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Essays on Credit Risk

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Contents

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Abstract

The financial crises in the early 2000s have given prominence to the financial markets' exposure to credit risk. To minimize credit risk, the risk that a borrower will fail to meet her contractual obligations, lenders seek to identify borrowers with a high probability of default prior to granting credit. In my dissertation I examine several screening devices that lenders utilize in alleviating adverse selection present on the credit market. In the first chapter, I ask whether the existence of informal collateral signals better loan repayment. Taking advantage of a unique dataset of household loans from a Czech commercial bank, I find that housing loans without lien on the property default less compared to loans with unspecified purpose. I also show that the interest rate differential between specific purpose loans and unspecified purpose loans is systematically higher than their default rate differential. In the second chapter, I investigate the role of loan contract terms in household loan demand and performance. Utilizing a sample of accepted and rejected Czech household loans, I find that loan demand for low-income borrowers is more sensitive to liquidity constraint and loan maturity changes than to interest rate changes. The results also suggest that by reflecting the borrower's riskiness in the interest rate, lenders discourage risky borrowers from obtaining short-term loans and this might then lead to their higher default probability. Finally, in the third chapter, I focus on credit ratings of financial/non-financial institutions that issued debt. The paper identifies the determinants of credit rating changes by the two incumbent rating agencies: S&P and Moody's. I show that there is a statistically significant difference in the rating evaluations of the two incumbent credit rating agencies, and that Fitch's increasing market share deepens the rating splits between S&P and Moody's. The results also suggest that sovereign ceilings ceased to be restrictive for non-financial institutions throughout the recent financial crises, and that S&P is a follower in its rating actions when compared to Moody's.

Abstrakt

Finanční krize po roce 2000 poukázali na důležitost expozice finančních trhů vůči úvěrovému riziku. Pro minimalizaci úvěrového rizika, tedy rizika, že dlužník nesplní své smluvní závazky, se věřitelé snaží identifikovat dlužníky s vysokou pravděpodobností defaultu před poskytnutím úvěru. Ve své disertační práci zkoumám několik prostředků kontroly, které věřitelé využívají k zmírnění nepříznivého výběru přítomného na úvěrovém trhu. V první kapitole si pokládám otázku, zda existence neformální záruky signalizuje lepší splácení úvěru. S pomocí unikátního souboru dat o úvěrech domácností z české komerční banky zjišťuji, že u úvěrů na bydlení bez zástavního práva k nemovitosti dochází k defaultu méně často ve srovnání s úvěry bez konkrétního účelu. Dále ukazuji, že rozdíl v úrokové míře mezi účelovými a neúčelovými úvěry je systematicky vyšší než jejich rozdíl v míře defaultu. Ve druhé kapitole zkoumám vliv podmínek v úvěrové smlouvě na poptávku domácností po úvěrech a na jejich výkon. S využitím vzorku přijatých a odmítnutých úvěrů českých domácností zjišťuji, že poptávka nízkopříjmových dlužníků je citlivější na likvidní omezení a změny data splatnosti než na změny úrokových sazeb. Výsledky také naznačují, že tím, že věřitelé zohledňují rizikovost dlužníka v úrokové sazbě, odrazují rizikové dlužníky od získání krátkodobých úvěrů, což potom může vést k vyšší pravděpodobnosti jejich defaultu. Ve třetí kapitole se zaměřuji na úvěrové ratingy finančních a nefinančních institucí, které emitují dluh. Tato studie identifikuje příčiny změn úvěrových ratingů u dvou zavedených ratingových agentur: S&P a Moody’s. Ukazuji, že existuje statisticky významný rozdíl v ratingových hodnoceních těchto dvou zavedených ratingových agentur a že rostoucí tržní podíl agentury Fitch dále prohlubuje rozdíly v ratinzích mezi S&P a Moody’s. Výsledky rovněž naznačují, že v průběhu finanční krize ratingové stropy jednotlivých zemí přestaly pro nefinanční instituce působit restriktivně a že agentura S&P je následovníkem ve svých ratingových akcích ve srovnání s Moody’s.

Preface

The rapid growth of the consumer and corporate lending market has drawn increased attention to the asymmetric information present between lenders and borrowers of credit. Stiglitz and Weiss's 1981 paper shows that lenders who are imperfectly informed about the default probability of borrowers may suffer from adverse selection when deciding whether to grant credit or not. Adverse selection occurs when, being aware of their own riskiness, "low-risk" borrowers with low probability of default are not willing to pay increased prices for credit in the form of higher interest rates, while "high-risk" borrowers with a high probability of default will accept them. To minimize this, lenders may choose to deny granting the credit rather than to increase its price. As the price fails to regain equilibrium in the market, market imperfection appears.

This thesis focuses on the prominence of private information evoking credit market failures. It examines several potential devices that might help lenders alleviate the adverse selection present on the credit market. Specifically, (1) it studies the effect of informal collateral on the default rate of household loans, (2) it offers a joint model for estimation of loan demand and loan performance, and examines whether a risk-based maturity setting improves the quality of granted household loans, (3) and it compares the information value and the timeliness of credit rating agencies in assessing the creditworthiness of debt issuers.

The first paper of the thesis focuses on the role of informal collateral in explaining household loan default. Consumers with insufficient resources can finance purchases by applying for specific purpose loans or unspecified purpose loans. The paper examines the default gap of these two types of loans using a unique dataset of household loans from a Czech commercial bank. In line with theoretical models that perceive collateral as a screening device mitigating adverse selection, the paper confirms a negative relationship between the default rate and the presence of informal collateral. More importantly, it is not the purpose of the loan, but mainly the unobserved characteristics of the borrower that drive the default rate. The paper also provides empirical evidence that the interest rate differential between specific purpose loans and unspecified purpose loans is systematically higher than their default rate differential. This is in line with the empirical literature according to which financial institutions are prudent in household loan pricing and charge high mark-ups when compared to mortgage or corporate loans. Nevertheless, this raises the question whether the interest rate of housing loans (being subject to tax-deductibility) should not be re-evaluated due to lack of their collateralization and higher average amount. The results of the first paper imply that information on informal collateral and the applicant's former loan types help reveal the creditworthiness of households, and therefore should be integrated parts of financial institutions' credit scoring methods.

In the second paper of the thesis I investigate the role of loan contract terms in the performance of consumer credit. Taking advantage of a sample of accepted and rejected household loans from a Czech commercial bank, I estimate the elasticity of loan demand and find that borrowers with a high probability of default are more responsive to maturity than interest rate changes. I also argue that risk-based pricing may lead to an increase in loan maturity and loan default, rather than alleviating the adverse selection present on the lending market. The finding is consistent with the theoretical prediction that reduced asymmetric information encourages "high-risk" borrowers to either request lower loan amounts or to prolong their loan maturity to compensate the lender for their riskiness. Therefore, banks seeking to mitigate adverse selection by developing risk-based pricing should also test the increasing riskiness of the borrower pool due to the sensitivity to loan duration. Empirical evidence suggests that loan performance is time-dependent and default depends on the choice of loan duration. The paper implies that in the restriction of the default the borrower's liquidity constraints and the loan maturity should also be considered alongside risk-based pricing.

The third paper examines the accuracy and timeliness of credit ratings in explaining the financial health of debt issuers. Although the desire to assess the financial strength of financial and non-financial institutions is strong, the creditworthiness of financial market participants is costly to determine. Using annual financial statement data and macroeconomic indicators covering 2005-2013 for 2 500 financial and non-financial institutions, this paper identifies the determinants of credit rating changes by two rating agencies: Moody’s and Standard & Poor’s. Empirical evidence suggests that while Moody’s is consistently more conservative in the assessment of default risk for non-financial institutions, Standard and Poor’s is consistently more conservative in its assessment of default risk for financial institutions. Fitch’s increasing market share deepens the rating disagreements between S&P and Moody’s. The results also suggest that sovereign ceilings ceased to be restrictive for non-financial institutions throughout the recent financial crises, and S&P is a follower in its rating actions when compared to Moody’s for both financial and non-financial institutions. Overall, the findings imply that policymakers should tighten supervision over the rating agencies, as their assessment of credit risk is highly influential for financial market participants.

