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Bank lending rates and the remuneration for risk: evidence from portfolio and loan level data

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Abstract

We employ interest rates and expected loss probabilities from the 2021 EBA Stress Test dataset and euro area credit registries to examine whether the risk-return relationship holds in banking. After controlling for bank, loan, and debtor characteristics as well as macroeconomic conditions, results indicate that a risk-return relationship in bank lending is present but varies significantly across and within borrower segments. While bank lending rates appear to be quite responsive to risks towards households, results suggest that banks only significantly increase interest rates towards non-financial corporations that reside in the riskiest quantiles of the distribution. This potentially implies the presence of a cross-subsidization effect of credit risk.

Keywords: risk-return, credit register, banking, loans, interest rates

JEL Classification: E51, E52, E58

Non-Technical Summary

We examine the possible existence and strength of the relationship between bank lending rates and borrower risk. Bank lending rates, or more specifically, interest premiums (margins), represent the ex-ante rate of return of a loan and therefore provide a way for banks to compensate for the risks they take on. Consequently, in line with prudent risk management practices, higher risk should yield higher margins. While early research on this matter dates back to decades ago, previous academic work often employs bank-level or country-level aggregates, which in general leads to rather coarse proxies for credit risk.

This paper overcomes this challenge by exploiting two distinct datasets. First, the EBA 2021 stress test dataset is used, comprising of bank portfolio-level data on household credit for consumption (HH-CC), household real estate (HH-RE), and non-financial corporations (NFC). Second, loan level data obtained from euro area credit registries is used to explore the risk-return relationship towards non-financial corporations on a more granular (sectoral) level.

In order to assess the relationship between risks and returns, a panel regression model is estimated which accounts for unobserved heterogeneity across banks and periods of time (i.e. bank and time fixed effects). At the same time, we control for various further characteristics pertaining to the bank, the debtor, the portfolio, the loan, and the prevailing macroeconomic environment. Furthermore, in order to account for potential non-linearities in the relationship, the data is split in different quantiles.

Results show that a risk-return relationship in bank lending is present but varies significantly across and within portfolio types. While bank lending rates seem to be quite responsive to risks towards households, banks seem to only significantly increase interest rates in the case of NFCs that reside in the riskiest quantiles of the distribution. In addition, results are further assessed through the introduction of a "credit risk premium per unit of risk" measure that takes into account the skewness of the expected loss distribution. The results from this new metric support the view that the pricing of NFC loans differs from that of household loans.

Finally, in order to assess whether bank lending rates compensate sufficiently for credit risk, a risk-free yielding credit risk premium is constructed as a benchmark. The comparison between the empirical and benchmark rate shows that households are charged significantly higher premiums than required to cover risks. This is in stark contrast with lending rates towards NFCs, where risks are for the most part insufficiently priced. This potentially implies the presence of a cross-subsidization effect of credit risk from households to NFCs.

1. Introduction

The banking sector is key in fostering economic growth by channelling funds from lenders to borrowers (Maudos and Guevara, 2004). Numerous researchers have pointed out over the past decades that this intermediation process has a high bearing on the real economy through macro-financial linkages. In this light, it is crucial that the process of borrowing and lending money is carried out in a sustainable manner, with risk management playing a central role.

As outlined by Markowitz (1952, 1959), a prudent approach to risk management should aim to optimize returns while minimizing risks. The most prominent risk factor in bank lending pertains to credit risk, reflecting the possibility that some loans will not be paid back in full. Thus, if not compensated properly, higher risk may potentially lead to significant losses. This is especially true in bank lending where sound risk management practices may be the decisive factor between financial stability and the severe repercussions of another banking crisis. Consequently, the ability to assess banks' risk taking across different lending products and risk levels has important implications on policy decisions. This includes the implementation of macroprudential measures that aim to reinforce the resilience of the financial system (Laeven et al., 2022). However, whether credit risk has been appropriately priced in the prevailing loan interest rates has not been properly examined in the past.

This paper attempts to fill this gap in the literature by exploring the risk-return relationship in bank lending quantitatively, using two different granular banking datasets. First, we retrieve data from the EBA 2021 Stress Test exercise which contains data on banks' portfolios such as Household-Real Estate (HH-RE), Household-Consumer Credit (HH-CC) and Non-Financial Corporations (NFC) across 45 geographies as well as 28 currencies for a sample of 89 banks. Second, we exploit loan-level data from euro area credit registries which permits an even more comprehensive analysis of bank lending but only to non-financial corporations (NFC).

To assess the risk-return relationship in bank lending, a panel regression model is estimated which accounts for unobserved heterogeneity across banks and periods of time (i.e. bank and time fixed effects). At the same time, we control for various other characteristics pertaining to the bank, the debtor, the portfolio, the loan, and the prevailing macroeconomic environment.

Moreover, to account for potential non-linearities in the relationship, the data is split in different quantiles.

Results show that a risk-return relationship in bank lending exists but differs significantly across and within portfolio types. While bank lending rates seem to be quite responsive to risks towards households, banks seem to significantly raise interest rates only in the case of NFCs that reside in the riskiest quantiles of the distribution. In addition, by taking the difference in credit risk across quantiles into account, we find that interest rate mark-ups across all borrower segments become less reactive to an increase in borrower's risks. This is evident especially in the NFC category, where it is found that interest rate margins from the top 50% of the expected loss distribution rise less than the increase in borrowers' credit risk.

Furthermore, in order to assess whether bank lending rates compensate sufficiently for credit risk, a risk-free yielding credit risk premium is constructed as a benchmark. By comparing this benchmark rate to empirical premiums, we show that banks seem to charge rather high margins rates to both household segments at the lower quantiles of the distribution. Conversely, margin rates for borrowers from NFC sectors are found to be set below the risk-free compensating threshold at the riskiest shares of the expected loss distribution. This behaviour suggests a cross-subsidization effect, especially from the low-risk household loans to the high-risk NFC loans.

Potential reasons for this effect may relate to higher regulatory requirements for household loans, as well as higher competition due to lower homogeneity across the terms and conditions of NFC loans.

With regards to the other variables, another potential avenue for a mispricing of risk is that of maturity. Results imply that longer maturities give rise to lower interest rate margins, a result in line with the literature (Entrop et al., 2014). While this implies that banks are willing to extend lower interest rate loans to households in exchange for a long-term cash flow, it may also lead to potential liquidity risk issues, especially in the advent of an upward yield curve shock.

In addition, the prevailing reference rate has a significant positive relationship with margins. Such a relationship suggests that higher interest rates could promote higher bank profitability, a view also supported by previous studies (e.g. Genay and Podjasek, 2014; Borio et al., 2017).

Policy-wise, the results leave one question unanswered: given that banks do not appear to charge the appropriate risk-adjusted interest rate, especially in the top quantiles, why do they risk extending credit to individuals or firms whose creditworthiness is ex ante low? Potential reasons for banks to deviate from the basic investment tenet can be to pursue strategic goals like gaining market shares or access to markets, or even perhaps shareholder pressure to increase profits via an expansion of the bank's balance sheet (see e.g. Jensen and Meckling, 1976).

While we do not profess to hold the answer to this very important question, we would note that the findings in this paper simply underline the need for extending loans in a prudent and conservative manner. As such, the granting of credit in firms or individuals whose creditworthiness is not high, or whose innovative nature has yet to provide evidence of the ability to repay, should perhaps be avoided. This is justified not only by the fact that it does not fit the profile of prudential banking (Michail, 2021) but it also does not offer any risk-adjusted returns that could compensate for the amount of risk assumed by the bank.

The following sections provide an overview of the existing literature, the data, as well as the methodology and identification method employed. Finally, results are analysed and discussed, while the last section concludes.

2. Literature Review

One of the basic tenets of finance theory is that higher assumed risk should be compensated with higher potential return. This has been illustrated in a variety of applications, notably in the investment realm, where, for example, stocks have been shown to compensate their higher volatility (risk) with higher long-run returns compared to safer (less volatile) assets such as Treasury yields (Malkiel and Xu, 1997). Other empirical tests of the stock market's risk and return relationship can be found, inter alia, in Xing and Howe (2003), Park (2009), Chen (2015), and Singh and Singh (2017), all of which highlight that a positive risk-return relationship exists, even though, at times weak.

With regards to the banking sector, the literature has focused mostly on either assessing the risk and return relationship via stock market returns (Elyasiani and Mansur, 2003; Neuberger, 1991), or on how monetary policy, via the risk-taking channel, can potentially affect bank lending policies. This realm has gathered much popularity in recent years (see, among others, Ghysels et al., 2016; Delis et al., 2017; Dell'Ariccia et al., 2017; Bonfim and Soares, 2018; Morais et al., 2019; Afanasyeva and Güntner, 2020; Michail et al., 2021). As the literature suggests, ex ante riskier borrowers receive more funding when interest rates are lower.

A different branch of the literature has instead been focusing on unravelling the determinants of banks' price-setting behaviour. For example, the dynamic dealership model, which was first introduced by Ho and Saunders (1981), assumes that banks are maximizing a utility function of terminal wealth that hinges on the non-synchronous arrival of loans and deposits. The bank pricing model of Ho and Saunders (1981) and the numerous extensions that followed, demonstrate a wide range of factors that may influence bank's lending rates, such as credit risk, market structure and risk aversion, (see, inter alia, Angbazo, 1997; Gropp et al., 2007; Maudos and Guevera, 2004; Hawtrey and Liang, 2008; and Saunder and Schumacher, 2000). While such studies brought considerable light to the drivers behind price setting behaviour in bank lending, the high level of aggregation usually employed could potentially average out certain interest rate determinants.

Furthermore, there has been no study, to the best to our knowledge, which directly employs a direct credit risk metric. Usual proxies include capital to assets ratios, loans to assets ratios, and NPL ratios, all of which are influenced by many exogenous factors, including the banks' risk appetite in the past, current macroeconomic conditions, and interest rate changes (see Michail et al., (2021) for more details).

Our dataset accounts for an accommodation of both the above-mentioned issues. First, it allows us to use loan-specific credit risk metrics, namely the probability of default and loss given default, whose combination, the expected loss, offers the clearest view on the ex-ante credit risk of a particular loan. Further to the loan-specific credit risk parameter, which allows us to better address the risk-return relationship in banking, our dataset is broad enough to allow for a generalization of the estimates. In particular, the EBA Stress Test dataset offers detailed data for 89 banks, across 3 loan segments, 28 currencies and 45 geographies, on the basis of actual 2020 data and projections based on macro-financial scenarios. The AnaCredit credit register allows for the use of around 5 million observations in total, hence allowing us more detailed information with regards to this relationship.

Results indicate the existence of a risk-return relationship in bank lending. However, interest rate mark-ups, especially in the NFC category, become less reactive to an increase in borrower risks at the rightmost (riskiest) part of the distribution. Lastly, a comparison between the empirical rate and a constructed, risk-free, benchmark rate shows that households are charged significantly higher premiums than required to cover risks. This is in stark contrast with lending rates towards NFCs, where risks are, for the most part, insufficiently priced.

3. Data

The heterogeneity in the pricing of different portfolios (sectors) highlight the need for granular exposure data and may caution against the use of bank-level or country-level aggregates which might average out the effect of certain interest rate determinants. In this light, this study exploits two datasets of different granularity. First, we employ the EBA Stress Test dataset, which comprises of portfolio-level loan data for banks across the euro area. Second, we retrieve data from the AnaCredit credit registry, which offers granular, loan-level information, however limited to Non-Financial Corporation (NFC) loans. More details on the datasets and specific variables can be found in the sections below.

