cities account for roughly 24 percent of observations. Exposures in urban centres are characterised by on average larger loan amounts (on average 13.6mil NOK vs 5mil NOK) due to the presence of larger firms.

2.3 Measuring default risk and private information with PD

In the following, we address two questions regarding the information content of the *PD*. First, we ask whether the PD estimates capture actual default risk. To test this, we use banks' PDs to predict defaults in our data. Second, we ask whether banks incorporate soft or private information about the borrower in these estimates. From the description of the variable, we assume that banks incorporate such private information in the reported *PD*. Yet, we are still dealing with a regulatory reporting which might give banks incentives to not fully disclose these proprietary information about the borrower. In addition, the estimated PDs are subject to regulatory requirements and guidelines from Financial Supervisory Authority of Norway (Finanstilsynet). According to the capital requirement framework, PDs for retail and corporate exposures may never be set below 0.03 percent. Moreover, PDs should preferably be based on data encompassing at least an entire business cycle. In Norway, PD calculations are required to be based on data that include the banking crisis of the early 1990s. Banks must increase PD estimates by a margin of conservatism, reflecting the expected range of estimation errors. The margin of conservatism must be larger if the data set and estimation methods are not satisfactory. Hence, the reported PDs may not fully reflect the banks' internal risk assessment. To judge this, we compare a model based on purely publicly available information and the model using *PD* and study the increment in explanatory power through the addition of *PD*.

To answer the first question, whether *PD* captures actual default risk, we regress *PD* on observed defaults. We observe $4,543$ defaults[5] which corresponds to a default rate of 3.62 percent of new bank-borrower relationships in the sample. We use a linear probability model in which we include a set of loan-level and firm-level variables that potentially impact default risk as well as fixed effects at the bank-market-year level. We follow the same specification and include the same variables that

[5] We count a default if the bank reports a PD of 100 for the borrower in the year of initiating the credit relationship or in the following years until the end of our sample.

we use and describe in detail in Section 3. In the Appendix in Table C2, we show that the *PD* is a significant predictor of actual default. A one percentage point higher estimated *PD* results in a 0.6 percentage point higher default rate (cf. column 1).[6]

To gain deeper insights into the information content of the variable, we compare the explanatory power of PD and an alternative measure of private information and we study the increment in explanatory power caused by adding PD to a model that is otherwise based on publicly available information.

We can use a model that predicts default solely based on public information. Still, there might be risk factors that are unobservable to the econometrician but not to the bank. The bank then has private information about the borrower. To capture these, we can either use *PD* or the residual from the regression with public information. The residual should contain risk factors which we did not account for with public information, but which can explain default. Hence, *PD* and the residual are both contenders as measures of private information (assuming that we used all relevant public information). To assess the relevance of private information in pricing, we follow Crawford, Pavanini, and Schivardi (2018) and look at borrowers that deal with several banks. This approach allows to introduce borrower fixed effects which absorb any information that both lenders might know but usually cannot be seen by the econometrician, i.e. if banks do not report the *PD* that we have in our data.

Our results in Table C2 in the Appendix show that the residuals are significant predictors of default as well as *PD*. However, when we study the contribution this unknown predictor has on explaining defaults we find it to be relatively low compared to PD.[7] Further, in line with the interpretation that *PD* is capturing private information that is contained in borrower fixed effects, the estimated effect and explanatory power of *PD* is smaller when we include borrower or borrower-year fixed effects, yet still significant. Differences in PD estimated by two (or more) banks for the same borrower still account for a significant difference in pricing and prediction of default, implying that default-relevant information varies between banks, even for the same borrower.

Overall, we are therefore confident that the PD captures relevant risks and reflects banks' private information.

2.4 Measures of competition

We assume a bank operates in a region if we observe that the bank has exposures to firms in that region. We chose municipalities as the delineation of a local market. This leaves us with ample variation in different measures of competition. More importantly, there is a strong relationship between interest rates and competition measures at the municipal level.

[6] A perfect prediction would imply a $1:1$ relationship between the two variables.

[7] First, while a change of one SD (8.39) in *PD* predicts a 5.15 percent higher default rate, a change of one SD (1.76) in the residual is associated with only a 0.33 percent higher chance of default. Second, while adding *PD* to the set of variables explaining defaults raises the explanatory power of the model (R^2 as well as R^2-within) by about 5 percent, adding the residual does not result in a sizeable increase of explanatory power (naught for R^2, 0.1 percent for R^2-within).

Table 2: Summary statistics of regional banking markets.

	(1) Obs	(2) Mean	(3) SD	(4) min	(5) Median	(6) max
Number of Banks	2,856	13.51	10.03	1	11	113
HHI	2,856	0.38	0.17	0.11	0.34	1
Number of Entrants	2,856	1.19	1.57	0	1	13
L(Total Credit)	2,856	6.45	1.78	1.32	6.36	13.2

Notes: The table shows summary statistics of *Number of banks*, *HHI*, *Number of entrants*, and *L(Total Credit)* at the municipality-level (kommuner) of which there are 357 in Norway.

In Table 2 we show the summary statistics of competition measures at the municipal level. The competition measures are calculated based on the credit exposure data. For this purpose we include also existing exposures, i.e. we do not only focus on newly created loans.

The first measure we report is the number of competitors within a municipality. On average, 14 banks operate within a municipality in any given year. Most competition is centred in Oslo where we observe a maximum of 113 banks. In some municipalities, banks have a monopoly, while almost half of the municipal banking markets are characterized by oligopolistic structures with two to 11 banks competing. In the analysis, we use a logarithmic transformation in order to include the variable in an approximately more normally distributed representation.

