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Risk-based pricing in competitive lending markets

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Abstract

We use unique relationship-level data which includes banks' private risk assessments of corporate borrowers to quantify how competition among banks affects the risk sensitivity of interest rates in the corporate credit market. We show that an increase in competition makes corporate lending rates less sensitive to banks' own assessment of borrower probability of default and this is more pronounced in market segments with a 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.

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1 Introduction

Banks' first line of defense against losses is their operating income. Adequate pricing of credit risk ("risk-based pricing") is a key ingredient for bank solvency and ultimately financial stability. At the same time, bank pricing strategies are likely a function of several factors, including the competitive situation. While competition naturally affects markups and interest rates in general, it potentially affects the overall importance of risk for interest rates as well. For instance, to preserve market shares, banks can put less emphasis on risk when setting interest rates.[1]

Understanding how competition affects risk-based pricing is important to judge how the competitive situation interacts with bank solvency. Studying the relationship between competition and the degree of risk-based pricing among banks is challenging, however, for at least two reasons. First, due to screening, banks' information set can be richer than that of an outsider, e.g., an econometrician. For an outsider, it is impossible to identify whether variation in the degree of risk-pricing stems from different pricing strategies or different risk assessments based on unobservable soft information. Second, it is likely that different types of banks are present in areas with different competitive pressures. This selection can potentially lead to a correlation between competition and risk-based pricing which is ultimately driven by unobserved bank characteristics.

In this paper we investigate how competition affects the sensitivity of interest rates to borrowers' probability of default (PD)[2], using a novel supervisory database on all outstanding corporate loans in Norway. The richness of our data lets us overcome both of the empirical challenges outlined above. In addition to a wide array of loan details, the data contains banks' own borrower-specific risk assessment, a key advantage relative to many existing credit registries. This allow us to account for borrower riskiness according to a risk measure plausibly accounting for both hard information (observable to outsiders)

[1]The Great Financial Crisis highlighted that competitive pressures can affect banks risk-management, such as less screening (Dell'Ariccia, Igan, and Laeven, 2012; Müller and Noth, 2018), an increase in the 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 along multiple dimensions. Alternative theories suggest that competition lowers banks' screening activity and thus affects loan terms (Broecker, 1990; Dell'Ariccia and Marquez, 2006; Heider and Inderst, 2012). However, the impact of competition on bank risk-taking is not unambiguous. More competition is associated with lower rates, which in turn induce borrowers to take less risk thus improving financial stability (Boyd and De Nicolo, 2005; Boyd, De Nicolò, and Jalal, 2006).

[2]Throughout the paper, we refer to risk and PD interchangeably.

and soft information acquired by the bank in the screening process. To overcome the second empirical challenge, we exploit the fact that our data covers the universe of corporate loans in Norway across many different markets, limiting concerns about selection. We can exploit the fact that banks operate in a wide range of local credit markets with different competitive pressures by assessing how the degree of risk-based pricing varies across local markets, but for the same bank in the same year.

Our main contribution to the literature is to document that an increase in competition, across several alternative and complementary empirical approaches, reduces the sensitivity of interest rates to banks' own assessment of borrowers' probability of default. We show that this effect is driven by banks that have low franchise values and results in lower risk-adjusted returns on regional loan portfolios. Our findings are consistent with the models commonly used to analyse the competition-fragility-nexus.

Our empirical analysis consists of three main steps. First, we use supervisory data on all outstanding corporate loans in Norway from 2012 to 2018 to document that borrower risk as captured by borrowers' probability of default has a sizeable and significant impact on the borrowing rate. In our data, banks report borrower-specific credit exposures along with relationship-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. We complement this data with bank- and firm-level information to account for bank and borrower characteristics that determine loan terms.

We use the data to explore banks' own PD measure. We document that a higher PD is associated with higher interest rates, also within externally issued credit rating classes, suggesting that a component of the PDs consists of banks' soft information.[3] According to our baseline estimation, a 1 percent increase in the PD increases the interest rate by 16 basis points on average. Looking within rating classes, a 1 percent increase in the PD increases the interest rate by 13 basis points.

Second, we exploit the granularity of our data to establish the effect of competition on the sensitivity of interest rates with respect to banks' own PD estimate. We use two conventional measures of competition: Herfindahl-Hirschman indicies (HHI) and the number of competitors in a local market. We complement this with an event study framework where we investigate the risk-based pricing of incumbents when a new bank enters their market. For the latter measure of competition, we first show direct evidence

[3] PD also has considerable explanatory power to predict firm defaults. We discuss this in more detail in subsection 4.1.

that the presence of new entrants intensifies competition. Specifically, new entrants offer consistently lower rates and larger loans, while also having looser credit standards as captured by the extent of collateralisation. Throughout the analysis, we focus on within bank-portfolio variation across regional markets that are characterised by different levels of competition.

Our main empirical finding is that an increase in competition reduces the extent to which interest rates are risk-based. The effect is quantitatively large. For instance, incumbent banks reduce the risk sensitivity of interest rates by approximately 42 percent following the entry of a competitor.[4] Competition also affects other aspects of lending standards. Specifically, we show that an increase in competition reduces the sensitivity of interest rates to the degree of collateralisation and Debt-to-Income (DtI) ratios on new corporate loans.

The impact of competition on risk-based pricing is 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). In these segments, banks can plausibly exert more market power (Santos and Winton, 2008) and private risk assessments potentially vary more (Ruckes, 2004). Overall, our results therefore show that competition affects risk pricing by banks in the corporate lending market, and suggest a novel way through which competition affects bank solvency.

Third and finally, we investigate the mechanism behind our main result. We consider two potential explanations for how this increase in competition affect banks' risk-pricing. The first explanation is motivated by the large literature building on the idea that competition erodes banks' franchise values and how low franchise values ultimately incentivise banks to take more risk. Riskier strategies may show in more lenient lending standards, including the risk sensitivity of prices. In line with this literature, we test whether banks with low franchise values are driving our results.[5] We focus on net interest margins (Repullo, 2004) and bank equity (Demsetz, Saidenberg, and Strahan, 1996) as proxies for banks' franchise values, in addition to bank size. A second potential mechanism is that higher competition leads to lower screening. Less screening makes banks' own PD estimates less informative about actual risk and thereby also observed interest rates less sensitive to the assessment. To check this hypothesis, we test whether the predictive abilities of bank PD estimates for actual defaults depend on the competitive situation. We do

[4]In a complementary analysis, we also show that banks assessment of PDs explain a smaller fraction of the variation in rates in relatively more competitive markets.

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

not find conclusive evidence that more competition leads to worse PD estimates. At the same time, we do find that banks with low net interest margins, low equity to total assets or banks that are small are driving our results across all competition measures. As such, our results are mostly consistent with a mechanism focused on the impact of competition on banks' franchise values.

Related literature Our paper relates to several strands of the literature. First, it relates to micro-level evidence on banks' risk-based 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 (Strahan, 1999; Berger, Frame, and Miller, 2005; Magri and Pico, 2011; Walke, Fullerton Jr, and Tokle, 2018). 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. Durrani, Metzler, Nektarios, and Werner (2022) investigates the impact of risk on loan returns using data from the 2021 EBA Stress Test. They document that interest rates on average are tied to expected losses, but that the strength of this relationship depends on borrower segments. Specifically, they show that the risk-sensitivity of interest rates are strongest for households and for high-risk firms. Our primary contribution to this literature is to establish the impact of competition on the risk sensitivity of interest rates, suggesting that risk-pricing is a strategic component of overall lending standards. In that sense, we relate to a literature that discusses the effect of competition on lending standards, especially loan availability (Carbo-Valverde, Rodriguez-Fernandez, and Udell, 2009) and prices (Degryse and Ongena, 2005; Rice and Strahan, 2010).

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). On the other hand, Boyd and De Nicolo

(2005) and Boyd et al. (2006) argues theoretically and empirically that higher competition – by lowering interest rates – can induce borrowers 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 findings provide a novel channel through which competition can affect financial fragility. Importantly, the channel operates primarily through banks with low franchise values.

2 Description of the data, sample, and main variables

2.1 Data

We use data from three different sources for the period from 2012 to 2018. Our main data source is a relationship-level supervisory dataset containing information on all firm-bank credit relationships in Norway within a given year. The data includes credit risk exposures to firms which are totaled over the calendar year, a borrower-specific probability of default (PD) that is estimated by the bank on an annual basis, 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. In subsection 4.1, we illustrate that the PD captures actual default risk and that it contains soft information compared to data that is observable to outsiders.