Although the financial crisis in the early 2000s was expected to represent an important structural break in the lending market, the findings of this thesis advocate that its impact is distinct across regions and sectors. On the Czech household loan market, there is a wide interest rate differential between loan types, though their default rate differential is systematically lower. Similar to the results of Horvath and Podpiera (2012), this suggests that banks impose a high risk margin on household loans and remain prudent in their pricing policy. While the introduction of risk-based pricing aims to limit adverse selection, the prolongation of loan maturity is likely to lead to a higher default probability even after the financial crisis. On the other hand, the worldwide market of debt issuers from financial and non-financial sectors experienced accelerated credit quality changes. During pre-crisis and sovereign-debt-crisis periods the reliance on prior rating actions of other agencies weakens, but remains highly statistically significant when compared to the other determinants of issuer rating change. Overall, this diminishing influence of the competitors’ behavior is likely to be caused by the increased motivation of rating agencies to protect their reputational capital in assessing credit risk.

Chapter 1

Loans for Better Living:
The Role of Informal Collateral

1.1 Introduction

Since the early 2000s, the ways consumers may finance their expenditures have become diversified to a large extent. The range of loan products is particularly wide for financing housing-related expenditures. In addition to mortgage loans and building savings schemes, individuals can apply for housing loans granted for financing investments related to a property (e.g. home purchase, home renovation, home equipment). The key distinction between mortgage and housing loans is that the repayment of the latter is not secured by a lien on the property. Hence, housing loans are notably more attractive to those who are not willing or able to secure their loan with property. Alternatively, if the loan is intended to finance expenditures that are not housing-related, the borrower can apply for consumer credit. The key distinction between consumer credit and housing loans is that housing loans are granted conditional on the ownership of the real estate they finance, even though it does not serve as collateral. In this paper, housing loans and consumer credit with a designated purpose are jointly referred to as specific purpose loans (‘purpose-loans’), while consumer credit without a designated purpose is referred to as unspecified purpose loans (‘non-purpose loans’). The latter is viewed as bearing the highest risk, as no information is available on the expenditure they are intended to finance.

The cost of the loan products varies by their perceived riskiness. Mortgage loans are secured (the financed property serves as collateral and can be claimed by the lender in case of borrower bankruptcy) - their interest rate and probability of default (henceforth referred to as ‘default rate’) is relatively low compared to other types of loans. At the end of 2013 in the Czech Republic, the interest rate on new mortgage loans was 3.4 percent, while the share of non-performing loans to total mortgage loans was 3.0 percent. By contrast, housing loans and consumer credit are unsecured loans (there is only a general claim on the borrower’s assets in the case of default), and their interest rates and default rates are substantially higher than for mortgage loans. As of the end of 2013 in the Czech Republic, the interest rates on new consumer credit and housing loans combined was at 14.5 percent, while the share of non-performing loans to total household loans was 12.2 percent for consumer credit and 8.4 percent for housing loans.[1] Nevertheless, the overall performance of household loans must be evaluated in the light of expected loss in case of default. In particular, the two loan types significantly differ in their recovery rate (i.e. the percentage of non-performing loan amount recovered by the lender). Unlike consumer credit, mortgage loans enjoy the presence of high recovery rate in case of default (the expected loss is relatively low), as the loans are secured by collateral (the financed property).

Although previous literature has long emphasized the role of collateral in mitigating the asymmetric information between lenders and borrowers at the time of loan granting, their conclusions are contradictory. The theoretical predictions of Boot, Thakor and Udell (1991), Manove and Padilla (2001) and Inderst and Mueller (2007)

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[1] Czech National Bank - ARAD database – Monetary and financial statistics, http://www.cnb.cz/cnb/STAT.ARADY_PKG.STROM_SESTAVY?p_strid=AAABAA&p_sestuid=&p_lang=EN

suggest that with higher collateral the probability of default rises. The authors support their findings with several main arguments: (1) when they require increased collateral, financial institutions often weaken their screening mechanisms, (2) to achieve financing, borrowers are likely to provide all the required collateral irrespective of their probability of default. A contrary view from Jimenez, Salas and Saurina (2006) supports the private information hypothesis; it says that collateral sorts loan applicants such that low-risk borrowers prefer to pledge their loans (due to their low probability of default) and have lower interest rates, while high-risk borrowers prefer not to pledge their loans (given their higher probability of default) and have higher interest rates.

Despite the broad debate on collateral and its impact on loan performance, limited research has focused on the role of informal collateral in the housing loan market. Housing loans finance home equity (similar to mortgage loans), but are granted without collateral (similar to standard consumer credit). Instead, their loan contract terms are conditional on informal collateral, which exists whenever the lender has evidence of the good the loan is intended to finance. For a housing loan, homeownership and an invoice verifying the purpose of the loan serves as evidence of informal collateral. These help individuals applying for a housing loan signal their better creditworthiness. Because the existence of informal collateral makes the borrower eligible for favorable loan contract terms without a lien on the property, the information asymmetry between the lender and the borrower might be more severe. This paper addresses this issue and tests the effectiveness of informal collateral in alleviating adverse selection on the household loan market. It contributes to the findings of Kocenda and Vojtek (2011), who were the first to study the default probability of Czech household loans with different purposes.

This empirical paper focuses on three questions. First, I test whether the existence of informal collateral influences the likelihood of successful loan repayment, by applying a probit model to measure the effect of different loan types on the borrower's default rate. Second, I examine whether the lower default rate on purpose-loans is driven by the type of product they are intended to finance. This is tested by including loan purpose and applicant type dummies into the probit model. The latter is derived from information on multiple loan contracts per applicant and accounts for the fact that applicants with different default probability select different loan purposes. Third, I test whether applicants with the same application characteristics and loan contract terms have the same default rate and interest rate differential, regardless of whether they apply for loans with specified or unspecified purpose. I tackle the issue of self-selection by using propensity score matching.

The paper exploits a unique dataset of over 207 000 rejected and accepted household loans from a Czech commercial bank.[2] It covers three different types of household loans granted from 2007 to 2013: housing loans, consumer credit with a designated purpose (jointly referred to as 'purpose-loans') and consumer credit without a designated purpose (referred to as 'non-purpose loans').

1.2 Why the Type of Household Loan Matters

1.2.1 Description of Household Loan Types

The share of non-performing loans[3] of total loans (hereafter, the "NPL ratio") varies substantially among the household loan types. Its significance is illustrated in Figure 1.1, which depicts the share of NPL in consumer credit[4], mortgage loans and housing loans in the Czech Republic. Whereas mortgage loans maintained a solid performance between 2002 and 2013, the share of problem loans in the case of consumer credit and housing loans sharply increased. Although neither consumer credit nor housing loans are backed by collateral, there is a 3.7 percentage point difference in their NPL ratio (based on the most recent results from August 2014).

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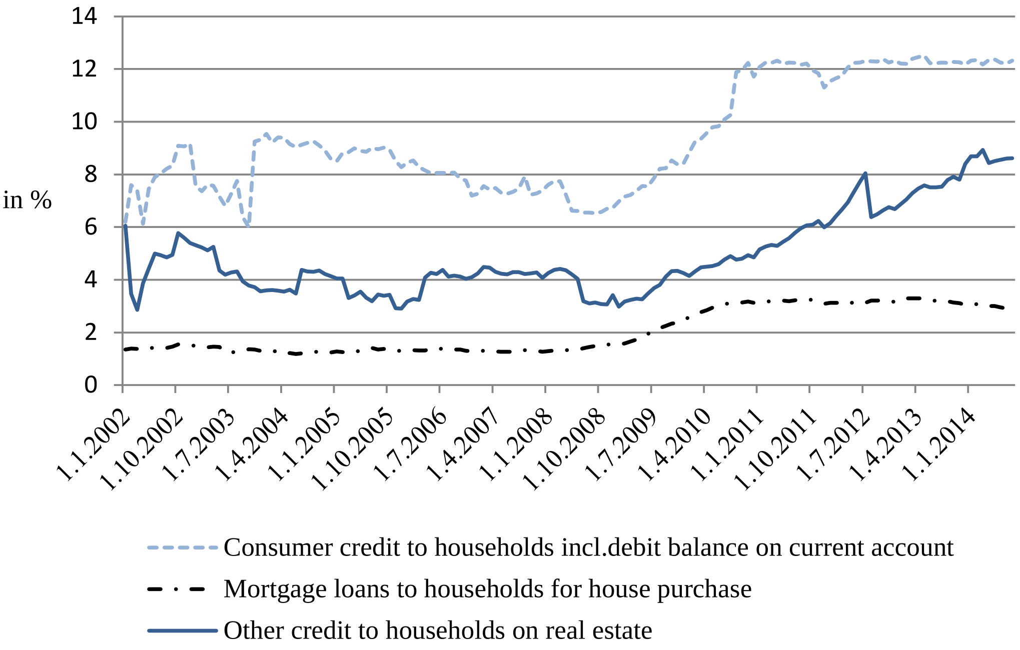
[2] The Bank does not wish to be explicitly identified.