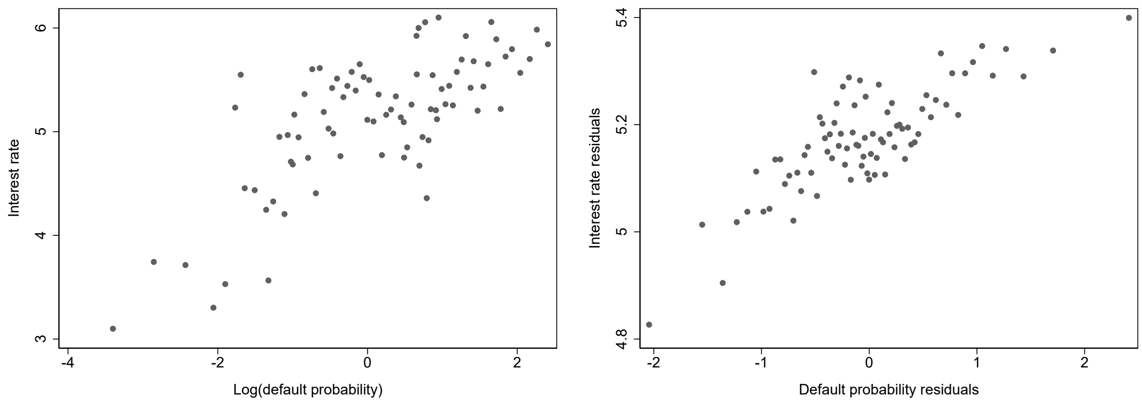
The second measure that we report are Hirschman-Herfindahl Indices. We calculate the HHI as the sum of squared market shares of all banks operating in a municipality. These indices capture market concentration. A high HHI indicates a concentrated market whereas a low HHI signal a more competitive environment. In Figure B1 in the appendix, we plot average prices against municipal HHI and number of competitors. We observe a positive relationship between market concentration and price (left panel) and a negative relationship between the number of competitors and prices (right panel), at least for markets with less than 40 competitors.[8]

A known critique of HHIs is that they do not measure contestability of the market. Hence, a highly concentrated market could still be very competitive in the sense that incumbents have to constantly defend their position against the threat of entry. Therefore, as a third measure of competition, we also look at market entries. That is, for each year we record whether any bank enter a local credit market. In most of the analysis using this as a measure of competition, we focus on the risk-pricing on incumbent banks.

3 Risk-based pricing

Before analyzing the impact of competition on risk-based pricing, we establish a broad stylized fact, namely that bank interest rates respond to the bank's own assessment of PD. This holds despite holding a wide range of other factors fixed including the credit rating.

[8]Estimations confirm these graphical results. Results are available upon request.



(a) Unconditional relation. (b) Residualized relation.

Figure 2: Conditional and unconditional relation between L(PD) and Interest Rate.

Notes: The points represent average interest rates and average default probabilities (PDs) of observations within percentiles of the depicted range of default probability. PD is in logarithms. The left panel shows the relationship as it appears in the data of our sample. The right panel shows the relation of the residuals of L(PD) and Interest Rate after orthogonalizing with the controls as in eq 1 and bank, year, and market fixed effects.

Risk-based pricing implies that banks set higher interest rates for borrowers with higher default risk. Empirically, we say that banks' interest-rates are risk-based if the interest rate is an increasing function of the PD. In the left panel of figure 2, we show the relation between PD and interest rate is increasing in our sample and approximately linear when we take the logarithm of PD.[9] The underlying correlation between *Log(PD)* and *Interest Rate* is 0.28, i.e. a one percent increase in PD is associated with on average 28 basis points higher interest rates. However, this relationship is unconditional and averaged over all observations. To properly ensure that we capture the relationship between the interest rate and borrower risk and not a third, unobserved, confounding factor, we proceed by investigating the relationship between Log(PD) and the interest rate, conditional on several control variables.

The set of control variables are aimed at alleviating four potentially confounding factors. First, banks manage credit risk by adjusting other loan terms than the interest rate. The use of collateral could dampen concerns of high default risk. Further, the bank could limit its exposure by extending smaller loans to riskier borrowers. We therefore control the size of a loan relative to other loans and relative to the borrower's size and whether the loan is fully covered by collateral or not or only partially.

Second, other aspects of the borrowing firm might be relevant for the interest rate as well as impact the PD estimate. Even if not pledged contractually, the firm's potential to provide collateral in form of fixed assets can be considered by a bank. Bargaining power might help to negotiate

[9] We take the logarithm because many observations center around small values of PD (90 percent of observations are below 11, 75 percent below 3) leading to a skewed distribution. As can be seen in figure C1 in the appendix, the relationship is steeper for small values of PD and flattens for higher values. These non-linearities do not appear in the logarithm of PD.

favourable terms. Overall financial strength, solid liquidity management, and reliable business models might indicate low credit risk. We attempt to capture these aspects by controlling for the share of fixed to total assets, the share of intangible assets, firm size and firm age, debt-to-equity ratio, and return-on-assets ratio. We further include the firms' rating which should capture credit risk as well as some of the above factors.[10] In doing so, we ensure that the estimated effect of PD reflects the non-public information that banks have about borrowers. We use use three dummy variables to control for rating which indicate whether the firm has received an A, B, or C rating, respectively. About 16 percent of firms in our sample do not have a public rating. These comprise the benchmark category. Furthermore, to address the differences in pricing strategies across industries, we control for the industry of the firm by introducing industry dummies based on NACE codes.

Third, the financial situation, product and funding costs of the lender could impact its pricing strategy. Therefore, we control for bank's financial ratios[11] and its size. We can further absorb any constant bank-specific pricing component by using bank fixed effects. In our baseline, we include bank×year fixed effects, so that we can abstract from any bank-specific components and focus on regional and/or borrower-specific differences in pricing within each banking institution.

Lastly, local macroeconomic conditions and economy-wide economic factors, such as the reference rate, can have an influence on rate setting. We filter out common macroeconomic factors by including year fixed effects as well as a region fixed effect or even region×year fixed effects. We complement this by controlling for the average market size measured as the logarithm of total credit exposure in a region when fixed effects are not included. We focus on municipalities as a the unit of geographical delineation.

The equation we estimate is given by (1).

$$Rate_{bfy} = Log(PD_{bfy}) + X_{bfy}^{Loan} + X_{fy}^{Firm} + X_{by}^{Bank} + X_{my}^{Market} + \delta_{b/f/i/m/y} + \epsilon_{bfy} \tag{1}$$

which can include different sets of fixed effects (δ) and of the aforementioned control variables (X) as long as they are not absorbed by fixed effects. The results are shown in Table 3.