3.1. EBA Stress Test 2021: Portfolio level dataset

The EBA stress testing exercise evaluates the solvency of banks by assuming a static balance sheet over the projected years 2021-2023 under both a baseline and an adverse scenario. The exercise is carried out by the EBA every two years in cooperation with the ECB, the European Systemic Risk Board (ESRB) and the national supervisor authorities. The sample consists of the largest significant banks supervised directly by the ECB. In parallel, the ECB conducts the Supervisory Review and Evaluation Process (SREP) stress test for banks that are not under the EBA sample but are evaluated under an identical stress testing approach. In this study, we use the 2021 EBA Stress Test template which contains data for 89 banks (of which 38 are under the EBA sample and 51 under the SREP sample) from the euro area and Norway.[2] The dataset

[2] For further information see: https://www.eba.europa.eu/eba-launches-2021-eu-wide-stress-test-exercise

holds information on credit exposures, risk parameters and interest margins for three portfolios (Household Real Estate – HH_RE, Household Consumer Credit – HH_CC, and Non-Financial Corporations – NFC) in 45 distinct countries for the year 2020 as well as projected data for the years 2021-2023 for the baseline and adverse scenario of the EBA Stress Test at an annual frequency.[3] Thus, in total 4 years of data for each scenario is available for this analysis with the initial historic year, i.e. year 2020, being the same for both scenarios. While we restrict the subsequent analyses on the years 2020-2023 of the baseline scenario in order to avoid distortions from extremer economic conditions, our findings are robust also with respect to the adverse scenario. The respective results for the adverse scenario are reported in the appendix.

To measure the return dimension in bank lending, we retrieve interest margins which are defined as the difference between lending rates and estimated charges corresponding to origination, management, and capital cost. In this paper, we consider only margins on new loans since these cover the banks' pricing decisions best with respect to debtors' risk at the time of the origination of the loan and do not reflect any potential subsequent changes in credit risk due to repayments, change in collateral value, etc. Next, we compute ex-ante credit risk of a particular portfolio as the product between (point in time) probability of default (PD) and loss given default (LGD). Even though the probability of default and losses given default are only available for the whole portfolio stock, given that the Stress Test methodology, by definition, applies a uniform exogenous shock to the aggregate portfolio, these metrics may still serve as the best available proxy for borrowers' risks for new loans.

To account for prevailing macroeconomic conditions, we include various control variables. The dataset contains portfolio level information on the reference interest rate that is defined as, "*the general underlying 'risk-free' rate relevant for the given instrument, as used by banks in the management of their interest rate risk in the banking book*" (2021 EU-Wide Stress Test Methodological Note). Next, we construct the variable "currency" that equals 1 if the portfolio is

[3] While the granularity for the credit risk template is quite high and would permit further distinctions by enterprise size, (e.g. SME and nonSME), or type of collateral, (e.g. real estate or non-real estate), the interest income templates do not offer the same level of granularity. Thus, credit exposures are aggregated to the exposure groups of household credit consumption (HH-CC), credit for household real estate purchases (HH-RE) as well as loans to non-financial corporations (NFC). The geographical distribution of the data can be found in the Appendix.

denominated in euro and 0 in all other cases. In the same vein, we control for a home bias, by setting the variable "home" to 1 if the portfolio's geographical exposure is the same as the bank's jurisdiction. In addition, we also include the portfolio's maturing profile, defined as *"the methodologically predefined average fraction of a year at which the maturing positions mature/reprice*" (2021 EU-Wide Stress Test Methodological Note), expressed in years.

In addition to the above, we also add a "size" variable, which is set to 1 if the investment ratio of the portfolio is larger than the median investment ratio in the portfolio segment sample.[4] Some researchers argue that a larger size of exposures could potentially have a positive effect on interest rates, since the larger the size of a transaction, the larger the potential loss will be (see e.g. Maudus and Guevara, 2004). On the other hand, others point out that larger transactions may enjoy a reduced interest rate since they reduce the frequency of operations and divide administrative costs across a larger base, which could decrease the bank's operating expenses (Hawtrey and Liang, 2008).

Lastly, we include bank-level control variables that according to the literature may drive the level of interest (margin) rates. We control for market power, which is proxied by the Lerner index, estimated through a translog function. A more detailed derivation of the Lerner index is provided in the appendix. Next, we control for the presence of implicit interest rates which can arise if banks charge higher margin rates to compensate for offering free banking services. We compute implicit interest payments as the difference between operating expenses and non-interest income over total assets. Another potential factor that relates to banks' interest rate decision pertains to risk aversion. As posited by the dynamic dealership model, the optimal bank interest margin increases as the bank becomes more risk adverse (Ho and Saunders, 1981). We aim to proxy for this notion through the leverage ratio. A bank with a higher leverage ratio[5] is assumed to be more risk averse than a bank with a leverage ratio on the lower side. Lastly, we also control for maturity mismatch which emerges due to the role banks play in transferring money from counterparties who are in surplus to agents who are in demand for funds. We proxy for this risk factor by simply computing the difference between the volume weighted average

[4]We follow Roncoroni et al. (2019) and compute "investment ratio" as the exposure of the portfolio divided by CET1 capital.

[5] In accordance with the Capital Requirements Regulation (CRR) Regulation (EU) No 575/2013, the leverage ratio is the bank's supervisory Tier 1 capital (numerator) divided by its total exposure (denominator).

of maturities on the assets and liabilities side. Descriptive statistics for the Stress Test dataset can be found in the Appendix.

3.2. AnaCredit Credit Register: loan level dataset

The AnaCredit credit register allows for a more detailed look at loans to NFCs as it contains loan-level data of all bank loans to NFCs in the euro area above a threshold of 25,000 EUR. In AnaCredit, new loans are identified by only considering the observation where reporting month and inception date of the loan match. For this exercise, data between September 2018 and April 2021 are considered, leading to over 11 million observations in total. Additional data-cleaning steps involve the removal of state guaranteed loans, observations with missing information on the debtor's sector or enterprise size as well as the removal of observations from the "Financial" and "Public" sectors. Winsorizing the remaining dataset to the 5th-95th percentile of the interest rate and the PD, as well as keeping only the "Credit Lines", "Financial Leases" and "Loans" loan types leaves about 5 million observations for the final analysis.

Apart from the fact that Anacredit is more granular, another difference with the ST dataset is that AnaCredit only includes the annualized agreed interest rate, as opposed to interest rate margins. Our model specification accounts for the difference by controlling for bank and time fixed effects, and therefore for unobserved heterogeneity across these two dimensions. Furthermore, the inclusion of the risk-free rate implicitly accounts for the cost of capital for banks; as such this database-related difference does not materially affect the conclusions reached. Data for the geographical coverage of the AnaCredit Dataset can be found in the Appendix.

As for the previous portfolio level dataset, we also include a similar set of control variables such as "currency", "home", which are defined in section 3.1, and "maturity" which for the loan level dataset is defined as the number of years until the contractual maturity date of the instrument is reached. We also include a proxy for the risk-free rate for each loan by mapping the inception and maturity date with that of zero-coupon yield curves provided by the ECB's statistical data warehouse.[6]

[6] For more information on how zero-coupon curves are computed, please see: https://www.ecb.europa.eu/stats/financial_markets_and_interest_rates/euro_area_yield_curves/html/index.en.html

Additionally, via AnaCredit it is possible to control for loan characteristics such as loan type, which in this paper is limited to “Credit Lines”, “Financial Leases” or “Loan” and collateral status of the loan (i.e. secured or unsecured). We also control for enterprise size of the borrower, which distinguishes between Micro, Small, Medium and Large enterprises.[7]

Lastly, we include bank control variables, such as the leverage ratio, implicit interest rates and market share. Market share is computed as the sectoral loan volume by bank divided by the total sectoral volume in the sample, while the leverage ratio and implicit interest rates are computed as defined in 3.1 Summary statistics can be found in the Appendix.

4. Econometric setup

In principle, the price of a loan should be set to compensate a bank for the cost of loan origination (funding and administrative expenses), the cost of equity, plus a credit risk premium. The credit risk premium is intended to cover the expected loss of the loan at the time of origination and should increase with the riskiness of the borrower at that time. To estimate the risk sensitivity of bank loan pricing, we make use of a set of linear panel regressions with bank and time fixed effects. In detail, the regression specification with regards to the portfolio dataset can be expressed as follows:

$$\begin{aligned} NIM_{k,i,j,t} = {} & \alpha_{k,i,j,t} + \beta EL_{k,i,j,t} + \sum_{s=1}^{N_1} \gamma_s BankControls_{s,k,i,t} \\ & + \sum_{s=1}^{N_2} \rho_s PortfolioControls_{s,k,i,j,t} + \sum_{s=1}^{N_3} \omega_s CountryControls_{s,j} \\ & + \sigma FixedEffects_{k,t} + \varepsilon_{k,i,j,t} \end{aligned} \tag{1}$$

where NIM refers to the interest margin, while subscripts k, i, j, t denote the bank, portfolio, country, and year, respectively.

The variable EL is computed as the product between PD and LGD for each individual portfolio. The $BankControls$ and $PortfolioControls$ vectors include variables described in section 3.1 to ensure that residuals only contain idiosyncratic effects. The vector $CountryControls$ controls

[7] The definition of the enterprise size is in accordance with the Annex to Recommendation 2003/361/EC and is based on enterprise’s turnover and number of employees.

for the geographical region of the borrower through fixed effects (country group definitions given in Appendix). Panel regressions are carried out for each portfolio type separately and span four years at an annual frequency (2020 + 3-year baseline projections).

The regression specification for the loan level dataset follows broadly the same structure and can be described as follows:

$$R_{i,j,t} = \alpha_{i,j,t} + \beta EL_{i,j,t} + \sum_{s=1}^{N_1} \gamma_s BankControls_{s,i,j,t} + \sum_{s=1}^{N2} LoanControls_{s,i,j,t} + \sum_{s=1}^{N3} \tau_s DebtorControls_{s,i,j,t} + \sum_{s=1}^{N4} \omega_s CountryControls_{s,j} + \sigma\, FixedEffects_{i,t} + \varepsilon_{i,j,t}$$

(2)

where $R_{i,j,t}$ refers to the annualized agreed interest rate and subscripts i, j, t refers to bank, loan and time. The vectors $BankControls$, $LoanControls$, $DebtorControls$ and $CountryControls$ refer to matrices containing further independent variables which are described above and in section 3.2.1. In a similar fashion as for the portfolio level dataset, regressions are estimated separately for each economic segment of corporate loans.