[3] According to CNB Regulation No. 123/2007, § 196, § 197 non-performing loans are receivables with default classified as substandard, doubtful or loss loans.

[4] The statistics cover consumer credit with both specified and unspecified loan purpose.

Figure 1.1: Share of non-performing loans on total loans (by household loan type)



Source: Czech National Bank (CNB) – ARAD database – Monetary and financial statistics. *Note:* (1) The statistic covers household loan provided in the Czech Republic. (2) Non-performing loans include substandard, doubtful or loss loans.

The loan-application process for consumer credit (with specified and unspecified purpose) and housing loans begins identically.[5] In order to assess the creditworthiness of their potential debtors and to decide whether to grant a loan, financial institutions use automated credit scoring techniques. Their main purpose is to estimate the probability that an applicant will default by a given time in the future. Lenders make loan-granting decisions based on the loan application information provided by their customers and the probability of default. Application information is evaluated by analyzing a sample of

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[5] On the household loan market, loan types and their loan contract terms vary substantially across individual loan providers. Prior to loan application, the borrower has indicative information (for random loan amount and a minimum interest rate offer, each lender publishes a menu of maturities and annuity payments) about the loan products and the lenders' offer from publicly available marketing materials. When entering the loan application process, the borrower uses this information to decide about his/her preferred loan type/maturity/amount given liquidity constraints – this requested loan type/maturity/amount can be considered the result of the searching process. Any changes in these parameters are assumed to be subject to a new loan application.

past customers who applied for a loan, whose records provide good information on subsequent loan performance history. Credit scoring divides loan applicants into ‘good’ and ‘bad’ and assists independent lending institutions in their loan-granting decisions. Kocenda and Vojtek (2011) provide an extensive survey of literature on existing credit scoring techniques (e.g. logistic regression, classification and regression trees) and compare their efficiency and discriminatory power.

1.2.2 The Role of Loan Contract Terms in Alleviating Adverse Selection

Loan contract terms for the individual household loan types differ. After mortgage loans (secured by a lien on a property), housing loans offer the second lowest interest rates. To be eligible for a favorable interest rate in the case of housing loans, the applicant must document both loan purpose and proof of homeownership.[6] The loan must finance a property-related investment, and the real estate should be in the name of the applicant. Although housing loans can be used to finance home renovation, home purchase (to some upper limit), or home equipment, they are not secured by a lien on the property as are mortgage loans.[7] Another advantage is that housing loans are also subject to favorable tax treatment. Upon fulfilling certain conditions, a borrower can deduct the interest expenses of housing loans when tax returns are filed. The interest rates of loans for vehicle purchases or other purposes are less favorable[8], as the loans are not backed by homeownership. Borrowers are obliged to submit an invoice verifying that the loan was used for the specified purpose, and are then entitled to the lower interest rates. If the borrower does not deliver this evidence, the price of the loan is raised to the interest rate level of loans without a specified purpose. Loans for

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[6] The terms and conditions of housing loans usually also include requirements on the share of total costs (e.g. 20 or 30 percent) to be financed from the borrowers’ own resources.

[7] After exceeding some upper loan limit, the bank may insist on securing a loan by collateral. Nevertheless, if the applicant decides to back his loan with property, then the loan application is changed to a mortgage loan request, due to the even lower interest rate it offers. In some cases the bank might require the property to be insured (the cost of insurance is paid by the borrower).

[8] Comparing loans for vehicle purchase or other purpose, the former offer more favorable loan contract terms. This is because vehicles are easier for the bank to repossess in case the borrower defaults.

unspecified purposes bear the highest interest rate. This is because individuals who cannot or who are not willing to specify the purpose of financing are perceived as risky. Although the lender usually keeps a record of whether the borrower owns real estate, unless there is a lien on property (as in the case of mortgage loans) or the applicant submits the invoice of property-related investment and the proof of homeownership to receive a loan (as in case of housing loans), homeownership is not regularly verified and cannot be considered as informal collateral.

Housing loans thus benefit from the presence of informal collateral.[9] Individuals providing evidence of loan purpose and homeownership can signal their creditworthiness and gain favorable loan contract terms. This can prevent market inefficiencies that arise on household loan markets when the borrower has private information related to loan repayment. To mitigate this asymmetric information between lenders and borrowers, the bank can design such loan contract terms (most importantly, set interest rates) that aim to reveal the borrower's risk type. This paper tests the effectiveness of informal collateral to alleviate adverse selection on the housing loan market, a field that has not previously been studied.

1.3 Methodology

This section outlines the identification strategy applied to measure the impact of household loan type on the borrower's default rate. To estimate the impact of loan type on a borrower's default rate, first the simple probit is applied. Compared to the linear probability model, the probit model offers a better modeling of dichotomous outcome estimation. Second, the propensity score matching is used to see how the results change after the potential selection bias on household loan market is accounted for. This paper does not model the process of loan approval and the setting of loan contract terms (loan

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[9] Pavan (2008) is the first to define the role of durable goods as informal collateral in the loan performance of unsecured debts.

amount, interest rate and maturity).[10] These are assumed to be the result of equilibrium outcome.

1.3.1 Probit Models

Hypothesis 1. The purpose of the loan has no impact on the probability of loan repayment.

The default rate is a function of information available about the borrower at the time of loan application. In Model 1 the probability of default is estimated by the following probit model:

$$Y_i^* = \beta_0 + X_i^{'}\beta_1 + \beta_2 PURPOSE_i + \varphi_i \tag{1.1}$$

where Y_i denotes default for borrower *i*, $X_i^{'}$ is the vector of application characteristics and the loan contract terms of application *i*, $PURPOSE_i$ is a categorical variable indicating the purpose of a loan (Table 1.A.1 in the Appendix summarizes the individual variables and their coding) and φ_i are unobserved factors assumed to have a standard normal distribution with zero mean and variance equal to one. Although the latent variable Y_i^* is not observed, Y_i takes the value of 0 if the borrower does not default ($Y_i^* < 0$) and Y_i takes the value of 1 if the borrower defaults ($Y_i^* > 0$). Assuming the standard normal cumulative distribution $\Phi(.)$ the probability of default can then be derived as follows:

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[10] Kuvikova (2015) estimates loan demand and loan performance jointly, while accounting for the number of successful payments until default using the endogeneity of loan contract terms, the potential sample selection on the household loan market. The paper also offers an alternative model for default estimation by utilizing a duration model that takes into account the number of successful payments until default.

$$\Pr(Y_i^* = 1 \mid PURPOSE_i, X_i) = \Phi(\beta_{0i} + X_i^{'}\beta_1 + \beta_2 PURPOSE_i + \varphi_i) \tag{1.2}$$

Although the coefficients of the probit model $(\frac{\partial \mathrm{E}(Y_i^*)}{\partial X_k} = \beta_k)$ express the direction of the impact of the explanatory variables on the binary outcome, unlike in the linear probability model they do not express the marginal effects and hence need to be calculated explicitly. To quantify the magnitude of the effect $(\frac{\partial \Pr(Y_i=1|X_i)}{\partial X_k})$ the average marginal effect is used. It expresses the impact of a one-unit change in the explanatory variable on the average change in the probability of the outcome variable.

Specifically, the null hypothesis tested in Model 1 is that $H_0 : \beta_2 = 0$.

Hypothesis 2. The type of applicant choosing loans with different riskiness does not affect the loan default.

Applicants with different default probability might select loans with certain loan purpose. To differentiate between the effect of loan type and the type of individuals that apply for certain loans, Model 2 is defined as

$$Y_i^* = \beta_0 + X_i^{'}\beta_1 + \beta_2 PURPOSE_i + \beta_3 APPTYPE_i + \varphi_i \tag{1.3}$$

where the categorical variable $APPTYPE_i$ indicates the applicant's type with respect to loan purpose. The variable is created using information on multiple loan contracts per applicant (both accepted and rejected loans), in which an applicant type dummy is assigned to each loan purpose *j*. This dummy takes the value of one if the loan application *i* is submitted by an individual who has already applied for a loan purpose *j*. This specification enables one to account for the unobserved individual heterogeneity connected to the good (certain applicants are more prone to buying riskier goods) and quantify whether the default is driven by the riskiness of the applicant or the riskiness of the good the loan is intended to finance (Bicakova, 2007).