The second data source is supervisory data on 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 available for limited liability companies. We use this data to explore the role of firm-specific factors, in addition to using the geographical information to construct regional banking markets.

2.2 Sample construction and description

We impose three restrictions when constructing our final sample. First, we restrict our attention to the first year a firm-bank relationship is observed to avoid double counting of persistent pricing decisions and to exclude changes in borrower quality driven by ex-post risk taking (moral hazard). Second, we focus on limited liability firms as we only have firm-level information for this subset. Limited liability firms make up the bulk of loan-relationships (78% of total new credit volume), have slightly larger loans and smaller PDs compared to the unconditional average.[6] Finally, we restrict attention to cases where we observe both, the interest rate and the PD. The final sample includes $125,399$ observations, i.e., about 17k bank-borrower relationships per year. It covers on average about 30% of total newly formed credit exposures. We report detailed summary statistics on the variables we use in Table 1.

[Table 1 about here.]

Banks In Norway, 128 unique banks operated between 2012 and 2018 of which 114 banks are in our sample. The remaining 14 banks are small and drop out due to not reporting PDs. Norway's banking market is concentrated (for a detailed description see Norges Bank (2020)). The top 2 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 and regionally-focused savings banks. The differences between banks are reflected in the standard deviation in total asset size 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 sector classification codes, banks lend to a variety of different firms. The most represented sectors, in which we observe 60 percent of firms, are construction, wholesale and retail, as well as real estate. Our data covers SMEs as well as large Norwegian corporations. The average firm in our sample has 82k NOK (9k USD)[7] in total assets.

[Figure 1 about here.]

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

[7] 1 USD $\approx$ 9 NOK, december 2021.

Bank-borrower relationships We observe 106,910 new credit relationships, where 24 percent of borrowers have relationships with more than one bank. The average loan volume is 7m NOK (780k USD), the median is 421k NOK (5k USD). Collateral is reported on 85 percent of credit relationships and almost half of the lending is fully collateralised. We observe 4, 204 defaults of those newly created credit relationships during our sample period which translates into a default rate of 3.96 percent which is close to the average default probability estimated by banks which is 3.19 percent. PDs vary from 0 to 100, where loans with a PD of 100 are those in default. In our main analysis, we use the logarithm of PD to account for the fact that many observations center around small values of PD (90 percent of observations are below 11 percent, 75 percent of observations are below 3 percent) leading to a skewed distribution. We discuss the PD variable in more detail in Section 4.1. 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.

2.3 Defining regional markets and measures of competition

To measure the competition in a market, we need to introduce a measure of the intensiveness of competition and define the market. For the former, we rely on three measures which we discuss in more detail below: concentration as captured by Herfindahl-Hirschman Indicies, the number of competitors and whether there has been a recent entrant in the market.

Armed with these competition measures, we need to define what constitutes a market. 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' locations to define regional banking markets. While some of the larger banks in Norway are active across the country, the majority of banks are locally-focused savings bank, typically tied to a municipality.

Our analysis uses municipalities as the level for observing banking competition. As we discuss in Appendix A, we also consider two alternative geographical delineations - counties and NUTS4 economic regions. To decide on which definition is the best, we focus the market definition which yields the strongest correlation between observed interest rates and the competition measures. As we discuss in Appendix A, there is a strong relationship between interest rates and the competition measures at the municipal level, and somewhat weaker relationship when focusing on NUTS4 or counties. This leaves us with ample variation in different measures of competition at the municipal level. We therefore proceed with municipalities as the boundary of a local market.

In Table 1 we also show the summary statistics of the competition measures at the municipal-year level. The competition measures are calculated based on the bank-borrower relationship data. We use the full data including the pre-existing relationships in addition to the newly created ones to construct proxies for competition, such as market shares and number of competitors across different markets.

On average, 14 banks operate within a municipality in any given year. Most competition is centered in Oslo where we observe a maximum of 113 banks. In some municipalities, banks have a monopoly, while half of the municipal banking markets are characterized by oligopolistic structures with two to 11 banks competing. In the analysis, we focus on the logarithm of the number of competitors due to the skewedness of the number of competitors.

The second measure that we use is a Hirschman-Herfindahl Index for each municipality. We calculate the HHI as the sum of squared market shares of all banks operating in a municipality within a given year. These indices capture market concentration. A high HHI indicates a concentrated market whereas a low HHI signal a more competitive environment.

A well-known critique of HHIs is that they do not measure the 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 enters a local credit market. We observe entries for about half of the market-year observations in our sample. When using this measure, we first verify that entrants indeed offer more aggressive lending terms than incumbents and hence constitute an increase in competition.

3 Methodology

In this section, we outline our methodology. We start by explaining how we isolate the effect of the probability of default on interest rates. We then discuss how to identify the effects of increased competition on this relationship. In terms of the latter, we rely on two approaches: a panel fixed effect regression which we refer to as a "within-bank" estimation outlined in subsection 3.2.1 and an event study framework outlined in subsection 3.2.2.

3.1 Quantifying the risk sensitivity of interest rates

To first quantify the risk-sensitivity of interest rates, we estimate the following equation

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

where we use index b for banks, f for firms, y for years, m for municipalities, and i for industries. The coefficient β captures the degree of risk-based pricing. In general, we expect the coefficient to be positive. To isolate the impact of PD on interest rates from other loan- and firm-specific factors, we include several control variables captured in X^{Loan}_{bfy} and X^{Firm}_{fy}, in addition to different sets of fixed effects (δ). In Table 1 we list and provide summary statistics of all variables explained here.

The set of control variables are aimed at alleviating four 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 firms. We therefore control for the size of a loan relative to other loans and relative to the firm's size, as well as whether the loan is fully covered by collateral or not or only partially.[8]

Second, other firm characteristics 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 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, 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.[9] In doing so, we ensure that the estimated effect of PD reflects the non-public, soft 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

[8]One drawback of the dataset is the absence of information on the maturity of the credit exposures. We therefore use a subset that allows us to control for maturity in the robustness analysis.

[9]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. See Table 2 for the variance of PD within rating classes.

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. 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. By doing this, we assume that marginal costs of making another loan are calculated at the bank-level and thus absorbed by the fixed effects. However, in some of our estimations we use firm×year fixed effects. Then, we control for bank's financial ratios using cost-income ratio, deposits-to-assets, equity ratio, liquidity ratio, net-interest-income ratio, return-on-equity, and loan loss provisions ratio, and its size.

Lastly, local macroeconomic conditions and economy-wide economic factors, such as the policy rate rate, can have an influence on rate setting. We usually filter out common macroeconomic factors by including 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.

3.2 Identifying the effects of increased competition on risk-based pricing

3.2.1 Within-bank estimation

To study whether competition affects the risk sensitivity of interest rates, we start by estimating the following equation:

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

where we use index b for banks, f for firms, y for years, m for municipalities, and i for industries. We include the controls discussed in Section 3.1.

By introducing the interaction term (*Log(PD)*×*Comp*), we assess whether the slope between risk and price (β) depends on the degree of competition in the market ($\beta + \gamma$), as captured by $Comp_{my}$. Our approach here relies on two measures for *Comp*: HHI and the logarithm of number of banks. Note that, as higher competition implies a lower HHI but a higher number of banks, we expect the estimated coefficients to be of opposite sign for these two measures to claim conclusive results. 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 key threat to identification is that banks with different overall risk-management practices choose different competitive environments. If banks with a risk management strategy that always entails less risk-sensitive interest rates 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 long-term risk management goal of a bank is usually set at the top-level of the bank. For instance, DNB – the largest bank in our sample – employs a separate director in charge of the overall risk-management strategy for the whole bank, and "The Board of Directors of DNB ASA sets the long-term risk profile targets".[10] Second, banks are present in multiple geographical areas. This allows us to exploit *within-bank*$\times$*year* variation in competition. Given that the long-term risk appetite is set at the top-level, this allows us hold such variation fixed. Specifically, to implement this strategy, we saturate our estimated regressions with bank$\times$year fixed effects. We tighten the specification further by using bank $\times$ year $\times$ market fixed effects (δ). By this, we additionally control for macroeconomic regional trends affecting banks pricing decision differentially.

A second 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 the actual effects are, if anything larger, they can lead us to falsely fail to reject the null hypothesis. To deal with this issue, we rely two conventional measures of competition, namely market concentration as captured by HHI and the (log) number of competitors, in addition to the event study outlined in the next section.