To allow for a more detailed view into the risk-return relationship in banking, we split the variable EL into 5 quintile and 10 decile groups for the portfolio and loan-level dataset respectively. We therefore rewrite equations (1) and (2) as follows:

$$\begin{aligned} NIM_{k,i,j,t} = \alpha_{k,i,j,t} &+ \sum_{n=1}^{5} \beta_n EL^{q_n}_{k,i,j,t} + \sum_{s=1}^{N_1} \gamma_s BankControls_{s,k,i,t} \\ &+ \sum_{s=1}^{N_2} \rho_s PortfolioControls_{s,k,i,j,t} \\ &+ \sum_{s=1}^{N_3} \omega_s CountryControls_j + \sigma FixedEffects_{k,t} + \varepsilon_{k,i,j,t} \end{aligned} \quad (3)$$

$$R_{i,j,t} = \alpha_{i,j,t} + \sum_{n=1}^{10} \beta_n EL^{d_n}_{i,j,t} + \sum_{s=1}^{N_1} \gamma_s BankControls_{s,i,j,t} + \sum_{s=1}^{N2} LoanControls_{s,i,j,t} + \sum_{s=1}^{N3} \tau_s DebtorControls_{s,i,j,t} + \sum_{s=1}^{N4} \omega_s CountryControls_{s,j} + \sigma\, FixedEffects_{i,t} + \varepsilon_{i,j,t} \quad (4)$$

where EL^{q_n} (EL^{d_n}) is equal to one if a portfolio (loan) resides in a given quintile (decile) group of the EL distribution and zero elsewhere. If the risk-return relationship holds, we would expect a positive and significant coefficient, with potentially increasing values, as we move from the lowest to the highest quintile (decile). On the other hand, if the coefficients are insignificant, then one could potentially question whether banks correctly price credit risk when it comes to bank lending. The results from the estimation can be found in the following section.

5. Results

5.1. EBA Stress Tests (Portfolio Level)

In table 1 we display the results from equation (1), estimated separately for loans to HH-CC, HH-RE and NFC. We find evidence that credit risk, proxied by EL, has a positive effect on interest margins on loans for all lending products. On average, the largest effect holds for HH-CC and, the weakest for NFC. More specifically, a one-unit increase in EL increases on average the interest margin by 0.60, 0.50 and 0.13 percentage points for HH-CC, HH-RE and NFC, respectively[8].

As regards the control variables, we find that the reference rate (i.e. the risk-free rate) has a significant positive effect on loans for HH-CC and NFC. The positive relationship between margins and the reference rate implies that banks do potentially exploit higher rates to obtain higher profits. The lack of a relationship between HH-RE and the reference rate can be attributed to the fact that real estate loans have a higher share of fixed interest rate, meaning that they are not as sensitive to interest rate fluctuations.[9] At the same time, HH-RE loans tend to be fixed for a longer period of time compared to HH-CC, which are usually repriced when market conditions change. As evidenced by our regression estimates, this appears easier to achieve for HH-CC portfolios, where the pass-through of a 1 percentage point increase in the risk-free rate is around 0.29 percentage points, while for NFCs the pass-through stands at around 0.14 percentage points. This also implies that the higher the average interest rate of the portfolio, the easier it is for banks to increase their margins. An additional explanation could also be that banks are finding it harder to price risk for HH-CC and NFC portfolios and hence seek to compensate that using the reference rate.

[8] Results are largely the same for the adverse scenario and reported in the Appendix.

[9] Fixed-rate HH-RE account for around 73% of all HH-RE loans, while for NFCs the amount stands at 53%. The difference is even higher in the largest countries (Germany, France, Italy), with a fixed-rate share of 98.6%, 97.2%, and 89.3% respectively.

We also find evidence for the presence of a discount towards portfolios that are denominated in euro, however limited to the HH-CC and NFC categories. The “home bias” variable is significant for NFC portfolios, i.e., banks tend to reduce interest margins with 0.24 percentage points when borrowers are residing in the same jurisdiction. This could potentially signal that, when it comes to NFCs, banks may only find it worthwhile to expand to foreign markets if this allows banks to charge higher rates.

The loan size is significant only for household portfolios. Interestingly, we see that the sign is opposite for consumer credit and mortgages which provide support for the conflicting theories on the effect of exposure size on margin rates. As denoted earlier, a larger size of exposures can have positive effect on margin rates since banks want to insure against the higher potential loss of the portfolio. This effect seems to take upper hand for consumer credit. At the other hand, larger exposures may enjoy a reduced interest rate since this may divide operational and administrative costs across a larger base. Estimates reveal that this effect is stronger for mortgages.

In addition, we find that the effect of “maturity” is negative across all portfolio types, suggesting that the longer the maturity in a loan, the lower the interest rate margin will be. While this is in accordance with the previous literature on the topic (Entrop et al., 2014), it provides another avenue for mispricing of risk, given that overall liquidity risk, or risk stemming from interest rate changes increases for longer maturities. This should also be taken in conjunction with the maturity mismatch variable, which appears to be positive; however, this is only significant for NFC portfolios, where a one unit increase in maturity mismatch generates on average 0.04 percentage points higher interest rate margins for corporate portfolios. As such, the potential for an undervaluation of risk with regards to the maturity profile of the loans appears to hold in the estimation.

Turning to the effect of bank control variables, our results support the findings of previous studies on bank level determinants of interest rates. However, we find some level of heterogeneity in the drivers of certain bank control variables among different portfolio types. For instance, results suggest that banks with a higher leverage ratio tend to charge higher interest rates on consumer loans confirming the findings of Gropp et al., (2014). This may be interpreted as banks that are more risk averse will require a higher interest rate on consumer loans in order to cover the higher cost of equity.

Table 1: Portfolio level dataset (EBA ST2021) - estimation results

Variable	HH CC	HH RE	NFC
Constant	-0.43	2.77***	1.48***
	(0.76)	(0.41)	(0.24)
Expected loss	0.60***	0.50***	0.13***
	(0.07)	(0.16)	(0.04)
Reference Rate	0.29***	-0.05	0.14***
	(0.07)	(0.03)	(0.02)
Currency	-1.52***	-0.1	-0.25***
	(0.25)	(0.14)	(0.06)
Home Bias	-0.28	-0.16	-0.24***
	(0.26)	(0.14)	(0.07)
Maturity	-0.09***	-0.03***	-0.03***
	(0.02)	(0.01)	(0.01)
Size	1.10***	-0.68***	-0.03
	(0.22)	(0.12)	(0.02)
Leverage ratio	0.30***	0.02	0.01
	(0.06)	(0.04)	(0.02)
Implicit interest rates	1.08***	0.68***	0.24***
	(0.36)	(0.23)	(0.01)
Lerner index	0.04 ***	0.02***	0.01***
	(0.01)	(0.01)	(0.00)
Maturity mismatch	0.03	0.08	0.04***
	(0.03)	(0.06)	(0.01)
Country Controls	Y	Y	Y
Bank Fixed Effects	Y	Y	Y
Time Fixed Effects	Y	Y	Y
Observations	1314	671	1541
R-squared	0.33	0.31	0.31

Notes: This table presents the average effect of expected loss on interest rate margins estimated through a panel regression with portfolio, bank, country and time controls. Portfolio level controls include the reference rate, currency, home bias, maturity and portfolio size. Bank level controls include the leverage ratio, implicit interest rates, Lerner index and maturity mismatch. Standard errors are clustered at the bank level. ***,**, and * denote significance at the 0.1, 1 and 5 percent level respectively.

Similar to Ho and Saunders (1981), Angbanzo (1997) and Saunders and Schumacher (2000), we find evidence for the presence of implicit interest rates for all lending products. The larger the divergence between operational expenses and non-interest income, the more banks appear to compensate for this in their loan charges. The relationship appears to be the strongest for consumer loans and the weakest for corporates, suggesting that banks indeed tend to compensate free banking services.

Table 2: Portfolio level dataset (EBA ST2021) - estimation results by quintiles

Variables	HH-CC	HH-RE	NFC
EL - Quintile 2	0.67	0.10	0.16
	(0.34)	(0.10)	(0.11)
EL - Quintile 3	1.07***	0.21**	0.23**
	(0.31)	(0.09)	(0.08)
EL - Quintile 4	1.34***	0.26***	0.36***
	(0.31)	(0.08)	(0.09)
EL - Quintile 5	3.00***	0.55***	0.39***
	(0.34)	(0.12)	(0.10)
Number of banks	89	89	89
Portfolio level controls	Y	Y	Y
Bank level controls	Y	Y	Y
Country controls	Y	Y	Y
Time fixed effects	Y	Y	Y
Observations	1314	671	1541
R-squared	0.34	0.30	0.32

Notes: This table presents the interest margin rate mark-up of a respective EL quintile estimated through a panel regression with portfolio, bank, country and time controls. Portfolio level controls include the reference rate, currency, home bias and portfolio size. Bank level controls include the leverage ratio, implicit interest rates, Lerner index and maturity mismatch. Standard errors are clustered at the bank level. ***,**, and * denote significance at the 0.1, 1 and 5 percent level respectively.

With respect to market power, results suggest that competition, proxied by the Lerner index, matters significantly on explaining the variation in interest rate margins for all three portfolio types. More specifically, a one percentage point increase in the Lerner index, gives rise to 0.04 percentages points and 0.02 percentage points higher interest rate margins for HH-CC and HH-RE portfolios respectively, while the increase amounts to 0.01 percentage points for NFC portfolios.

To examine whether risk-return relationship is linear, we estimate equation (1) by swapping the variable EL with EL quintile dummies. In table 2, the coefficients, starting from “quintile 2”, refer to the mark up compared to the lowest 20% of the EL distribution for each lending product, i.e. the quintile in which the EL is at its lowest. As the results suggest, the relationship is positive and increasing along the quantiles, however implying a non-linear response to credit risk. This is more pronounced in the case of HH-CC, where, for the highest credit risk quantile, banks impose on average a mark-up of 3 percentage points compared to the first quintile of the distribution. For the second highest credit risk quantile, the mark-up is only 1.34 percentage points.

In the other two segments, the difference, although present, is much lower. In particular, the average mark-up for HH-RE stands at only 0.55 percentage points at the top risk quintile, yet it is still almost 2.5 times higher than the one charged in the third quintile. An even smaller change occurs in the NFC portfolio, where the mark-up increases from 0.23 to 0.39 percentage points in comparison to the first quintile.

These results lead to two conclusions: first, that ex ante low risk customers in the first two quantiles will be treated largely the same, regardless of whether they are at the lowest 5% or the lowest 40% of the EL distribution. As such, there appears to be some level of credit risk, below which banks are unwilling to change its pricing. Second, mark-ups towards consumer credit portfolios are much higher than for mortgages and corporates. The high sensitivity in the upper quantiles for consumer portfolios can be partly be explained by the wider dispersion of ELs for consumer loans. At the same time, no statistically significant difference appears to exist between the two top quintiles in the NFC category, implying that borrowers at the 65% and 90% percentile will be charged the same interest rate margin.

5.2. AnaCredit Estimation Results (loan-level)

We now turn to the estimation results of equation (2) which considers interest rates for loans towards NFC's. We split up lending to NFCs by economic sectors as it can be assumed that the borrower composition in each sector or the sector's dependency on the economic cycle might influence banks' loan pricing decisions.

We find evidence across all economic sectors that credit risk, proxied by EL, has a positive effect on the interest rate charged on loans. A one-unit increase in EL brings on average the highest change for the manufacturing sector and the lowest for the real estate and trade sectors. The results are in accordance with the ones of the previous section, as we find that the coefficient estimates for EL average around the 0.13 value estimated before. This suggests that the relationship between EL and interest rates is robust on both the portfolio and the loan level.

The results on loan level data are in line with the portfolio level dataset when it comes to the risk-free rate. As the results suggest, it appears that a positive relationship holds between the risk-free rate and interest rates in general, albeit significant in five out of eight sectors. Construction is the sector with the greatest passthrough, at 0.88 percentage points, with other services reporting a 0.62 percentage points passthrough. As for the portfolio level dataset, the positive sign of the risk-free rate implies that banks do appear to exploit higher rates to impose potentially higher margins.