Specifically, the null hypothesis tested in Model 2 is that $H_0 : \beta_3 = 0$.

1.3.2 Propensity Score Matching

Hypothesis 3. The average effect of loan purpose on the loan default is not significantly different from zero when similar applicants are compared.

In estimating the effect of loan type on the default rate of borrowers, self-selection becomes an issue. Specifically, borrowers applying for a purpose-loan may differ significantly from those applying for a non-purpose loan. To account for self-selection and check the robustness of results based on probit regression, the matching approach is utilized. The method is used for estimating causal effects, and aims to resemble a randomized experiment by comparing treated and control groups with similar distribution of covariates.[11] Contrary to a standard regression approach that might suffer from selection on unobservable characteristics, matching is a non-experimental method that focuses on controlling for observables. As the method is non-parametric, it does not impose a functional form and requires fewer assumptions than the regression approach.[12]

In order to see whether the default rate of purpose-loans differ from the default rate of non-purpose loans, I take advantage of the non-experimental matching method suggested by Rosenbaum and Rubin (1983). The method allows us to quantify the impact of treatment programs that differ across individuals. In particular, it describes

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[11] Stuart (2010) offers a detailed review of matching techniques.

[12] Angrist (1998) argues that the primary difference between the estimates of the approaches lies in the weights corresponding to the explanatory variables. Whereas in the regression model the weights are larger when the variance of treatment is larger, in the matching approach the weights are larger when the probability of treatment is larger.

what would have happened in the absence of treatment. The method assumes that the selection of individuals into control and treatment groups is based on a sufficient number of observables, where the unobservables are assumed to be unimportant.

Two potential outcomes of probability of default are compared: y_{1i} is the probability of default for purpose-loans and y_{0i} is the probability of default for non-purpose loans. I assume that a population of borrowers exists in which everyone is equally eligible to choose between the two types of loans. I observe y_{1i} only if $D_i = 1$ (the borrower applied for a purpose-loan) and observe y_{0i} only if $D_i = 0$ (the borrower applied for a non-purpose loan).

Assuming the borrower has a choice between loan types, the aim is to measure whether the purpose makes a difference in the default rate of borrowers. The average effect of treatment on treated (ATT, hereafter) is chosen to quantify the average effect of loan type on the probability of default:

$$E(y_{1i} - y_{0i} \mid D_i = 1) = E(y_{1i} \mid D_i = 1) - E(y_{0i} \mid D_i = 1).$$

If the choice of loan type was completely random, i.e. $E(y_{0i} \mid D_i = 1) = E(y_{1i} \mid D_i = 0)$, we could simply compare the treatment group (the borrower applied for a loan with specified purpose) and control group (the borrower applied for a loan with unspecified purpose) as in a randomized experiment. However, as we deal with a non-randomized observational dataset on application characteristics, the treatment and control groups are not comparable before the treatment. Thus, a non-parametric matching method[13] is required to estimate the average effect of loan type. This reduces the bias caused by confounding factors in observational datasets where the assignment of customers to the treatment and control groups is not random. Controlling for confounding factors, the

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[13] The matching estimators can identify and give consistent estimates of the choice of loan type on default rates under the following two assumptions: (1) D_i is independent of (y_{1i}, y_{0i}) conditional on $X = x$. (2) $c < P(D_i = 1 \mid X = x) < 1 - c$, for some $c > 0$. The first assumption (the unconfoundedness assumption) ensures that, conditional on the application characteristics of the borrower, the loan type is independent of the default rate of the borrower. The second assumption (the identification assumption) allows for borrowers of the two loan types to have similar application characteristics and thus they can be compared.

matching method corrects for the selection bias by balancing the distribution of covariates in the treated and control groups.

As I deal with a large number of application characteristics when testing the null hypothesis, I take advantage of the propensity score matching.[14] This approach groups the pre-treatment characteristics of each individual into a single scalar and the matching is realized solely on this propensity score.[15] The propensity score matching is done by pairing each treated individual with one or more individuals from the control group based on their propensity scores. Motivated by Heckman, Ichimura and Todd (1997), who compare different matching methods depending on sample size, I use the "nearest neighbor" method for ATT estimation. Specifically, the null hypothesis tested in Model 3 is that $H_0 : E(y_{1i} - y_{0i} \mid D_i = 1) = 0$.[16]

1.4 Data

In order to analyze the default pattern of the Czech household loan market, a dataset of over 207 000 household loans covering the entire Czech Republic has been obtained. The random sample of household loans utilized in this paper is drawn from a Bank, which (based on total assets) belongs among the top 3 banks operating in the Czech banking sector.[17] The dataset consists of application information on those individuals who were granted/rejected a household loan between 2007 and 2013, together with their monthly repayment status. The data observation period lasts until 2013. Table 1.A.1 in the Appendix lists the available information on household loans.

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[14] Abadie and Imbens (2002) suggest that a bias of simple matching estimators exists, and the simple method might be not suitable in cases where there is a wide range of covariates.

[15] Rosenbaum and Rubin (1983) define the propensity score as the propensity towards exposure to treatment 1 given the observed pre-treatment covariates. In other words, the propensity score is the probability of being granted a purpose loan, conditional on the borrower's application characteristics and the loan contract terms.

[16] Admittedly, endogeneity might cause an identification issue, as the certain types of borrowers prefer certain types of loans. Nevertheless, as the default probability is analyzed conditional on the type of loan, the matching estimation is considered to be appropriate.

[17] The Bank has a market share of 20% for traditional bank products in the Czech Republic. It is part of an international financial group with its core market in Central and Eastern Europe.

The dataset can be considered as representative for studying household loan performance from several aspects. First, the observed default rate and the interest rate in the sample (4.9 percent and 13.4 percent respectively) is comparable to the average default rate and interest rate statistics in the Czech Republic (4.1 percent and 13.9 percent) for 2007-2013. Second, the sample includes only CZK-denominated loans, and the vast majority of loans in the Czech Republic are CZK-denominated (the share of loans to households denominated in foreign currency is below 1 percent).[18] Third, the structure of households with respect to monthly income is comparable to the national statistics.[19] As depicted in Figure 1.A.1 in the Appendix, the mean monthly income observed in the sample copies the mean monthly income in the Czech Republic for all four age buckets. The income of households in the sample is also analogous to the mean income in other countries in Central and Eastern Europe, though it is significantly lower than the average in the European Union. Importantly, it has to be acknowledged that the characteristics of borrowers applying for household loans might be somewhat worse or distinct from the characteristics of the entire population.

The selection of variables predicting default is driven by the information the Bank includes on their loan application form (the borrower's application characteristics and the loan contract terms). Nevertheless, following Kocenda and Vojtek (2011), I also conduct a single factor analysis to check the discriminatory power of the variables applied in the Bank's credit scoring. The overall information value of the application characteristics is calculated as the sum of information values for each category of application characteristics, defined for loan application i as

$$\text{Information Value}_i = \ln(\text{Odds}_i)\left(\frac{Default_i}{Default} - \frac{NoDefault_i}{NoDefault}\right) \quad (1.4)$$

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[18] Czech National Bank: ARAD database - Monetary and financial statistics, http://www.cnb.cz/cnb/STAT.ARADY_PKG.STROM_SESTAVY?p_strid=AABBAA&p_sestuid=&p_lang=EN

[19] Eurostat, http://ec.europa.eu/eurostat/web/household-budget-surveys/database

$$\text{Odds}_i = \left(\frac{Default_i}{Default}\right)\left(\frac{NoDefault}{NoDefault_i}\right) \tag{1.5}$$

where *Default* represents the total number of defaulted loans and *NoDefault* represents the total number of loans that were repaid. The information value of application variables summarized in Table 1.A.2 confirms that the majority of application characteristics have an information value of between 0.1 and 0.2. The higher the information value, the higher the discriminatory power of the variable with the given categorization.