A natural question to this identification is how we can disentangle between the markup and the price of risk. A markup can be defined as the component of a price which exceeds marginal costs or the competitive benchmark of a price. The markup is thus clearly a function of competition. When pricing a risky asset, the price should also reflect a risk premium. Our identification implicitly assumes that the markup does not depend on credit risk of the individual borrower. As much as the markup is not borrower-specific, we absorb for markups at the bank-level, bank-market-level, or industry-level. Following

[10]See https://www.ir.dnb.no/sites/default/files/results/pilar3-dnb-2016-engelsk.pdf.

this definition of markups, we estimate the effect of competition on the risk premium.[11]

3.2.2 Event study with market entry

We also investigate how risk pricing by incumbent banks is affected by new banks entering their regional market. Specifically, we estimate the following

$$Rate_{bfy} = \beta Log(PD_{bfy}) + \gamma Log(PD_{bfy}) \times PostEntry_{my} + X^{Loan}_{bfy} + X^{Firm}_{fy} + I_{iy} + \delta_{bmy} + \epsilon_{bfy} \tag{3}$$

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

An advantage with this approach is that we can compare behavior of entrants and incumbents to shed light on how entrants potentially intensifies competition. To do so, we employ a within-borrower estimation that allows us to identify purely supply-side driven effect of entry on bank lending standards. For this exercise, we restrict the sample to those firms that entered into relationships with more than one bank within a year. We then compare the lending terms of incumbent banks versus new entrants to the same firm. We estimate

$$Y_{bfy} = \beta Entrant_{bmfy} + X^{Loan}_{bfy} + X^{Bank}_{by} + \delta_{fy} + \epsilon_{bfy} \tag{4}$$

where we include firm-time fixed effects, the same loan-level controls we have used so far and bank-level characteristics (CIR, Deposit Ratio, Equity Ratio, Liquidity Ratio, LLP Ratio, NIM, ROE, and bank size). As a dependent variable, we look at the interest rate (*Rate*), whether the exposure is fully collateralized (*Collateralized*), if not, then the share that is collateralized (*Collateral Share*), as well as at the loan volume (*Log Loan)*. We cluster the standard errors at the firm-level.[12] The results are reported in Table 5.

[11] If allowing for borrower-specific markups, our identification serves to test whether there are risk-dependent markups. One has to accept that both, markup and risk premium, are artificial concepts not to be found in the contractual loan terms and as such open to how we define and measure them. Following standard theory that defines the markup as a function of the inverse interest rate elasticity of loan demand, we prefer to present our results as the effect of competition on the risk-sensitivity of interest rates rather than a risk-dependent markup.

[12] Results are robust to bank-level clusters as well. However, we follow the literature that used within-borrower estimation using credit registries here.

[Table 5 about here.]

By using this narrower identification, we restrict the sample to 6,812 firms that established new bank relationships with more than one bank within any given year. We find that banks that entered the regional market of the firm in that same year extended on average larger loans (column 4) at lower interest rates (column 1) compared to the incumbent bank. The effects are economically significant. The entrant approves on average an exposure that is more than 40 percent larger than that of the incumbent while the interest is reduced by on average 26 basis points. We further find that the chance that these exposures are are fully covered with collateral reduces by 10 percent (column 2). If loans are only partially covered with collateral, however, we cannot find a significant difference between entrant and incumbent (column 3). Overall, this analysis reveals quite aggressive competition strategies that can affect the lending practices of incumbents.

4 Information value of banks' risk estimates and their use in pricing

4.1 Measuring soft information on loan default risk with PD

Given the importance of banks' PD estimates in our empirical analysis, we explore two dimensions of this variable. First, we ask whether the PD estimates capture actual default risk. Second, we ask whether banks incorporate soft information about the firm in these estimates. From the description of the variable, we assume that banks incorporate such soft 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. [13]

[Table 3 about here.]

[13] 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 answer the first question, we regress the following relationship in different specifications and models

$$\text{Default}_{bf} = F\Big(PD_{bfy}\Big) \tag{5}$$

where *Default* is a dummy variable equal to one if a firm defaults on a given loan during our sample after being given credit. In Table 3, we show that the *PD* is a significant predictor of actual default independent of how we specify the default prediction model. The unconditional correlation between PD and *Default* is 0.59 (cf. column 1 panel A). When we follow the same specification and include the same control variables that we use in equation (2) and describe in detail in Section 3, we find that a one percentage point higher *PD* results in a 0.586 percentage point higher default rate (cf. column 3 panel A). In panel B column 3, we show that a one percent increase in PD is associated with a 2.3 percentage point higher default rate. If a firm has multiple credit relationships, the firm can default on one loan while still performing on others. When studying only firms that have more than one bank-relationship, we still find the differences in PD estimates between banks lending to the same firm to significantly predict higher actual default risk (cf. column 5 panel A and B). This indicates that the default information which is priced not only refers to firms' fundamentals but also to the effect of loan characteristics on default. To better capture the non-linear nature and the binary response of the dependent, we also tested logit models (panel C) and probit models (panel D) as in Becker, Bos, and Roszbach (2020).

To answer the second question, i.e., whether PD incorporates banks' soft information about the borrowers, we assess the relevance of PD as a proxy of soft information in comparison to observable information and alternative measures of soft information.[14] To do so, we estimate and compare four models defined as

$$\begin{aligned}
&(M0) \quad \text{Default}_f = && && X_{bfy} + \delta_{bmy} + \epsilon_{bfy} \\
&(M1) \quad \text{Default}_f = PD_{bfy}+ && && X_{bfy} + \delta_{bmy} + \epsilon_{bfy} \\
&(M2) \quad \text{Default}_f = && && \text{SoftInfo}_{bfy}+X_{bfy} + \delta_{bmy} + \epsilon_{bfy} \\
&(M3) \quad \text{Default}_f = PD_{bfy}+ && && \text{SoftInfo}_{bfy}+X_{bfy} + \delta_{bmy} + \epsilon_{bfy}
\end{aligned} \tag{6}$$

where model $M0$ is a default prediction model using only observable (public) information. The results are reported in table 4. By comparing $M0$ and $M1$, we see whether PD

[14] Soft information here is meant as not-publicly observable information. One could also use the term private information.

adds significant default-related information to publicly available data. Model $M2$ tests whether this is also the case for an alternative measure of soft information. Contrasting $M1$ and $M2$, allows us to compare the incremental explanatory power of PD and the alternative proxy. Finally, model $M3$ tests whether PD has an explanatory power beyond the alternative measure of soft information.

[Table 4 about here.]

Since soft information usually cannot be observed, an econometrician working without the PD variable can presume to find default-related relevant information in regression residuals or fixed effects. In line with this reasoning, we test two alternative measures. First, we use the residual variation in interest rates from a regression containing only observable information. The specification of the model from which we take the residuals mirrors the one in equation (2) where we include industry and bank-market-year fixed effects as well as control variables for the bank-firm relationship and firm-level information. However, we do not include PD as an explanatory variable. The results of contrasting this residual measure of soft information and PD are displayed in the upper panel of table 4. Both proxies for soft information, PD (column 2) and the residual (column 3), are significant predictors of default. Yet, PD is a stronger predictor. By comparing the R2 of models 2 and 3 to model 1, we find that including PD raises the explanatory power of the prediction model by about 0.05 percent, while including the residual only adds 0.0001 percent relative to a model based only on observables. Further, the coefficient on PD is 0.587 which is closer to 1, the ideal benchmark for the relationship between PD estimation and actual default, than 0.195, the coefficient on the residual.

The second alternative measure of soft information that we use is borrowed from Crawford, Pavanini, and Schivardi (2018). These researchers circumvent the fact that they do not have information on banks' PD estimates (as we have) by focusing on firms that deal with several banks and thus introducing firm-time fixed effects which should absorb any soft information that these lenders might have but which cannot be seen by the econometricians. The specification of the model from which we take the fixed effects mirrors the one in column 5 of table 3 where we include firm-year fixed effects as well as control variables for the bank-firm relationship, except PD, and bank-level information. In line with the interpretation that *PD* captures soft information that is contained in firm fixed effects, the estimated effect and explanatory power of *PD* is smaller when we include firm or firm-year fixed effects (cf. columns 4 and 5 in table 3). The results of contrasting PD with this fixed-effects based measure of soft information are shown in the lower panel of table 4. We re-estimate model M0 based on the limited subsample of observations of firms that establish multiple bank-relationships within any one year. Again, we find both proxies to be significant predictors of default while PD adds significantly more explanatory power to the prediction model (+0.0209 percent) than the firm-time fixed effects (+0.0001 percent). Further, the coefficient on PD is almost three-times as large as the coefficient on the fixed effects.