In line with the findings based on the portfolio dataset, all things equal, banks charge higher interest rates on non-EURO denominated loans in the loan level dataset, which is estimated to be significant for six of the eight sectors. Such a practice could potentially reflect a sort of FX hedging, given that currency movements may be large and unexpected. At the same time, the home bias, i.e. loans to non-domestic borrowers, turns out to be largely insignificant. Most likely, the different borrower compositions of both data sets play a decisive role with regard to this covariate. Loan maturity is also highly significant, in line with the results of the Stress Test database. As we have previously suggested, the potential for an undervaluation of risk with regards to the maturity profile of the loans appears to hold in the estimation, underlining another avenue that could potentially be explored by future research. With regards to the loan type, borrowers with leases are charged substantially higher interest rates compared to borrowers who have loans, perhaps also due to lower collateral values.

Micro and small enterprises are charged higher interest rates than their larger peers. Possible reasons for this include the fact that smaller firms demand smaller loans but have the same administrative costs as large ones, while smaller firms are usually perceived to be riskier and overall less stable. Additionally, smaller firms are equipped with less negotiation powers and could therefore be regarded as price-takers, making it relatively more attractive for banks to charge higher rates.

Results depict a negative relationship between market share and interest rates which appears to be in contrast with the previous section, where was found that higher market power proxied by the Lerner index, results in higher margins on portfolios. One reason may be that banks utilize lower interest rates to generate higher market shares but exploit higher rates at a state of higher market power.[10]

Another important finding is that the Post-Covid dummy is significant and negative in the Construction and Manufacturing sectors, implying that, since March 2020 banks have been charging around 0.45 percentage points lower interest rates in the two sectors.

Table 4 reports the results from equation (4), where the EL variable is swapped with 10 dummy variables. The relationship between higher credit risk and interest rates depends highly on the economic sector, where the strongest relationship can be observed in the construction, manufacturing, and agriculture sectors with mark-ups reaching up to 1.88, 1.77, and 1.17 percentage points respectively at the peak. In addition, the risk-return relationship for services, other services, and trade is ambiguous. For these sectors, banks tend to react only to an increase in borrowers' risks if borrowers' ELs are relatively close to the centre of the distribution and again only at the top decile.

Furthermore, even in the sectors where a strong risk-return relationship appears to exist, we observe only little variation in the coefficients across the whole distribution. For instance, in the real estate sector, borrowers from the 3rd decile are charged an interest rate mark up of 0.313 percentage points in comparison to the safest borrowers in the first (lowest risk) decile. Although, by definition, risks are going up, borrowers at the 7th decile are charged a 0.328 percentage points mark ups, just 0.015 higher than borrowers from the 3rd decile. This raises questions on whether banks sufficiently adjust their loan rates in light of borrowers' risks. Similar findings can also be seen in other sectors, e.g. in the construction and agriculture sectors where the coefficients between the 5th and the 9th or the 9th and the 10th decile are hardly different, respectively. One reason for the lack of variation in the coefficient estimates could be that the actual distance of risks between the deciles has been neglected so far which we take into account in the next section.

[10] Further analysis is needed to disentangle the effect of market shares, market power and market structure on bank lending which we leave for future research.

Table 3: Loan level dataset (AnaCredit) - estimation results

Variable	agriculture	costruction	information	manufacturing	other services	real estate	service sector	trade
constant	2.298**	1.820*	2.698***	1.258***	4.944**	3.045***	2.064	0.566
	(0.78)	(0.84)	(0.69)	(0.33)	(1.71)	(0.51)	(1.16)	(0.41)
EL	0.118***	0.190***	0.230***	0.249***	0.133**	0.096***	0.110*	0.096**
	(0.03)	(0.04)	(0.04)	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)
currency	-1.023*	0.348	-1.189**	-0.800***	-0.456	-0.011	-1.178***	-0.976***
	(0.42)	(0.33)	(0.39)	(0.23)	(0.42)	(0.47)	(0.25)	(0.1)
Unsecured	-0.254	-0.458***	-0.427***	-0.687***	-0.207	-0.207**	-0.113	-0.062
	(0.16)	(0.10)	(0.11)	(0.09)	(0.23)	(0.07)	(0.14)	(0.11)
Maturity	-0.046*	-0.059***	-0.101**	-0.059*	-0.109***	-0.040***	-0.051*	-0.062
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)
Loan type: Leases	1.178**	1.225***	1.210**	1.393***	2.234***	1.640**	1.323**	2.206***
	(0.40)	(0.33)	(0.40)	(0.38)	(0.60)	(0.53)	(0.49)	(0.55)
Loan type: Loan	0.034	0.550	0.426	0.278	0.108	0.255	0.093	0.610
	(0.10)	(0.29)	(0.30)	(0.22)	(0.19)	(0.15)	(0.44)	(0.35)
Domestic	-0.859*	-0.304	-0.942	-0.195	-1.196	-0.780	-1.126	-0.423
	(0.37)	(0.84)	(0.55)	(0.41)	(0.82)	(0.55)	(0.61)	(0.27)
Medium	0.334	0.232	0.313***	0.053	0.380*	-0.479	0.488**	0.016
	(0.34)	(0.17)	(0.09)	(0.07)	(0.15)	(0.26)	(0.15)	(0.05)
Micro	1.000**	1.171**	1.118***	1.090***	1.019***	-0.218	1.295***	0.951***
	(0.34)	(0.39)	(0.18)	(0.16)	(0.11)	(0.27)	(0.20)	(0.20)
Small	0.728*	0.883	0.696**	0.550***	0.18	-0.032	0.644***	0.229
	(0.31)	(0.45)	(0.22)	(0.12)	(0.19)	(0.11)	(0.1)	(0.15)
Market Share	-0.005	-0.012***	-0.002	-0.009***	-0.003	-0.003	-0.008**	-0.008
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Leverage	-0.070	-0.003	-0.045	-0.007	-0.131	-0.047	-0.035	-0.018
	(0.05)	(0.05)	(0.04)	(0.03)	(0.07)	(0.04)	(0.06)	(0.02)
Implicit Interest rates	-0.031	-0.029	-0.032	0.002	-0.103	0.004	-0.029	-0.013
	(0.02)	(0.03)	(0.02)	(0.01)	(0.07)	(0.03)	(0.03)	(0.02)
Post-Covid	-0.167	-0.544**	-0.653	-0.361**	-0.049	-0.266	-0.399	-0.156
	(0.14)	(0.20)	(0.33)	(0.11)	(0.44)	(0.22)	(0.27)	(0.15)
risk free rate	0.302*	0.883***	0.359*	0.373***	0.618*	0.309	0.534	0.31
	(0.12)	(0.23)	(0.16)	(0.1)	(0.29)	(0.25)	(0.27)	(0.2)
Country controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Time Fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	121596	149231	44190	526228	29124	65648	198138	3617108
R-Squared	0.31	0.45	0.49	0.34	0.43	0.41	0.40	0.36

Notes: This table present the average effect of loan-level expected loss on interest rates estimated through a panel regressions with loan, firm, bank, country and time controls. Loan level controls include loan type, currency, home bias and collateral status. Debtor level controls include enterprise size. Bank level controls include the leverage ratio, market share and implicit interest rates. Standard errors are clustered at the bank level. ***,**, and * denote significance at the 0.1, 1 and 5 percent level respectively.

Table 4: Loan level dataset (AnaCredit) - estimation results by deciles

Variable	agriculture	costruction	information	manufacturing	other services	real estate	service sector	trade
EL - Decile 2	0.390***	1.076*	0.461*	0.342***	0.210	0.253***	0.720***	0.013
	(0.06)	(0.44)	(0.20)	(0.07)	(0.11)	(0.05)	(0.15)	(0.06)
EL - Decile 3	0.533**	0.988*	0.582**	0.383***	0.055	0.313***	-0.152	0.108
	(0.15)	(0.40)	(0.22)	(0.09)	(0.19)	(0.04)	(0.20)	(0.12)
EL - Decile 4	0.529***	0.991**	0.009	0.640***	-0.638	0.298***	0.193*	0.266
	(0.14)	(0.33)	(0.10)	(0.08)	(0.44)	(0.07)	(0.09)	(0.15)
EL - Decile 5	0.744***	1.255**	0.2425	0.779***	-0.105	0.325***	0.424*	0.325
	(0.09)	(0.41)	(0.20)	(0.10)	(0.25)	(0.06)	(0.19)	(0.17)
EL - Decile 6	0.672***	1.221**	0.467**	0.811***	0.342**	0.333***	0.272	0.255
	(0.11)	(0.45)	(0.17)	(0.11)	(0.11)	(0.09)	(0.19)	(0.17)
EL - Decile 7	0.743***	1.263**	0.789***	0.947***	0.244	0.328***	0.330	0.228
	(0.09)	(0.45)	(0.18)	(0.13)	(0.24)	(0.07)	(0.17)	(0.14)
EL - Decile 8	0.823***	1.300*	0.845***	1.014***	0.207	0.568***	0.081	0.303
	(0.15)	(0.57)	(0.22)	(0.11)	(0.23)	(0.12)	(0.18)	(0.16)
EL - Decile 9	1.039***	1.486**	0.994***	1.250***	0.116	0.553***	0.214	0.368
	(0.11)	(0.50)	(0.20)	(0.15)	(0.35)	(0.12)	(0.27)	(0.21)
EL - Decile 10	1.167***	1.880***	1.472***	1.773***	0.711**	0.690***	0.797***	0.652**
	(0.13)	(0.51)	(0.24)	(0.14)	(0.24)	(0.12)	(0.22)	(0.24)
Loan level controls	Y	Y	Y	Y	Y	Y	Y	Y
Bank Level Controls	Y	Y	Y	Y	Y	Y	Y	Y
Debtor Level Controls	Y	Y	Y	Y	Y	Y	Y	Y
Country Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
observations	121596	149231	44190	526228	29124	65648	198138	3617108
R-squared	0.302	0.476	0.516	0.349	0.450	0.418	0.426	0.370

Notes: This table presents the interest rate mark-up of a respective EL decile estimated through a panel regression with loan, firm, bank, country and time controls. Loan level controls include loan type, currency, home bias and collateral status. Debtor level controls include enterprise size. Bank level controls include the leverage ratio, market share and implicit interest rates. Standard errors are clustered at the bank level. ***,**, and * denote significance at the 0.1, 1 and 5 percent level respectively.

6. Assessing the results

6.1 Premium per unit of risk

Up to now, results with respect to the quintile (or decile) mark-ups have disregarded the difference in the degree of credit risk between them. This is of high relevance as it may be that the banks' indifference to an increase of ELs in the centre of the distribution could be explained by the skewness of the distribution. To address this issue, we construct a new measure, namely the credit risk premium per unit of risk, which is computed as the fraction between the estimated credit risk mark-up of a given quintile (decile) and the average distance in EL. More formally, this can be expressed as follows:

$$premium_{i,n} = \frac{coeffEL_{i,n}}{distanceEL_{i,n}}$$

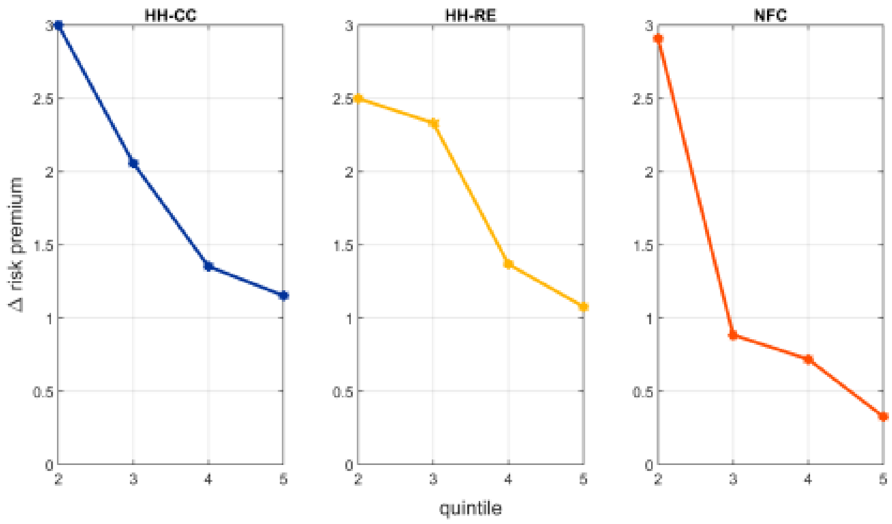
Where $coeffEL_{i,n}$ is the EL coefficient in the regression defined in (3) and (4) for portfolio type (economic sector) i and quintile (decile) n. The term $distanceEL_{i,n}$ is computed as $\overline{EL_{\iota,n}} - \overline{EL_{\iota,1}}$, i.e. the average EL of quintile (decile) n minus the average EL of the first quintile (decile). Calculating this new measure provides a different angle on how banks react to an increase in credit risk as it shows whether lending rates grow in proportion with borrower's risks.