1.4.1 The Expected Impact of Loan Contract and Application Characteristics on Default

Table 1.A.1 in the Appendix summarizes the expected impact of loan term characteristics and application characteristics on the probability of loan default based on the related literature. The first set of variables include loan contract terms (Table 1.A.1, Panel A), which describe the loan the borrower and lender agreed on. Several application and loan term characteristics might signal a borrower's low probability of default. Recent literature findings suggest that lower default is likely on loans of high amounts (Dobbie and Skiba, 2013), on loans with a specific purpose (Kocenda and Vojtek, 2011), and for loans that were evaluated by applying risk-based pricing[20] (Adams, Einav, and Levin, 2009). A high credit bureau score expresses the applicant's low indebtedness (the score is highest if the borrower has no other debt) and a high behavioral score expresses the applicant's good repayment history (the score is the highest if the borrower has had no problems in previous debt repayment).

The second set of variables contains individual application characteristics (Table 1.A.1, Panel B), which represent the socio-demographic characteristics of the potential borrower at the time of loan application. From the application characteristics, the

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[20] The Bank has been applying risk-based pricing (i.e. pricing based on the borrower's expected riskiness) since January 2012.

likelihood of bankruptcy is expected to diminish for older (Dobbie and Skiba, 2013), female (Chandler and Ewert, 1976), married and university-graduated applicants (Kocenda and Vojtek, 2011). In addition, previous literature suggests that employment with stable income (Gross and Souleles, 2002), home ownership (Adams et al., 2009) and long employment duration (Kocenda and Vojtek, 2011) should also have a positive impact on loan repayment. Certain application characteristics might be omitted from credit scoring models. Chandler and Ewert (1976) show that if gender is allowed, men have a significantly smaller chance of being granted a loan. This can be because other variables, like low income and part-time employment, signal good repayment behavior in the case of females, but bad repayment behavior in the whole population. In order to estimate the probability of default, this paper uses the list application information (including gender) that the Bank applies in its credit scoring model.

1.4.2 Descriptive Statistics

The descriptive statistics of the application characteristics and loan contract terms are presented in Table 1.A.3 in the Appendix. The mean values of personal loan information suggest that an average borrower has been employed for more than 5 years and has an average net income above CZK 17 000 monthly. On average the applicants were approved for a loan amount of CZK 100 000 with a four-and-a-half-year maturity at an interest rate of 14 percent.

Although there are several different definitions of ‘defaulted’ loans, similar to the literature on installment loans (Gross and Souleles, 2002; Barron, Chong, and Staten, 2008), I measure loan performance using delinquency rate as a proxy for expected default rate. I consider a loan to be in default if the borrower is more than 30 days overdue on any payment connected with the loan. Later, for the purposes of the sensitivity analysis, I use the definition set by the Basel Committee on Banking Supervision (2004): a loan is considered to be in default if the borrower is more than 90 days overdue on any payment connected with the loan. Table 1.1 summarizes the default rate of loans by loan type.

Table 1.1: Default rate by loan type

Loan type	No default	Default	Accepted loans	Acceptance rate
Unspecified purpose	94.5%	5.5%	91 305	50.9%
Specified purpose	98.6%	1.4%	14 454	51.4%
Total	100 508	5 219	105 759	50.9%

Note: Random sample of household loans, data from 2007-2013.

Purpose-loans include loans for home purchase, home renovation, purchase of home equipment, purchase of a new/used car and loans for other purposes (e.g. mobile phone, computers, etc.) and represent 14% of the total dataset (accepted and rejected loans). Table 1.2 presents the default rate and interest rate differentials of accepted loans. Consistent with national statistics, housing loans (loans for home purchase, home renovation, and purchase of home equipment) have a lower default rate than consumer credit with unspecified purpose by around 3.5%. The interest rates reflect how easy it would be for the bank to repossess assets from the borrower in the case of default: the cheapest are housing loans (connected to the ownership of property), then loans for vehicle purchase (connected to car ownership), and the least favorable interest rate is for loans with other or unspecified purposes.

1.5 Results

The results of estimating the effect of application characteristics and loan contract terms on borrowers' probability of default conforms to expectations. The estimation results from the probit model and propensity score matching suggest that the impact of loan purpose on the probability of default rate is significant. Interestingly, the default rate differential between purpose-loans and non-purpose loans is much smaller than the interest rate differential.

Table 1.2: Default rates and interest rates per loan purpose

Loan purpose	Default rate	Interest rate	Accepted loans	Acceptance rate
Unspecified purpose	5.5%	14.0%	91 305	50.9%
Home purchase	2.3%	8.1%	3 171	51.2%
Home renovation	1.2%	8.2%	6 818	51.4%
Home equipment	1.3%	7.8%	477	38.9%
New/used car purchase	1.6%	11.6%	251	48.6%
Other purpose	0.8%	13.4%	3 737	54.2%
Total	4.9%	13.4%	105 759	50.9%

Note: Random sample of household loans, data from 2007-2013.

1.5.1 The Effect of Informal Collateral on Loan Default

In order to interpret the effect of the individual loan determinants on the probability of default while keeping all the other covariates constant, I follow Greene (2003) and calculate the marginal effects from the estimation results. Table 1.3 displays the calculated average marginal effects of the probit model with corresponding standard errors for Model 1 and Model 2. [21]

Panel A of Table 1.3 summarizes the probit estimation results with respect to loan term characteristics. The results from Model 1 indicate that the hypothesis that the purpose of the loan has no impact on the probability of loan repayment can be rejected. In particular, the probability of default decreases with an indicated loan purpose. Applicants with clear intentions and carefully planned objectives default less. Specifically, as a result of financing a home purchase, the borrower's probability of default decreases on average by 3.6 percentage points (compared to a non-purpose loan).

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[21] The reference group for the application factor variables is always the one with the lowest coding (summarized in Table 1.A.1 in the Appendix) and the individual estimates refer to indicated changes in the dependent variable due to a change in the particular application characteristic compared to its reference group. For example, according to the positive sign of education level, relative to primary education being the reference group, the higher a customer's level of education, the lower the predicted default is expected to be.

Table 1.3: Probit estimation results (Panel A – Loan term characteristics)

Dependent variable: Default		Model 1	Model 2
		dy/dx (Delta method - standard error)	
Risk-based pricing		-0.043***	-0.043***
		(0.001)	(0.001)
Approved amount		-0.003***	-0.003***
		(0.001)	(0.001)
Loan maturity		0.026***	0.026***
		(0.001)	(0.001)
Loan purpose	Home purchase	-0.036***	-0.028***
		(0.002)	(0.005)
	Home renovation	-0.034***	-0.010
		(0.002)	(0.007)
	Home equipment	-0.037***	-0.039***
		(0.006)	(0.006)
	New/used car purchase	-0.036***	0.835
		(0.008)	(17.367)
	Other purpose	-0.028***	0.031**
		(0.004)	(0.012)
Applicant type	Home purchase		-0.014
			(0.009)
	Home renovation		-0.037***
			(0.008)
	Home equipment		0.011
			(0.014)
	New/used car purchase		-0.352
			(9.828)
	Other purpose		-0.062***
			(0.006)
N		105 759	105 759
R^2		0.2079	0.2132
Prob> chi2		0.000	0.000
Loglikelihood ratio (LR) chi2		8 647.4	8 864.8

Note: (1) The estimates denote the calculated average marginal effects for factor levels (dy/dx) expressing the discrete change from the base level. (2) The reference groups for the categorical variables are the following: Loan purpose - Non-purpose loans; Application type – Applicants only requesting non-purpose loans. (3) Only statistically significant results (***, **, and * denote significance at the 1%, 5%, and 10% levels) are presented. Standard errors are in parenthesis.

The effect of financing home renovation, purchase of home equipment or a used car is analogous. Applicants funding other purposes (e.g. mobile phones, computers, etc.) are also less likely to have repayment difficulties, though the default only declines by 2.8

percentage points on average (compared to a non-purpose loan). This is natural as these applicants most likely finance one-time expenditures that have a relatively short lifespan (unlike investments in real estate). These findings complement the results of Kocenda and Vojtek (2011), who also utilize data from a Czech commercial bank and find that compared to loans for house building, loans with other purposes (e.g. renovation, the purchase of an apartment, land or house) have a higher estimated probability of default. Nevertheless, this paper goes further and aims to compare the default rate and pricing differential of purpose-loans and non-purpose loans after accounting for potential selection bias.