Overall, the analysis discussed above highlights that the PD captures default risk and accounts at least in part for the soft information of borrowers. These results are in line with the findings in Weitzner, Beyhaghi, and Howes (2023) who show that banks' PD estimates rightly predicts firm outcomes using data from a set of US banks.

4.2 Risk-based pricing

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

[Figure 2 about here.]

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 the log(PD) and the interest rate is increasing in our sample and is approximately linear.[15] 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 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. To do so, we estimate equation (1).

[Table 6 about here.]

First, in column 1 of Table 6 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

[15] 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. However, our results are not sensitive to using log(PD) or PD.

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 (with $X_{bfy}^{Loan} + X_{fy}^{Firm}$ detailed in subsection 3.1) to ensure that we look at loans that are otherwise more comparable. This reduces the impact of log(PD) slightly, i.e., the effect of a 1 percent increase in the PD is now a 13 basis points increase in the borrowing rate.

All in all, the results in this section suggests that borrower PDs –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-based pricing is affected by the competitive setting.

5 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 the degree of risk-based 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.

5.1 Main results

[Table 7 about here.]

The main results are in Table 7. We estimate Eq. 2 and are interested in measuring the coefficient γ. 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 *Log(N Competitors)* is negative and significant, indicating that prices are more risk sensitive in markets with fewer competitors.Finally, we use the event study design detailed in subsection 3.2.2 to investigate whether the degree of risk-based 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 7. Incumbent banks significantly reduce the degree of risk-based pricing when a new competitor enters the market. The event study has an attractive feature, in the sense that it is fairly straightforward to assess the size of the effect. Comparing the risk sensitivity of interest rates in markets with a new entrant with other markets, our results suggest that incumbent banks reduce the risk sensitivity by almost 42 percent in reaction to a new competitor, suggesting that the impact of increased competition on the degree of risk-based pricing is both statistically and economically significant.

We further assume the effect should be stronger in markets with high information asymmetries where rents to information are potentially higher and it is easier for banks to exert market power. Across all competition measures, our results are driven by more opaque borrowers. To illustrate this, we adopt two proxies. First, we follow Santos and Winton (2008) and use small- or medium-sized firms (using the median asset size as the cut-off) for borrowers that are more bank-dependent and therefore more exposed to banks' market and pricing power. Second, we use the credit rating to focus on riskier firms for whom lending standards could vary more (see "cross-sectional interpretation" in Ruckes (2004)). 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 competition affect the risk sensitivity of interest rates to high-risk firms. Next, we estimate the relationship separately for small- and medium-sized firms (column 4) and large firms (column 5). For both the number of competitors as competition measure and the event study focusing on the degree of risk-based pricing of incumbent banks following the entry of a competitor, we find that the risk sensitivity of loans to SMEs is affected while the risk sensitivity of loans to large firms is unaffected by a change in competition. When using HHI as a concentration measure, we find that competition affects the risk sensitivity of loans to both SMEs and large firms, but that the impact is more than twice the size for SMEs.

These results also underline that reverse causality is not likely at play in this setting. If banks would choose to compete less in markets of high sensitivity, we would have expected to find the opposite result. Competition should have only a weak effect in markets that are highly sensitive to information, such as the SME market. The results further point out that we are not just measuring a non-linearity in the relationship of PD and interest rates where the riskiness of the firm correlates with the intensity of competition in its market. Within the market segment of riskier firms, we find significant variation of risk-sensitivities according to the competitive environment. This identification is based on banks lending to comparable firms in more and less competitive markets.

The main finding is robust to concerns arising from the limitations of our data and choices of variable definitions. One of these shortcomings is the missing information on the maturity of loans. However, we can infer the maturity of a subset of loans which are those were the relationship ends within our sample period. Using only these observations as well as those that we see defaulting within the sample period, we show in table 8 that the results are not affected when controlling for maturity in this reduced sample. The results in the lower panel of table 8 also show that the finding is robust to including LGD (loss given default) as a control variable, with the exception of the entry-study.[16] We further show in appendix A that the effect is equally present in larger banking markets (NUTS3 and NUTS4 regions). Our results are also confirmed when using an alternative approach to measure an effect of competition on risk-sensitivities. In addition to the methodology outlined in 3, we further investigate whether the explanatory power of PDs vary across samples with different degrees of competition. In Table 9 we report the results from such an exercise, where we show that the within-R2 increases by approximately 17 percent when going from a high to a low HHI municipality. These results are consistent with the results discussed above.

Overall, these findings suggests that (1) competition affects the degree of risk-based pricing and that (2) these effects are driven by loans to firms for which banks more easily can exert market power.

5.2 Mechanism

Why does an increase in competition lead 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 induces banks to be less risk averse. As such, risk sensitivity of prices can decline as part of an overall riskier strategy. 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 then re-estimate equation (2) for different subsamples, based on these proxies.

[Table 10 about here.]

We present the results for the subsample analysis in Table 10. The results are mainly driven by banks with low equity ratios, low NIM or banks that are small. Using the

[16] We obtain the main finding also in a log-log model as well as without logarithms of *PD* or *N Comp*.

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), 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 the degree of risk-based pricing as competition increases (lower HHI) for all bank types although the point estimates on those banks with lower franchise values are higher.

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. According to Broecker (1990), it is hard for banks to commit to screening in an equilibrium under price competition. Dell'Ariccia and Marquez (2006) point out that incentives to deviate from a "screening equilibrium" increase with competition since more market shares can be gained by undercutting competitors prices. Further Heider and Inderst (2012) highlight how loan officers' effort might be diverted form screening to marketing activities under increased competition. Recently, Yannelis and Zhang (2023) argue that competition in consumer markets can undermine incentives to invest into screening. 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 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.

[Figure 3 about here.]

The resulting mean absolute errors from the forecasting exercise are shown in Figure 3. While 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.[17]

Although other explanations may be important for understanding the findings in Section 5, our results point in the direction of lower franchise values as an explanation for why an increase in competition leads to less risk pricing.

5.3 Competitive lending standards

Competition may undermine the quality of lending standards (Ruckes, 2004; Dell'Ariccia and Marquez, 2006). As we have shown above, risk-sensitivity of prices is one strategic element subject to adjustment under competitive pressure. To see how this component fits into the overall lending strategy of banks, we here analyse risk-sensitivity jointly with other lending standards. This way, we would be able to see if a decreasing risk sensitivity of interest rates is accompanied by other looser lending standards or compensated by more stringent requirements in other loan terms.

For this analysis, we introduce two more loan terms: Debt-to-income ratio and collateral ratio. The Debt-to-Income (DtI) ratio is defined as the ratio of borrowers' annual interest costs over profit before interests, taxes, and depreciation (EBITDA). The ratio should reflect the ability of a firm to pay additional interest out of current net income. The collateral ratio is defined as the collateral value relative to the loan amount and shows which share of the loan is collateralized. In the analysis of this latter ratio, we restrict the sample to a subset of around 37,000 observations where the loan is covered with collateral but not entirely.[18]

To formalize the relationship between competition and the sensitivity of interest rates with respect to other lending terms, we employ the same methodology as before but focus on how competition affects the sensitivity of interest rates with respect to the *Collateral ratio* and the *Debt-to-Income Ratio*. The results are reported in Table 11.

[17] 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.

[18] Overall, we observe collateral value for 82 percent of observations in our baseline sample. So far, we used the dummy *Collaterized* to control for collateral. The dummy is one if the collateral covers exposure to 100 percent or more and zero otherwise. In the baseline sample, 46 percent of observations are fully covered with collateral. We now focus on the case when collateral is reported but less than total exposure.

[Table 11 about here.]

Usually, the firm may expect a discount if a higher share of the loan is covered with collateral. Accordingly, the coefficient on *Collateralized Share* is negative when it is significant. Further, the results show a significant influence of competition on this discount (except when we use Log(N Comp) as the competition measure). In columns 1 and 2, we show that the discount becomes smaller as markets become less competitive. For example, the discount on an average collateral share decreases by 30 basis points between a market with low concentration (1st quartile of HHI) and a market with high concentration (4th quartile of HHI).[19]In columns 5 and 6, we find that incumbent banks increase their discount on collateral after entry occurred. We further find that competition affects the sensitivity of interest rates towards Debt-to-Income ratios. As we would expect, higher DtI ratios are associated with higher interest rates (see positive significant coefficient on DtI in columns 3 to 6). This penalty, however, decreases as competition gets stronger. For example, incumbent banks drop the penalty after entry (columns 5 and 6 show a marginal effect of close to 0 in case of entry). As can be seen in columns 2 and 6, competition affects the interest rate sensitivity towards PD and Collateral Share or DtI simultaneously. Overall, less risk sensitive prices seem not be compensated by stricter pricing of collateral or DtI. These findings indicate that more competitive markets not only feature less risk-sensitive prices but looser lending standards.