First, in column 1 of Table 3 we see that abstracting from time-invarying bank- and market conditions (by including $\delta_b + \delta_m + \delta_y$), on average there is a positive relationship between banks' PD estimate and the interest rate within any year. A one percent higher default probability estimate leads to an on average 16 basis points higher interest rate for the borrower. In column 2 we interact the fixed effects such that we are estimating now within bank-market-years (δ_{bmy}), while in in column 3 we additionally control for confounding effects as described above (i.e. with $X_{bfy}^{Loan} + X_{fy}^{Firm}$). We see that this is important as the coefficient on Log(PD) is slightly lower (13 basis points) when estimating among more comparable loan terms and borrowers. This is the baseline specification which we use in the remainder of our analysis. We show here that there is on average a robust positive significant relationship between borrowers' default risk and the interest rate, which holds within

[10] Our results are robust to excluding *Rating* as a control but it seems a relevant pricing factor and furthermore is not strongly correlated to *PD* due to its discrete nature.

[11] Specifically, cost-income ratio, deposits-to-assets, equity ratio, liquidity ratio, net-interest-income ratio, return-on-equity, and loan loss provisions ratio.

Table 3: Robust correlation between PD and interest rates with gradual fixed effects saturation.

Fixed Effects	(1) B M Y	(2) BMY	(3) BMY	(4) B MY
Log(PD)	0.161***	0.176***	0.129***	0.122***
	(0.036)	(0.035)	(0.029)	(0.028)
Loan-level controls				
Collateralized			-0.170***	-0.125*
			(0.064)	(0.072)
Loan/Assets			0.002**	0.001*
			(0.001)	(0.001)
Log(Loan)			-0.479***	-0.485***
			(0.050)	(0.049)
Firm-level controls				
A-Rated			0.013	0.028
			(0.058)	(0.054)
B-Rated			0.153**	0.161***
			(0.062)	(0.057)
C-Rated			0.307***	0.310***
			(0.114)	(0.111)
Fixed Asset Ratio			-0.003	-0.002
			(0.002)	(0.002)
Intangibles Ratio			0.006***	0.006***
			(0.002)	(0.001)
Debt Ratio			0.002***	0.002***
			(0.000)	(0.000)
ROA			-0.001*	-0.001
			(0.001)	(0.001)
Age			0.002	0.002
			(0.001)	(0.001)
Log(Assets)			0.089	0.087
			(0.074)	(0.071)
Industry Dummies	Yes	Yes	Yes	Yes
Bank-level Controls	No	No	No	Yes
Observations	124,759	120,842	106,349	108,341
R2	0.185	0.301	0.388	0.342
R2-within	0.006	0.007	0.134	0.144

Notes: Clustered standard errors at the bank-level in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Market fixed effects are defined at the municipal level. In the first column, we include bank fixed effects, market fixed effects, and year fixed effects. In columns 2 and 3, we interact these and include bank-market-year fixed effects. In column 4, we use bank fixed effects and market-year fixed effects. We add bank-level controls which comprise CIR, deposit ratio, equity ratio, liquidity ratio, LLP ratio, NIM, ROE, and log(assets). Fixed effects are interacted and defined at the bank- (B), market- (M), and year- (Y) level.

Table 4: Interaction of bank-specific price determinants and risk-sensitivity.

Bank Variable:	(1) Deposit Ratio	(2) Liquidity Ratio	(3) LLP Ratio	(4) NIM	(5) Equity Ratio
Log(PD)	0.011	0.181***	0.160***	0.236***	0.177***
	(0.037)	(0.050)	(0.030)	(0.073)	(0.060)
Log(PD) x Bank Var	0.004***	-0.005**	-0.125***	-0.048*	-0.005
	(0.001)	(0.002)	(0.046)	(0.026)	(0.006)
Effect of 1 SD of *Bank Var*	0.060	-0.023	-0.030	-0.037	-0.013
Controls	L,F,I	L,F,I	L,F,I	L,F,I	L,F,I
Fixed Effects	BMY	BMY	BMY	BMY	BMY
Observations	106,349	105,277	105,277	105,277	105,277
R2-within	0.136	0.138	0.138	0.139	0.138

Notes: Clustered standard errors at the bank-level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is *Interest Rate*. The columns define the bank variable that is used in the interaction. We include loan-level and firm-level covariates as well as industry dummies and bank-market-year fixed effects as in the baseline specification (same as in Table 3 column 3).

banks in any regional market independent of the regional and national macroeconomic conditions or the industry. Further, this correlation holds independent of other borrower and loan characteristics. For example, higher PDs increase the interest rate for firms of comparable size and with comparable collateral (and the same rating category) in the same industry and in the same market receiving a loan from the same bank.

In column 4, we show that on average riskier loans are priced higher across banks within regional banking markets in any given year. Column 4 shows the estimate for regional and industry-specific banking markets is almost the same.

As we have argued above, some firm- and loan characteristic also determine the riskiness of an exposure. Risk-based pricing can also be derived from the estimated coefficient on the rating class dummies. A B-Rating is associated with on average 15.3 basis points higher interest rates, a C-rating even with an additional 30.7 basis points. Exposures which are 100 percent collateralized or more have lower rates. A one standard deviation increase in the loan-to-assets-ratio translates into a 8.6 basis points higher lending rate. We find that larger exposures are relatively cheaper. An increase in loan size by one percent, decreases lending rates on average by 47.9 basis points. With respect to firm characteristics, we see that companies with higher intangible asset ratios and higher debt ratios have to pay on average 0.6 and 0.2 basis points more respectively, while firms with higher return on assets pay on average 0.1 basis points less. The other coefficients are insignificant in our baseline specification although their signs are as expected.

We take a closer look at the interaction of bank-specific price determinants and the risk sensitivity of prices in Table 4. First, as shown in column (1) of Table 4, we find that banks with higher deposit ratios display on average more risk sensitive pricing. Second, we find that banks with weaker liquidity ratios (column 2), lower provisions (column 3), and lower net interest margins (column 4) show more sensitive pricing patterns. When losses accrue these banks would have less buffers and hence it would be desirable for them to have an income stream which is more closely matched to its risk position. Yet, we cannot find a statistically significant interaction for equity ratios.

Because these variables operate on different scales, we compare their effects on risk-sensitive pricing in terms of a one standard deviation change in the variable. We see that the effect of a 1 standard deviation higher deposit ratio is strongest elevating prices by about 6 basis points (for a constant PD) while the other heterogeneities among banks amount to around 2 to 4 basis point differences in prices.

All in all, the results in this section suggests that borrower risk - conditional on a large set of bank, borrower, regional and macroeconomic controls - significantly affect the pricing of loans. In the next section, we turn to the main question of the paper, namely whether the degree of risk-pricing is affected by the competitive setting.

