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Numeracy and the Quality of On-the-job Decisions: Evidence from Loan Officers

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Abstract

We examine how the numeracy level of employees influences the quality of their on-the-job decisions. Based on an administrative dataset of a retail bank we relate the performance of loan officers in a standardized math test to the accuracy of their credit assessments of small business borrowers. We find that loan officers with a high level of numeracy are more accurate in assessing the credit risk of borrowers. The effect is most pronounced during the pre-crisis credit boom period when it is arguably more difficult to pick out risky borrowers.

Keywords: behavioral banking, numeracy, loan officers, screening

JEL classification numbers: G21, J24

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1. Introduction

Employers in a broad range of industries place significant weight on the numerical skills of job applicants when hiring new employees. Numerical skills are also associated with better labor market outcomes among workers (Koedel and Tyhurst, 2012; Joensen and Nielsen, 2009). These two observations suggest that employees with strong numerical skills are more productive or make better on-the-job decisions. Numerical skills themselves may foster better decision making as employees are better able to draw meaning from numerical information (Peters et al. 2006). Alternatively, numeracy may be correlated with other personal traits – IQ or social skills – which improve decision speed or quality (Burks et al. 2009). While it is plausible that high levels of numeracy are associated with better job-related decision making, there is almost no empirical evidence to support this conjecture.

This paper empirically examines the relation between employee numeracy and the quality of on-the-job decisions. Our analysis focuses on decisions made by loan officers in a retail bank. A key task of loan officers is the screening of loan applicants, i.e. the assessment of the borrowers' creditworthiness.[1] We study how the numeracy of loan officers relates to the accuracy of their credit assessments of small business borrowers: Are loan officers with high numeracy better able to identify those borrowers who ex-post turn out to be risky? With the unique dataset provided by the bank we are able to match loan officers' performance in a standardized numeracy test with data on all loan applications that they process (before the test). The loan-level data contain information on the requested loan terms, the borrower, the initial credit assessment by the loan officer, the approval decision and, for the approved loans, the granted loan terms as well as regular updates of

[1] Apart from client acquisition and advising customers, the US Bureau of Labor Statistics mentions the gathering, verification and analysis of applicants' information and the loan approval decision as typical tasks of a loan officer (see http://www.bls.gov/ooh/business-and-financial/loan-officers.htm).

the loan performance. The sample period 2007 – 2010 further allows for the analysis of a heterogeneous influence of numeracy during a credit boom and bust phase.

Small business lending provides an ideal framework to study the relationship between numeracy and the quality of on-the-job decision making. The production and processing of information is a core function of financial intermediaries (Diamond, 1984). Two key features of small business lending allow us to study the importance of loan officer numeracy in this function. First, the lending methodology applied by most small business lenders leaves discretion to the individual loan officer in screening potential borrowers (Berger and Udell, 1995). The screening process requires loan officers to collect, verify and assess both quantitative and qualitative information. Loan officers' skills can strongly influence the collection or processing of information. Hence, differences in skills across loan officers should translate into a difference in the quality of client screening. Second, loan officers make a large number of comparable lending decisions for which outcomes are quantitatively measurable. By comparison, for most skilled professionals on-the-job performance is difficult to measure and hardly comparable across employees.

We face two identification challenges when studying the relation between loan officer numeracy and the accuracy of credit assessments: First, the assignment of loan applications to loan officers is hardly random – and is likely to be related to loan officers' numeracy levels. A profit maximizing bank should allocate the most skilled loan officers to those tasks where their skills can generate the highest profit.[2] Intuitively we would expect banks to allocate those loan applications which are more difficult to assess to their most skilled loan officers. In this case, our estimates of the effect of numeracy on the screening accuracy could be downward biased. However, it is also

[2] Fang et al. (2014) show that fund families allocate their most skilled managers to less efficient market segments. In less efficient markets skills have the highest reward and the allocation maximizes profits.

feasible that the allocation of loan applications is driven by borrower characteristics that most strongly influence the bank's profit but that, at the same time, make the assessment easier. For instance, the most skilled loan officers might be assigned to larger clients, which also have more accurate financial information, leading to an upward bias of our estimates. The detailed loan-level data at hand help us to account for differences in borrower and application characteristics which may confound the relationship between loan officer numeracy and the accuracy of credit assessments.

Second, other loan officer characteristics such as education, age, gender, or job experience might be correlated with both loan officers' numeracy level and their screening accuracy. Our estimates may therefore suffer from an omitted variable bias and represent a spurious relationship between numeracy and screening accuracy. Our administrative dataset includes information on education, age, gender and experience which allows us to control for these confounding loan officer characteristics.

Our results show that loan officers with higher numeracy make more accurate credit assessments. Accuracy is hereby measured by the discriminatory power of the ex-ante risk scores assigned by loan officers: Those borrowers classified as risky ex-ante are more likely to fall into payment arrears ex-post than those borrowers classified as less risky. Subsample analyses suggest that numeracy is especially important for accuracy in the pre-crisis credit boom when information asymmetries seem strongest. Before the crisis, high numeracy loan officers are clearly better able to discriminate borrowers by their creditworthiness than low numeracy loan officers. This difference in accuracy between loan officers with high and low numerical skills decreases in the crisis period due to a considerable improvement in the accuracy of low numeracy loan officers.

Previous research has shown that numeracy is correlated with an array of cognitive and social skills which may prove essential in the screening of small and opaque borrowers. Individuals with higher numeracy seem less prone to framing effects (Peters et al., 2006), and seem better able to anticipate social behavior (Burks et al., 2009). Thus, loan officers with higher levels of numeracy can be expected to be more accurate in verifying and interpreting hard information as well as evaluating soft information. Individuals with higher numeracy have also been found to be more patient (Frederick, 2005; Burks et al., 2009), which might imply that they are better able to take the longer-term future into account when assessing borrowers' credit risk. Our happenstance data does not allow us to disentangle the effect of pure numerical skills, i.e. the ability to understand and work with numbers, from correlated personal traits, such as general cognitive ability or social skills. However, our results highlight that a simple test which captures numerical skills and correlated personal traits can be used to identify employees with better decision making skills.

Our findings contribute to a broader literature in finance, economics and psychology that analyzes how numerical skills affect corporate and personal[3] decision making as well as labor market performance. Experimental research provides evidence that numeracy influences strategies used for decision making and the quality of the decisions taken. Individuals with higher numeracy have superior judgment abilities (Ghazal et al. 2014) and are more likely to choose the normatively better option with a higher expected value (Pachur and Galesic, 2013).

Empirical studies based on field data document that numeracy, cognitive skills and financial literacy are associated with better personal financial decisions. Investors with higher IQ are able to select mutual funds with lower fees (Grinblatt et al., 2015), are less prone to the disposition effect and are able to generate higher returns (Grinblatt et al., 2012). Individuals with lower financial literacy more frequently transact in high-cost manners, e.g., they pay higher credit card fees or use more high-cost debt (Lusardi and Tufano, 2009). Gerardi et al. (2013) document significantly higher mortgage default rates among individuals who are not able to perform basic mathematical

[3] See Reyna et al. (2009) for an overview on health decisions.

calculations. And, in a sample of members of the US military, Agarwal and Mazumder (2013) find that a higher math test score is associated with fewer personal finance mistakes related to credit card use and home equity loans compared to other skills tested in the Armed Forces Qualifying Test (AFQT).

Labor economics provides evidence that employers value math skills in the hiring process (Koedel and Tyhurst, 2012) and that more mathematical education results in better labor market outcomes (Joensen and Nielsen, 2009).[4] These findings support the conjecture that employees with high numeracy are more productive and make better on-the-job decisions. However, to our knowledge, there is only one study connecting a concept related to numerical skills to job performance.[5] Burks et al. (2009) find that truck drivers with higher cognitive skills are more likely to avoid planning mistakes that could lead to performance failures such as arriving late for deliveries. Our study extends the literature by providing unique evidence for the effect of numeracy on on-the-job performance among skilled professionals.

Our findings also contribute to a strand in the empirical banking literature which studies the role of loan officers in bank internal decision making. Recent studies have analyzed the influence of internal organization (e.g. Liberti and Mian, 2009; Hertzberg et al., 2010; Brown et al., 2015; Qian et al., 2015) and incentives (e.g. Agarwal and Ben-David, 2016; Berg, 2015; Cole et al., 2015). Other papers focus on loan officers' characteristics that might explain why certain loan officers perform better within a given organizational and incentive structure. Existing work looks at the influence of loan officers' gender (Beck et al., 2013), experience (Andersson, 2004;

[4] Joensen and Nielsen (2009) show that higher earnings are mainly the results of differences in career paths and not of differences in earnings of individuals following a comparable career path.

[5] A recent literature analyses the importance of CEO traits and skills for performance. Custodio and Metzger (2014) show that CEOs' financial expertise is correlated with differences in firms' financial policies that benefit performance. Kaplan et al. (2012) study CEOs involved in private equity deals and document a positive correlation between their skills (performance in a general ability test and execution skills) and their performance. Further, a related strand of literature analyzes the impact of fund manager skills on fund performance (e.g., Chevalier and Ellison, 1999; Li et al., 2011).

Bruns et al., 2008), education (Bruns et al., 2008) and traumatic experiences (Morales-Acevedo and Ongena, 2015). We add to this literature by documenting an important role of loan officers' numerical skills for the quality of lending decisions.

Finally, we contribute to the recent literature which examines lending standards over the business cycle (e.g. Berger and Udell, 2004; Dell'Ariccia and Marquez, 2006; Dell'Ariccia et al., 2012; Beck et al., forthcoming). In line with Becker et al. (2016), we provide evidence for a lower accuracy of internal risk ratings during the credit boom, pointing towards higher information asymmetries. We add to the literature by showing that loan officer skills are most important during this boom phase with strong information asymmetries.

The remainder of this paper is organized as follows. In section 2, we describe the institutional background and in Section 3 we derive hypotheses from the existing literature. In section 4 we describe our data, while we explain our methodology in section 5. We present our results in section 6 and conclude in section 7.

2. Institutional background

2.1. The bank and its lending process

The bank that provided us with the data is a country-wide retail bank in Romania. It is part of an international banking group and serves mainly micro and small enterprises as well as households. The bank does not substantially differ in terms of business practices and loan products from small US or other European commercial banks which specialize in relationship lending to small businesses. One potential difference to some commercial lenders is the incentive structure of the bank: The bank regularly agrees with branch managers and loan officers on performance goals. However, while the achievement of these goals may affect the career path of employees within the bank, goal achievement is *not* financially incentivized through performance pay.

Our analysis focuses on first-time loans to small businesses with amounts of up to 30,000 Euro. These "micro" loans make up the bulk of the bank's loan portfolio. The credit assessment and approval process for these loans follows a standardized process which is illustrated in Figure 1.[6]

[Figure 1]

In a first step, prospective borrowers fill in a paper-based application form and submit it to the closest bank branch. For first time borrowers, the application is filled out without loan officer involvement and is therefore not influenced by loan officer skills. Clients state their requested amount, requested currency and requested maturity and provide information on the loan purpose, other bank relationships as well as the ownership structure and the free cash flow or disposable income of the firm.

Each loan application is then assigned to a loan officer within the branch where the borrower submitted the application. The allocation of an application to a loan officer is first and foremost based on loan officers' available capacity. That said, our data reveals that some loan officers do have an industry focus or tend to process predominantly requests of either small or large volumes.

In a second step, the assigned loan officer screens the application. During an on-site visit, the loan officer verifies the quantitative information provided in the application such as accounting data that allow for the computation of disposable income or free cash flow. Further, the loan officer assesses collateral values, the entrepreneur's character and overall managerial quality as well as

[6] Our description of the lending process is based on extensive interviews with loan officers and credit risk managers of the bank.

the market outlook for the business. Concurrently, the bank's back office provides credit registry information on the borrower to the loan officer.[7] It is important to note that many of the banks' first-time micro loan applicants have never had another bank loan before and henceforth no credit registry information exists. If information is available it becomes part of the credit risk assessment. The bank has a policy that loans with very negative credit registry information (e.g., the days of arrears within the last two years are above a certain threshold) or with clearly poor financial information are rejected as early as possible in the screening process. For all other loan applications the loan officer enters the collected qualitative (managerial quality and market outlook) and verified quantitative information into a standardized spread sheet to retrieve the initial risk score. Generally, the risk score can take on values from 1 (lowest risk class) to 5 (highest risk class).

In a third step, the loan officer suggests loan terms (volume, currency, maturity) and recommends the lending decision to the credit committee.[8] For the majority of loan applications in our sample there are two members in the credit committee: the branch manager and the loan officer. The credit committee evaluates the provided information, verifies the risk score, reviews the loan officer's suggestion and makes a final lending decision. The bank's policy is to not grant first loans with an initial risk score exceeding 3. Accordingly, we only observe initial risk scores from 1 to 3 and treat firms with initial scores other than 1 as risky.

In case of a positive lending decision (70 percent of the applications) and if the client accepts the loan terms (95 percent of the offered loans), the loan is disbursed and the repayment performance reported semi-annually.

[7] Unfortunately, we do not have access to the credit registry information.
[8] Interest rates are largely standardized for the loans in our sample (as is the usual practice with micro loans), i.e. that they are mainly determined by the size of the loan and are not fully risk-adjusted.