5.4 Implications for bank solvency

In this section, we provide further results on the importance of risk-sensitivity for bank solvency. Specifically, we trace the effect of high risk-sensitivity of interest rates on bank portfolio returns. To do so, we aggregate the risk-adjusted returns from the bank-firm relationships in our sample and study the effect of risk-sensitivity on these aggregate returns. Aggregate returns take into account that income from one loan can offset defaults in another within the overall loan portfolio of a bank, thereby, allowing us to study the impact of risk-sensitivity on banks' potential to generate profits.

We construct this measure for each banks' regional portfolios. First, we calculate the net return for each loan by summing interest income in the first two years after origination and by subtracting write-downs and total defaults if they occur any time after origination,

[19] We calculated the difference in the average effect at the mean of *Collateral Share* (0.27) at the 25th percentile of HHI (0.21) and the 75th percentile of HHI (0.34). The former gives on around 1 percentage point discount, the latter 0.72 percentage points.

and then scale this by the total initial exposure. We then calculate the average net return for each bank in each market and each year. We thus get the average risk-adjusted return on the loan portfolio that a bank earned in a given municipality and a given year. [20]

To study how risk-based pricing affects banks' portfolio returns, we estimate a market-year specific risk-sensitivity coefficient for each bank by regressing *Log(PD)* on *Interest Rate* with the same set-up as in Table 6 individually for each bank-market-year. We simplify the analysis by using a dummy *High Risk-Sensitivity* indicating an above the average risk-sensitivity coefficient. This also serves to avoid bias in the estimation of standard errors through the introduction of an estimated regressor that itself might be subject to measurement error. We then estimate

$$Y_{bmy} = \beta \textit{High Risk-Sensitivity}_{bmy} + X^{Loan}_{bmy} + X^{Firm}_{bmy} + \delta_{by} + \delta_m + \epsilon_{bmy} \tag{7}$$

where use the same loan-level and firm-level controls as before but we also average them to represent the market-portfolio of each bank in any given year. We further introduce bank-year fixed effects so that we can compare the effect of different sensitivities within banks. The results are reported in Table 12.

[Table 12 about here.]

As shown in column 1, we find for the full sample that high risk-sensitivity increases risk-adjusted returns. Banks earn on average 0.6 percentage points higher rents in markets where they have high risk-sensitive prices relative to markets where they operate with low risk-sensitivity which is almost a 10 percent increase on their average return of 6.2 percent.[21] As we demonstrate in subsection 5.2, the effect is stronger for banks with low franchise values (columns 2 and 4). These banks reduce the risk-sensitivity in response to competition and accordingly earn between 0.8 and 0.9 percentage point lower rents in markets with low risk-sensitivity. As the results in columns 3 and 5 show, banks with high franchise values do not earn significantly different returns in markets where their prices are more or less sensitive to risk.

We further find that high risk sensitivity can only increase returns for banks in those markets with riskier firms, i.e. markets where information asymmetries, risks, and the

[20]Interest income is the product of the reported interest rate and drawn exposure. We also used more than two years of interest income. However, we expect most maturities to be longer than our sample period and would then put more weight on income originated at the beginning of our sample. We get similar results when instead of averaging returns, we sum-up income and costs from all loans first and calculate the return relative to total exposure.

[21]Results are similar when comparing different banks within the same municipality-year.

pricing of risk-related information are more relevant (cf. columns 6 and 8). These are the markets where competition is most likely to reduce risk sensitivity, as we have shown in section 5. Overall, these results demonstrate that competition ultimately reduces risk-adjusted returns in regional banking markets for low franchise banks through the channel of lowering risk-based pricing.

6 Conclusions

In this paper, we analysed the impact of competition on pricing of credit risk exposures in the Norwegian corporate loan market. We find that banks use soft information in their PD estimates in addition to hard information which is publicly available, such as firm ratings or firms' financial accounts. We provide evidence that an increase in competition induces banks to be less likely to use this information, especially in environments where information asymmetries are more severe. Banks with low franchise values are more likely to vary their risk-pricing behaviour across different competitive settings. We show therefore that risk-pricing is one potential channel of the competition-fragility nexus.

Experiences from the Great Financial Crisis demonstrated that banks can neglect risk-adequate pricing under strong competition. We find that reduced risk-sensitivity is also associated with other weakening lending standards. Yet, that does not necessarily mean weak standards. That is to say, less sensitive pricing must not be mispricing. However, the tendency to react with lesser risk sensitivity might only be truly threatening in a particular crisis while our data covers mostly normal times. 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 are also relevant from a microprudential perspective. We demonstrated that risk-sensitivity impacts returns on regional credit portfolios. 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 and our paper illustrates that risk pricing is not invariant to the competitive setting, calling for additional scrutiny when competition is high.

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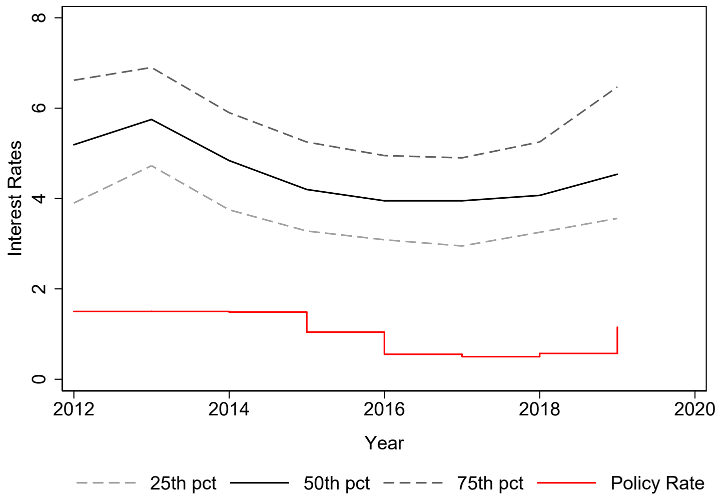
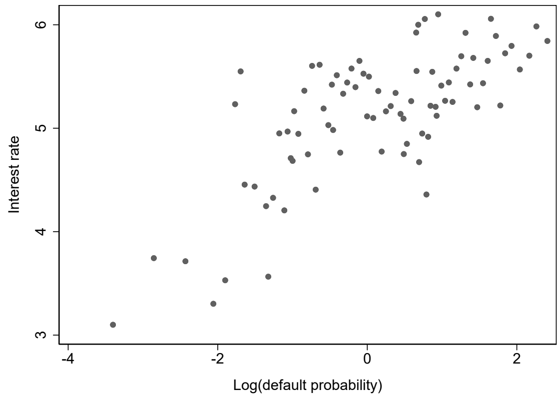
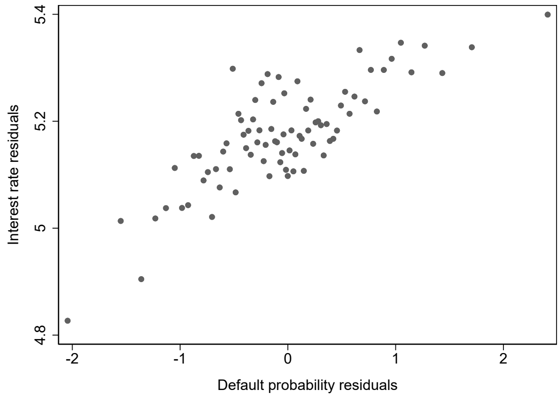


Figure 1: Median interest rate and policy rate over time.

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.



(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 equation (2) and bank, year, and market fixed effects.