4 Competitive risk-based pricing

As we showed in the previous section, borrower risk is a significant ingredient for the pricing of loans. In this section, we turn to the main question of the paper, namely whether risk-pricing is affected by competition. Shedding light on this is interesting in terms of understanding the determinants of credit spreads in itself, but it can also provide micro-evidence on the potential underlying channels of the competition-fragility view.

4.1 Methodology

To study whether competition affects the sensitivity of interest rates to risk, we estimate the following equation:

$$Rate_{bfy} = \beta Log(PD_{bfy}) + \gamma Comp_{my} + \eta Log(PD_{bfy}) \times Comp_{my} + X_{bfy}^{Loan} + X_{fy}^{Firm} + \delta_{bmy} + \epsilon_{bfy} \quad (2)$$

By introducing the interaction term (*Log(PD)*$\times$*Comp*) we assess whether the slope between risk and price (β) depends on the degree of competition in the market ($\beta + \eta$), as captured by $Comp_{my}$. To interpret our estimates as capturing the causal impact of competition on risk-pricing, there are several potential threats to identification we need to address.

The first threat to identification is that it is inherently hard to measure the degree of competition intensity. Such measurement challenges imply that our estimates may be affected by measurement error, something that most likely attenuates any estimated impact of competition on risk-pricing. While attenuation would imply that our potential estimates are if anything larger, they can lead us to falsely fail to reject the null hypothesis. To deal with this issue, we adopt several approaches.

First, we use two conventional measures of competition, namely market concentration as captured by HHI and the (log) number of competitors. Second, we complement our analysis by investigating how risk-pricing by incumbent banks is affected by new banks entering their regional market. Specifically, we estimate the following

$$Rate_{bfy} = \beta Log(PD_{bfy}) + \eta Log(PD_{bfy}) \times PostEntry_{my} + X^{Loan}_{bfy} + X^{Firm}_{fy} + \delta_{bimy} + \epsilon_{bfy} \quad (3)$$

for the sample of incumbent banks in a municipality m, where *PostEntry* is a dummy variable which is defined yearly for each regional market and equals one in any year when a new bank entered the regional market and zero in the years before an entry occurs.

To the extent that we pick up qualitatively similar patterns across all these measures, we can be reasonably sure that we have (1) identified measures that captures competition and (2) that attenuation bias is not too severe.

A second key threat to identification is that banks with different risk-management practices chose different competitive environments. If banks with a less risk-sensitive interest rate schedule select into markets where competition is high, this would lead us to estimate a negative impact of competition on risk-pricing which we may falsely interpret as the causal effect of competition on risk-pricing.

To deal with this issue, we exploit the following two institutional details: First, the risk appetite of a bank is most likely set at the top-level of the bank. Second, banks are present in multiple geographical areas. This allows us to exploit *within-bank*×*year* variation in competition. Given that risk-appetite is set at the top-level, this allows us to hold variations in risk-appetites fixed. Specifically, to implement this strategy, we saturate our estimated regressions with bank × year fixed effects.

4.2 Results

The results are reported in upper two panels of Table 5. The coefficient of the interaction with HHI in column 1 is positive and significant which means that prices are more sensitive to risk in more highly concentrated regional markets. Correspondingly, the coefficient on the interaction with *L(N Competitors)* is negative and significant indicating that prices are more risk sensitive in markets with fewer competitors.[12] In the bottom panel, we use an event-study design detailed in eq. 3 to investigate how risk-pricing for market incumbents potentially change when a new competitor enters the market. We include bank-firm level and firm-level controls as in the baseline estimation as well as bank-market-year fixed effects. The results are reported in the lower panel of Table 5. We estimate that incumbent banks reduce the risk-sensitivity by almost 42% in reaction to a new competitor.

[12]We show in Table B2 in the Appendix that these results still hold at the level of banking markets which are defined as economic regions and starts to dissolve when banking markets of the size of counties are studies.

Table 5: Competitive risk-based pricing.

	(1) All Firms	(2) B/C Rated	(3) A Rated	(4) SMEs	(5) Large Firms
Log(PD)	0.077**	0.063*	0.085***	0.089**	0.087***
	(0.030)	(0.034)	(0.031)	(0.043)	(0.026)
HHI	0.074	-0.227	0.095**	-0.018	0.184**
	(0.053)	(0.152)	(0.048)	(0.099)	(0.083)
Log(PD) x HHI	0.132***	0.172***	0.077	0.173**	0.071*
	(0.043)	(0.058)	(0.052)	(0.073)	(0.038)
Loan-,Firm-, Ind.-Controls	Yes	Yes	Yes	Yes	Yes
Bank-Market-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	106,349	17,682	70,874	45,026	58,723
R2-within	0.134	0.122	0.135	0.103	0.135
Log(PD)	0.279***	0.287***	0.197**	0.356***	0.154**
	(0.078)	(0.072)	(0.099)	(0.111)	(0.064)
Log(PD) x Log(N Comp)	-0.046**	-0.047**	-0.025	-0.062**	-0.012
	(0.018)	(0.018)	(0.023)	(0.030)	(0.014)
Loan-,Firm-, Ind.-Controls	Yes	Yes	Yes	Yes	Yes
Bank-Market-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	106,349	17,682	70,874	45,026	58,723
R2-within	0.134	0.122	0.135	0.103	0.135
Log(PD)	0.201***	0.233***	0.177***	0.240***	0.170***
	(0.043)	(0.045)	(0.055)	(0.046)	(0.049)
Log(PD) x Post Entry	-0.084**	-0.121**	-0.075	-0.083*	-0.071
	(0.039)	(0.049)	(0.048)	(0.042)	(0.045)
Loan-,Firm-, Ind.-Controls	Yes	Yes	Yes	Yes	Yes
Bank-Market-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	87,667	14,957	56,946	38,272	47,496
R2-within	0.135	0.127	0.134	0.105	0.135

Notes: Clustered standard errors at the bank-level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is *Interest Rate*. The columns define the sample of firms on which estimation is based. Competition variables are defined at the municipality-level. The upper two panels show results from estimating eq. 2 where in the upper panel *HHI* is used as the competition variable and in the middle panel *Log(N Competitors* is used. The lower panel shows results from estimation eq. 3 on the sample of incumbent banks. *Post-Entry* is a dummy which is equal to one in the years where banks entered a particular municipality and equal to zero in the years before those entries. All estimations include loan-level and firm-level controls, industry dummies, and bank-market-year fixed effects.