When controlling for unobserved individual heterogeneity, the negative relationship between loan purpose and default probability is altered. The applicant's type might be viewed as a proxy for assessing the ordering of expenditures by borrowers. Based on historical observations the applicant's type should indicate his/her unobserved riskiness (i.e. what type of loan product the individual is more inclined to apply for). Housing loans are more likely to be chosen by risk-lover individuals (i.e. they invest the borrowed money in a property), while consumer credit with unspecified purpose is most likely to be chosen by less thoughtful individuals (i.e. the borrowed money is not necessarily invested and might finance unpremeditated consumption). The results summarized in Panel A of Table 1.3 suggest that when controlling for the applicant's type, the role of loan purpose in explaining default might be prevailed by the applicant's type. Specifically, the hypothesis from Model 2 (the type of applicant choosing loans with different riskiness does not affect the loan default) can be rejected. After accounting for the applicant's type (*j* dummies created for borrowers who applied for the loan purpose *j* at least once), the effect of the loan purpose diminishes and it is a different type of borrower with unobserved riskiness that drives the default rate. Compared to non-purpose loans, home renovations default less by 3.7 percentage points solely due to the fact that these borrowers have higher repayment incentives than loans without specific purpose. In the case of applicants financing a home purchase, the effect of loan purpose overweighs the effect of applicant type in explaining the lower default. The lower default rate of home equipment loans is also driven by the loan type. The applicant type has the most extreme impact on loans for other purposes (e.g. loans for mobile phones, computers, etc.): although borrowers of these durable goods default more, it is the applicant's lower riskiness that drives the better loan repayment. These findings are in line with Bicakova (2007), who presents qualitatively similar results on a sample of Italian household loans.

The remaining loan contract terms have similar influence on default probability for Model 1 and Model 2. In line with the findings of Dobbie and Skiba (2013), default declines with the approved loan amount. This result is surprising given the asymmetric information between lenders and borrowers that stimulates the prominence of moral hazard (i.e. default is more likely on larger loans, while borrowers do not pay for the increased default costs) on the household loan markets (Adams et al., 2009). On the other hand, the default increases with longer loan maturity similar to Adams et al. (2009). This is predictable as default is more probable over a longer time period. Interestingly, interest rates turn out to be statistically insignificant. A credit bureau score (indicating the applicant's indebtedness) can also successfully reveal the borrower's riskiness. Both Gross and Souleles (2002) and Barron et al. (2008) confirm that the higher the credit bureau score, the less likely the borrower will default. The behavioral score (indicating the applicant's repayment history) encompasses information about whether the borrower historically accepted/rejected and repaid/defaulted on loans. The higher the score, the better the applicant's credit history and the better his/her future loan repayment behavior. These results follow the findings of Marshall, Tang and Milne (2010) who argue that a longer lending relationship improves the quality of loan portfolios.

Application characteristics explain loan performance well and conform to expectations. Panel B of Table 1.3 indicates that the results are stable across the models. From the set of variables, monthly income is perceived as a key indicator of a borrower's creditworthiness. With respect to its relationship to loan repayment, it is expected that the higher the applicant's monthly income, the lower the probability s/he will go bankrupt. Similarly to Gross and Souleles (2002), this paper provides empirical evidence that after accounting for other application characteristics, the impact of monthly income on default probability is very low in magnitude. This is also in line with Kocenda and Vojtek (2011), who find that including income in the credit scoring specification improves discrimination between ‘good’ and ‘bad’ applicants only marginally. Although Marshall et al. (2010) highlight that students are less likely to default, Model 1 and Model 2 cannot support this finding with statistically significant results. Instead, pensioners have on average (by 2.5 percentage points) a lower default rate than employed applicants. The level of education is also a key characteristic that indicates how reliable the borrower will be in repaying the loan. Applicants with only primary school education have the highest probability of default. In line with the results of Kocenda and Vojtek (2011), with every additional level of education the likelihood of loan default declines. Similarly, I also find that a lower probability of default is expected for married applicants (due to the assumption that they have an additional source of income in the case of job loss), and borrowers employed for a longer period or employed by a public organization (due to the assumption that they are more risk-averse). The results suggest that borrowers who own real estate are also less likely to default (similar to Adams et al., 2009). Application and loan term characteristics not presented in Table 1.3 yield statistically insignificant estimation results.

1.5.2 Default and Interest Rate Differential between Purpose-Loans and Non-Purpose Loans

To predict the probability that an applicant for a household loan will default, lenders need a credit scoring model that captures the behavior of an average applicant. The information most frequently used is the repayment behavior of applicants who were granted a loan; the characteristics of those applicants who were denied a loan is not recorded. Yet estimating the probability of default only on a sample of accepted applicants and then applying it to the sample of all applicants leads to biased estimates of the parameters. This exclusion of rejected applicants then results in an underestimation of the predictive power of the credit scoring model.

Table 1.3: Probit estimation results (Panel B – Application characteristics)

Dependent variable: Default		Model 1	Model 2
		dy/dx (Delta method - standard error)	
Behavioral score		-0.001***	-0.001***
		(0.001)	(0.001)
Credit bureau score		-0.001***	-0.001***
		(0.001)	(0.001)
Female		-0.008***	-0.008***
		(0.001)	(0.001)
Education	Secondary (general)	0.029***	0.029***
		(0.006)	(0.006)
	Post-secondary (technical)	-0.020***	-0.020***
		(0.007)	(0.007)
	Secondary (vocational)	-0.011**	-0.010**
		(0.005)	(0.005)
	University	-0.026***	-0.025***
		(0.005)	(0.005)
Employment status			
	Pensioner	-0.025***	-0.025***
		(0.002)	(0.002)
Employment duration		-0.001***	-0.001***
		(0.001)	(0.001)
Employment type	Bank/insurance company	-0.041***	-0.040***
		(0.003)	(0.003)
	Private company	-0.014***	-0.013***
		(0.002)	(0.002)
	Public organization	-0.018***	-0.018***
		(0.002)	(0.002)
Net monthly income		0.001**	0.001**
		(0.001)	(0.001)
Marital status	Married	-0.012**	-0.012**
		(0.006)	(0.006)
Housing status	Living with parents	-0.025***	-0.024***
		(0.004)	(0.004)
	Sharing property	-0.021***	-0.020***
		(0.005)	(0.005)
	Personal property	-0.026***	-0.025***
		(0.004)	(0.004)
N		105 759	105 759
R^2		0.2079	0.2132
Prob> chi2		0.000	0.000
Loglikelihood ratio (LR) chi2		8 647.4	8 864.8

Note: (1) The estimates denote the calculated average marginal effects for factor levels (dy/dx) expressing the discrete change from the base level. (2) The reference groups for the categorical variables are the following: Education – Secondary (technical); Employment status – Employed; Employment type, Marital status, Housing status – Unspecified by the applicant. (3) Only statistically significant results (***, **, and * denote significance at the 1%, 5%, and 10% levels) are presented. Standard errors are in parenthesis.

In order to ensure that borrowers with the same application characteristics are compared when quantifying the impact of loan purpose on the probability of default, propensity score matching is applied. The ATT is estimated in the following steps:

First, on the sample of household loan application data where all individuals have a unique observation, I estimate the propensity score on the individual characteristics by fitting a logistic regression:

$$PURPOSEL_i = \beta_0 + \beta_1 X_i + \varepsilon_i, \tag{1.6}$$

Where $PURPOSEL_i$ is the binary variable taking the value of one for purpose-loans and taking the value of zero for non-purpose loans, X_i is the set of application characteristics and ε_i is the error term. This gives the predicted probability of loan type based on the set of application characteristics as a composite score.

As a second step, I test whether the above specification is applicable. That is, after the propensity score is created, I test for the balancing hypothesis. It says that observations with the same propensity score must have the same distribution of application characteristics independent of loan type. The results of the balancing hypothesis summarized in Table 1.A.4 in the Appendix suggest that a significant part of the covariates is well-balanced.

Finally, once the propensity score satisfies the balancing hypothesis, I examine the effect of loan type on default by using propensity score matching. Specifically, I group applicants with similar application characteristics and loan contract terms to show that the variation in default rate remains even after controlling for observable borrower risk. The ATT estimation results using the “nearest neighbor” matching method with bootstrapped standard errors are summarized in Table 1.4. The results suggest that the hypothesis that the average effect of loan purpose on the loan default is not significantly different from zero when similar applicants are compared can be rejected. Purpose-loans have a 0.7 percentage point lower default rate when compared to non-purpose loans.