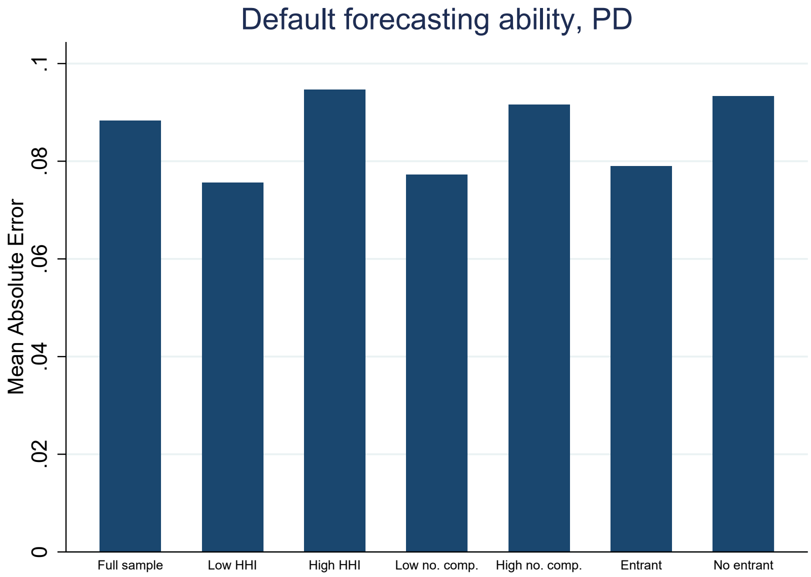


Figure 3: Prediction errors, different subsamples.

Notes: This figure shows 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.

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
Log(PD)	106,910	0.11	1.41	-5.52	-1.90	0.18	2.41	4.61
Market-level competition measures - municipalities								
HHI	1,874	0.51	0.23	0.13	0.23	0.47	1	1
N Comp	1,874	13.72	10.63	1	5	11	32	113
Log(N Comp)	1,874	2.43	0.59	0	1.61	2.40	3.47	4.73
Post Entry	1,615	0.71	0.45	0	0	1	1	1
Bank-firm-level controls								
Collateralized	106,910	0.46	0.50	0.00	0.00	0.00	1.00	1.00
Loan/Assets	106,910	34.45	43.50	0.00	0.13	18.60	101.46	295.78
Log(Loan)	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
Intangibles 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
Log(Assets)	99,764	8.54	1.79	0.00	5.91	8.43	11.70	20.49
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 2.

Table 2: 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 3: Prediction models of default using PD.

Dependent: Default	(1) Correlation	(2) Within Bank-Year	(3) Baseline	(4) Within Firm	(5) Within Firm-Year
(A) Linear Model					
PD	0.590***	0.665***	0.586***	0.451***	0.353***
	(0.014)	(0.159)	(0.147)	(0.025)	(0.050)
Controls	None	None	L F	L B F	L B
Fixed Effects	None	BMY	BMY	F B Y	FY
Observations	106,349	106,349	106,349	61,726	18,970
R2	0.065	0.157	0.169	0.577	0.626
(B) Log-Linear Model					
Log(PD)	1.535***	3.178***	2.337***	0.990***	0.707***
	(0.058)	(0.570)	(0.425)	(0.170)	(0.212)
Controls	None	None	L F	L B F	L B
Fixed Effects	None	BMY	BMY	F B Y	FY
Observations	106,349	106,349	106,349	44,126	18,887
R2	0.052	0.114	0.132	0.565	0.617
(C) Logit Model					
PD	0.048***	0.048***	0.038***		
	(0.001)	(0.001)	(0.001)		
Marginal Effect	0.0017	0.0017	0.0014		
Controls	None	None	L F		
Dummies	None	I Y	Y		
Observations	106,349	106,345	106,345		
Pseudo R2	0.055	0.076	0.107		
(D) Probit Model				*polynomial*	
PD	0.026***	0.026***	0.021***	0.024***	
	(0.000)	(0.000)	(0.001)	(0.008)	
Marginal Effect	0.0021	0.002	0.0016	0.0017	
Controls	None	None	L F	L F	
Dummies	None	I Y	Y	I Y	
Observations	106,349	106,345	106,345	106,345	
Pseudo R2	0.072	0.094	0.135	0.152	

Notes: Robust standard errors are reported in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). The dependent variable is a dummy indicating whether a firm defaulted on a loan within the sample or not. The independent variable of interest is *PD* in panel A, C, and D or *Log(PD)* in panel B. The specifications in each column have different additional control variables and fixed effects at different levels which are explained by the letters. L stands for bank-firm level, F for firm-level, B for bank-level, Y for year-level, M for market-level, and I for industry-level. In the upper panel A we use a linear model, in panel B we use a log-linear model, in panel C we use a logit model, and in panel D a probit model. In the last column of panel D, we use a five-degree polynomial probit model. The polynomial terms are significant but close to zero and not displayed here.

Table 4: Soft information about default in PD.

	(M0)	(M1)	(M2)	(M3)
(A) Residual pricing information as a proxy for soft information				
PD		0.587***		0.586***
		(0.147)		(0.146)
Residual			0.195***	0.126**
			(0.064)	(0.051)
Loan, Firm, Industry Controls	Yes	Yes	Yes	Yes
Bank×Market×Year FEs	Yes	Yes	Yes	Yes
Observations	106,349	106,349	106,349	106,349
R2	0.1204	0.1691	0.1207	0.1693
ΔR2 (vs M0)		0.0487	0.0003	0.0489
(B) Firm-Time fixed effects as a proxy for soft information				
PD		0.424*		0.424*
		(0.244)		(0.244)
Firm-Time FEs			0.155*	0.128*
			(0.080)	(0.072)
Loan, Firm, Industry Controls	Yes	Yes	Yes	Yes
Bank×Market×Year FEs	Yes	Yes	Yes	Yes
Observations	12,429	12,429	12,429	12,429
R2	0.2096	0.2305	0.2097	0.2306
ΔR2 (vs M0)		0.0209	0.0001	0.021

Notes: Clustered standard errors at the bank-level in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). The dependent variable is a dummy indicating whether a firm defaulted on a loan during the sample period. In the first column, we use only observable variables at the bank-firm level and firm-level as well as bank-market-year fixed effects and industry dummies to predict loan default. In the second column, we add *PD* as an explanatory variable. In the third column in the upper panel, we use the residual from a regression specified exactly as model M0 in column 1 but using *Rate* as the independent variable as an additional independent variable. In the third column in the lower panel, we use the firm-year fixed effects from a model using loan-, and bank-level controls and borrower-time fixed effects to predict the loan rate (cf. specification of the model in column 1 of table 5). In the fourth column, we include both, *PD* and the residual or fixed effect regressor. In the last row of each panel, we show how the difference in R2 between the model estimated in the respective column and model M0 in the first column.

Table 5: Lending standards of entrants versus incumbent banks.

	(1)	(2)	(3)	(4)
Dependent Variable:	Rate	Collateralized	Coll.Share	Log(Loan)
Entrant	-0.265**	-0.108***	3.710	0.461***
	(0.120)	(0.032)	(3.010)	(0.070)
Log(PD)	0.028	-0.054***	-0.897	0.002
	(0.022)	(0.006)	(0.567)	(0.014)
Interest Rate		-0.004	-2.350***	-0.191***
		(0.004)	(0.365)	(0.010)
Collateralized	0.023			0.047
	(0.061)			(0.042)
Log(Loan)	-0.469***	-0.001	3.668***	
	(0.024)	(0.007)	(0.667)	
Loan/Assets	0.004***	0.000	-0.079***	0.033***
	(0.001)	(0.000)	(0.027)	(0.001)
CIR	0.009***	-0.005***	-0.554***	0.009***
	(0.003)	-0.001	(0.138)	(0.002)
Deposit Ratio	0.015***	0.004***	0.124***	0.016***
	(0.002)	(0.000)	(0.041)	(0.001)
Equity Ratio	0.002	0.010**	-0.807	0.027***
	(0.016)	(0.004)	(0.631)	(0.010)
Liquidity Ratio	0.008	-0.001	-0.237	-0.017***
	(0.006)	(0.001)	(0.329)	(0.004)
LLP Ratio	-0.104	0.291***	1.745	0.347***
	(0.089)	(0.020)	(1.949)	(0.055)
NIM	-0.208***	-0.133***	4.548***	-0.174***
	(0.049)	(0.011)	(1.606)	(0.032)
ROE	-0.019***	-0.004***	-0.154*	0.007***
	(0.003)	(0.001)	(0.084)	(0.002)
Bank Size	-0.085***	-0.024***	0.513	0.068***
	(0.025)	(0.006)	(1.148)	(0.015)
Firm×Year FE	Yes	Yes	Yes	Yes
Observations	14,470	7,636	2,325	14,470
R2	0.634	0.650	0.626	0.790
R2-within	0.158	0.234	0.283	0.469

Notes: Clustered standard errors at the borrower-level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is named in the column heads. Entrant is defined as dummy indicating the bank that first reports exposures in the municipality. The table show results from estimating equation (4).