2.2. The numeracy test

To perform the credit assessment described above loan officers require diverse skills. We have an indicator of loan officers' numerical skills in the form of a score on a math test conducted in February 2010. All loan officers employed at that date were obliged to take the test at the same time at selected locations in the country. The test was announced on short notice so there was limited time for preparation. Passing the math test (there was an option to retake the test) was a requirement for the continuation of the employment relationship. The math test was prescribed by the international banking group to all its subsidiaries worldwide and thus can be considered as exogenous to the Romanian subsidiary – and its loan officers - which we study. The test measured basic numerical skills on the level of high school math covering percentage calculations, probability theory, logic and geometric understanding and equations.[9] Thus, the test is a comprehensive measure of numeracy comparable to tests discussed in Ginsburg et al. (2006).

2.3. The economic environment

Romania experienced a substantial lending boom over the period 2000 to 2007 during which the stock of credit relative to GDP increased from 7% to 35%. Credit to firms and households grew in some years by more than 50%. Figure 2 illustrates that lending volumes slowed down significantly and economic growth turned negative in the last quarter of 2008. With the crisis hitting Romania in 2009, the share of non-performing loans in banks' portfolios rose sharply. These underlying economic conditions had a severe impact on the bank that we study. Figure 3 shows that its total assets, gross loans and total deposits decreased in 2009 while its non-performing loan

[9] Three example questions from the test are provided in Appendix 1. The test was part of a series of tests such as a more advanced math test as well as an accounting test. The additional tests were taken at different dates and only completed by a subgroup of loan officers who took the first math test. Hence, we focus on the first math test as our measure of numerical skills.

ratio increased sharply. After years of branch network expansion, several branches were also closed in 2010.

[Figure 2]

[Figure 3]

Our dataset covers both pre-crisis and crisis years so that we can analyze potential heterogeneities in the effect of numeracy on loan officers' decision quality over a boom and bust cycle. Based on the macroeconomic and bank variables, we classify our sample into two subperiods. The pre-crisis period lasts up to the third quarter of 2008 with positive GDP and credit growth and very low non-performing loan rates. We classify October 2008 to February 2010 (when the math test was conducted) as the crisis period over which Romania's GDP dropped significantly and non-performing loan rates increased steadily.

3. Hypothesis development

We examine whether loan officers with higher levels of numeracy are more accurate in assessing the creditworthiness of small businesses. As mentioned above, our measure of numeracy captures the effect of pure numerical skills as well as that of potentially correlated personal traits such as general cognitive ability or social skills. In the following we clarify how numeracy, cognitive abilities and social skills may affect the accuracy of credit assessments at our bank.

We measure loan officers' screening performance by the accuracy of the initial risk score that they assign to each borrower. We therefore need to consider which components of the initial risk score are potentially influenced by numeracy. As described above, the initial risk score is based on quantitative financial statement information as well as qualitative information on managerial quality and the firm's market outlook. The loan officer enters this information into a spreadsheet, which then automatically calculates the risk score based on the underlying model. The process does not require any manual calculations. Therefore, any difference in accuracy should originate from differences in the loan officers' input to the rating model rather than from their ability to simply calculate numbers. We expect higher numeracy to improve the verification and interpretation of quantitative information as well as the precision of qualitative information.

While all loan officers receive the quantitative financial statement information with the loan application, they need to verify the provided information during the on-site visit. A first source of heterogeneity could stem from differences in the quality of the financial information verification. Peters et al. (2006) show that higher numeracy individuals are less prone to framing effects and are able to draw stronger and more precise affective meaning from numbers and comparisons using numbers. Thus, we expect high numeracy loan officers to be able to verify the hard information in a more accurate and objective way.

During the on-site visit, loan officers also evaluate borrowers on two qualitative dimensions. First, loan officers assess the borrower's character.[10] Loan officers evaluate, for instance, to what extent a borrower is discouraged from defaulting, e.g. through social norms and moral constraints.[11] Second, an assessment of the borrower's managerial quality is required. Based on the past development of the firm and the on-site observations loan officers evaluate the borrower's capability to manage the firm. This assessment arguably also requires social skills. There is evidence that cognitive skills are useful for social interaction. Burks et al. (2009) find in their experimental study in a sample of American trainee truckers that individuals with higher cognitive skills are in a prisoner's dilemma game better able to anticipate the behavior of the first

[10] The assessment of character is a standard process of a borrower assessment, e.g. in the 5Cs (Character, Capacity, Capital, Collateral and Conditions) framework mentioned in any banking textbook.
[11] Similar to a trust game, social conventions can help to overcome asymmetric information (Karlan, 2005).

mover. The assessment of the firm's market outlook could be influenced by numerical skills through several channels. Framing effects and the skill to draw precise affective meaning (Peters et al. 2006) as well as the higher likelihood to choose the normatively better option with a higher expected value (Pachur and Galesic, 2013) may influence the precision of the market outlook analysis.

4. Data

We merge two bank-internal administrative datasets. The loan officer data comprises all loan officers that passed the numerical test in February 2010 and contains information on loan officer characteristics including their numeracy score. The credit file data contains information on the loans (and loan applications) that were handled by these loan officers between 2006 and 2013. Appendix 2 provides definitions and full sample summary statistics of all credit file variables that we employ in our analysis. Appendix 3 shows summary statistics by subperiod.

4.1. Loan officer data

We have information on the characteristics of the 155 loan officers who obtained the minimum passing score (*Numeracy score*) of 65% or higher in the above described math test.[12] The *Numeracy score* reflects the share of correctly answered questions. We exclude loan officers whose highest degree is not a bachelor degree (21 loan officers) to ensure that a potential effect of numeracy on loan officers' risk score accuracy is not driven by heterogeneity in education. Further, we exclude 6 loan officers who only processed loans after the numeracy test took place. Figure 4 provides a histogram of the *Numeracy score* of the 128 loan officers in our final sample. We use dummy variables to distinguish three levels of numeracy. *Low numeracy* is a dummy variable that

[12] We were not able to obtain information on 38 loan officers with numeracy scores below 65%.

is 1 for loan officers with a numeracy score between 65% and 80%, *Medium numeracy* is a dummy variable that is 1 for loan officers with an numeracy score from 80% to 89% and *High numeracy* is a dummy variable that is 1 for all loan officers with a numeracy score of 90%-100%.[13]

[Figure 4]

Table 1 displays the average numeracy score, gender, age and work experience for our sample of loan officers by numeracy level. Table 1 shows that loan officers with a medium level of numeracy are more often female and more experienced than both high and low numeracy loan officers.

[Table 1]

4.2. Credit file data

Our initial credit file dataset consists of all 37,988 loan applications submitted over the period 2006 – 2013 to the bank and processed by loan officers who passed the numeracy test in February 2010. Out of these applications, 6,048 did not enter the screening stage due to formal errors, very negative credit registry information or because the client did not want to proceed further. We therefore observe 31,940 loan applications which were processed, out of which the bank made 22,485 loan offers (70%). In 1,136 cases, the client did not accept the loan offer so that the raw dataset contains 21,349 granted loans.

[13] The thresholds ensure that roughly one third of the loan applications in our final analysis sample are handled by loan officers in each numeracy level. In robustness tests we set the thresholds so that one third of loan officers are in each numeracy category and we use the linear numeracy score. In both cases results remain qualitatively unchanged.

For our analysis, we restrict the raw dataset in several ways. We focus our analysis on the period July 2007 to February 2010. Since our sample contains only loans processed by loan officers that took the numeracy test in February 2010, there are very few loans in the sample for 2006 and early 2007. We begin our sample in July 2007 to ensure a sufficient number of loans per quarter and to cover a long enough pre-crisis period (5 quarters). In order to rule out any influence of the numeracy test itself, we exclude all loan applications made after the test. Furthermore, we only include installment loans up to 30,000 Euros into our analysis because the large majority of applications is targeted towards such micro loans. Applications for larger volumes are less frequent and most often processed by credit analysts.[14] Our loan sample contains only first-time borrowers. Since no information from previous loans is available for first time borrowers, screening is most difficult and any effect from numeracy should be most prevalent. Also, the focus on first-time borrowers ensures that the assignment of loan applications to loan officers is not influenced by past loan performance.[15]

Our final dataset contains 5,928 loan applications and 3,619 loans granted to firms without prior credit relationships with the bank. These loan applications were screened by 128 loan officers at 31 bank branches over the period July 2007 to February 2010.

For each loan application, we know which loan officer handled it and can therefore match loan application and loan officer data. For loan applications, the dataset further contains information on the requested amount, the requested currency[16], the opening date of the client's

[14] Our initial sample covers 14 credit analysts. They are excluded from the analysis since their job description differs from the job description of loan officers.

[15] This comes at the disadvantage that we cannot observe differences over a client relationship as for example documented for credit rationing by Kirschenmann (2016).

[16] Only 2% of loans were granted in a currency different from the requested currency (for 1% of loans, the application was in Euro and the granted loan in RON and for 1% of loans the application was in RON and the granted loan in Euro). There is no evidence that adjustments of the loan currency substantially differ by the level of loan officer numeracy and that bank-wide changes influencing the loan currency (e.g. the funding structure (Brown et al., 2014)) would affect loan officers with different numeracy differently.

account with the bank as well as the involved bank branch. For granted loans, the dataset contains additional information on the borrowing firm at application date (financial information, industry, and firm age), the granted loan terms (volume, currency, interest rate, collateral, maturity) and the initial internal risk rating. In our analysis, the variable *Risky* reflects the initial risk rating at loan disbursement. The binary variable takes on the value 1 if a loan is assigned an initial risk score of 2 or 3 and zero if the loan is assigned a risk score of 1. In our final sample used in the empirical analysis, we have 2,757 loans with an initial risk score of 1 and 816 (46) loans with an initial score of 2 (3).

We further have semi-annual information on the performance of granted loans as measured by the days in payment arrear. We construct the variable *Arrears* which captures the performance of each loan during the first 24 months after the loan was disbursed. We focus on the first 24 months since initial credit assessment processes in commercial banks are designed to capture potential loan defaults in the first years after disbursement.[17] For each loan, the days in arrear are reported for end of June and end of December. Hence, we can retrace when exactly each loan falls into arrears for at least 30 days for the first time. The binary variable *Arrears* then takes on the value 1 if a loan falls into arrears for at least 30 days within the first 24 months. On average, 8 percent of the loans in our final sample fall into arrears for at least 30 days during the first 24 months of their maturity. The Kaplan-Meier plot in Figure 5 displays the share of non-risky (grey line) and risky (black line) loans that have *not* fallen into 30-day arrears over the first 24 months after loan disbursement. At each point in time, the share of non-risky loans that is not in arrears is higher than the share of risky loans not in arrears, with the difference between the two increasing steadily. The figure also

[17] In small business lending, banks typically update their credit assessment annually, when new financial statement data on the firm becomes available through its annual accounts.

highlights that the incidence of falling into arrears occurs quite evenly distributed over time for both risky and non-risky loans.

[Figure 5]

5. Methodology

Our objective is to estimate the relationship between loan officer numeracy and the accuracy of their credit assessments. Consider a bank which is recruiting loan officers from a population of interest, i.e. in our case college graduates. The bank is interested in how the accuracy of its credit assessments will change if it hires college graduates with high numerical skills rather than college graduates with lower numerical skills.

For a given portfolio of loan applications L the bank is thus interested in estimating the average treatment effect of replacing a low numeracy loan officer with a high numeracy loan officer. We define A as the accuracy level and N as the numeracy level of the loan officer employed by the bank. The average treatment effect is then given by:

$$ATE = E[A(N = high, L) - A(N = low, L)] \tag{1}$$

In order to estimate the average treatment effect in equation (1) one possible experiment would be the following: First, the bank randomly chooses loan officers from the population of interest (e.g. college graduates). The bank then randomly assigns loan applications to these loan officers. We would then measure the accuracy of the credit assessments A for each loan officer.

And we would compare the average accuracy of loan officers with a high numeracy level to the average accuracy of loan officers with a low numeracy level.[18]

Our empirical analysis of the administrative data presented above deviates from this ideal experiment in two main dimensions: measurement and identification. First, the available data does not allow us to measure the accuracy of credit assessments at the loan officer level, but only for groups of loan officers. Second, loan officers in our sample are hardly randomly chosen, and loan applications are hardly randomly assigned to loan officers. In the following, we first discuss how we measure the accuracy of credit assessments. We then discuss identification.

5.1. Measuring and comparing loan officer accuracy

We measure the accuracy of loan officers' credit assessments by comparing their ex-ante risk assessment of a borrower to the ex-post performance of that borrower's loan. This approach follows the methodology applied to assess the discriminatory power of internal rating systems, i.e. the system's ability to discriminate ex-ante between defaulting and non-defaulting borrowers (BIS, 2005).