As shown in figure 1, for all three portfolios, we find that the credit risk premium per unit of risk represents a steadily decreasing curve, implying that mark-ups in margin rates for portfolios become less reactive to an increase in borrower's risks. We note that this behaviour is expected, given that there is a minimum level of mark-up that would need to be applied on the interest rate, regardless of whether the riskiness of the borrower is very low. This would ensure that the bank would make some profit (or at least break even), regardless of how low its risk would be. However, that mark-up per unit of risk cannot remain stable as the borrower's riskiness increases, as it would lead to extremely high interest rates. Hence, as the borrower becomes riskier, the mark-up per unit of risk would need to decline.

For both HH portfolios, the calculated premium stays significantly above unity across all risk quintiles implying that the increase in margins across quintiles remains higher than the increase in credit risk. For NFC portfolios, however, the premium drops below 1 from the third quintile on indicating that interest rate margins rise less than the increase in borrowers' credit risk.

This marked difference between portfolios seems to suggest that risk pricing may not be sufficiently reflected in lending rates towards NFC portfolios. As suggested before, even though the decline is justified given ceilings usually imposed on interest rates so that they do not become extremely high, a mark-up below unity suggests that the bank does not even compensate for the risk that it is assuming.

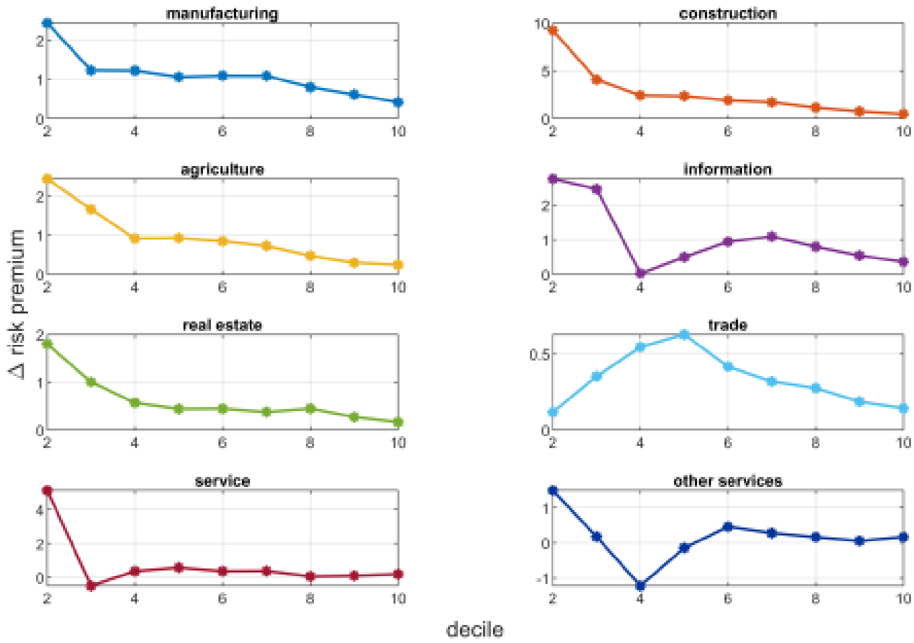
Figure 1: Portfolio level dataset (EBA ST2021) - Credit Risk Premium per Unit of risk



Notes: This figure displays the credit risk premium per unit of risk for each expected loss quintile for HH-CC (left), HH-RE (middle) and NFC (right) based on estimations on portfolio level data computed as the fraction between the estimated credit risk mark-ups as defined in equation (3) and the average distance in EL between quintile n and quintile 1.

Adding the credit risk premiums for the loan level dataset yields, on first sight, a rather heterogeneous picture across sectors. For the manufacturing, agriculture, real estate and service sector, the credit risk premiums resemble a similar development as for the whole NFC sector based on the portfolio level data, i.e. from a very low decile on, banks' charged premiums increase disproportionally with the increase in borrowers' credit risk. For the construction sector, the curve seems to exhibit overly reactive premiums at the lower tails of the distribution, whereas the curve breaches the disproportionally lower risk territory only from the 9^{th} decile on. The information, trade and other services sectors can be considered as outliers since insignificant coefficients distort the metric heavily and therefore complicate a comprehensive interpretation.

Figure 2: Loan level dataset (AnaCredit) - Credit Risk Premium per Unit of risk



Notes: This figure displays the credit risk premium per unit of risk for eight different economic sectors based on estimations on loan level data computed as the fraction between the estimated credit risk mark-up as defined in equation (4) and the average distance in EL between decile n and decile 1.

6.2 Benchmarking the results

While this credit risk premium per unit of risk elucidates the risk-return relationship further it does not answer the question yet whether bank's loan price setting actually covers borrowers' risks. To do so, we set up a theoretical interest rate in order to benchmark our findings. The subsequent comparison can be done for both the interest mark-ups, i.e. the original coefficients as well as the premium per unit of risk of the previous section. As both comparisons lead to similar results, we restrict the analysis subsequently to the more intuitive mark-ups and show the comparisons with the premiums in the annex.

In detail, we compute the minimum spread that would ensure that the expected value of the portfolio (loan) equals the risk-free rate. This theoretical risk-free yielding mark-up can be interpreted as the absolute minimum mark-up that banks need to charge in order to generate a risk-free compensating return.[11] Thus, any portfolio (or loan) that falls below this threshold may be unwarranted. We derive this threshold by following the approach prescribed in Resti and Sironi (2012). More formally, we posit the following the following equation:

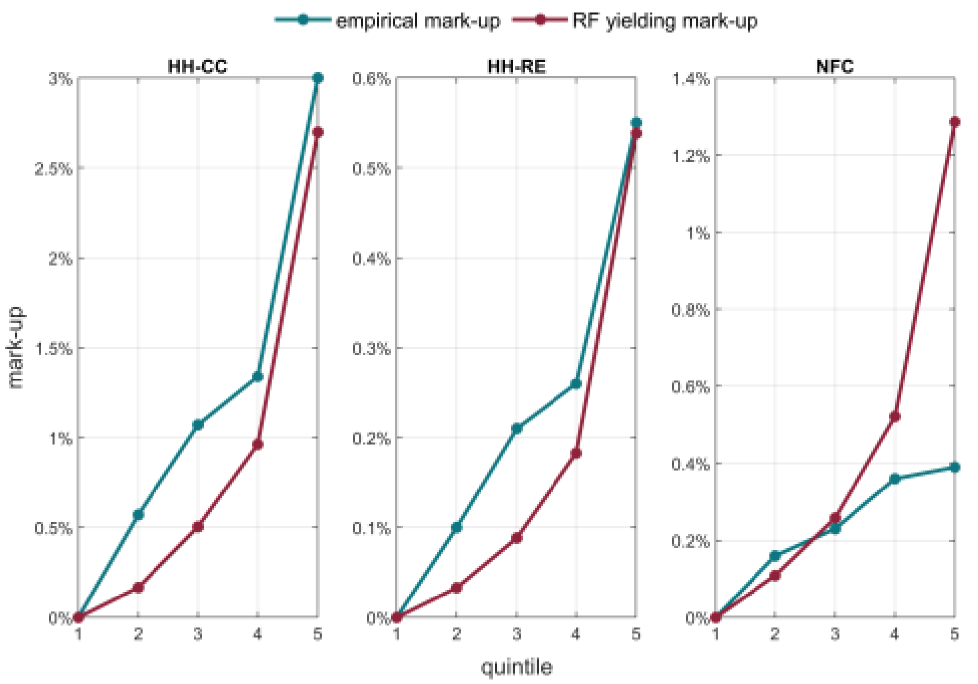
$$(1 + rf + s)\,[(1 - PD) + \,(1 - LGD)PD] \; = \; (1 + rf) \qquad (5)$$

Where rf denotes the risk-free rate, s the spread, PD the probability of default and LGD the loss given default. As shown in the appendix, equation (5) can be manipulated to yield the following:

$$s = \frac{EL(1 + rf)}{1 - EL} \qquad (6)$$

Which implies that the spread s is equal to the cost of the expected loss. For the portfolio-level dataset, we use the reference rate as the risk-free rate. With respect to the loan level dataset, we proxy the risk-free rate through zero-coupon yield curves as described above.

Figure 3: Portfolio level dataset (EBA ST2021) - empirical vs RF yielding mark-up



Notes: This figure displays the empirical (blue) and RF yielding mark-up (red) across expected loss quintile for HH-CC (left), HH-RE (middle) and NFC (right) based on estimations on portfolio level data. Empirical mark-ups are estimated as defined in equation (3), while RF yielding mark-ups are computed as defined in equation (6).

[11] Naturally, this theoretical premium does not account for banks' additional cost of lending resulting from operating costs, regulatory requirements, and so on.

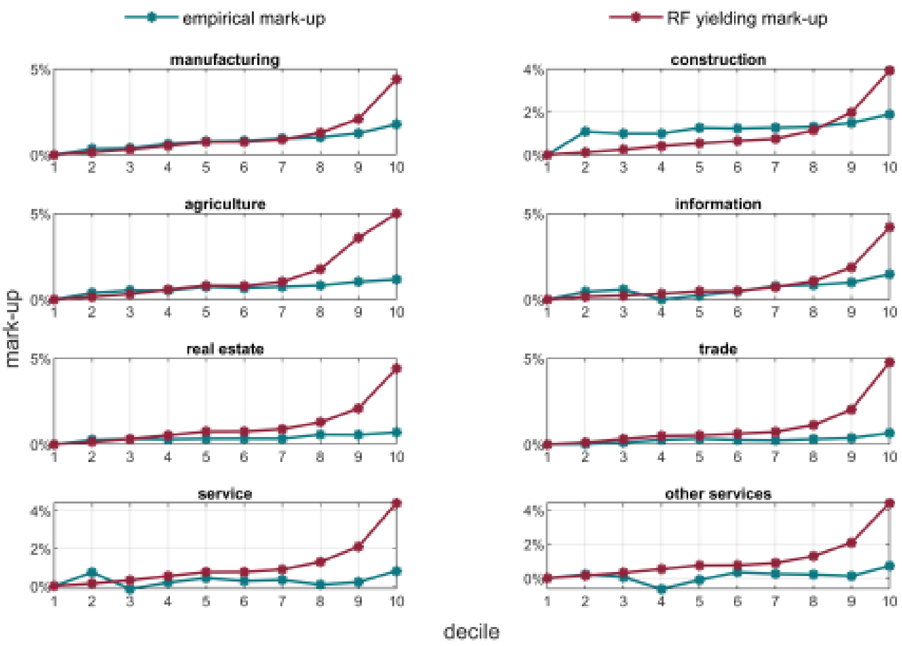
6.2.1 Empirical vs Risk Free Yielding Mark-Ups

Figure 3 presents the empirical and the theoretical risk-free yielding mark-up for each quintile as obtained from the portfolio dataset. The empirical mark-ups are simply the coefficient estimates from equation (3) and reported in table 3. They can be interpreted as the average mark-up charged by banks when a portfolio moves to a riskier EL quintile.