Table 6: Robust correlation between PD and interest rates.

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)
Relationship-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)
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 (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$). Each column defines the set of fixed effects that are used in the regression. They can be defined at the bank(B)-, market(M)-, and year(Y)-level. 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. In column 4, we add bank-level controls which comprise CIR, deposit ratio, equity ratio, liquidity ratio, LLP ratio, NIM, ROE, and log(assets).

Table 7: 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. In column 2, the sample is reduced to firms with a B or C rating, while the sample in column 3 comprises only A-rated firms. In columns 4 and 5, we split the sample along the median of the firm size distribution. Competition variables are defined at the municipality-level. The upper two panels show results from estimating equation (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 equation (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 relationship-level and firm-level controls (as in Table 6), industry dummies, and bank-market-year fixed effects.

Table 8: Robustness of competitive risk-based pricing.

	(1)	(2)	(3)
Competition variable:	HHI	Log(NComp)	Post Entry
Log(PD)	0.040	0.236***	0.194***
	(0.026)	(0.079)	(0.048)
Log(PD)×*Competition*	0.173***	-0.0391**	-0.110**
	(0.036)	(0.018)	(0.045)
Time-to-Maturity	-0.0175*	-0.017*	-0.014
	(0.009)	(0.009)	(0.011)
Loan-,Firm-, Ind.-Controls	Yes	Yes	Yes
Bank-Market-Year FE	Yes	Yes	Yes
Observations	45,623	45,623	42,623
R2-within	0.136	0.135	0.136
Log(PD)	0.0551	0.176**	-0.0131
	(0.0353)	(0.0686)	(0.104)
Log(PD)×*Competition*	0.118***	-0.0229**	0.107
	(0.0409)	(0.0114)	(0.108)
LGD	0.0309**	0.0309**	0.0309**
	(0.0121)	(0.0121)	(0.0121)
Loan-,Firm-, Ind.-Controls	Yes	Yes	Yes
Bank-Market-Year FE	Yes	Yes	Yes
Observations	30,954	30,954	30,929
R2-within	0.206	0.206	0.206

Notes: Clustered standard errors at the bank-level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The estimated models are the same as in column 1 of Table 7. In the upper panel, we include only new loan relationships in the sample that we observe either defaulting or ending within our sample period. We add *Time to maturity* as a covariate which is calculated as the remaining years before the bank-firm relationship is terminated. In the lower panel, we add *LGD*, loss given default as reported for regulatory purposes by IRB banks, as a control variable which reduces the sample.

Table 9: Change in R2 across competition intensity

	High Competition	Low Competition
Within-R2	13.3 %	15.5 %
Change (in %)		≈17 %

Notes: This table reports the change in within-R2 when regressing the interest rate on $\log(PD)$, in addition to same set of controls and fixed effects as in our baseline regression (2), for two subsamples. The "High Competition" subsample contains municipality x years where the HHI is below the median, while the "Low Competition" subsample contains municipality x years where the HHI is above the median.

Table 10: Franchise Value 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)×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)	-0.075***	0.005	-0.074***	-0.002	-0.055**	-0.025
×Log(N Comp)	(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)	-0.100**	-0.016	-0.081*	-0.080	-0.120**	-0.004
×PostEntry	(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 banks on which estimation is based. In columns 1 and 2, we sample is split along the median *Equity Ratio* of banks in the baseline sample. In columns 3 and 4, the sample is split along the median *Net Interest Margin* (NIM) of banks in the baseline sample. In column 6, we use only observations from the largest 5 banks, in column 5 we use all remaining banks. Competition variables are defined at the municipality-level. The table show results from estimating equation (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 relationship-level and firm-level controls (as in Table 6), industry dummies, and bank-market-year fixed effects.

Table 11: Interest Rate Sensitivity towards other Lending Standards.

	(1)	(2)	(3)	(4)	(5)	(6)
Competition:	HHI		Log(N Comp)		Post-Entry	
Collateral Ratio	-0.445**	-0.016	0.024	0.019	-0.038	-0.006**
	(0.180)	(0.025)	(0.253)	(0.254)	(0.077)	(0.003)
Collateral Ratio x *Competition*	0.826**	0.386***	-0.069	-0.068	-0.171**	-0.08***
	(0.398)	(0.135)	(0.076)	(0.076)	(0.068)	(0.003)
Log(PD)	0.091***	-0.438**	0.092***	0.228**	0.117***	0.204***
	(0.026)	(0.179)	(0.026)	(0.112)	(0.039)	(0.061)
Log(PD) x *Competition*		0.798**		-0.040		-0.103**
		(0.398)		(0.028)		(0.052)
L, F, I Controls	Yes	Yes	Yes	Yes	Yes	Yes
BxMxY FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,935	36,935	36,935	36,935	28,304	28,304
R2-within	0.168	0.168	0.167	0.167	0.16	0.174
DtI Ratio	-0.001	-0.001	0.002**	0.002**	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
DtI Ratio x *Competition*	0.003**	0.004**	-0.001*	-0.001*	-0.001*	-0.001*
	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Log(PD)	0.125***	0.062**	0.125***	0.283***	0.134***	0.201***
	(0.027)	(0.031)	(0.027)	(0.079)	(0.034)	(0.043)
Log(PD) $\times$ *Competition*		0.208*		-0.048***		-0.088**
		(0.114)		(0.018)		(0.039)
L, F, I Controls	Yes	Yes	Yes	Yes	Yes	Yes
BxMxY FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	105,867	105,867	105,867	105,867	87,226	87,266
R2-within	0.134	0.134	0.134	0.134	0.134	0.134

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 variable that is used for *Competition.* Competition variables are defined at the municipality-level. *Collateral Ratio* is defined as collateral value over total credit risk exposure as reported in the credit exposure data. *DtI Ratio* is the Debt-to-Income Ratio defined as a firms' interest costs to EBITDA as reported in annual reports. In the upper panel, the sample is restricted to observations with reported collateral value which is less than the loan amount (0 $<$*Collateral Ratio*$<$ 100). In columns (5) and (6) in the upper and lower panel, the sample is further reduced to incumbents following the entrance of a new competitor in their regional market. All estimations include relationship-level and firm-level controls (as in Table 6), industry dummies, and bank-market-year fixed effects.

Table 12: Aggregate effect of risk-sensitive pricing on risk-adjusted portfolio returns.

	(1) Full Sample	(2) Low Equity	(3) High Equity	(4) Low NIM	(5) High NIM	(6) Non-A rated	(7) A rated	(8) SME Firms	(9) Large Firms
Dependent Variable: Average risk-adjusted returns on the bank-market level									
High Risk-Sensitivity	0.006**	0.009***	0.000	0.008**	0.004	0.015**	-0.000	0.014***	0.002
	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)	(0.007)	(0.003)	(0.005)	(0.005)
Agg Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agg Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,647	2,251	2,327	2,410	2,173	1,584	2,862	2,108	2,366
R-squared	0.272	0.339	0.310	0.322	0.322	0.413	0.299	0.327	0.317

Notes: Clustered standard errors at the bank-level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is the average risk-adjusted return on credit risk exposures. Returns were first calculated for each bank-firm relationship as the interest income in the first two years after origination net of write-downs and full default that occur any time after origination relative to the original exposure. Then, returns were averaged at the bank-market-year level. *High Risk-Sensitivity* is a dummy indicating an above the average risk-sensitivity coefficient. The coefficients are estimated by regressing *Log(PD)* on *Interest Rate* with the set-up as in Table 6 individually for each bank-market-year. The subsamples in columns 2 to 9 are defined as in tables 7 and 10. For columns 6 to 9, the loan returns averages were calculated separately for the two subsamples of firms. All regressions include relationship- and firm-level covariates that were also averaged over the bank-market-year as well as bank-year and market fixed effects.

Table 13: Definitions of variables.