For each granted loan in our sample we observe the initial risk rating as assigned before loan disbursement by the loan officer. We hereby distinguish *Risky* (initial risk score = 2 or 3) from non-risky (initial risk score =1) loans. We also observe whether a loan falls into *Arrears* within 24 months of disbursement. A loan officer who is very accurate in assessing the creditworthiness of borrowers would classify most loans as non-risky which ex-post are not in arrears, while he would

[18] An alternative experiment would be to randomly hire loan officers from the same population of interest (college graduates). Then the bank would randomly assign the recruited loan officers to a numeracy training. After the training the bank would randomly assign loan applications to loan officers. We would then compare the accuracy of the credit assessments of those who received training to those who did not. We analyze a similar case in the Internet Appendix (see https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2997114 and section 6.5). The bank organized math trainings in 2011 and 2012 to prepare employees for a second math test. Exploiting the staggered introduction of the trainings, we do not find evidence for a significant impact of the training attendance on loan officers' rejection decisions or accuracy.

classify most loans as risky that fall into arrears. Thus, in the portfolio of loans handled by an accurate loan officer we should see that the share of defaulting loans among those classified as risky is much higher than the share of defaulting loans among those classified as non-risky. By contrast, the portfolio of a loan officer who is not accurate at all would display a similar share of defaulting loans, irrespective of whether the loan was rated as risky or non-risky.

[Figure 6]

The bar charts in Figure 6 display the share of loans falling into arrears by risk rating, loan officer numeracy and sub-period. Starting with the total sample in the top panel, the graph shows that borrowers initially classified as risky (grey bar charts) are more likely to fall into arrears than borrowers initially classified as non-risky (white bar charts), and the discriminating power is largest for the high numeracy loan officers. The same pattern holds for the crisis period. For the pre-crisis sample we find that for *low* numeracy loan officers a higher share of non-risky loans falls into payment arrear than of risky loans. Hence, during this period the initial rating of these loan officers is unable to discriminate borrowers by creditworthiness.

To formally measure and compare the accuracy of credit assessments across loan portfolios processed by loan officers with different numeracy scores we choose the following methodology:[19] Consider a portfolio consisting of $l = 1 \ldots L$ loans and the following linear regression:

$$Arrears_l = \alpha + \beta \cdot Risky_l + \varepsilon_l \tag{2}$$

[19] An alternative approach for measuring the discriminatory power of risk ratings is to calculate the accuracy ratio (see e.g., Engelmann et al., 2003; Moodys, 2003; BIS, 2005). The accuracy ratio compares the ratio of the correctly classified loans within a loan portfolio to the classification of a perfect model and a random model. However, a major drawback of using the accuracy ratio for our purpose is that there is no method for formally comparing the measure across loan portfolios, i.e. for loans processed by low numeracy as opposed to high numeracy loan officers.

The estimated coefficient β from this regression provides us with an indicator of the discriminatory power of the initial risk rating for the underlying portfolio of loans. If the risk rating cannot discriminate between those loans which fall into arrears and those that do not, we would yield an estimated coefficient of β=0.[20] If the risk rating perfectly discriminates between those loans which fall into arrears and those that do not, we would yield an estimated coefficient of β=1.[21]

Applying equation (2) we can formally compare the discriminatory power of the risk rating across two portfolios of loans l and l'. Specifically, we can estimate β within portfolio l and β' within portfolio l'. We can then compare the estimated coefficients β and β' with a Chow test. This is the methodology we pursue in this paper to measure and compare the accuracy of credit assessments by loan officer numeracy. We split our sample of 3,619 loans into three portfolios based on whether the loan was processed by a high, medium or low numeracy loan officer. Applying equation (2) to each subsample separately we estimate β^{high}, β^{medium} , and β^{Low}. We then compare these estimated coefficients applying a Chow test.

Note that theoretically we could estimate equation (2) separately for each loan officer. We would then obtain a measure of individual loan officer accuracy as depicted in equation (1). However, with the administrative data at hand it is not feasible to estimate accuracy indicators at the loan officer level with reasonable precision. The precision of the estimated coefficient β in the linear regression (2) depends on the size of the underlying loan portfolio and the share of loans which actually default. A crucial limitation to studies of bank credit risk is that only a small share of loans actually defaults. In our sample 8% of the loans enter into payment arrears within 24

[20] In this case the estimated constant a would equal the average default rate in the portfolio.
[21] In this case the estimated constant a would equal zero and *Risky* would be perfectly collinear with *Arrears*.

months of loan disbursement. Our sample consists of 3,619 granted loans handled by 128 loan officers and thus an average of 28 loans per loan officer. With a default rate of 8% this implies that on average just over 2 loans fall into arrears per loan officer. Given the limited number of loans handled by each loan officer and the low default rate it is thus not feasible to precisely measure the accuracy ratio at the loan officer level.

5.2. Identification

We apply regression (2) to measure the accuracy of the initial risk ratings separately for the portfolios of loans processed by (all) high numeracy, medium numeracy and low numeracy loan officers, respectively. The comparison of β^{high}, β^{medium}, and β^{Low} will provide us with an unbiased estimate of the effect of numeracy on loan officer accuracy if (i) observed numeracy is orthogonal to other loan officer characteristics which may affect the accuracy of their credit assessments and (ii) loan applications are randomly assigned to loan officers. It is unlikely that either of these assumptions hold. Our analysis thus faces two main identification challenges. First, other loan officer characteristics such as education, age, gender or job experience might be correlated with both, loan officers' numeracy levels and the accuracy of their credit assessments. Second, the assignment of loan applications to loan officers is likely to be influenced by numeracy or related characteristics and therefore the unobserved counterfactual accuracy is not equal to the observed outcomes.

To address these identification challenges, we augment equation (2) with two vectors of control variables that capture loan officer characteristics LO_j and loan application characteristics X_i. We estimate the following linear probability model for each numeracy level n separately[22]:

$$Arrears_{i,j} = \alpha + \beta_n \cdot Risky_i + \delta \cdot LO_j + \gamma \cdot X_i + \varepsilon_{i,j} \quad (3)$$

As discussed above, the coefficient of primary interest in equation (3) is β_n. It captures the discriminatory power of the initial rating *Risky* within the portfolios of loans processed by loan officers with numeracy level n.

LO_j is a vector of observable loan officer characteristics that are likely to be correlated with numeracy and the accuracy of loan officers' credit assessments. Beck et al. (2013) find that the loan portfolios of female loan officers perform better than those of male loan officers. Since the effect is most pronounced when female loan officers handle loans of female borrowers, they conclude that female loan officers are better in building trust relationships with their clients. *Female* thus is a dummy that is 1 of the loan officer is female and 0 if male. Andersson (2004) and Bruns et al. (2008) show that job experience or specific human capital might matter for loan officers' lending decisions and the decision process. We therefore include *Experienced* which is a dummy variable that is 1 for loan officers who have worked with the bank for more years than the median of work years at the math test date (2.13 years). *Age* captures the age of the loan officer in years to control for the general life experience of the loan officers.

X_i is a vector of loan-level covariates controlling for factors that could potentially influence the assignment of a loan application to a high numeracy loan officer and be correlated with the potential accuracy of the credit assessment, i.e. the difficulty of assessing the creditworthiness of

[22] In robustness tests we estimate the same effect in a non-linear logit model and in a linear probability model using the linear numeracy score but with interaction terms pooling the observations from all numeracy levels. The results confirm our main findings.

the borrower. A profit-maximizing bank should employ the most skilled loan officers where their skills can generate the highest profit. Intuitively, we would expect banks to allocate those loan applications which are most difficult to assess to their best loan officers. However, it is also feasible that the allocation of loan applications is driven by borrower characteristics that most strongly influence the bank's profit but that, at the same time, make the assessment easier. For instance, the more able loan officers might be assigned to deal with the larger clients, which also have more accurate financial information.

We would like to control for all loan-level or firm-level characteristics which may confound the relationship between loan officer numeracy and the potential accuracy of credit assessments. At the same time we should avoid using endogenous control variables, i.e. firm-level or loan-level variables which may be influenced by the numeracy level of the loan officer processing the application. We therefore employ two sets of application and firm control variables. Basic controls contain loan and firm characteristics elicited in the loan application form: The measurement of these variables is thus arguably independent of the loan officer's numeracy level. *Ln(Requested amount)* controls for the volume of the application and *Request Euro* for the requested currency. *New client*, a binary variable equal to 1 if a client has no account history with the bank, and *Time relationship,* a variable reflecting the years that a firm has an account at the bank, control for the level of information about the firm that is available within the bank and thus are also measures of opaqueness.

Extended firm-level controls include variables which are elicited or verified during the credit assessment process: *Leverage, ln(Sales), Young firm, Agriculture and Total assets/requested amount*. These variables allow controlling for firm size, riskiness, industry and opaqueness in more detail. However, these variables are also potentially influenced by the loan officer's verification procedure and are therefore potentially endogenous control variables. *Ln(Sales)* controls for the size of the applicant and *Total assets/requested amount* for the relative size of the loan application. *Leverage*, defined as the debt capital and the applied loan amount over equity, should provide some obvious signals about the riskiness of the loan application. *Agriculture* is a dummy variable taking on the value 1 if a firm is active in agriculture. *Young firm*, a binary variable capturing firms that were founded less than 5 years prior to the loan application, controls for the firm's opaqueness.

We further include branch fixed effects and quarter fixed effects. The branch fixed effects control for the general local economic and cultural environment as well as branch-specific practices. The branch fixed effects are also important to control for the time-invariant characteristics and the numeracy of the branch manager as he forms part of the credit committee that checks the credit score and makes the final lending decision.[23] The quarter fixed effects control for the changing macroeconomic conditions during the boom and bust cycle.[24]

Regarding the interpretation of our results, we note that our observable measure of numeracy is very likely correlated with unobservable personal traits of loan officers such as general cognitive ability and social skills. This implies that our estimated "effect" captures the combined effect of numerical skills and the broader set of correlated cognitive and social skills. Our results can therefore not be interpreted as the potential gain to a bank (or other employers) of promoting the numerical skills of employees, e.g. through an education intervention. Rather our results can inform us about the potential gain to a firm of hiring staff with high observable numerical skills (and related, but less observable, cognitive and social abilities).

[23] Unfortunately, we do not have comprehensive and detailed information on the branch manager characteristics and the credit committee. We have information on the composition of the credit committee from mid-2010 onwards and for 80% of the loans the credit committee consists of the loan officer and the branch manager. For the other 20% the credit committee consists of the branch manager and of a credit risk officer located at the bank's headquarter. Therefore, the branch dummies do not fully capture the influence of the credit committee or the branch manager.

[24] For example, in the first quarter of 2009 more than 95% of issued loans in the sample were classified as risky compared to 10%-20% in the quarters before and after. Obviously, the bank made some short-term adjustments to its policies at the beginning of the crisis, however these adjustments apply to all loan officers independent of their numeracy level.

6. Results

6.1. Numeracy and accuracy

Table 2 presents our baseline analysis for different sets of control variables. In each column the coefficient of *Risky* reflects the degree to which loan officers in that subsample are able to discriminate borrowers by their creditworthiness. Hence, a higher estimate for *Risky* reflects more accurate credit decisions. Results of the Chow test comparing the coefficients across numeracy levels are presented in the bottom panel of the table. Columns 1 – 3 display results of the estimation controlling only for basic control variables, loan officer controls and branch fixed effects. In columns 4 – 6 we add quarter fixed effects and in columns 7 – 9 extended control variables. Standard errors are heteroscedasticity robust and clustered at the loan officer level.

Considering the specification with basic controls and branch fixed effects only, the magnitude of the estimated coefficient of *Risky* is substantially larger in the sample of loans processed by high numeracy loan officers (column 3: 0.249) as compared to loans processed by low numeracy loan officers (column 1: 0.112) or medium numeracy loan officers (column 2: 0.116). Chow tests reported in the bottom part of the table confirm that the credit assessments of high numeracy loan officers are significantly more accurate than those of low numeracy loan officers. We yield almost identical results in the specifications including quarter fixed effects (columns 4-6) and extended controls (columns 7-9). Estimating the difference in accuracy by numeracy of the loan officer in the full sample with interaction terms confirms that high numeracy loan officers are more accurate than low numeracy loan officers (see Appendix 4 for a corresponding linear probability model and Appendix 5 for a logit model).[25]

[Table 2]

Appendix 6 shows that the higher accuracy of high numeracy loan officers is confirmed for various subsamples of borrowers. Whether loan officers assess borrowers from agriculture vs. other industries (columns 1-6) or young vs. older firms (columns 7-12), the high numeracy loan officers are more accurate in their credit assessments than the low numeracy loan officers (although the difference is not significant in the sample spilt by firm age). Interestingly, however, we find that the length of the bank-borrower relationship does matter. The estimated coefficient of *Risky* is not significant at any numeracy level and there is no significant difference between the high and the low numeracy loan officers in their accuracy when assessing new clients, i.e. borrowers that have only recently opened an account or do not have an account at the bank at all (columns 13-15). By contrast, when assessing existing clients (columns 16-18), the estimated coefficient of *Risky* is significant at all numeracy levels, and high numeracy loan officers are significantly more accurate in their credit assessments than low numeracy loan officers. Given that we only examine applications from first-time borrowers at the bank, these results confirm that observing account activity provides useful information for banks when assessing borrowers' creditworthiness (Mester at al. 2007; Norden and Weber 2010).

[25] In addition, in Appendix 7 we replace the three numeracy categories by the linear numeracy score and show that our results do not hinge on the construction of the numeracy categories. Appendix 8 reports results for the sample of loan officers from all educational backgrounds (controlling for education) and shows that our main results are not driven by the selection of the loan officer sample.