Across all competition measures, our results are driven by more opaque borrowers where rents to information are potentially higher. Although this is not directly measurable, we follow two approaches to proxy for it. First, we assume that soft information is more relevant in the case of high-risk borrowers and that market power might be more effectively used against high-risk firms as these might find it harder to switch to a different bank. We show in column 3 that the interaction is insignificant for low-risk loans, those with an A-rating, while the estimate in column 2 illustrates that especially interest rates of high-risk exposures show higher risk-sensitivity in less competitive banking markets. Second, we estimate the relationship separately for small and medium sized firms (SMEs) (column 4) and large firms (column 5), as we expect SMEs to both be more opaque and to have lower bargaining power. Our findings confirm that banks' own PD estimates are insignificant for large firms but highly significant for SMEs, consistent with banks being more able to exert market power in response to a change in the competitive setting on SMEs compared to larger clients. While bank lending tend to be the only source of external funding for SMEs, larger firms have access to bond funding. If banks raise lending margins, large clients may prefer bond funding.

4.3 Mechanism

Why does an increase in competition leads to a weaker relationship between risk and interest rates? We consider two, complementary mechanisms.

The first potential mechanism focuses on how competition erodes bank franchise values and therefore lead banks to be less risk-sensitive. To investigate whether this is driving the results, we proxy bank franchise values using intermediation margins (Repullo, 2004) and equity to total assets (Demsetz et al., 1996). Finally, we also compare differences according to bank size as a third proxy.

We present the results for the subsample analysis in Table 6. The results are mainly driven by the banks with low equity ratios and low NIM. Using the number of competitors as the competition variable (mid panel) or employing the event-study design (lower panel), we document that the effect of increased competition on risk-sensitivity is only significant for banks with below median equity ratios (column 1) and below median net interest margins (column 3) as well as for small banks (column 5). When we use HHI as the competition variable (upper panel), we estimate a significant decrease in risk-sensitivity as competition increases (lower HHI) for all bank types although the point estimates on those banks with lower franchise values are higher. All in all, these results are consistent with a model where there is a positive relationship between risk-based pricing and franchise value, and where competition reduces franchise value.

The second potential mechanism focuses on banks' screening incentives in a setting where there is asymmetric information between banks and firms about default probabilities. Screening incentives may change in response to increased competition (Broecker, 1990). To the extent that higher competition gives banks incentives to reduce costly screening activities, our measure of PD would be less informative about actual bank default and banks would rely less on such information. As a result, it is likely that observed interest rates would be less sensitive to banks' PD estimates.

To investigate whether more competition leads to less informative PDs, we do the following. First, we randomly assign loans into equally large estimation and test samples. We then estimate a linear relationship between observed defaults and banks' own PD estimates, conditional on municipality×bank×industry×year fixed effects for loans in our estimation sample. We then use the same model to predict default rates for the test sample, and compute the mean absolute forecasting

Table 6: Mechanism and Competitive Risk-Based Pricing

	(1) Low Equity	(2) High Equity	(3) Low NIM	(4) High NIM	(5) Small Banks	(6) Large Banks
Log(PD)	0.138***	0.011	0.139***	0.019	0.067	0.114***
	(0.033)	(0.029)	(0.035)	(0.031)	(0.042)	(0.023)
HHI	0.147*	0.007	0.125	0.030	0.038	0.166**
	(0.082)	(0.069)	(0.085)	(0.065)	(0.073)	(0.037)
Log(PD) x HHI	0.141*	0.114***	0.141*	0.113***	0.150***	0.112***
	(0.080)	(0.033)	(0.084)	(0.031)	(0.057)	(0.012)
L,F,I Controls	Yes	Yes	Yes	Yes	Yes	Yes
BxMxY FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,752	52,597	53,728	52,621	71,661	34,688
R2-within	0.126	0.171	0.126	0.169	0.157	0.129
Log(PD)	0.436***	0.037	0.435***	0.068	0.302***	0.242**
	(0.091)	(0.068)	(0.092)	(0.104)	(0.102)	(0.054)
Log(PD)xLog(N Comp)	-0.075***	0.005	-0.074***	-0.002	-0.055**	-0.025
	(0.022)	(0.017)	(0.022)	(0.025)	(0.024)	(0.019)
L,F,I Controls	Yes	Yes	Yes	Yes	Yes	Yes
BxMxY FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,752	52,597	53,728	52,621	71,661	34,688
R2-within	0.127	0.171	0.127	0.169	0.157	0.129
Log(PD)	0.271***	0.066*	0.257***	0.129	0.217***	0.161***
	(0.048)	(0.037)	(0.045)	(0.084)	(0.051)	(0.025)
Log(PD) x PostEntry	-0.100**	-0.016	-0.081*	-0.080	-0.120**	-0.004
	(0.044)	(0.027)	(0.042)	(0.074)	(0.050)	(0.032)
L,F,I Controls	Yes	Yes	Yes	Yes	Yes	Yes
BxMxY FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	50,320	49,769	50,673	49,416	66,998	33,091
R2-within	0.129	0.169	0.129	0.168	0.159	0.131

Notes: Clustered standard errors at the bank-level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is *Interest Rate*. The columns define the sample of firms on which estimation is based. Competition variables are defined at the municipality-level. The table show results from estimating eq. 2 where in the upper panel *HHI* is used as the competition variable, in the mid panel *L(N Competitors)* is used. The bottom panel focuses on the risk-pricing of incumbents following the entrance of a new competitor in their regional market. All estimations include loan-level and firm-level controls, industry dummies, and bank-market-year fixed effects.

error. We do the exercise for low- and high-competitive samples, where we define high-competitive samples as consisting of municipalities where the HHI is below the sample median, the number of competitors is above the sample median or there is an entry by a competing bank.