Variable	Definition
Variables at the bank-firm-year level	
Interest Rate	The average interest rate a firm was charged by a bank during one year on loans outstanding, guarantees, or drawn credit lines [in percent,0-100].
Log(PD)	The probability of default of the firm estimated by the bank [in percent, logarithmized].
Collateralized	Dummy indicating whether an exposure is 100 percent or more covered with collateral [0/1].
Collateral Ratio	Ratio of the collateral value the bank reports to have available for the exposure to total exposure [0-X].
Loan/Assets	Ratio of the total exposure (outstanding loans, guarantees, and drawn credit lines) to firm's total assets [0-100, winsorized at 1%].
Log(Loan)	Total exposure (outstanding loans, guarantees, and drawn credit lines) [in mil NOK, logarithmized].
Variables at the market-year level	
HHI	Hirschman-Herfindahl-Index (HHI) is defined as the sum of squared market shares of all banks present in the defined market. Market shares are calculated as the total exposure of a bank to firms located in the market relative to the total exposure of all banks to the firms located in the market. Markets are delineated as municipalities in the main analysis (economic regions, states in the appendix). [0-1]
Log(N Comp)	The number of competitors (N Comp) comprises every bank that has exposures to firms that are located in the defined market [X, logarithmized].
Post Entry	Dummy indicating the year in which one or more banks entered into the defined market relative to the year before entry [0/1].
Variables at the bank-market-year level	
Entrant	Dummy indicating a bank that has entered the defined market in any given year [0/1].
Variables at the bank-year level	
CIR	Cost-Income-Ratio is defined as the ratio of administrative costs (summing the wage bill and other operative costs) to operating income which is the sum of interest income and fee& commissions income. [0-X]
Deposit Ratio	Ratio of total deposits to total assets [0-100].
Equity Ratio	Ratio of total equity to total assets [0-100].
Liquidity Ratio	Ratio of liquid assets (defined as assets at the central bank and interbank assets) to total assets [0-100].
LLP Ratio	Ratio of loan loss provisions (LLP) to gross loans [0-100].
NIM	Net-Interest-Margin (NIM) is defined as the ratio of net interest income to interest bearing assets which sum-up interbank assets, total net loans & receivables, and interest bearing securities [0-100].

Table 13: (Continued) Definitions of variables.

Variable	Definition
(continued) Variables at the bank-year level	
ROE	Return-on-Equity (ROE) is defined as the ratio of profit before taxes (EBT) to total equity [0-100].
Log(Assets)	Total assets of the bank [in mil NOK, logarithmized].
Variables at the firm-year level	
A-Rated	Dummy indicating whether the firm has an A-Rating [0/1].
B-Rated	Dummy indicating whether the firm has an B-Rating [0/1].
C-Rated	Dummy indicating whether the firm has an C-Rating [0/1]. (The remaining category are non-rated firms.)
Fixed Assets Ratio	Ratio of total fixed assets to total assets [0-100, winsorized at 1%].
Intangibles Ratio	Ratio of intangible assets to total assets [0-100, winsorized at 1%].
Debt Ratio	Ratio of total debt to total assets [0-100, winsorized at 1%].
DtI Ratio	Debt-to-Income (DtI) Ratio is defined as the ratio of expenditures on interest to profit before interest, taxes, and depreciation (EBITDA) [0-X].
ROA	Return-on-Assets (ROA) is defined as the ratio of profit before interests, taxes, and depreciation (EBITDA) to total assets [0-100, winsorized at 1%].
Log(Assets)	Total assets of the firm [in mil NOK, logarithmized].

Notes: This table provides a description of the main variables used for the empirical analysis reported in the paper. Additional variables that are used in specific robustness test are defined in the footnotes of the respective tables.

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 B1 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

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.

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 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 main specification from 5 at the NUTS3- and NUTS4-level. 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 to 4 also confirm that risk pricing gets less sensitive as competition increases.

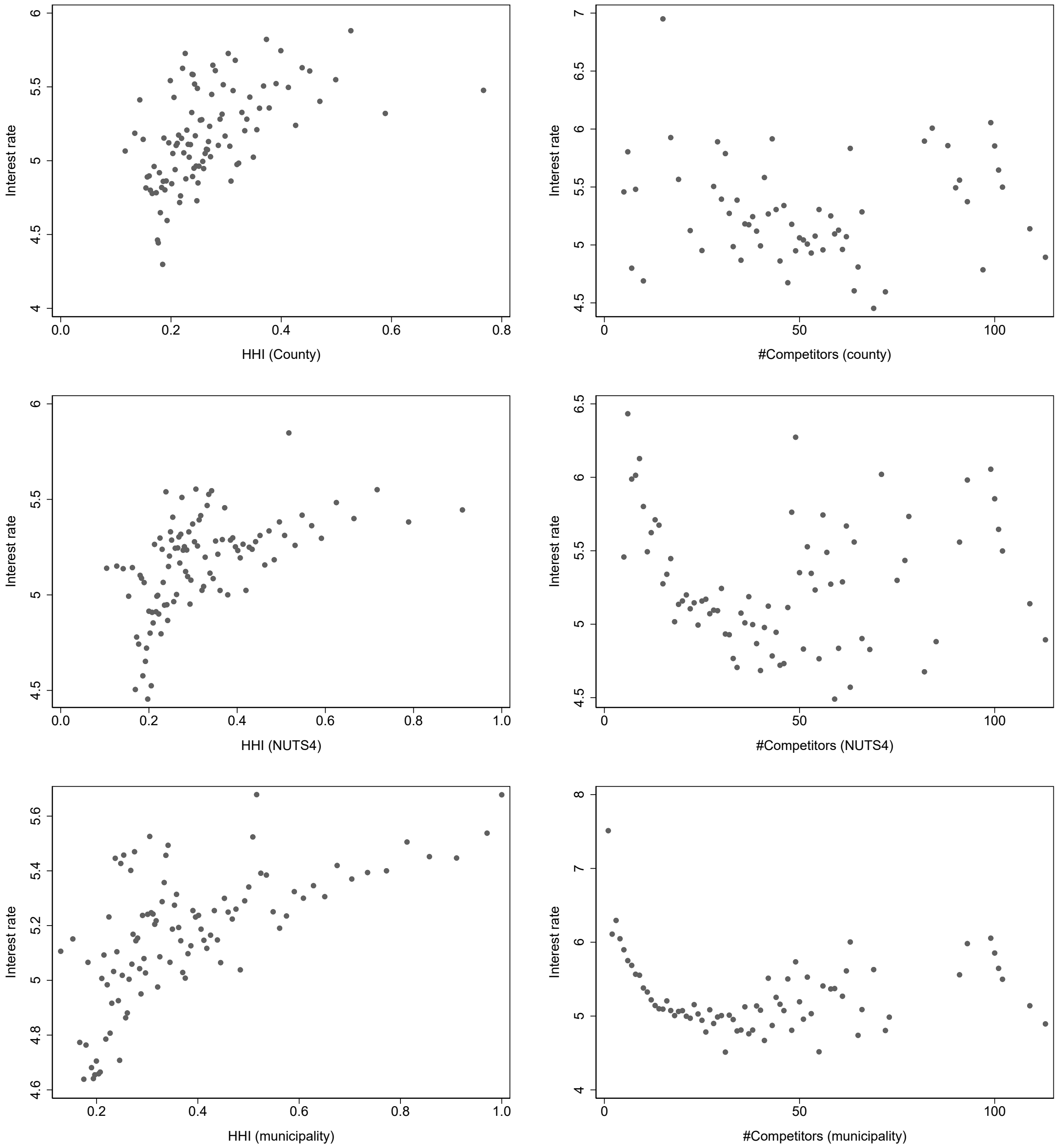


Figure B1: Regional competition and pricing.

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).

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

	(1)	(2)	(3)	(4)
Competition variable:		HHI	Log(NComp)	Post Entry
		Market: Economic Regions (NUTS4)		
Log(PD)	0.126***	0.0721**	0.421***	0.205***
	(0.027)	(0.028)	(0.102)	(0.044)
Log(PD)×*Competition*		0.160***	-0.0832***	-0.0923**
		(0.048)	(0.024)	(0.045)
Loan, Firm, Ind. Controls	Yes	Yes	Yes	Yes
Fixed Effects	BMY	BMY	BMY	BMY
Observations	108,370	108,370	108,370	107,127
R2-within	0.134	0.134	0.134	0.135
		Market: Counties (NUTS3)		
Log(PD)	0.127***	0.0775**	0.701***	0.236***
	(0.0264)	(0.0362)	(0.203)	(0.0488)
Log(PD)×*Competition*		0.174*	-0.143***	-0.125**
		(0.103)	(0.046)	(0.056)
Loan, Firm, Ind. Controls	Yes	Yes	Yes	Yes
Fixed Effects	BMY	BMY	BMY	BMY
Observations	109,056	109,056	109,056	109,043
R2-within	0.134	0.134	0.135	0.134

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 upper panel, competition variables (HHI and Log(N Comp) and Post Entry) 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 the lower panel, the competition variables are defined at the county level. The estimations include bank-market-year (BMY) fixed effects. We further added loan-, and firm-level control variables as well as industry dummies.

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