Are high-numeracy loan officers more accurate in their credit assessments because they are better able to draw meaning from “hard” quantitative information on the borrower or because they can better assess soft “qualitative” information? In Appendix 9 we examine – separately for low, medium and high numeracy loan officers - to what extent the risk classification of a borrower is related to observable characteristics of the borrower and his application. We find that there is no significant difference in the influence of observed application or borrower characteristics on the risk classification. This suggests that the higher accuracy of high numeracy loan officers is not primarily driven by a different interpretation of well observable, “hard” financial information.

In Appendix 10 we examine to what extent the risk classification of the loan officer helps predict loan arrears beyond the available hard financial information on the borrower. The degree to which this is the case provides us with an indicator of the value of the loan officer’s assessment of soft, qualitative information about the borrower. Columns 1, 3 and 5 of Appendix 10 show that the R^2s of the simple regressions containing only the basic controls vary very little between the three numeracy groups. However, when adding the *Risky* indicator in columns 2, 4 and 6, the R^2 is much higher in the regression for the high numeracy loan officers than for the medium and low numeracy loan officers. Results including the extended controls are qualitatively the same. This suggests that high numeracy loan officers are more accurate because they are better able to collect and assess the soft information that enters the rating decision.

Our estimates in Table 2 account for differences in average borrower characteristics between the pools of loans processed by high, medium and low numeracy loan officers. However, the loan portfolios may also differ with respect to the variation in observable characteristics across borrowers. The higher accuracy of high numeracy loan officers might therefore be partially explained by the fact that it is just easier for them to classify risky versus safe borrowers, because there is more variation in the pool of loans they process. Appendix 11 compares the distribution of observable borrower characteristics for the pool of loans processed by low, medium and high numeracy loan officers. We find that the standard deviation of some variables (*Time relationship*, *Leverage*, *Total assets/requested amount*) is indeed somewhat higher in the pool of loans processed by high numeracy loan officers. That said, the range of the distributions of all variables largely overlaps. Thus, our main results can hardly be explained by the fact that high numeracy loan officers have more variation to exploit in their loan portfolios.

6.2. The influence of the crisis

In Table 3 we present separate results for the subsample of loans in the pre-crisis and crisis periods. We report the results for the model with all controls, branch fixed effects and quarter fixed effects. For both subperiods the difference between the estimates of *Risky* for low and high numeracy loan officers is statistically significant at the 5%-level. The difference is, however, larger in the pre-crisis period (0.231 vs. 0.131). In the pre-crisis period (column 1) the predictive power of the risk rating of loans processed by low numeracy loan officers is even worse than a random assignment. The ability to discriminate borrowers by quality improves significantly for all numeracy levels in the crisis period with the improvement being largest for the low numeracy loan officers.[26] These findings are in line with Becker et al. (2016) who show that it is most difficult to accurately sort borrowers according to their riskiness during boom periods in which informational frictions are highest.

[Table 3]

[26] Chow tests show that the difference in the estimate of *Risky* between the pre-crisis and crisis period is 0.265*** for low numeracy loan officers and 0.208*** (0.156**) for medium (high) numeracy loan officers.

An alternative explanation for the improved accuracy of low numeracy loan officers (compared to high numeracy loan officers) could be that they became more rigorous in their assessment of loan applicants once the crisis started. An analysis of the processing time of loan applications by numeracy level over our sample period shows that, on average, the processing time increases for all loan officers after the start of the crisis (see Appendix 12). However, mean processing times increase the least for low numeracy loan officers. Thus, the relative improvement in the accuracy of low numeracy loan officers does not seem to be driven by a more diligent assessment.

Another potential explanation for the above results could be that the hiring policy at the bank changed once the crisis unfolded. Appendix 13 reports results for the subsample of only those loan officers who worked at the bank already before the crisis and we find our main results confirmed. The improved accuracy in the crisis period therefore does not stem from the hiring of better loan officers after the start of the crisis. Rather do these results corroborate that it is most difficult to sort borrowers according to their riskiness during boom periods.[27]

6.3. The influence of gender and experience

Our results so far establish a clear role for numeracy in loan officers' screening performance. Previous research has shown that loan officers' lending decisions and performance are also related to their gender (Beck et al., 2013) and experience (Andersson, 2004; Bruns et al.

[27] An additional concern could be that low and high numeracy loan officers experience arrear events of the loans that they granted before the crisis at different points in time, which could systematically influence their screening behavior during the crisis. When we compare Kaplan-Meier survival estimates (available upon request) for loans disbursed in the pre-crisis period by low, medium and high numeracy loan officers, we do not find systematic differences in the timing when arrears occur. For instance, independent of the loan officer's numeracy level almost no arrear events occur during the first six months after a loan's disbursement and the incidence of arrears slowly increases the longer the time since a loan's disbursement.

2008). In Table 4 we explore how gender and experience affect the accuracy of loan officers' credit assessments in our sample.

First, we replicate our full sample estimates of loan officer accuracy (Table 2) by gender and experience, rather than by numeracy. The results presented in Table 4 show no significant gender or experience effect in loan officer accuracy. These results are not necessarily in conflict with the results of Beck et al. (2013). Beck et al. (2013) focus on loan performance rather than accuracy and show that the interplay between the loan officers' and the clients' characteristics (such as gender) is important. In our study, we lack the information on the gender of the borrower.

[Table 4]

[Table 5]

In Table 5 we explore potential interaction effects between numeracy, gender and experience. We start by comparing the effect of numeracy on accuracy for female (columns 1 - 3) vs. male (columns 4 - 6) loan officers. Interestingly, we find a significant effect of numeracy on accuracy only in the subsample of male loan officers. Thus, the difference in the screening accuracy across numeracy levels stems mainly from the male loan officers. We further compare the effect of numeracy on accuracy for inexperienced loan officers (columns 7-9), i.e. those with work experience at the bank of up to two years at the test date, vs. experienced loan officers with more than two years of experience at the test date (columns 10 – 12). The results from these columns suggest that numeracy seems to have a stronger effect on accuracy among inexperienced loan officers.

6.4. Loan rejections

The analysis so far has focused on the sample of granted loans and studied the accuracy of loan officers' credit assessments. However, if numeracy is related to the ability to pick out risky borrowers, it might also lead to systematic differences between the samples of loans which are approved when the application is handled by low, medium and high numeracy loan officers. The observed differences in the screening performance of loan officers of different numeracy levels would then be influenced by their preceding approval vs. rejection decisions.

Our dataset covers all loan applications processed by our sample of loan officers during the sample period. Figure 7 displays the development of the quarterly rejection rate for first time applicants by the level of the loan officers' numeracy. Over the entire sample period 39% of all loan applications are rejected (see also Appendix 2b). Low numeracy loan officers display substantially lower rejection rates (32%) compared to loan officers with medium numeracy (40%) and high numeracy (42%).

[Figure 7]

[Table 6]

In Table 6, we estimate a linear probability model of the rejection decision. The dependent variable is *Rejection*, which is a dummy variable that is 1 if the loan application is rejected and 0 if it is approved. All regressions include as explanatory variables the loan application characteristics *Request Euro, (Ln) Requested amount, New client* and *Time relationship*. All regressions further include controls for loan officer characteristics (gender, experience, age) as well as for branch and quarter fixed effects.

In columns 1 - 3 of Table 6 we estimate the model separately for low numeracy, medium numeracy and high numeracy loan officers. The results suggest that – at all levels of numeracy –

loan officers are more likely to reject applications for large loans as well as applications from new clients or existing clients with a short relationship with the bank. We then compare the column 1-3 coefficients across numeracy levels applying Chow tests. We find no significant difference between coefficients of low and high numeracy loan officers. Thus the rejection behavior of loan officers seems to be similarly related to observable borrower characteristics, independent of the loan officer's numeracy level.

The observed differences in average rejection rates between the low versus medium / high numeracy loan officers could be caused by differences in the assigned application pool. Comparing the characteristics of loan applications (see Appendix 2b) highlights that medium and high numeracy loan officers are indeed more likely to handle loan applications with a larger requested loan size as well as applications from new clients. In columns 4 - 6 of Table 6, we examine whether loan officer numeracy influences rejection rates conditional on loan application characteristics. We pool the samples of applications across loan officers and add our indicators of *High numeracy* and *Medium numeracy* to the regression model. Column 4 reports results for the full sample period, while columns 5 - 6 report results for the pre-crisis and crisis period separately. The column 4 - 6 estimates show that, controlling for loan application characteristics, high numeracy loan officers are significantly more likely to reject loans than low numeracy loan officers. Over the entire observation period the estimated difference in rejection rates is 4.3 percentage points. This amounts to more than one-tenth of the average rejection rate in the sample (39%) and accounts for more than one-third of the observed difference in rejection rates between low and high numeracy loan officers. The sub-period analysis shows that there is no significant difference in the rejection rate before the crisis (column 5) but that the significantly higher rejection rate of high compared to low numeracy loan officers observed in the full sample stems from the crisis period (column 6).

The Table 6 results show that high numeracy loan officers are more likely to reject observationally similar loan applications than low numeracy loan officers. This finding suggests that high numeracy loan officers may be assigned loan applications which are riskier based on application and borrower characteristics that are unobservable to us.

To what extent does the difference in loan rejection rates by high versus low numeracy loan officers imply that our main results on screening accuracy (Table 2) are biased? The estimated effect of numeracy on accuracy would be upward (downward) biased if borrowers whose loan application was approved by high numeracy loan officers are easier (more difficult) to assess than borrowers whose loan application was approved by low numeracy loan officers. Given that – conditional on observable characteristics - high numeracy loan officers reject more loan applications than low numeracy officers, it seems more plausible that their sample of approved loans is more difficult (rather than easier) to assess. We therefore argue that – if anything – our estimates of the effect of numeracy on accuracy in Table 2 is downward biased.

6.5. The effect of a math training

The above analysis suggests that initial ratings assigned by loan officers with high numeracy are more accurate than ratings assigned by loan officers with low numeracy. But can a bank improve the accuracy through a targeted investment in loan officers' numerical skills or are observed differences mainly related to the cognitive abilities of loan officers? Our bank subsequently implemented four-day math trainings over the years 2011 and 2012 to prepare employees for a second math test.[28]

[28] While recent studies mainly analyzed the impact of trainings for small-business bank clients (e.g. Karlan and Valdivia, 2011; Drexler et al., 2014), our setting allows to study the influence of a training for loan officers.

Our Internet Appendix[29] presents estimates for the impact of the math training on loan officer accuracy and rejection rates. We exploit the staggered implementation of the training and apply a within loan officer analysis. We do not find a significant influence of the math training on loan officer accuracy nor on their rejection decisions. However, our analysis is limited to a low number of loan officers (59) and only allows us to compare a limited number of loan applications in a short period of time after the training. That said, the findings presented in our Internet Appendix suggest that the difference in accuracy between high and low numeracy loan officers may rather be related to general cognitive ability or social skills than to easily teachable math skills.

7. Conclusion

We provide novel evidence documenting that employees with high numerical skills make more accurate on-the-job decisions. In the context of small business lending we relate the numeracy of loan officers to the accuracy of their credit assessments. In line with findings from experimental studies, we document significant differences in accuracy between loan officers with low versus high numeracy. Initial ratings assigned by high numeracy loan officers are better able to predict which borrowers will default and which will not.

The difference in accuracy between high and low numeracy loan officers is most pronounced in the pre-crisis credit boom phase. This finding is in line with Becker et al. (2016) who show that it is most difficult to accurately sort borrowers according to their riskiness during boom periods in which informational frictions are highest. Our results thus provide evidence that hiring skilled loan officers is most important during boom times when separating borrowers by quality is most difficult. Our findings further show that higher numerical skills are a complement

[29] See https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2997114.

to other characteristics (gender, experience) that have been connected to improved loan performance in the literature.

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Figure 1. Lending process

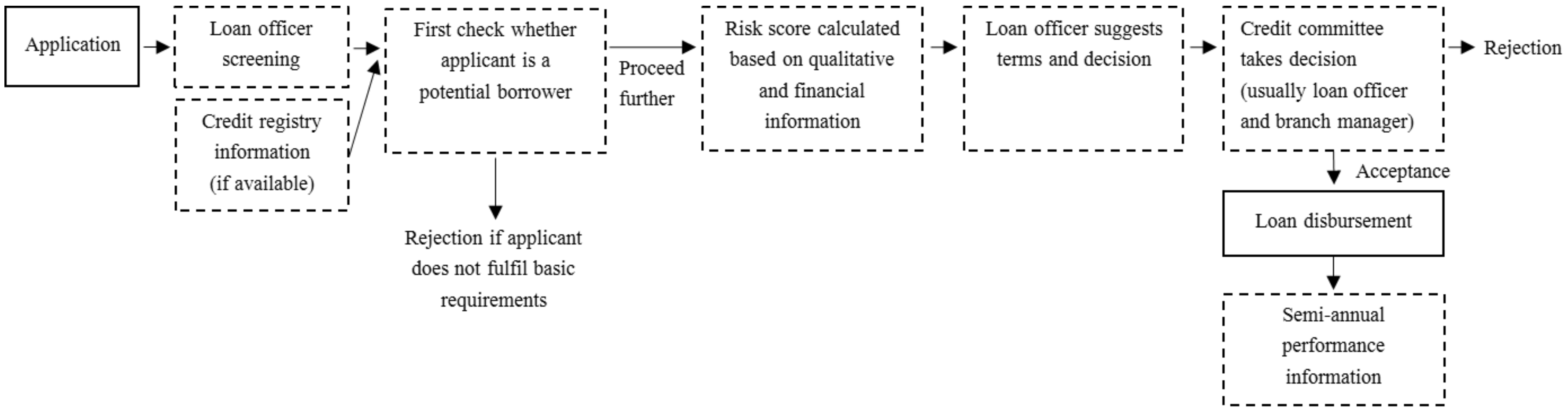


Figure 2. Economic development and crisis period

The figure displays the development of the Romanian economy over the sample period. Values of GDP at market prices are from the ECB. Lending volumes and non-performing loans ratios are from the Romanian central bank (NBR). The non-performing loans ratio is only available on quarterly basis from 2009Q3 on. Prior to 2009Q3, annual values were extrapolated.