As the figure shows, the empirical mark-up appears to be higher than the theoretical one for the HH portfolios, implying that banks tend to compensate for risks. In fact, for HH_CC portfolios the gap between actual and theoretical premium amounts to about 0.40-0.60 percentage points for borrowers from all quintiles but the first one. For the HH_RE portfolio, the different scaling leads to a gap of about 0.08-0.12 percentage points for debtors of the second to fourth quintile. However, in both HH-CC and HH-RE, the estimates suggest that the difference is smaller for the top quantile of risk, implying that banks may tend to over-price risk in the first quantiles to compensate for additional risk in the last ones. This is especially true for the NFC category, where, from the third quintile onwards, no proper compensation is charged for the assumed risk. Put differently, portfolios that reside in the upper three quintiles are charged a mark-up that is lower than one would require in order to yield a risk-free compensating return. This marked difference between portfolios shows that the risk-return relationship seems to be overly pronounced in both HH portfolios whereas it is not sufficiently represented in the NFC portfolio. Many reasons could explain banks disproportionate pricing behaviour. For instance, higher regulatory requirements for HH-CC lending, as it is usually not collateralized and riskier than other lending products, might lead banks to request significantly higher premiums than our benchmark premium which, as mentioned above, does not take regulatory requirements into account. Furthermore, many household consumption items are offered with payment in instalment options with pre-arranged creditors. This might heavily limit competition, as borrowers may not easily choose a bank with lower rates. Further, as the loan volume of HH-CC loans is usually considerably smaller than in the other two segments, the unit costs of lending for banks might be the highest and, thus, require higher premiums. Regarding HH-RE loans, since they are usually collateralized, banks may apply lower risk weights or LGDs. In addition, as mortgage loans represent usually the highest debt burden for households, household borrowers might be incentivized to spend considerably more time looking for better credit conditions, which intensifies the competition among banks that might also lead to lower premiums. All in all, these significant differences between sectors could imply that the higher mark-up for risk in the HH portfolios, especially in the middle and lower end of the distribution, could serve as a cross-subsidization of risk with regards to the mispricing of risk in the NFC portfolio.

The results pertaining to the NFC portfolio, are further explored using the AnaCredit loan-level data and focussing on economic sectors. Analogous to above, empirical mark-ups are estimated by equation (4) and thereupon reported in table 4. As per Figure 4, there is a large deviation between the theoretical risk-free (purple line) and the empirical mark-up, especially in the last two deciles of the distribution. Interestingly, risk appears to be sufficiently priced in the manufacturing, construction, agriculture and information sectors, up until the 7th or 8th percentile. The reason behind this may lie in higher collateral values. As with all other sectors, this changes after the 8th percentile. On the other hand, in the real estate services sector a constant underpricing of risk appears to hold. The results from the trade and both service sectors seem to suggest that pricing is largely insensitive to the borrower's credit risk as the coefficients are statistically insignificant until the 10th decile.

Figure 4: Loan level dataset (AnaCredit) - empirical vs RF yielding mark-up



Notes: This figure displays the empirical (blue) and RF yielding mark-up (red) across expected loss deciles for eight economic sectors based on estimations on loan level data. Empirical mark-ups are estimated as defined in equation (4), while RF yielding mark-ups are computed as defined in equation (6).

7. Conclusions

Is higher risk associated with higher potential returns in the banking sector? To answer this question, we have employed interest rates and expected loss probabilities from the 2021 Stress Tests dataset and the AnaCredit credit register. After controlling for bank, loan, debtor and macroeconomic characteristics, results suggest that the risk-return relationship is present but varies significantly across and within borrower segments.

While banks tend to charge higher rates to riskier borrowers, such changes are non-linear. For example, ex ante low-risk customers in the first two quintiles will get, ceteris paribus, the same interest rate margin, irrespective of whether they are at the lowest 5% or the lowest 40% of the EL distribution. As such, there appears to be some level of credit risk below which banks are unwilling to change their pricing.

Furthermore, by taking the distance between quantiles into account and calculating the credit risk premium per unit of risk, we find that interest rate mark-ups across all borrower segments become less responsive to an increase in borrower's risks.

Finally, by means of setting up a risk-free yielding benchmark, we are able to infer that the empirical interest mark-ups to both household segments significantly exceed the risk-free yielding benchmark mark-up, especially in the lower quantiles of the EL distribution. This is in contrast with lending rates towards NFCs, where risks are for the most part insufficiently priced. This behaviour suggests a cross-subsidization effect, especially from lower-risk household loans to higher-risk NFC loans. Potential reasons for this effect may relate to higher regulatory requirements for household loans, as well as higher competition due to lower homogeneity across the terms and conditions of NFC loans.

With regards to the other control variables, another potential avenue for a mispricing of risk is that of maturity. Results imply that longer maturities relate to lower interest rate margins, a result that is in line with the literature (Entrop et al., 2014). This is more pronounced for HH-CC loans, due to the fact that such products tend to have longer maturities. While this implies that banks are willing to extend lower interest rate loans to households in exchange for a long-term cash flow, it may also lead to potential liquidity risk issues, especially in the advent of an upward yield curve shock.

Policy-wise, results suggest that banks do not appear to always charge the appropriate risk-adjusted interest rate, especially in the case of NFCs that reside in the riskiest quantiles of the distribution. Potential explanations on this may relate to banks pursuing strategic goals like gaining market shares or access to markets, or even perhaps shareholder pressure to increase profits via an expansion of the bank's balance sheet (see Jensen and Meckling, 1976). However, such practices may lead to inefficient capital allocation and financial stability issues as under-pricing of credit risk may leave banks exposed to significant losses should the viability of risky borrowers be challenged in the advent of severe macro-financial shocks (Helmersson et al, 2021).

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APPENDIX

Stress Test Data Overview

Figure 5: Geographical distribution (number of portfolios, shares in %)

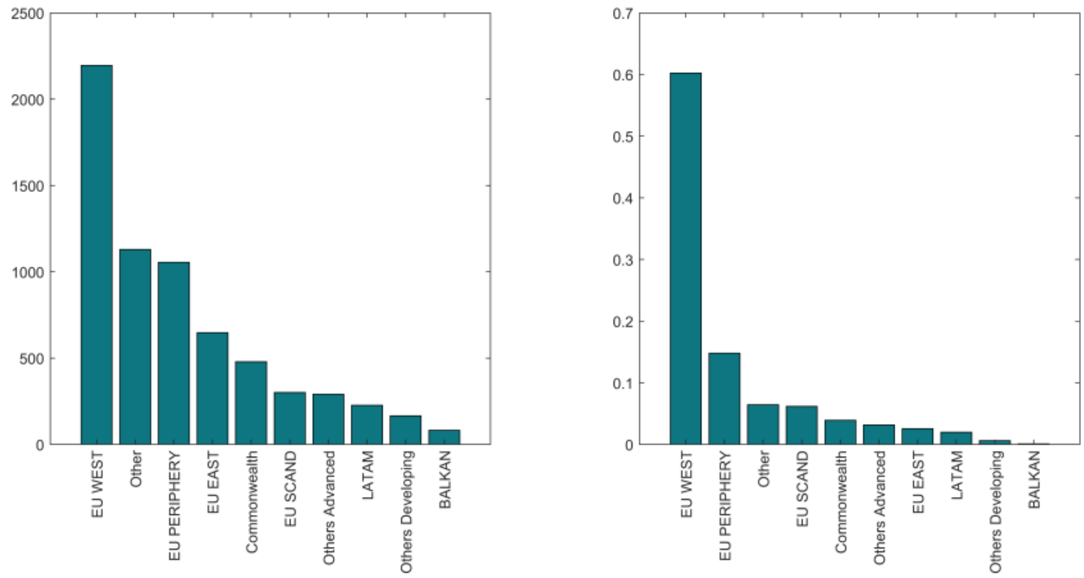


Table 5: Descriptive Statistics - Portfolio level dataset (EBA ST2021)

Variable	observations	Mean	std dev	25th percentile	50th percentile	75th percentile
interest rate margins (%)	3712	2.83	2.61	1.38	2.06	3.35
EL (%)	3712	0.50	0.81	0.10	0.26	0.59
reference rate (%)	3712	0.27	1.49	-0.45	-0.19	0.60
Maturity	336	7.21	6.40	3.40	5.37	9.02
Lerner index (%)	336	27.82	12.95	18.76	28.52	39.06
implicit interest rates (%)	336	-0.52	0.50	-0.64	-0.52	-0.31
leverage ratio (%)	336	6.43	1.92	5.00	6.02	7.11
maturity mismatch	336	5.53	2.72	3.79	5.66	6.52

Figure 6: Histogram Interest Margin Rates (left) and Expected loss (right)