Table 1.4: Default rate differential - ATT estimation results

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Default rate	Unmatched	0.0137	0.0550	-0.0413	0.0019	-21.34
	Sample	Treated	Controls	Difference	Bootstrap Std. Err.	z
	ATT	0.0138	0.0206	-0.0067	0.0023	-2.88

Note: (1) “Treated” and “Control” stands for purpose-loans and non-purpose loans, respectively. (2) A loan is in default if the borrower is more than 30 days overdue on any payment connected with the loan.

The statistically significant result at a 1% level is achieved by matching over 14 000 purpose-loans with over 90 000 non-purpose loans (Table 1.A.5 in the Appendix). When compared to the unmatched sample results, for the matched sample, the default rate differential between purpose-loans and non-purpose loans decreased by 3.4 percentage points.

To see the interest rate differential between the two loan types, propensity score matching is conducted on the same observable characteristics and loan contract terms. The results summarized in Table 1.5 suggest that after controlling for observable characteristics, purpose-loans have 3.6 percentage point higher interest rates than non-purpose loans. The test of the balancing hypothesis (summarized in Table 1.A.6 in the Appendix) is favorable and only two observations are off common support (summarized in Table 1.A.7 in the Appendix) during the propensity score matching.

The high interest rate differential for loans with similar default probability is further evidence of the heterogeneity in pricing policy for different loan types. In the example of the Czech Republic, Horváth and Podpiera (2012) show that the interest rate for household loans does not follow the market interest rate as closely as those of other types of loans. Alternatively, the authors suggest that the high interest rate for household loans is linked to the high risk margin that financial institutions impose on these loans. This paper goes further and points out that the high risk margin can be the result of mispricing or the conservative loan-granting strategy of the financial institution. Therefore, the pricing policy of financial institutions should be closely monitored in order to limit subsequent difficulties in household loan repayment.

Table 1.5: Interest rate differential - ATT estimation results

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Interest rate	Unmatched	9.5712	13.9741	-4.4030	0.0214	-206.12
	Sample	Treated	Controls	Difference	Bootstrap Std. Err.	z
	ATT	9.5714	13.1382	-3.5668	0.0344	-103.80

Note: “Treated” and “Control” stands for purpose-loans and non-purpose loans, respectively.

1.6 Sensitivity Analysis

To test the validity of the identification strategy, propensity score matching is performed applying an alternative definition of default. In particular, I use the definition set by the Basel Committee on Banking Supervision (2004) and consider a loan to be in default if the borrower is more than 90 days overdue on any payment connected with the loan. Table 1.A.8 in the Appendix summarizes the default rate of loans by loan type under the original definition (default occurs after 30 days overdue in payments) and the alternative definition (default occurs after 90 days overdue in payments). By relaxing the definition of default, the sample of loans in default is significantly reduced (from 5 219 to 3 744 observations). More importantly, after the definition change there is a substantial drop in the default rate differential between purpose-loans and non-purpose loans (from 4.1pp to 3.1pp).

The sensitivity analysis indicates that controlling for observable characteristics, the small difference between the default rate of the two loan types remains. The estimation results with the alternative definition of default are presented in Table 1.6 - the ATT is equal to 0.6 percentage points and is statistically significant at a 1% level;[22]that is, when comparing applicants with same characteristics and loan contract terms, purpose-loans have a default rate of only 0.6 percentage points higher than non-

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[22] The detailed results of the propensity score matching are available upon request.

Table 1.6: Sensitivity analysis - ATT estimation results

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Default rate	Unmatched	0.0082	0.0397	-0.0315	0.0017	-19.05
	Sample	Treated	Controls	Difference	Bootstrap Std. Err.	z
	ATT	0.0083	0.0144	-0.0061	0.0019	-3.26

Note: (1) "Treated" and "Control" stands for purpose-loans and non-purpose loans, respectively. (2) A loan is in default if the borrower is more than 90 days overdue on any payment connected with the loan.

purpose loans. Hence, the alternative definition of default confirms the validity of the identification strategy and the robustness of the results.

Borrowers' sensitivity across loans with and without purpose was tested by interacting loan purpose with application characteristics. The results suggest that the effect of application characteristics on default does not vary for different types of loans as none of the regression coefficients on the interaction terms were statistically significant at 1% level.

1.7 Conclusion

Loans to households constitute the largest part of the banking loan portfolios in several economies.[23] This paper addresses a primary problem of lending institutions; that is, how to evaluate customers' probability of default prior to granting loans. Utilizing data from a large set of household loans from the Czech Republic, the default rates of purpose-loans and non-purpose loans are analyzed and compared.

The paper offers several contributions to the current literature on the household loan market. First, the results provide evidence that housing loans are defaulted less

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[23] For instance, as at the end of 2013 in the Czech Republic, loans to individuals represented (first largest) 49.0 percent, and loans to non-financial corporations represented (second largest) 38.9 percent of loans granted in the economy (Czech National Bank - Financial Market Supervision Report 2013, http://www.cnb.cz/en/supervision_financial_market/aggregate_information_financial_sector/financial_market_supervision_reports/index.html)

often. The existence of informal collateral (i.e. evidence of homeownership and invoice about loan purpose) signals better loan repayment. This is in line with theories that consider collateral as a tool to alleviate adverse selection on the household loan market. Second, the default rate differentials between household loan types are in several cases not driven by the purpose they intend to finance, but the type of borrower. This effect is most significant in the case of loans for home renovation. Third, controlling for observable application characteristics and loan contract terms, the default rate differential between purpose-loans and non-purpose loans decreases, though the interest rates differential between these two types of loans remains substantial. Specifically, while purpose-loans have, on average, only a 0.7pp higher default rate, their interest rate is 3.6pp higher than for non-purpose loans.

These findings provide evidence of the asymmetric information present on the household loan market. Borrowers applying for purpose-loans and non-purpose loans have very similar default probability, but are charged substantially different interest rates. This is in line with the empirical literature, according to which, financial institutions are prudent in household loan pricing and charge a high mark-up when compared to mortgage or corporate loans. Nevertheless, this raises a question whether the interest rate for housing loans (being subject to tax-deductibility) should not be re-evaluated due to their lack of collateralization and higher average amount.

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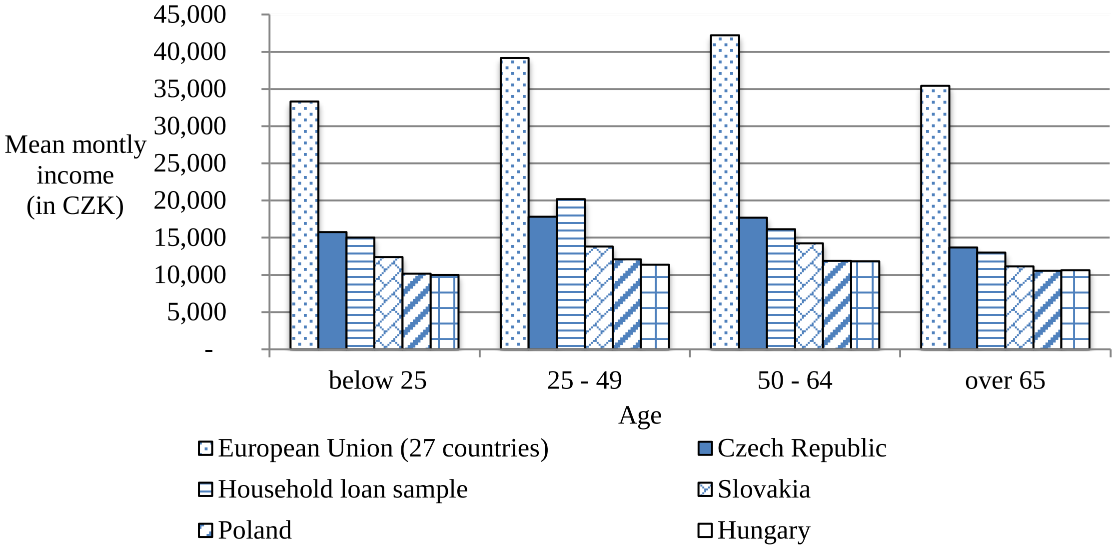
Appendix

Figure 1.A.1: Comparison of the mean monthly income



Source: Eurostat. *Note*: The figure depicts the mean monthly income between years 2007-2013.