The resulting mean absolute errors from the forecasting exercise are shown in Figure 3. While

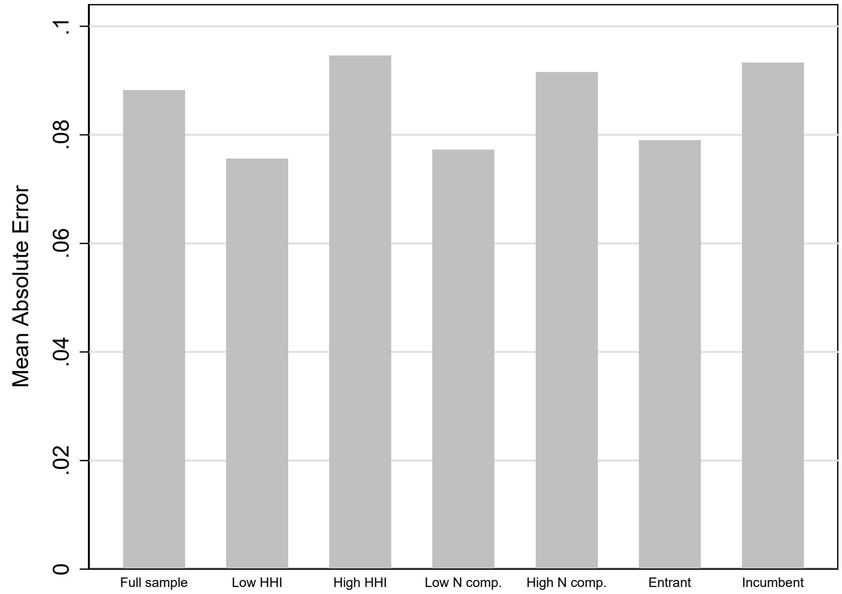


Figure 3: Prediction errors, different subsamples.

Notes: This figure the mean absolute error of a forecasting exercise, where we estimate a model of actual default probabilities as a linear function of observed PDs, in addition to municipality×bank×industry×year fixed effects. We estimate the model on an estimation sample and compute the mean absolute error based on differences in predicted and observed PDs in a test sample. The exercise is done for various samples according to the competitive scenario. "Low HHI" refers to a sample of municipality×years where the loan HHI is below median, "High HHI" refers to a sample of municipality×years where the loan HHI is above the median, "Low N comp." refers to a sample of municipality×years where the number of competitors is below the median, "High N comp." refers to a sample of municipality×years where the number of competitors is above the median, "Entrant" refers to a sample of municipality×years where a new bank enters the market, while "Incumbent" refers to a sample of municipality×years where there is no new bank entering.

we find evidence that the mean absolute error is larger in municipality×years with a relatively high number of competitors compared to municipality×years with a relatively low number of competitors, consistent with the mechanism outlined above, we find an opposite pattern when stratifying municipality×years according to the loan HHI or whether or not a new bank has entered the market. Thus, it is not conclusive in our sample that higher competition leads to less screening and therefore lower informativeness of banks' own PD estimates.[13]

Although other explanations may be important for understanding the findings in Section 4, our results point in the direction of lower franchised values as an explanation for why an increase in competition leads to less risk-pricing.

5 Conclusions

In this paper, we analyse the impact of competition on risk-pricing of credit risk exposures in the Norwegian corporate loan market. The data contains a unique variable about banks' private assessment of borrower risk which allows us to study the use of private information for price setting

[13] We draw similar conclusions if we only include bank PDs in the set of covariates in the estimating regression, i.e. if we drop the fixed effects.

and its determinants. We find that banks use private information in their PD estimates in addition to hard information which is publicly available, such as firm ratings or firm's financial accounts. We provide evidence that banks are more likely to use this information in environments where they have high market power and information asymmetries are more severe. We further show that banks with weaker capitalization or lower profitability tend to set prices with higher risk sensitivity.

Experiences from the Great Financial Crisis demonstrated that banks can neglect risk-adequate pricing under strong competition. Although we do not want to make any claims on the overall welfare effects of an increase in competition in banking markets, our results suggest that supervisors and macroprudential authorities should be particularly vigilant in times with strong competition, as risk could be building up in such situations. Our results further point out that some degree of market power might be beneficial to allow broader pass-through of relevant information to prices. This becomes more relevant in times of uncertainty when public information can be misleading or hard to judge.

Our results are also relevant from a microprudential perspective. Capital regulation aims to provision for unexpected losses and hence implicitly relies on accounting rules and banks' income strategies to provide sufficient funds for expected losses. Risk-adequate pricing is therefore an prerequisite for banks' solvency. Our results suggest that banks - especially weaker banks - make indeed use of risk-adjustment in the pricing credit risks.

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A Defining regional banking market competition

To identify proper regional banking markets in Norway, we can study three different delineations: 20 counties ("fylker", "NUTS3"), 86 economic regions ("NUTS4"), and 357 municipalities ("kommuner"). In Table 2 we show the summary statistics of competition measures at those three regional levels. We assume a bank operates in a region if we observe that the bank has exposures to firms in that region. We do not observe whether the bank operates a branch in the region. On average, 48 banks operate within a county, 26 banks within an economic region, and 14 banks within a municipality in any given year. Most competition is centred in Oslo which is both a county, economic region and municipality. Almost half of the municipal banking markets are marked by oligopolistic structures with one to 11 banks competing. We observe less oligopolistic markets, the broader the definition we use for regional markets.

We calculate Hirschman-Herfindahl Indices (HHI) as the sum of squared market shares of all banks operating in a region. These indices captures market concentration and are reported in the upper panel in columns (4) to (6). A high HHI indicates a concentrated market whereas a low HHI signals a more competitive environment. Markets are on average (and at the median) more concentrated considering counties or economic regions (NUTS4). A known critique of HHIs is that they do not measure contestability of the market. Hence, a highly concentrated market could still be very competitive in the sense that incumbents have to constantly defend their position against

Table B1: Summary statistics of regional banking markets.

	(1)	(2)	(3)	(4)	(5)	(6)
	County	NUTS4	Muni's	County	NUTS4	Muni's
Observations	160	688	2,856	160	688	2,856
		Number of banks			HHI	
Mean	48.18	25.61	13.51	0.26	0.28	0.38
SD	21.11	15.05	10.03	0.11	0.11	0.17
Min	4	4	1	0.14	0.1	0.11
Median	45.5	22	11	0.24	0.27	0.34
Max	113	113	113	0.76	0.76	1
		Number of entrants			Market size (L(Total Credit))	
Mean	3.05	2.03	1.19	10.6	8.8	6.45
SD	2.56	2.13	1.57	1.25	1.18	1.78
Min	0	0	0	6.53	6.53	1.32
Median	3	1	1	10.63	8.57	6.36
Max	11	13	13	13.2	13.2	13.2

Notes: The table shows summary statistics of *Number of banks* (upper left), *HHI* (upper right), *Number of entrants* (lower left), and *L(Total Credit)* (lower right) at three different regional levels. Columns (1) and (4) show statistics based on the county-level (fylker) of which there are 20. Columns (2) and (5) follow the definitions of economic regions (NUTS4) according to Statistics Norway. Columns (3) and (6) use municipalities (kommuner) of which there are 357.