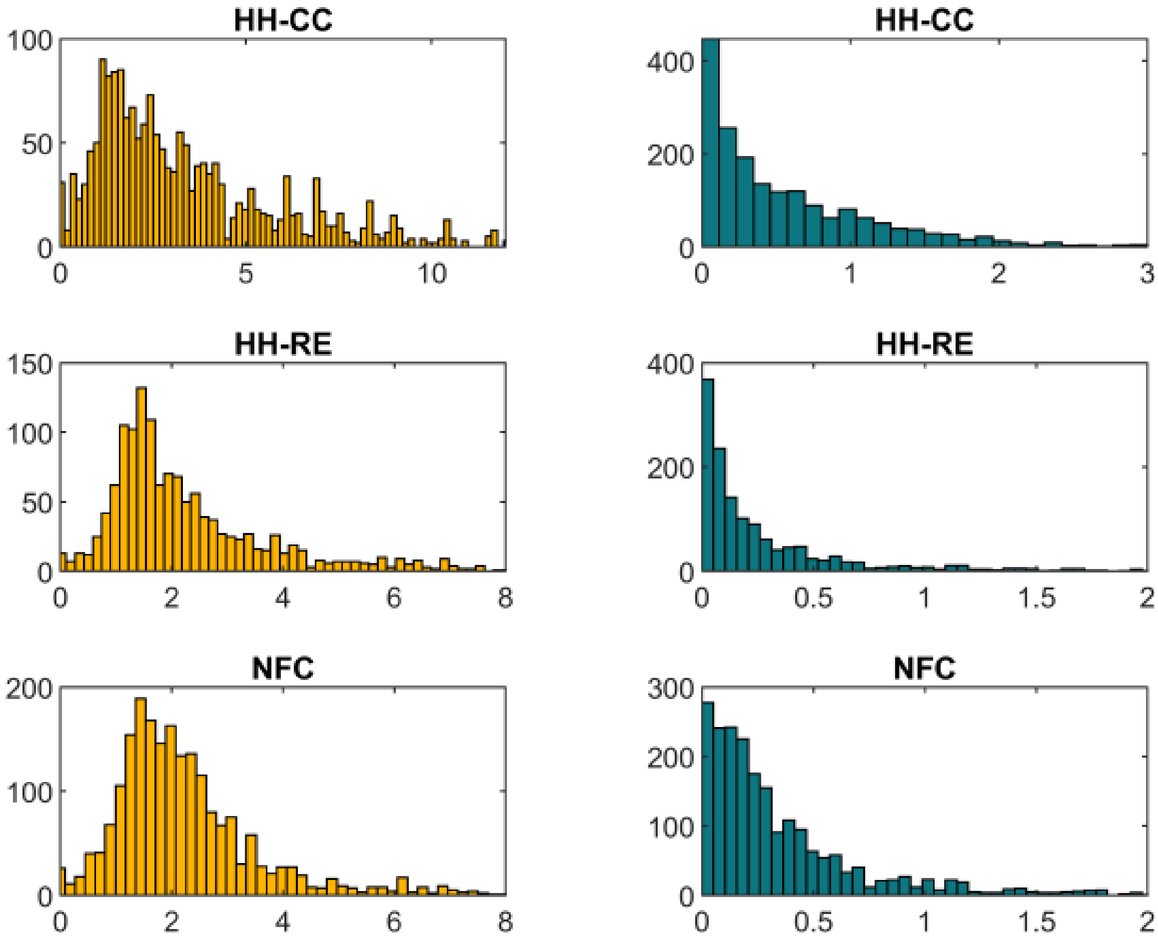
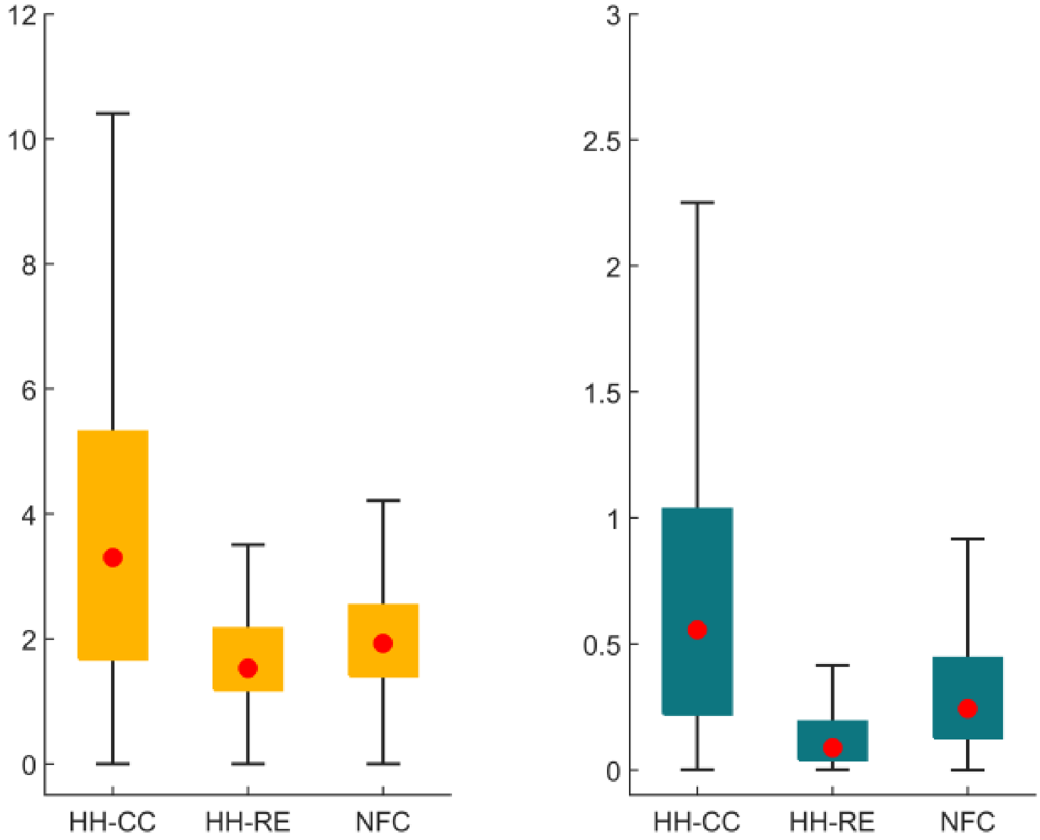


Figure 7: Boxplot Interest Margin rates (left) and Expected loss (right) in %



AnaCredit Data Overview

Figure 8: Geographical distribution (number of loans in 100000s, shares in %)

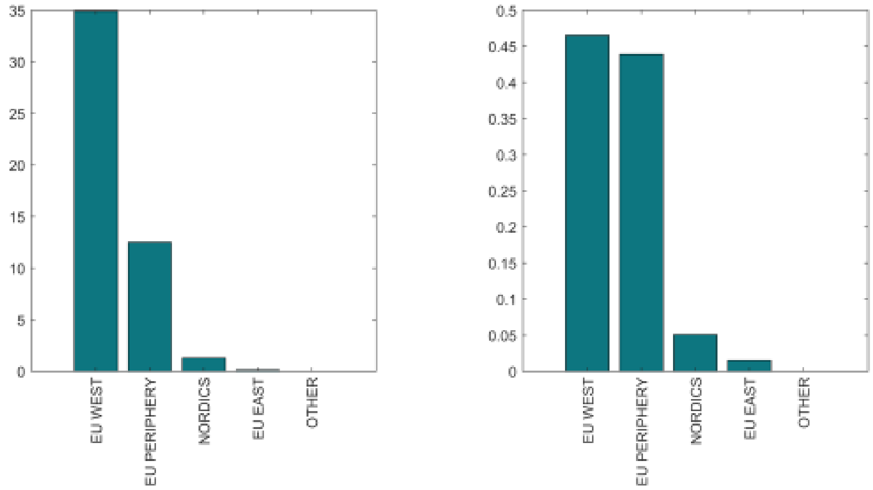


Table 6: Descriptive Statistics - Loan level dataset (AnaCredit)

Variable	observations	Mean	std dev	25th percentile	50th percentile	75th percentile
Interest rate (%)	4904441	2.32	1.35	1.75	1.98	2.72
Risk free rate(%)	4904441	-0.03	0.55	-0.61	-0.03	0.29
EL (%)	4904441	1.10	1.48	0.27	0.61	1.09
Maturity	4904441	1.24	2.51	0.17	0.33	1.00
Market Share (%)	18278	30.02	19.42	12.96	26.43	47.89
Leverage (%)	1040	16.35	4.15	12.47	16.69	20.66
Implicit Interest rates (%)	1040	0.95	2.37	0.24	0.47	0.79

Figure 9: Histogram Interest Rates (left) and Expected loss (right) (number of loans in 100000s)

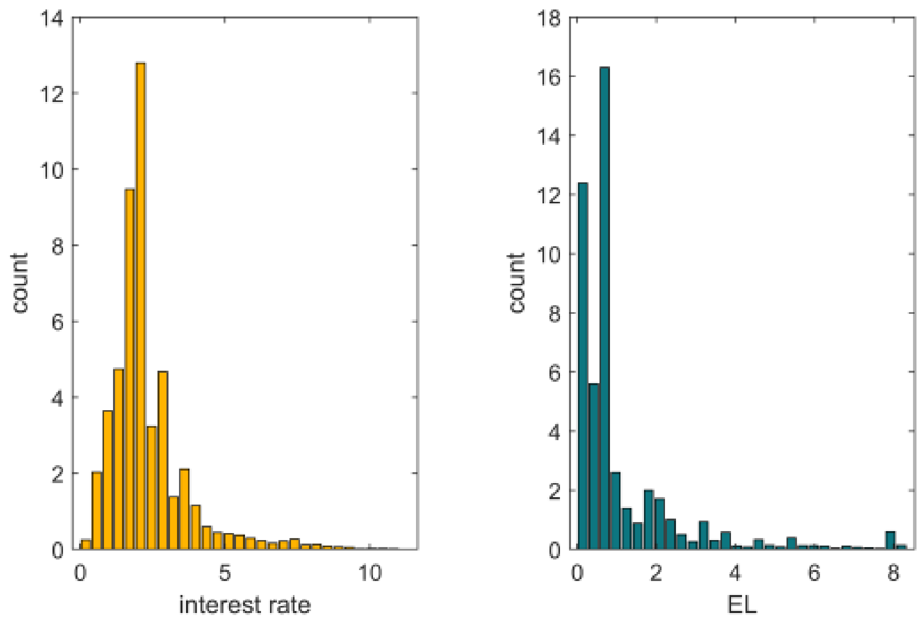
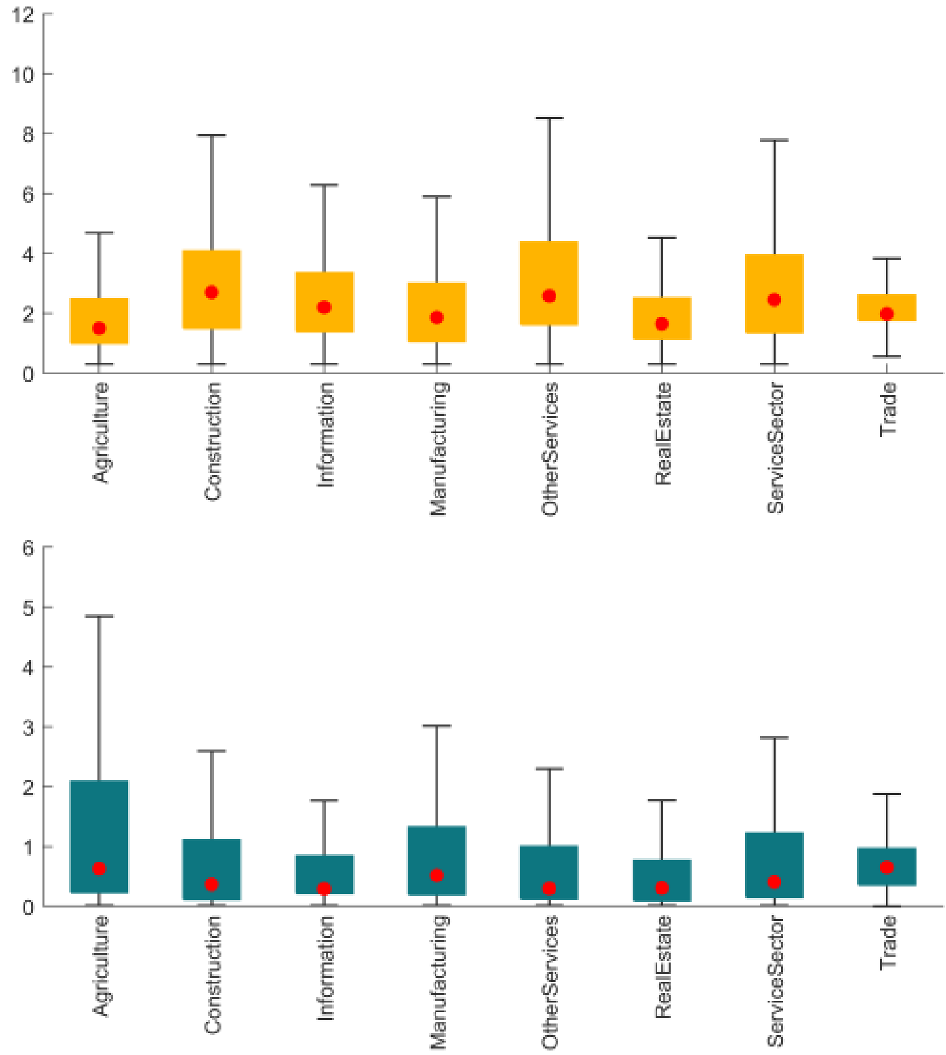