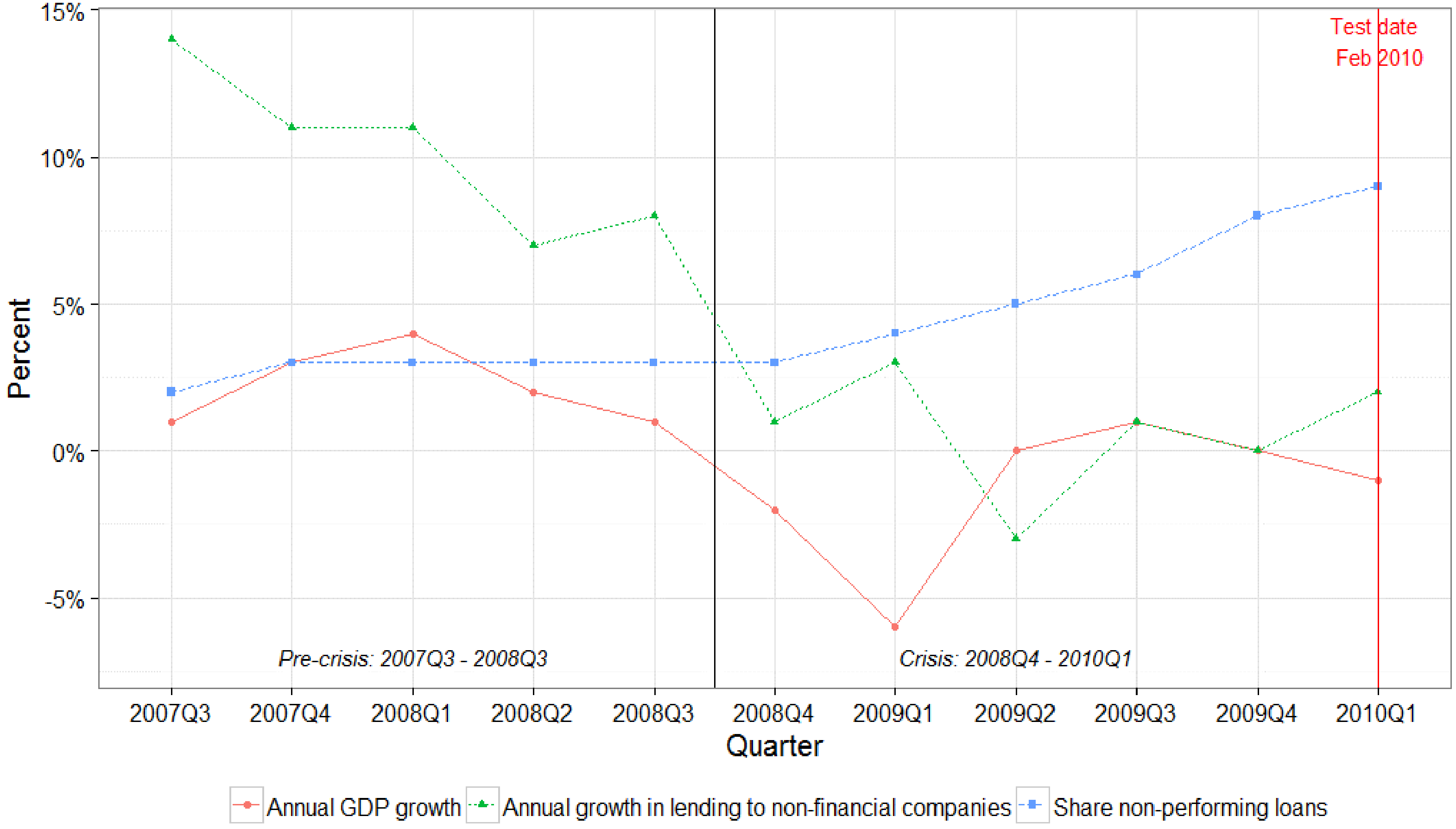


Figure 3. Development of the bank

Development of the bank's total assets, total deposits, gross loan portfolio, branches and loan performance based on annual reports. The total assets, total deposits, gross loan portfolio and the number of branches are indexed at Dec 2007 = 100.

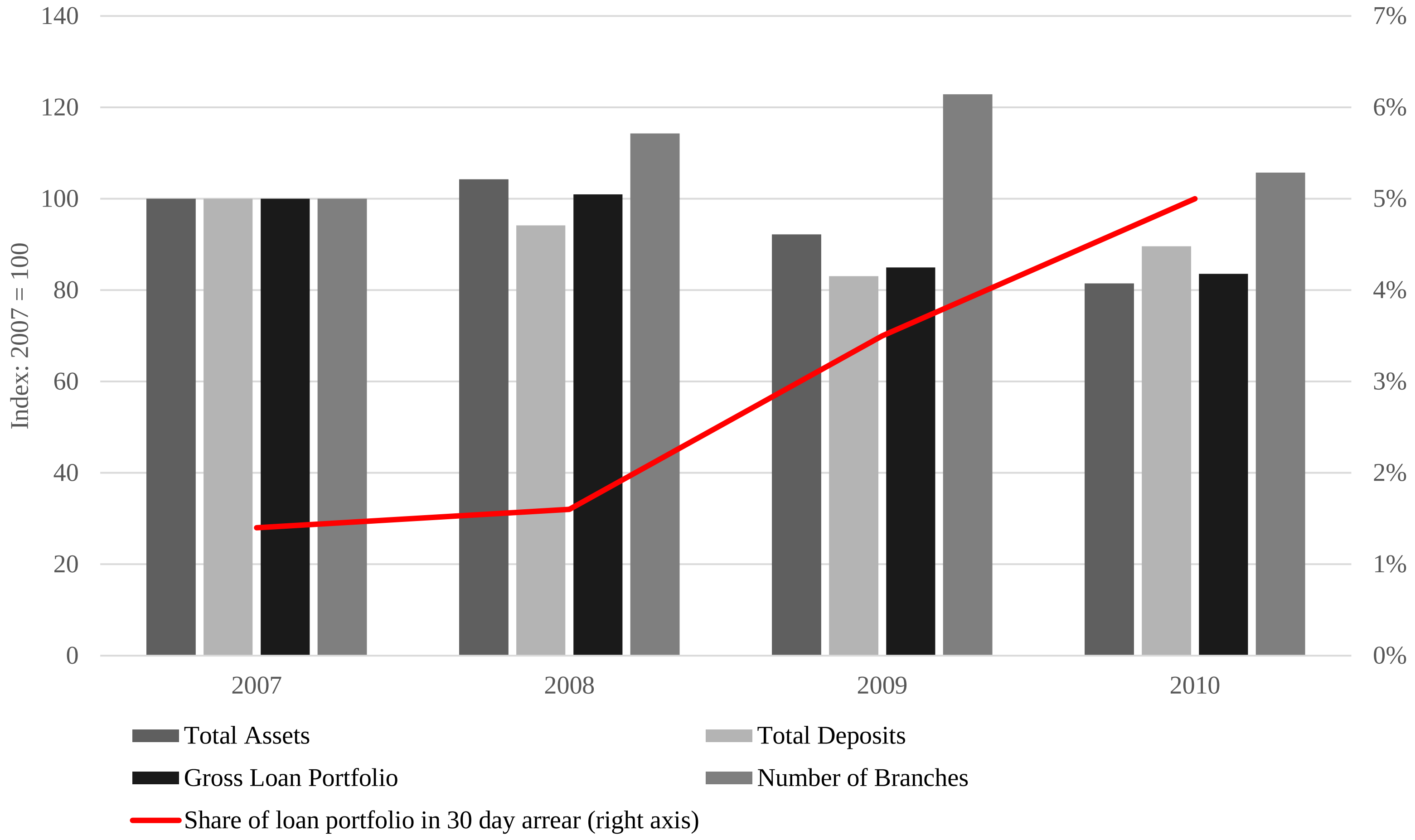


Figure 4. Distribution of numeracy score in loan officer sample

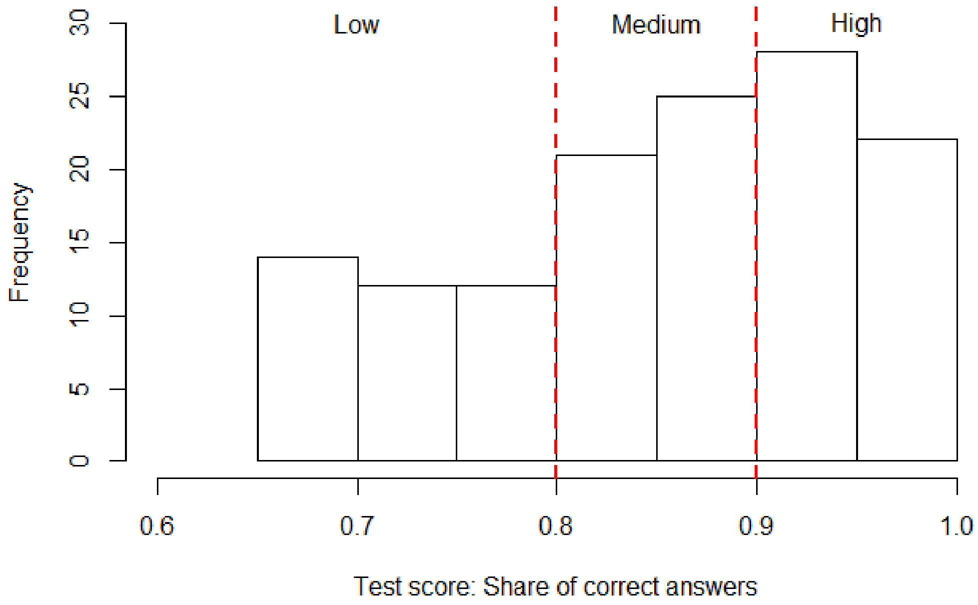


Figure 5. 30 day arrears over the first 24 months

The graph displays the share of loans falling into 30 day arrear over the first 24 months. The lines display the share of loans that have not been in 30 day arrear at any time after disbursement.

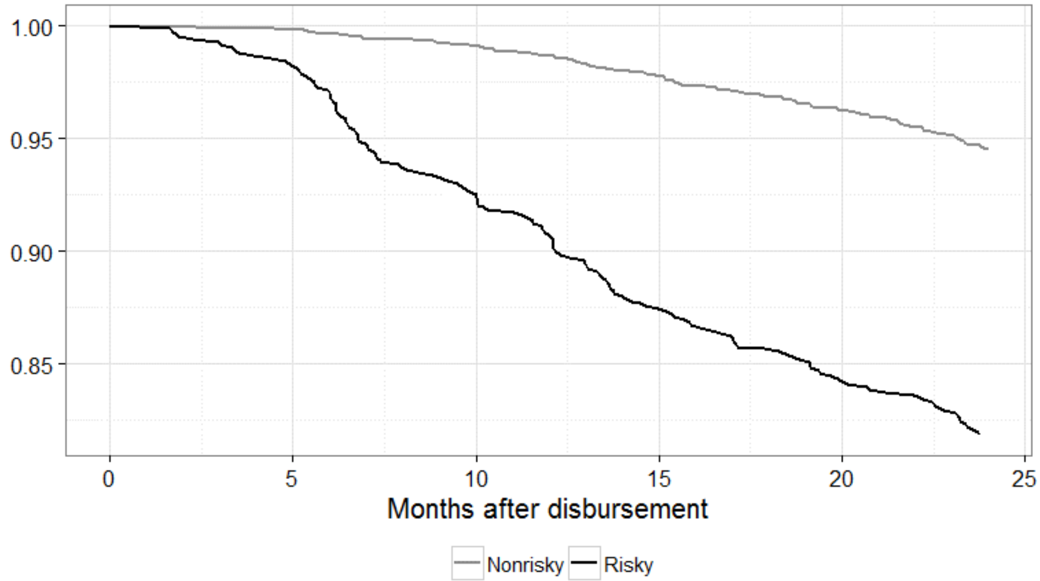


Figure 6. Accuracy of initial rating

The figure displays the share of loans in 30 day payment arrear within 24 months after loan issuance by initial risk rating and numeracy.