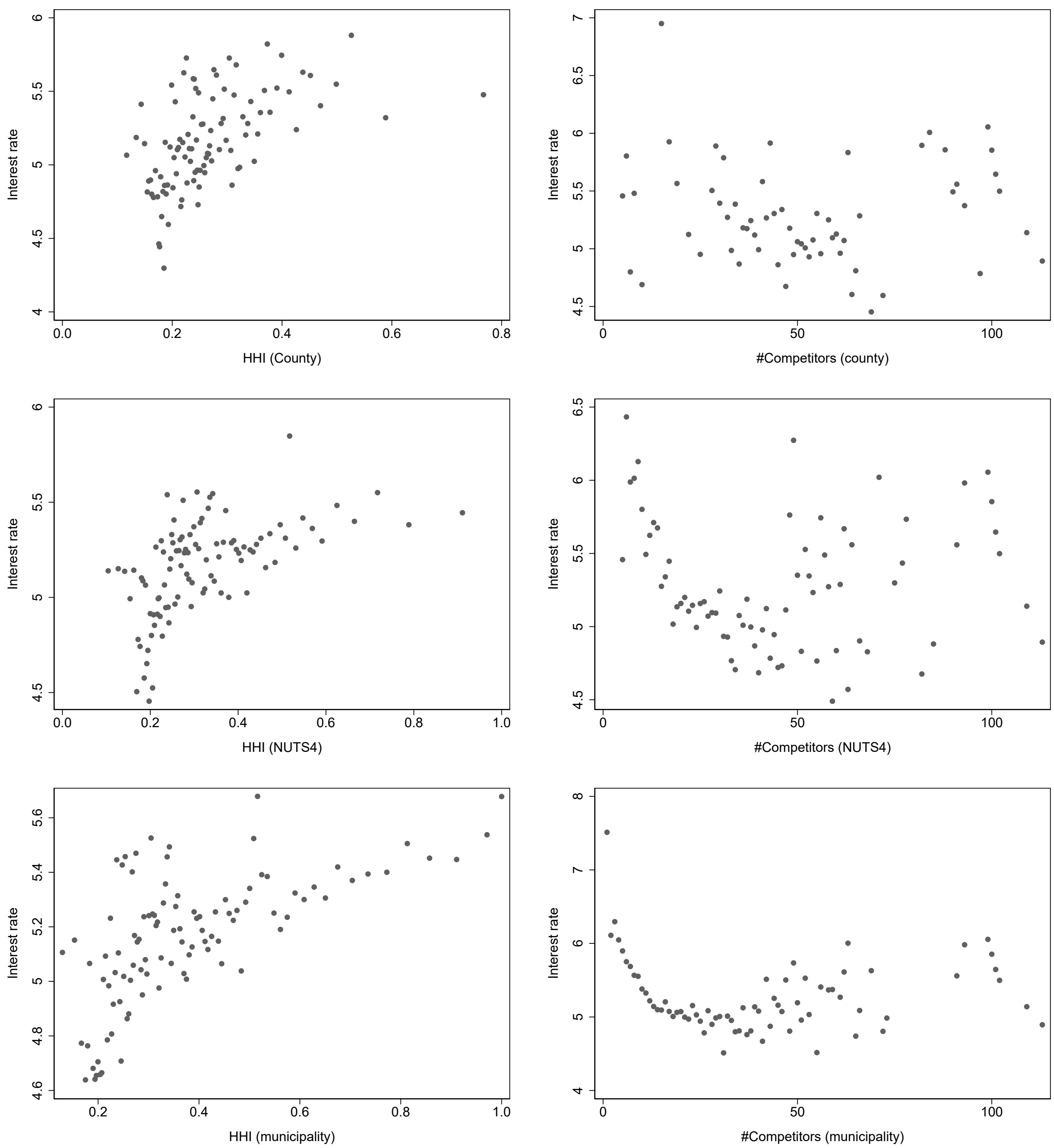


Figure B1: Regional competition and pricing.

Notes: The left panel shows the relationship between regional concentration measured as the Hirschman-Herfindahl Index (HHI) and interest rates. The points represent average interest rates and average HHIs of observations within percentiles of HHI. The right panel shows the relationship between the number of competing banks in a regional market and interest rates. Points represent average interest rates for the discrete number of banks. The upper panel is calculated on the county level (fylke), the middle panel uses NUTS4 regions (economisk regioner), and the lower panel shows results on the municipal level (kommuner).

the threat of entry.

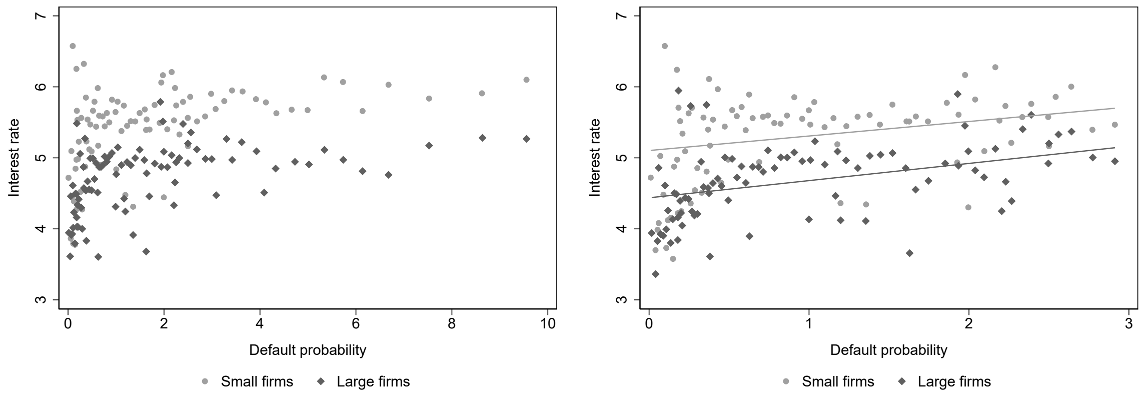
In Figure B1, we plot average prices relative to these competition measures. The left panel shows a positive relationship between concentration (HHI) and price which is more pronounced in smaller regional markets, such as municipalities (lower left graph). The relationship between the number of competitors and prices is depicted in the right panel and seems less obvious, especially for counties (upper right graph). Interestingly, the pattern gets clearer when we zoom in on more fine-grained geographical areas. In the lower right graph, we see that in municipal banking markets with less than 15 competitors, one additional competitor is on average associated with lower interest rates. Estimations in Table B2 test the relationship between rates and competition that was derived from Figure B1 in columns 1 and 3. We further repeat the main estimations from 4 at the NUTS3- and NUTS4-level in columns 2 and 4. Overall, the results support our analysis at the municipal level. First, we consistently see a positive significant relationship between PD and prices at the NUTS3 and NUTS4 level. Results in columns 2 and 4 also confirm that risk-pricing gets less sensitive as competition increases.