Table 6: Descriptive Statistics - Loan level dataset (AnaCredit)

Variable	observations	Mean	std dev	25th percentile	50th percentile	75th percentile
Interest rate (%)	4904441	2.32	1.35	1.75	1.98	2.72
Risk free rate(%)	4904441	-0.03	0.55	-0.61	-0.03	0.29
EL (%)	4904441	1.10	1.48	0.27	0.61	1.09
Maturity	4904441	1.24	2.51	0.17	0.33	1.00
Market Share (%)	18278	30.02	19.42	12.96	26.43	47.89
Leverage (%)	1040	16.35	4.15	12.47	16.69	20.66
Implicit Interest rates (%)	1040	0.95	2.37	0.24	0.47	0.79

Figure 10: Boxplot Interest Rates (upper) and Expected loss (lower) in %



Lerner Index

The Lerner index (Lerner, 1934) measures the monopoly power of a firm by computing the discrepancy between output price and marginal cost. In context of the banking sector, the Lerner index can be formulated as follows:

$$Lerner_{it} = (P_{TA_{it}} - MC_{TA_{it}}) / P_{TA_{it}}$$

Where $P_{TA_{it}}$ is the price of total assets for bank i at time t and $MC_{TA_{it}}$ is the marginal cost of total assets for bank i at time t. The price of total assets is calculated as the fraction between total income (interest and non-interest) and total assets, while marginal costs are computed through a translog function that consist of a single output price and three input prices. The output price is total assets, while the input prices are the price of borrowed funds (interest rate expenses), staff expenses (to approximate the price of labour) and operational expenses (to approximate the price of physical capital) retrieved from confidential supervisory data. To calculate the marginal cost for each bank, we first estimate the following log cost function by following Martinez-Peria (2010), Anginer et al. (2014) and Avignone et al. (2022):

$$
\begin{aligned}
\log(C_{it}) = \; & \alpha + \beta_1 \log(Q_{it}) + \beta_2 (\log(Q_{it}))^2 + \beta_3 \log\left(W_{1,it}\right) + \beta_4 \log\left(W_{2,it}\right) \\
& + \beta_5 \log\left(W_{3,it}\right) \\
& + \beta_6 \log(Q_{it}) \log\left(W_{1,it}\right) \\
& + \beta_7 \log(Q_{it}) \log\left(W_{2,it}\right) \\
& + \beta_8 \log(Q_{it}) \log\left(W_{3,it}\right) + \beta_9 \log\left(W_{1,it}\right)^2 + \beta_{10} \log\left(W_{2,it}\right)^2 \\
& + \beta_{11} \log\left(W_{3,it}\right)^2 + \beta_{12} \log\left(W_{1,it}\right) \log\left(W_{2,it}\right) \\
& + \beta_{13} \log\left(W_{1,it}\right) \log\left(W_{3,it}\right) + \beta_{14} \log\left(W_{2,it}\right) \log\left(W_{3,it}\right) + \gamma BankDummies \\
& + \varepsilon_{it}
\end{aligned}
$$

Where C_{it} denote bank costs which is simply the sum of interest rate expenses $(W_{1,it})$, staff expenses $(W_{2,it})$and operational expenses $(W_{3,it})$ and Q_{it} denote total assets.

The above equation is estimated by using a constrained ordinary least squared approach to ensure homogeneity of degree one in the input prices. We apply the following constraints:

$$\beta_3 + \beta_4 + \beta_5 = 1$$

$$\beta_6 + \beta_7 + \beta_8 = 0$$

$$\beta_9 + \beta_{12} + \beta_{13} = 0$$

$$\beta_{10} + \beta_{12} + \beta_{14} = 0$$

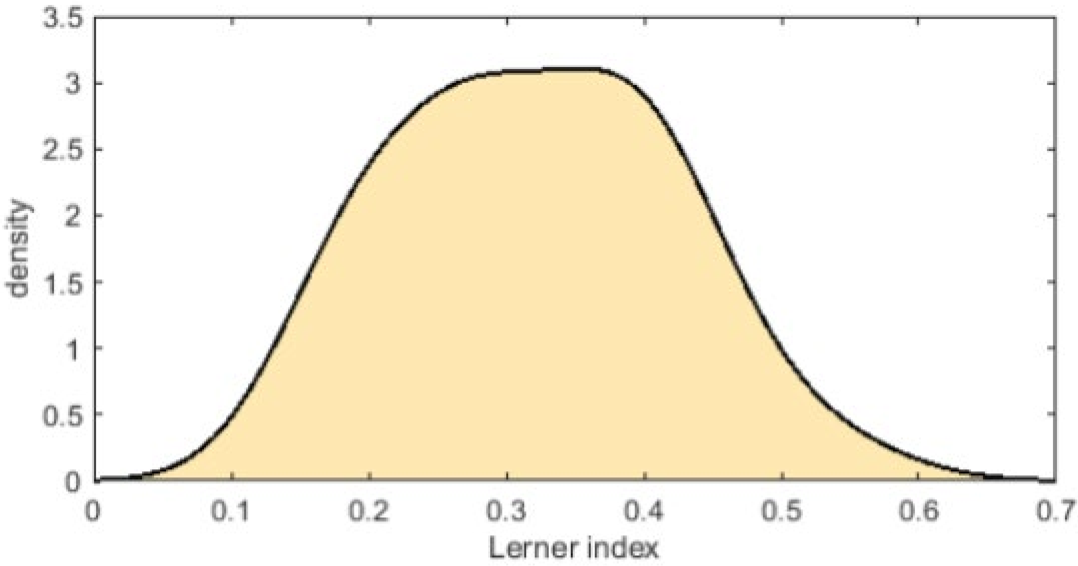
$$\beta_{11} + \beta_{13} + \beta_{14} = 1$$

Finally, after estimating the coefficients in the log cost function equation, we derive the marginal cost as follows:

$$MC_{TA_{it}} = \frac{C_{it}}{Q_{it}} [\beta_1 + 2\beta_2 \log(Q_{it}) + \beta_6 \log\left(W_{1,it}\right) + \beta_7 \log\left(W_{2,it}\right) + \beta_8 \log\left(W_{3,it}\right)]$$

The distribution of the estimated values of the Lerner index is found to be between 0 and 0.7 (see figure 11), where a higher value corresponds to higher market power.

Figure 11: Kernel density plot - Lerner Index in %



Minimum Spread

In order to cover the expected loss on a loan, the bank needs to apply a rate, equal to the risk-free rate rf plus a spread s, that makes the expected return on the loan (given its probability of default PD and the loss given default LGD) equal to that of a risk-free investment of the same amount. The analysis below, follows the one presented in Resti and Sironi (2012), page 452.

$$Expected\ value\ =\ risk\ free\ rate$$

Which can be expressed as:

$$(1+rf+s)\ [(1-PD)+\ (1-LGD)PD]\ =\ (1+rf)$$

If we use the expression $EL\ =\ PD.LGD$ and manipulate the equation above, we get:

$$(rf+s)=\frac{(1+rf)}{1-EL}-1\ \ =>\ (rf+s)=\frac{(rf+EL)}{1-EL}=>\ s=\frac{EL(1+rf)}{1-EL}$$

As such, the above implies that the spread s is equal to the cost of the expected loss.

Averse scenario ST 2021

Table 7: Portfolio level dataset (EBAST2021- Adverse Scenario) - estimation results

Variables	HH CC	HH RE	NFC
Constant	0.57	1.77***	1.35***
	(0.70)	(0.35)	(0.27)
Expected loss	0.64***	0.43***	0.14***
	(0.20)	(0.18)	(0.05)
Reference Rate	0.14**	-0.05	0.09**
	(0.07)	(0.06)	(0.05)
Currency	-1.09**	-0.07	-0.19*
	(0.50)	(0.30)	(0.11)
Home Bias	-0.53	-0.13	-0.21***
	(0.37)	(0.15)	(0.08)
Maturity	-0.08*	-0.03**	-0.03
	(0.04)	(0.01)	(0.03)
Size	0.86*	-0.63***	-0.17
	(0.54)	(0.20)	(0.10)
Leverage ratio	0.38***	0.01	0.01
	(0.10)	(0.05)	(0.03)
Implicit interest rates	1.21**	0.84**	0.32***
	(0.01)	(0.35)	(0.15)
Lerner Index	0.04**	0.01**	0.01
	(0.01)	(0.00)	(0.01)
Maturity mismatch	0.03	0.08	0.04***
	(0.03)	(0.10)	(0.01)
Country Controls	Y	Y	Y
Bank Fixed Effects	Y	Y	Y
Time Fixed Effects	Y	Y	Y
Observations	815	425	1012
R-squared	0.31	0.29	0.28

Notes: This table presents the average effect of expected loss on interest rate margins estimated through a panel regression with portfolio, bank, country and time controls under the adverse scenario of ST2021. Portfolio level controls include the reference rate, currency, home bias, maturity and portfolio size. Bank level controls include the leverage ratio, implicit interest rates, Lerner index and maturity mismatch. Standard errors are clustered at the bank level. ***,**, and * denote significance at the 0.1, 1 and 5 percent level respectively.

Table 8: Portfolio level dataset (EBA ST2021 - Adverse scenario) - estimation results by quintiles

Variables	HH-CC	HH-RE	NFC
EL - Quintile 2	0.74*	0.14	0.15
	(0.42)	(0.42)	(0.42)
EL - Quintile 3	0.93**	0.19*	0.26**
	(0.44)	(0.11)	(0.10)
EL - Quintile 4	2.01***	0.33***	0.37**
	(0.58)	(0.11)	(0.16)
EL - Quintile 5	2.70***	0.47***	0.41***
	(0.74)	(0.18)	(0.16)
Number of banks	89	89	89
Portfolio level controls	Y	Y	Y
Bank level controls	Y	Y	Y
Country controls	Y	Y	Y
Time fixed effects	Y	Y	Y
Observations	815	425	1012
R-squared	0.37	0.32	0.30

Notes: This table presents the interest margin rate mark-up of a respective EL quintile estimated through a panel regression with portfolio, bank, country and time controls under the adverse scenario. Portfolio level controls include the reference rate, currency, home bias and portfolio size. Bank level controls include the leverage ratio, implicit interest rates, Lerner index and maturity mismatch. Standard errors are clustered at the bank level. ***,**, and * denote significance at the 0.1, 1 and 5 percent level respectively.

Country Group Definitions

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
EU Core	**EU Mediterranean**	**EU East**	**Scandinavian**	**Balkan Countries**	**Commonwealth**	**Latin America**	**Others (Advanced)**	**Others (Developing)**
Austria	Cyprus	Bulgaria	Denmark	Croatia	United Kingdom	Brazil	Japan	Turkey
Belgium	Greece	Slovenia	Finland	Serbia	Australia	Chile	United States	Macao
Germany	Italy	Czech Republic	Norway	North Macedonia	New Zealand	Colombia	Canada	Mozambique
Luxembourg	Ireland	Hungary	Sweden			Peru		Kazakhstan
Monaco	Malta	Poland				Mexico		Russian Federation
Netherlands	Portugal	Romania						Other
France	Spain	Slovakia						
Switzerland								

Notes: EU refers to geographical Europe

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