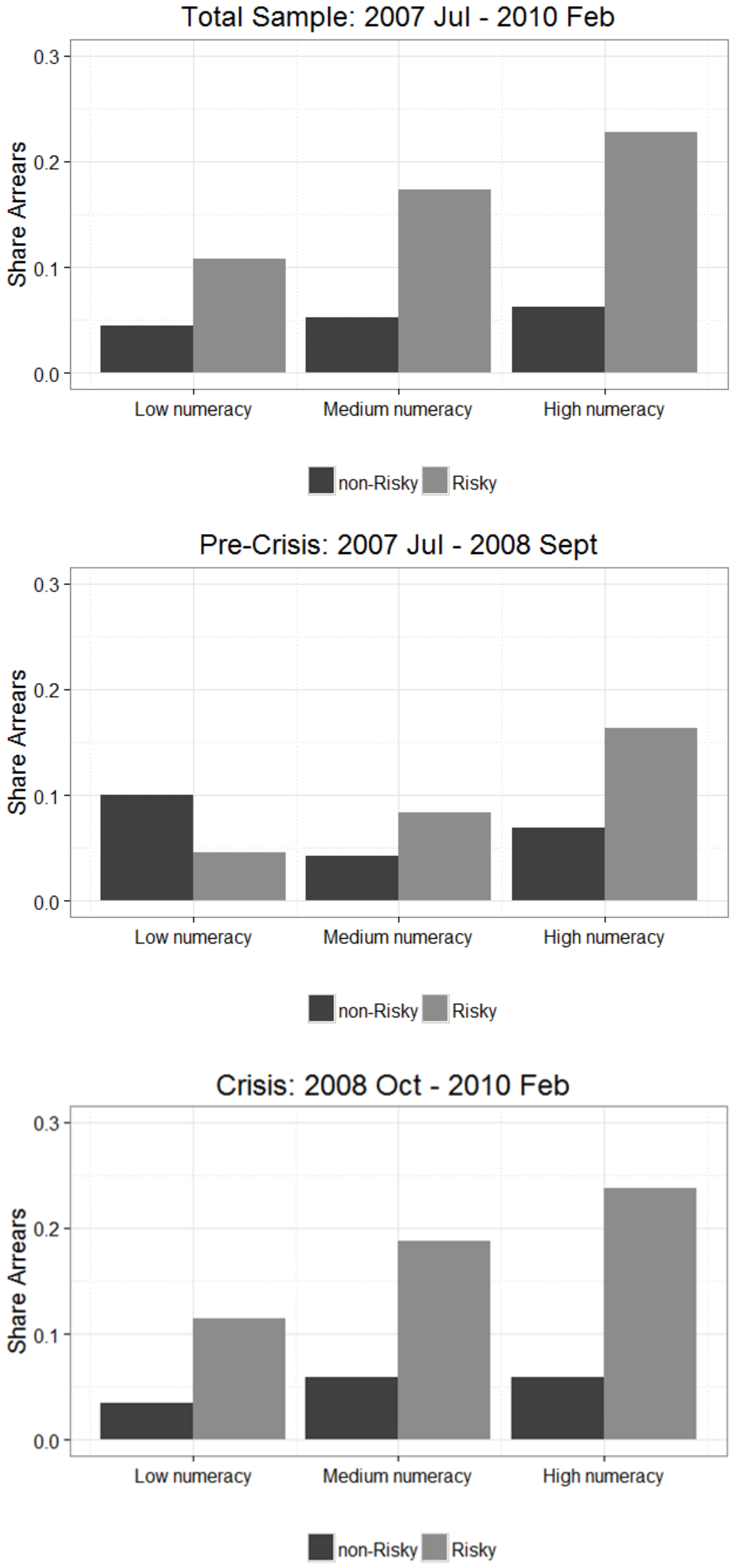


Figure 7. Quarterly rejection rate by numeracy over the sample period

Share of rejected first time borrowers by quarter and level of numeracy.

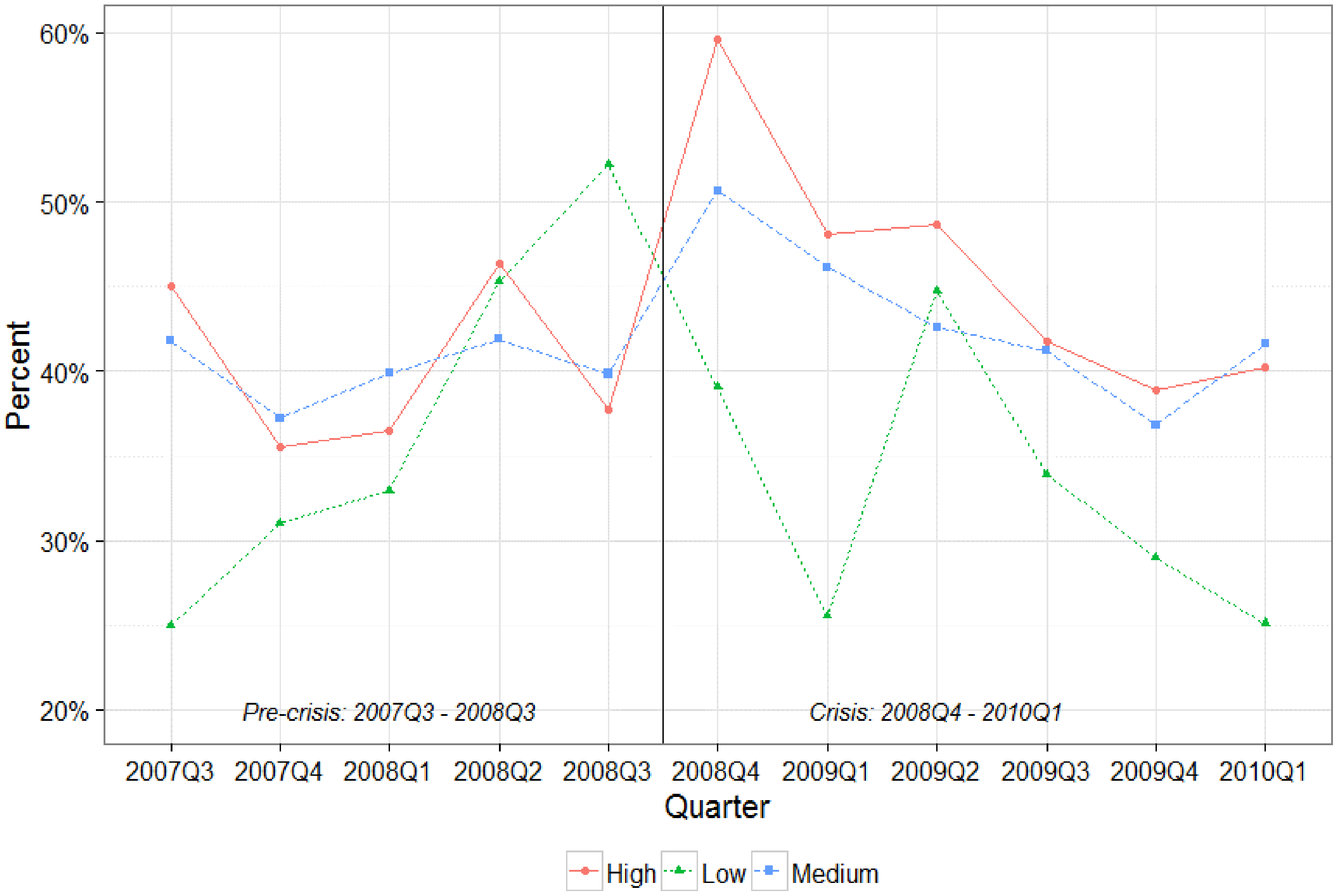


Table 1. Loan officer summary statistics

Numeracy	Low	Medium	High	Total
Score Range in %	65 - 79	80 - 89	90 - 100	
Nr Loan officers	34	38	56	128
Initial numeracy score	0.72	0.85	0.95	0.86
Female	0.56	0.76	0.63	0.65
Experienced	0.38	0.63	0.54	0.52
Age	31.97	32.18	32.66	32.34

Table 2. Numeracy and accuracy: Full sample results

The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1.

We compare the coefficients of Risky by numeracy level using a Chow test.

OLS regression	Total sample: 2007 Jul - 2010 Feb								
	Basic controls			Basic controls with Quarter FE			Extended controls with Quarter FE		
Numeracy level	Low	Medium	High	Low	Medium	High	Low	Medium	High
Dep var: Arrears	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risky	0.112**	0.165***	0.249***	0.115**	0.173***	0.264***	0.095*	0.163***	0.254***
	(0.044)	(0.046)	(0.041)	(0.048)	(0.043)	(0.044)	(0.048)	(0.044)	(0.042)
Mean Arrears	0.058	0.079	0.108	0.058	0.079	0.108	0.058	0.079	0.108
Observations	1,072	1,225	1,322	1,072	1,225	1,322	1,072	1,225	1,322
R-squared	0.064	0.100	0.129	0.076	0.112	0.146	0.096	0.137	0.167
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	No	No	No	No	No	No	Yes	Yes	Yes
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Difference in coefficients of Risky: P-values of Chow test in parentheses									
Compared to high numeracy	-0.137**	-0.084		-0.149**	-0.091		-0.159***	-0.091	
	(0.02)	(0.165)		(0.02)	(0.13)		(0.01)	(0.124)	
Compared to medium numeracy	-0.053		0.084	-0.058		0.091	-0.068		0.091
	(0.397)		(0.165)	(0.363)		(0.13)	(0.287)		(0.124)

Table 3. Numeracy and accuracy: Subperiod analysis

The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1.

We compare the coefficients of Risky by numeracy level using a Chow test.

OLS regression	Pre-crisis: 2007 Jul - 2008 Sept			Crisis: 2008 Oct - 2010 Feb		
Numeracy level	Low	Medium	High	Low	Medium	High
Dep var: Arrears	(1)	(2)	(3)	(4)	(5)	(6)
Risky	-0.111*	-0.006	0.131*	0.154***	0.202***	0.287***
	(0.062)	(0.035)	(0.072)	(0.049)	(0.051)	(0.048)
Mean Arrears	0.092	0.046	0.085	0.052	0.095	0.115
Observations	152	391	294	920	834	1,028
R-squared	0.210	0.173	0.139	0.114	0.159	0.212
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Difference in coefficients of Risky: P-values of Chow test in parentheses						
Compared to high numeracy	-0.242***	-0.137*		-0.133**	-0.085	
	(0.005)	(0.067)		(0.046)	(0.208)	
Compared to medium numeracy	-0.105		0.137*	-0.048		-0.085
	(0.103)		(0.067)	(0.485)		(0.208)

Table 4. Gender, experience and accuracy

The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1.

We compare the coefficients of Risky by numeracy level using a Chow test.

OLS regression	Total sample: 2007 Jul - 2010 Feb			
	Gender		Experienced	
	Female	Male	No	Yes
Dep var: Arrears	(1)	(2)	(3)	(4)
Risky	0.195***	0.175***	0.217***	0.177***
	(0.032)	(0.047)	(0.046)	(0.033)
Mean Arrears	0.086	0.082	0.101	0.074
Observations	2,055	1,564	1,253	2,366
R-squared	0.130	0.130	0.159	0.114
Basic controls	Yes	Yes	Yes	Yes
Extended controls	Yes	Yes	Yes	Yes
Loan officer controls	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Difference in coefficients of Risky: P-values of Chow test in parentheses				
Compared to male	0.020			
	(0.728)			
Compared to experienced			0.040	
			(0.467)	

Table 5. Numeracy and accuracy: Subsample by gender and experience

The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1.
We compare the coefficients of Risky by numeracy level using a Chow test.

	Total sample: 2007 Jul - 2010 Feb											
	by gender						by experience at application					
OLS regression	Female			Male			<=2 years			>2years		
Numeracy level	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Dep var: Arrears	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Risky	0.117*	0.179***	0.221***	0.065	0.123*	0.271***	0.045	0.190***	0.231***	0.181	0.130***	0.253***
	(0.060)	(0.058)	(0.049)	(0.090)	(0.055)	(0.077)	(0.034)	(0.062)	(0.071)	(0.119)	(0.044)	(0.060)
Mean Arrears	0.065	0.089	0.105	0.050	0.065	0.113	0.049	0.093	0.102	0.072	0.063	0.115
Observations	551	731	773	521	494	549	657	656	687	415	569	635
R-squared	0.126	0.154	0.204	0.160	0.151	0.229	0.108	0.189	0.203	0.173	0.172	0.213
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference in coefficients of Risky: P-values of Chow test in parentheses												
Compared to high numeracy	-0.104	-0.042		-0.206*	-0.148*		-0.186**	-0.041		-0.072	-0.123*	
	(0.159)	(0.569)		(0.067)	(0.099)		(0.014)	(0.648)		(0.565)	(0.083)	
Compared to medium numeracy	-0.062		0.042	-0.058		0.148*	-0.145**		0.041	0.051		0.123*
	(0.431)		(0.569)	(0.563)		(0.099)	(0.034)		(0.648)	(0.665)		(0.083)

Table 6. Numeracy and loan rejections

The dependent variable Rejection is a binary variable equal to 1 if a loan application was rejected and 0 otherwise. Loan officer controls include Female, Experienced and Age. Standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1

We compare the coefficients of available application controls in the subsample analysis (1) - (3) using a Chow test. Results suggest that there is no significant difference in the coefficients of application controls in the subsamples of low and high numeracy loan officers. Comparing coefficients of the medium numeracy subsample to high/low subsamples, the only significant difference (10%-level) exists for Request Euro between medium and high numeracy.