Table B2: Competitive risk-based pricing in larger regional banking markets.

	(1)	(2)	(3)	(4)
	Economic Regions (NUTS4)		Counties (NUTS3)	
Log(PD)	0.129***	0.076**	0.129***	0.081**
	(0.028)	(0.030)	(0.028)	(0.037)
HHI	-0.149**	-0.044	0.263**	0.014
	(0.075)	(0.068)	(0.121)	(0.080)
Log(PD) x HHI		0.158***		0.172*
		(0.048)		(0.102)
Loan, Firm, Ind. Controls	Yes	Yes	Yes	Yes
Fixed Effects	BY	BMY	BY	BMY
Observations	109,569	108,370	109,569	109,056
R2-within	0.137	0.134	0.137	0.134
Log(PD)	0.131***	0.421***	0.130***	0.699***
	(0.029)	(0.102)	(0.029)	(0.202)
Log(N Comp)	-0.656**		-1.460**	
	(0.262)		(0.724)	
Log(N Comp)^2	0.120**		0.228**	
	(0.046)		(0.105)	
Log(PD) x L(N Comp)		-0.082***		-0.142***
		(0.024)		(0.046)
Loan, Firm, Ind. Controls	Yes	Yes	Yes	Yes
Fixed Effects	BY	BMY	BY	BMY
Observations	109,569	108,370	109,569	109,056
R2-within	0.14	0.135	0.14	0.135

Notes: Clustered standard errors at the bank-level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is *Interest Rate*. In the first two columns competition variables (HHI and Log(N Comp)) are defined at the NUTS4 level of economic regions. Economic regions consist of several municipalities and are defined based on economic ties between them and do not necessarily coincide with an administrative unit. In columns 3 and 4 the competition variables are defined at the county level. The estimations include bank-year (BY) fixed effects in columns 1 and 3 and bank-market-year (BMY) fixed effects in columns 2 and 4. We further added loan-, and firm-level control variables.

B Additional figures and tables



(a) PDs until 90th percentile.

(b) PDs until 75th percentile.

Figure C1: Risk-based pricing for small and large firms.

Notes: The points represent average interest rates and average default probabilities (PDs) of observations within percentiles of the depicted range of default probability. Small firms have on average total assets below the median of total assets. Large firms have on average above median total assets. The left panel shows observations until the 90th percentile of PDs. Most observations have PDs below 3 percent. The right panel shows observations until the 75th percentile.

Table C1: Summary statistics of *Interest Rate* and *PD* within rating classes.

Rating	(1) N	(2) Mean	(3) p10	(4) p50	(5) p90	(6) SD
PD						
A	59,472	2.07	0.18	0.78	3.78	5.73
B	13,571	5.84	0.18	2.53	12.45	11.49
C	2,370	15.20	0.18	5.28	40.08	24.38
not rated	11,336	3.26	0.26	2.50	5.72	6.30
Interest Rate						
A	59,472	5.09	2.81	4.75	7.53	2.50
B	13,571	5.51	3.15	5.25	8.10	2.43
C	2,370	6.01	3.66	5.75	9.05	2.50
not rated	11,336	4.88	3.05	4.70	6.61	2.10

Notes: Ratings which are reported as AAA, AA, or A are summarized to category A. Column 1 shows the number of observations within each rating category. Column 2 shows the mean of PD in the upper and the mean of Interest Rate in the lower panel within each rating class. Similarly, columns 3 to 5 show the 10th, 50th, and 90th percentile of these variables, and column 6 shows the standard deviation.

Table C2: Predicting default using PD and the pricing residual.

	(1) Baseline	(2) Within Firm	(3) Within Firm	(4) Firm-Year
Dependent: Default				
PD	0.614***	0.330***	0.291***	0.163**
	(0.172)	(0.120)	(0.093)	(0.079)
Residual	0.186**	0.083	0.062	0.171***
	(0.075)	(0.058)	(0.082)	(0.055)
Effect of 1 SD of PD	5,153	0,479	0,346	0,243
Effect of 1 SD of Residual	0,327	0,227	0,146	0,235
Observations	86,749	45,443	25,893	14,125
R2	0.260	0.568	0.701	0.606
Bank-Firm-level controls	Yes	Yes	Yes	Yes
Firm-level controls	Yes	Yes	Yes	No
Bank-level controls	No	Yes	No	Yes
Fixed effects	BIMY	BY+F	BIMY+F	FY
R2 w/o PD w/o Residual	0.211	0.559	0.697	0.604
R2 w/o PD with Residual	0.211	0.559	0.697	0.604
R2 with PD w/o Residual	0.259	0.568	0.701	0.606
SD (PD)	8,393	1.453	1.19	1.488
SD (Residual)	1.756	2,732	2,355	1,376

Notes: Clustered standard errors at the bank-level in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). The upper panel shows the coefficient of PD from a regression as in eq. 1. The regression in column (1) is equal to the one of column (4) in table 3. The regressions in columns (2) and (3) have firm fixed effects, the regression in column (4) has firm-year fixed effects. In the second panel we take the same regression specification as above and add the residual of that regression but regress on a dummy which is one if the firm defaults. In the lower panel, we further show the R2 of corresponding regressions on default but where we have either excluded PD or the residual or both.