	Subsample by numeracy level			Total sample:	Pre-Crisis:	Crisis:
	Low	Medium	High	2007 Jul - 2010 Feb	2007 Jul - 2008 Sep	2008 Oct - 2010 Feb
Dep var: Rejection	(1)	(2)	(3)	(4)	(5)	(6)
High Numeracy				0.043**	0.006	0.053***
				(0.019)	(0.051)	(0.019)
Medium Numeracy				0.025	-0.020	0.021
				(0.019)	(0.045)	(0.024)
Ln(Requested amount)	0.058***	0.047***	0.054***	0.054***	0.033***	0.064***
	(0.012)	(0.010)	(0.011)	(0.007)	(0.010)	(0.009)
Request Euro	0.041	0.098***	0.021	0.056**	0.008	0.072***
	(0.042)	(0.029)	(0.040)	(0.021)	(0.042)	(0.026)
Time relationship	-0.013*	-0.024**	-0.024***	-0.020***	-0.023**	-0.021***
	(0.007)	(0.009)	(0.008)	(0.004)	(0.011)	(0.005)
New client	0.495***	0.523***	0.546***	0.528***	0.543***	0.518***
	(0.047)	(0.029)	(0.031)	(0.020)	(0.037)	(0.025)
Mean Rejection	0.322	0.404	0.423	0.390	0.399	0.387
Observations	1,581	2,055	2,292	5,928	1,392	4,536
R-squared	0.425	0.390	0.413	0.398	0.356	0.421
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Appendix 1: Example Questions from the Numeracy Test

The 3 questions below are taken from the bank's numeracy test. They are representative for the overall level of difficulty of the test.

1. Calculate the value of the following expressions. [3.3]

   (3 pts. for each correct answer)

$$\frac{\left(\frac{3}{4}+2\right)}{\left[\frac{2\cdot 3-2\cdot(-6)}{3}-7\right]}=$$

2. Calculate the original price if the current price of 88 EUR was obtained after the original price was first increased by 10% and then decreased by 4%. [4.15]

   (4 pts. for the correct answer)

3. Six friends want to buy a piece of land, each paying an equal share. The day before the contract is signed two of the friends decide to withdraw their offer. The remaining four friends must therefore each increase their share by 4500 EUR in order to be able to pay the asking price. Calculate the price of the land. [6.4]

   (5 pts. for the correct answer)

Appendix 2a. Summary statistics and variable definitions

Panel A: Granted loans	Obs	Mean	SD	Min	Max	Mean Low	Mean Medium	Mean High	Description
Dependent Variables									
Arrears	3619	0.08	0.28	0.00	1.00	0.06	0.08	0.11	Dummy = 1 if 30 day payment arrear within first 24 months
Variables of Interest									
Risky	3619	0.24	0.43	0.00	1.00	0.21	0.22	0.28	Dummy = 1 if initial score >1
Low numeracy	3619	0.30	0.46	0.00	1.00	1.00	0.00	0.00	Dummy = 1 if low numeracy loan officer; score<0.8
Medium numeracy	3619	0.34	0.47	0.00	1.00	0.00	1.00	0.00	Dummy = 1 if medium numeracy loan officer; score 0.8-0.89
High numeracy	3619	0.37	0.48	0.00	1.00	0.00	0.00	1.00	Dummy = 1 if high numeracy loan officer; score 0.9-1
Numeracy score	3619	0.84	0.11	0.65	1.00	0.70	0.84	0.95	Numeracy score as measured in the test
Transformed numeracy score	3619	0.54	0.30	0.00	1.00	0.15	0.55	0.85	Transformed numeracy score: (Numeracy score - 0.65) /0.35
Basic controls									
Ln(Requested amount)	3619	8.30	0.98	4.76	10.31	8.05	8.41	8.40	Ln(requested amount in EUR)
Requested amount in Euro	3619	6187	5900	117	30000	5111	6539	6734	Requested amount in EUR
Request Euro	3619	0.16	0.37	0.00	1.00	0.15	0.13	0.19	Dummy = 1 if requested loan in Euro
Time relationship	3619	1.66	1.66	0.00	7.47	1.62	1.60	1.74	Years since bank account at bank; 0 if no account
New client	3619	0.34	0.47	0.00	1.00	0.32	0.37	0.32	Dummy = 1 if account since <0.1 year
Extended controls									
Leverage	3619	1.02	1.66	0.02	20.00	0.87	1.02	1.15	(Debt capital + requested loan)/Equity)
ln(Sales)	3619	7.30	1.47	3.24	12.54	6.93	7.50	7.42	Ln(Sales in EUR)
Young firm	3619	0.26	0.44	0.00	1.00	0.18	0.32	0.27	Dummy = 1 if firm Age <5
Agriculture	3619	0.53	0.50	0.00	1.00	0.71	0.41	0.49	Dummy = 1 if agricultural firm
Total assets/requested amount	3619	5.86	12.53	0.04	449.62	5.37	5.62	6.48	(Fixed assets and chattel items) /Requested amount
Loan officer controls									
Female	3619	0.57	0.50	0.00	1.00	0.51	0.60	0.58	Dummy = 1 if loan officer female
Experienced	3619	0.65	0.48	0.00	1.00	0.58	0.76	0.62	Dummy = 1 if loan officer experience > median at test date
Experience at application	3619	0.45	0.50	0.00	1.00	0.39	0.46	0.48	Dummy = 1 if loan officer experience at application date >2years
Age	3619	32.36	2.71	27.00	41.00	32.59	32.33	32.19	Age in years

Appendix 2b. Summary statistics and variable definitions

Panel B: Loan applications	Obs	Mean	SD	Min	Max	Mean Low	Mean Medium	Mean High	Description
Dependent Variable									
Rejection	5928	0.39	0.49	0.00	1.00	0.32	0.40	0.42	Dummy = 1 if application rejected by the bank
Variables of Interest									
Low numeracy	5928	0.27	0.44	0.00	1.00	1.00	0.00	0.00	Dummy = 1 if low numeracy loan officer; score<0.8
Medium numeracy	5928	0.35	0.48	0.00	1.00	0.00	1.00	0.00	Dummy = 1 if medium numeracy loan officer; score 0.8-0.89
High numeracy	5928	0.39	0.49	0.00	1.00	0.00	0.00	1.00	Dummy = 1 if high numeracy loan officer; score 0.9-1
Control variables									
Ln(Requested amount)	5928	8.46	0.99	4.76	10.31	8.23	8.54	8.55	Ln(requested amount in EUR)
Requested amount in Euro	5928	7191	6461	117	30000	6028	7488	7728	Requested amount in EUR
Request Euro	5928	0.18	0.39	0.00	1.00	0.17	0.15	0.22	Dummy = 1 if requested loan in Euro
Time relationship	5928	1.07	1.55	0.00	7.50	1.15	1.00	1.08	Years since bank account at bank; 0 if no account
New client	5928	0.57	0.49	0.00	1.00	0.52	0.61	0.58	Dummy = 1 if account since <0.1 year

Appendix 3. Variable mean by period and numeracy level

	Pre-crisis: 2007 Jul - 2008 Sep			Crisis: 2008 Oct - 2010 Feb		
Panel A: Granted loans	Low	Medium	High	Low	Medium	High
Obs	152	391	294	920	834	1028
Dependent Variables						
Arrears	0.09	0.05	0.09	0.05	0.09	0.11
Variables of Interest						
Risky	0.14	0.09	0.17	0.22	0.28	0.31
Low numeracy	1.00	0.00	0.00	1.00	0.00	0.00
Medium numeracy	0.00	1.00	0.00	0.00	1.00	0.00
High numeracy	0.00	0.00	1.00	0.00	0.00	1.00
Numeracy score	0.73	0.85	0.95	0.70	0.84	0.95
Transformed Numeracy score	0.22	0.56	0.84	0.14	0.55	0.86
Basic controls						
Ln(Requested amount)	8.79	8.42	8.78	7.93	8.40	8.29
Requested amount in Euro	9563	7135	9001	4376	6259	6085
Request Euro	0.09	0.02	0.08	0.17	0.18	0.23
Time relationship	1.12	1.09	1.07	1.71	1.84	1.94
New client	0.40	0.42	0.43	0.30	0.35	0.29
Extended controls						
Leverage	0.73	0.93	1.17	0.89	1.06	1.14
ln(Sales)	7.90	7.40	7.96	6.77	7.55	7.27
Yong firm	0.35	0.35	0.46	0.15	0.31	0.22
Agriculture	0.53	0.49	0.30	0.73	0.37	0.55
Total assets/requested amount	6.06	4.92	5.25	5.26	5.94	6.84
Loan officer controls						
Female	0.63	0.57	0.64	0.50	0.61	0.57
Experienced	0.93	0.97	0.96	0.52	0.66	0.52
Experience at application	0.34	0.14	0.44	0.39	0.62	0.49
Age	33.32	32.71	32.89	32.47	32.16	31.99

Panel B: Loan applications	Low	Medium	High	Low	Medium	High
Obs	253	651	488	1328	1404	1804
Dependent Variable						
Rejection	0.40	0.40	0.40	0.31	0.41	0.43
Control variables						
Ln(Requested amount)	8.74	8.53	8.81	8.13	8.54	8.47
Requested amount in Euro	9'240	7'924	9'333	5'416	7'285	7'294
Request Euro	0.08	0.03	0.07	0.18	0.21	0.26
Time relationship	0.69	0.69	0.67	1.24	1.14	1.19
New client	0.63	0.63	0.64	0.50	0.59	0.56

Appendix 4. Accuracy on loan level: Total sample with interaction terms

The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1

OLS regression	Total sample		Pre-crisis		Crisis	
Dep var: Arrears	(1)	(2)	(3)	(4)	(5)	(6)
High numeracy x Risky	0.064	0.149**	0.170**	0.193**	0.048	0.139**
	(0.039)	(0.059)	(0.072)	(0.076)	(0.042)	(0.065)
Medium numeracy x Risky	0.015	0.066	0.076	0.089	0.003	0.052
	(0.043)	(0.057)	(0.052)	(0.062)	(0.048)	(0.063)
High numeracy	0.011		-0.067**		0.025	
	(0.013)		(0.027)		(0.016)	
Medium numeracy	-0.011		-0.054*		0.003	
	(0.014)		(0.029)		(0.017)	
Risky	0.160***	0.100**	-0.046	-0.070	0.202***	0.147***
	(0.037)	(0.046)	(0.039)	(0.050)	(0.041)	(0.047)
Mean Arrears	0.083	0.083	0.068	0.068	0.088	0.088
Observations	3,619	3,619	837	837	2,782	2,782
R-squared	0.096	0.126	0.076	0.102	0.124	0.156
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	No	Yes	No	Yes	No	Yes
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	No	Yes	No	Yes
Numeracy level x Quarter	No	Yes	No	Yes	No	Yes

Appendix 5. Accuracy on loan level: Logit regression

This table contains results of a logit model. Effects are displayed as marginal effects at the mean using the delta method. The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1

Logit regression: Marginal effects	Total sample		Pre-crisis		Crisis	
Dep var: Arrears	(1)	(2)	(3)	(4)	(5)	(6)
High numeracy x Risky	0.065	0.110*	0.071	0.130*	0.063	0.059
	(0.040)	(0.057)	(0.058)	(0.074)	(0.043)	(0.067)
Medium numeracy x Risky	0.004	0.061	0.034	0.030	0.005	0.022
	(0.041)	(0.053)	(0.049)	(0.035)	(0.045)	(0.067)
High numeracy	0.014		-0.062*		0.011	
	(0.011)		(0.036)		(0.010)	
Medium numeracy	-0.001		-0.075**		0.026**	
	(0.009)		(0.033)		(0.011)	
Risky	0.103***	0.121***	0.039*	0.018	0.112***	0.149***
	(0.016)	(0.021)	(0.022)	(0.023)	(0.017)	(0.022)
Mean Arrears	0.083	0.083	0.068	0.071	0.087	0.088
Observations	3610	3598	801	789	2759	2759
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	No	Yes	No	Yes	No	Yes
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	No	Yes	No	Yes
Numeracy level x Quarter	No	Yes	No	Yes	No	Yes

Appendix 6. Accuracy on loan level by client characteristics and relationship length

The table shows results for clients of different characteristics (agriculture vs. other industries and young vs. older) and by relationship length (new client vs. existing client). The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level: *** p<0.01, ** p<0.05, * p<0.1.
We compare the coefficients of Risky by numeracy level using a Chow test.

Industry	Agriculture			Not Agriculture			Young firms (<5 years)			Not Young firm (>= 5 years)			New client			Existing client		
Numeracy level	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
Dep var: Arrear	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Risky	0.120	0.187**	0.345***	0.072	0.154***	0.227***	0.123	0.169***	0.231***	0.137*	0.164***	0.282***	0.018	0.072	0.013	0.124**	0.192***	0.330***
	(0.071)	(0.067)	(0.091)	(0.067)	(0.051)	(0.040)	(0.093)	(0.060)	(0.060)	(0.075)	(0.049)	(0.056)	(0.049)	(0.054)	(0.070)	(0.059)	(0.053)	(0.052)
Observations	757	504	648	315	721	674	190	394	358	882	831	964	341	455	419	731	770	903
R-squared	0.076	0.122	0.195	0.161	0.127	0.205	0.275	0.152	0.272	0.104	0.129	0.191	0.160	0.141	0.158	0.113	0.207	0.238
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference in coefficients of Risky: P-values of Chow test in parentheses																		
Compared to high num.	-0.225**	-0.158		-0.155**	-0.073		-0.108	-0.062		-0.145	-0.118		0.005	0.059		-0.206***	-0.138*	
	(0.042)	(0.142)		(0.033)	(0.242)		(0.272)	(0.433)		(0.107)	(0.101)		(0.953)	(0.477)		(0.006)	(0.054)	
Compared to medium num.	-0.067		0.158	-0.082		0.073	-0.046		0.062	-0.027		0.118	-0.054		-0.059	-0.068		0.138*
	(0.473)		(0.142)	(0.300)		(0.242)	(0.641)		(0.433)	(0.755)		(0.101)	(0.425)		(0.477)	(0.373)		(0.054)

Appendix 7. Accuracy on loan level: Linear model of numeracy score

The table displays results of the linear influence of the numeracy score. The numeracy score (values 0.65 - 1) is transformed so that the lowest value is 0 and the highest is 1: (numeracy score -0.65)/0.35. Hence, the coefficients reflect the effect of moving from the lowest to the highest numeracy score.

The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1

OLS Regression	Total sample period		Pre-Crisis		Crisis	
Dep. var: Arrears	(1)	(2)	(3)	(4)	(5)	(6)
Transformed numeracy score x Risky	0.091	0.177**	0.184*	0.226**	0.083	0.183**
	(0.062)	(0.083)	(0.099)	(0.103)	(0.069)	(0.092)
Transformed numeracy score	0.017	0.005	-0.059	0.066	0.032	0.036
	(0.017)	(0.044)	(0.036)	(0.070)	(0.022)	(0.058)
Risky	0.068	0.082	-0.056	-0.094	0.083*	0.117*
	(0.042)	(0.055)	(0.054)	(0.065)	(0.048)	(0.059)
Mean Arrears	0.083	0.083	0.068	0.068	0.088	0.088
Observations	3,619	3,619	837	837	2,782	2,782
R-squared	0.094	0.125	0.071	0.101	0.123	0.155
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	No	Yes	No	Yes	No	Yes
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	No	Yes	No	Yes	No	Yes
Numeracy level x Quarter	No	Yes	No	Yes	No	Yes

Appendix 8. Accuracy on loan level: All loan officers

This table contains results of the sample including loan officers from various educational backgrounds (Highest degree high school, bachelor and master). The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced, Age and Education. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1.

We compare the coefficients of Risky by numeracy level using a Chow test.

OLS regression	Total Sample: 2007 Jul - 2010 Feb			Pre-crisis: 2007 Jul - 2008 Sept			Crisis: 2008 Oct - 2010 Feb		
Numeracy level	Low	Medium	High	Low	Medium	High	Low	Medium	High
Dep var: Arrears	(1)	(2)	(3)	(1)	(2)	(3)	(4)	(5)	(6)
Risky	0.109**	0.173***	0.226***	-0.088	0.019	0.120*	0.155***	0.211***	0.251***
	(0.041)	(0.041)	(0.040)	(0.064)	(0.050)	(0.071)	(0.042)	(0.046)	(0.045)
Mean Arrears	0.065	0.082	0.103	0.091	0.052	0.095	0.061	0.095	0.106
Observations	1,245	1,354	1,539	175	422	336	1,070	932	1,203
R-squared	0.093	0.138	0.143	0.192	0.161	0.140	0.115	0.159	0.189
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference in coefficients of Risky: P-values of Chow test in parentheses									
Compared to high numeracy	-0.117**	-0.053		-0.208**	-0.101		-0.096	-0.04	
	(0.036)	(0.343)		(0.018)	(0.217)		(0.107)	(0.528)	
Compared to medium numeracy	-0.064		0.053	-0.107		0.101	-0.056		0.04
	(0.253)		(0.343)	(0.152)		(0.217)	(0.349)		(0.528)

Appendix 9. Influence of loan characteristics on Risky

This table displays results of a linear probability model estimation. The dependent variable Risky is a binary variable equal to 1 if a loan was classified as risky at loan disbursement. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1

	Total Sample: 2007 Jul - 2010 Feb			Difference in coefficients P-values of Chow test in parentheses		
OLS regression	Low	Medium	High	Low vs medium	Low vs high	Medium vs high
Dep var: Risky	(1)	(2)	(3)			
Ln(Requested amount)	-0.006	0.008	-0.015	-0.014	0.009	0.023
	(0.018)	(0.018)	(0.017)	(0.588)	(0.719)	(0.362)
Request Euro	0.485***	0.508***	0.372***	-0.023	0.113	0.136
	(0.102)	(0.070)	(0.060)	(0.848)	(0.324)	(0.131)
Time relationship	-0.009	-0.006	0.007	-0.003	-0.016	-0.013
	(0.010)	(0.011)	(0.011)	(0.812)	(0.288)	(0.434)
New client	-0.044	-0.039	0.014	-0.005	-0.058	-0.053
	(0.029)	(0.031)	(0.037)	(0.894)	(0.206)	(0.268)
Leverage	0.019**	0.016	0.024***	-0.005	-0.005	-0.008
	(0.009)	(0.011)	(0.006)	(0.813)	(0.617)	(0.482)
ln(Sales)	0.009	0.018	0.031**	-0.009	-0.022	-0.013
	(0.015)	(0.013)	(0.014)	(0.669)	(0.276)	(0.464)
Young firm	0.069	0.002	0.002	0.067	0.067	0.000
	(0.044)	(0.029)	(0.036)	(0.19)	(0.229)	(0.992)
Agriculture	-0.058	-0.083**	-0.042	0.025	-0.016	-0.041
	(0.038)	(0.041)	(0.044)	(0.636)	(0.781)	(0.48)
Total assets/requested amount	0.000	0.002	0.000	-0.002	0.000	0.002
	(0.002)	(0.001)	(0.001)	(0.435)	(0.891)	(0.288)
Mean Risky	0.207	0.221	0.279			
Observations	1,072	1,225	1,322			
R-squared	0.639	0.486	0.523			
Basic controls	Yes	Yes	Yes			
Extended controls	Yes	Yes	Yes			
Loan officer controls	Yes	Yes	Yes			
Branch FE	Yes	Yes	Yes			
Quarter FE	Yes	Yes	Yes			

Appendix 10. Predictive power of hard information

This table displays the predictive power of application and firm variables for the outcome variable Arrears. The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1.

	Basic controls						Basic and Extended controls					
Numeracy level	Low		Medium		High		Low		Medium		High	
Dep var: Arrear	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Risky		0.107**		0.177***		0.262***		0.083*		0.156***		0.252***
		(0.042)		(0.046)		(0.041)		(0.044)		(0.046)		(0.040)
Observations	1,072	1,072	1,225	1,225	1,322	1,322	1,072	1,072	1,225	1,225	1,322	1,322
R-squared	0.017	0.033	0.008	0.054	0.003	0.088	0.036	0.044	0.040	0.074	0.026	0.102
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

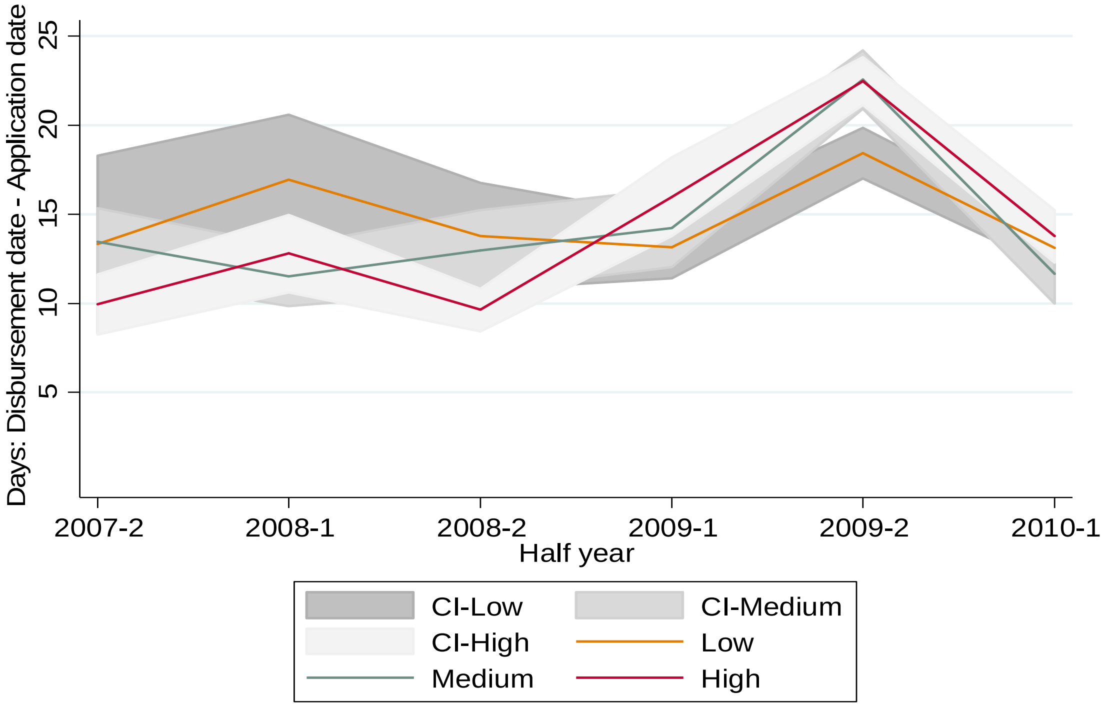
Appendix 11. Distribution of firm characteristics

This table displays the distribution of all continuous firm control variables.

Variable	Numeracy	Mean	SD	p10	p25	p50	p75	p90
	low	8.05	1.02	6.62	7.28	8.16	8.78	9.41
Ln(Requested amount)	medium	8.41	0.92	7.18	7.77	8.46	9.14	9.54
	high	8.40	0.96	7.10	7.77	8.46	9.14	9.59
	low	1.62	1.56	0.00	0.00	1.44	2.69	3.88
Time relationship	medium	1.60	1.70	0.00	0.00	1.23	2.65	4.17
	high	1.74	1.70	0.00	0.00	1.49	2.89	4.18
	low	0.87	1.41	0.15	0.25	0.47	0.97	1.97
Leverage	medium	1.02	1.57	0.17	0.30	0.57	1.12	2.27
	high	1.15	1.92	0.16	0.29	0.61	1.30	2.31
	low	6.93	1.51	5.18	5.84	6.70	7.93	8.94
ln(Sales)	medium	7.50	1.39	5.88	6.48	7.23	8.58	9.39
	high	7.42	1.47	5.74	6.40	7.15	8.53	9.45
	low	5.37	6.82	1.04	1.82	3.42	6.09	11.68
Total assets/requested amount	medium	5.62	12.81	0.97	1.72	3.19	6.15	11.41
	high	6.48	15.48	0.90	1.68	3.33	6.69	13.33

Appendix 12. Processing time of loan applications over time

The figure displays the average processing time of loan applications by half year and numeracy level. The processing time is defined as Disbursement date - Application date. 95-% confidence bands are shown as shaded areas.



Appendix 13. Accuracy on loan level: Only loan officers who were in pre-crisis sample

This table contains results for the subsample of loan officers who were already working at the bank in the pre-crisis period. The dependent variable Arrears is a binary variable equal to 1 if a firm went into 30 day payment arrear within the first 24 months of the loan. Basic controls include Ln(Requested amount), Request Euro, Time relationship, New client. Extended controls include Leverage, ln(Sales), Young firm, Agriculture, Total assets/requested amount. Loan officer controls include Female, Experienced and Age. Standard errors in parentheses; standard errors are clustered on loan officer level; *** p<0.01, ** p<0.05, * p<0.1.

We compare the coefficients of Risky by numeracy level using a Chow test.

OLS regression	Total Sample: 2007 Jul - 2010 Feb			Pre-crisis: 2007 Jul - 2008 Sept			Crisis: 2008 Oct - 2010 Feb		
Numeracy level	Low	Medium	High	Low	Medium	High	Low	Medium	High
Dep var: Arrears	(1)	(2)	(3)	(1)	(2)	(3)	(4)	(5)	(6)
Risky	0.029	0.183***	0.250***	-0.111*	-0.006	0.131*	0.134	0.235***	0.290***
	(0.074)	(0.050)	(0.052)	(0.062)	(0.035)	(0.072)	(0.112)	(0.056)	(0.062)
Mean Arrears	0.074	0.073	0.104	0.092	0.046	0.085	0.063	0.089	0.112
Observations	404	1,028	1,047	152	391	294	252	637	753
R-squared	0.144	0.156	0.152	0.207	0.172	0.138	0.197	0.204	0.207
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan officer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Branch FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Difference in coefficients of Risky: P-values of Chow test in parentheses									
Compared to high numeracy	-0.221***	-0.067		-0.242***	-0.137*		-0.156	-0.055	
	(0.009)	(0.333)		(0.005)	(0.067)		(0.188)	(0.492)	
Compared to medium numeracy	-0.154*		0.067	-0.105		0.137*	-0.101		0.055
	(0.069)		(0.333)	(0.103)		(0.067)	(0.383)		(0.492)