Table 1.A.1: The list of personal loan information
(Panel A – Loan term characteristics)

Variable description	Variable name in dataset	Encoding	Expected effect on default	Recent literature
Loan term characteristics				
Loan approval indicator	APPROVED	dummy		
Approved amount (in CZK)	AAMOUNT	continuous	-	Dobbie and Skiba (2013)
			+	Adams et al. (2009)
Interest rate (in %)	IR	continuous		
Approved loan maturity (in months)	AMATURITY	continuous	+	Adams et al. (2009)
Risk band	NRISK			
Very low-risk		1		
Low-risk		2		
High-risk		3		
Very high-risk		4		
Credit bureau information	CBINFO	dummy		
Purpose-loan	PURPOSEL	dummy	-	Kocenda and Vojtek(2011)
Loan purpose	PURPOSE			
Non-purpose loan		1		
Home purchase		2		
Home renovation		3		
Home equipment		4		
New/used car purchase		5		
Other purpose		6		
Risk-based pricing	RBPRICING	dummy	-	Adams et al. (2009)

Note: Random sample of household loans, data from 2007-2013.

Table 1.A.1: The list of personal loan information
(Panel B – Application characteristics)

Variable description	Variable name in dataset	Encoding	Expected effect on default	Recent literature
Application characteristics				
Age (in months)	AGE	continuous	-	Dobbie and Skiba (2013)
Female	FEMALE	dummy	-	Chandler and Ewert (1976)
Marital status	MARITS			
Unspecified		1		
Divorced		2	+	Barron et al. (2008)
Married		3	-	Kocenda and Vojtek (2011)
Partner		4		
Single		5		
Widow/er		6		
Education	EDU			
Secondary (technical)		1		
Secondary (general)		2		
Post-secondary (technical)		3		
Secondary (vocational)		4		
Post-secondary (vocational)		5		
University		6	-	Kocenda and Vojtek (2011)
Housing status	HOUSE			
Unspecified		1		
Living with parents		2		
Sharing property		3		
Personal property		4	-	Adams et al. (2009)
Renting		5		
Student dormitory		6		
Employment status	EMPLOYS			
Employed		1		
House wife		2		
Pensioner		3		
Student		4	-	Marshall et al. (2010)
Employment duration (in months)	EMPLOYY	continuous	-	Kocenda and Vojtek (2011)
Employment type	EMPLOYT			
Unspecified		1		
Bank/insurance company		2		
Entrepreneur		3	+	Marshall et al. (2010)
Foreign company		4		
Private company		5		
Public organization		6	-	Kocenda and Vojtek (2011)
Net monthly income (in CZK)	INCOME	continuous	-	Gross and Souleles (2002)
Region (NUTS2)	REGION	dummy		
Credit bureau score	CBSCORE	continuous	-	Barron et al. (2008)
Application score	APPSCORE	continuous		
Behavioral score	BEHAVSCORE	continuous	-	Marshall et al. (2010)

Note: Random sample of household loans, data from 2007-2013.

Table 1.A.2: Information value of application characteristics

Variable	No default	Default	Total	Odds	Information value
Education					0.2
Secondary (technical)	1 108	108	1 216	2	
Secondary (general)	6 775	690	7 465	2	
Post-secondary (technical)	1 713	48	1 761	1	
Secondary (vocational)	43 951	1 813	45 764	1	
Post-secondary (vocational)	36 512	2 371	38 883	1	
University	10 480	190	10 670	0	
Employment type					0.3
Unspecified	45 331	3 222	48 553	1	
Bank/insurance company	2 142	20	2 162	0	
Entrepreneur	2 246	201	2 447	2	
Foreign company	3 029	380	3 409	2	
Private company	28 023	912	28 935	1	
Public organization	19 768	485	20 253	0	
Marital status					0.1
Unspecified	896	76	972	2	
Divorced	17 638	943	18 581	1	
Married	45 385	1 672	47 057	1	
Partner	905	63	968	1	
Single	32 304	2 342	34 646	1	
Widow/er	3 411	124	3 535	1	
Gender					0.0
Male	53 205	3 269	56 474	1	
Female	47 334	1 951	49 285	1	
Housing status					0.2
Unspecified	2 685	245	2 930	2	
Living with parents	15 922	1 121	17 043	1	
Sharing property	3 333	248	3 581	1	
Personal property	59 617	1 892	61 509	1	
Renting	18 976	1 712	20 688	2	
Student dormitory	6	2	8	6	
Employment status					0.0
Employed	86 999	4 654	91 653	1	
House wife	1 747	122	1 869	1	
Pensioner	11 698	437	12 135	1	
Student	95	7	102	1	
Loan purpose					0.2
Non-purpose loan	86 283	5 022	91 305	1	
Home purchase	3 098	73	3 171	0	
Home renovation	6 734	84	6 818	0	
Home equipment	471	6	477	0	
New/used car purchase	247	4	251	0	
Other purpose	3 706	31	3 737	0	

Note: Random sample of household loans, data from 2007-2013.

Table 1.A.3: Descriptive statistics (Panel A – Loan term characteristics)

Variable name	Mean	Std. Dev.	Min	Max
Loan term characteristics	Accepted loans (N=105 759)			
Approved amount (in CZK)	93 653	82 100	4 000	1 000 000
Approved loan maturity (in months)	54.0	26.5	1.0	134
Interest rate (in %)	13.4	2.8	3.7	25.9
Default indicator	0.04	0.19	0	1
Purpose-loan	0.102	0.303	0	1
Credit bureau score	318	269	-40	1 120
Application score	178	222	-4	998
Behavioral score	454	192	0	1 012

Note: Loan characteristics are available only for approved loans.

Table 1.A.3: Descriptive statistics (Panel B – Application characteristics)

Variable name	Mean	Std. Dev.	Min	Max
Application characteristics	Accepted and rejected loans (N=207 640)			
Age (in months)	485	155	216	1 159
Female	0.479	0.500	0	1
Marital status				
Divorced	0.184	0.387	0	1
Married	0.418	0.493	0	1
Partner	0.012	0.107	0	1
Single	0.335	0.472	0	1
Widow/er	0.010	0.100	0	1
Education				
Secondary (general)	0.103	0.303	0	1
Post-secondary (technical)	0.015	0.120	0	1
Secondary (vocational)	0.400	0.490	0	1
Post-secondary (vocational)	0.387	0.487	0	1
University	0.084	0.278	0	1
Housing status				
Living with parents	0.170	0.375	0	1
Sharing property	0.033	0.180	0	1
Personal property	0.541	0.498	0	1
Renting	0.220	0.414	0	1
Student dormitory	0.000	0.009	0	1
Employment status				
House wife	0.030	0.172	0	1
Pensioner	0.142	0.349	0	1
Student	0.001	0.029	0	1
Employment duration (in months)	71	90	0	579
Employment type				
Bank/insurance company	0.017	0.129	0	1
Entrepreneur	0.027	0.161	0	1
Foreign company	0.032	0.176	0	1
Private company	0.261	0.439	0	1
Public organization	0.178	0.383	0	1
Net monthly income (in CZK)	17 451	11 861	1	500 000
Credit bureau information	0.756	0.429	0	1
Risk band				
Low-risk	0.362	0.480	0	1
High-risk	0.122	0.327	0	1
Very high-risk	0.029	0.167	0	1
Loan approval indicator	0.510	0.500	0	1

Note: Loan characteristics are available only for approved loans.

Table 1.A.4: Balancing hypothesis – Default rate estimation

Application and loan term characteristics	Mean			t-test	
	Treated	Control	%bias	t	p>|t|
Risk-based pricing	0.342	0.569	-51.4	-39.45	0.000
Behavioral score	476.66	516.14	-20.0	-17.66	0.000
Credit bureau score	385.14	513.48	-47.1	-39.92	0.000
Interest rate	9.642	10.344	-26.8	-23.78	0.000
Loan maturity	2.736	2.739	-0.5	-0.50	0.615
Approved amount (in CZK)	2.713	2.731	-2.0	-2.24	0.025
Age	485.14	507.5	-16.1	-14.74	0.000
Female	0.435	0.462	-5.5	-4.59	0.000
Secondary (general)	0.037	0.036	0.2	0.19	0.849
Post-secondary (technical)	0.020	0.016	3.5	2.96	0.003
Secondary (vocational)	0.471	0.471	-0.1	-0.08	0.934
Post-secondary (vocational)	0.293	0.300	-1.4	-1.24	0.216
University	0.170	0.173	-0.8	-0.60	0.549
House wife	0.018	0.016	1.5	1.29	0.196
Pensioner	0.063	0.081	-6.4	-6.03	0.000
Student	0.001	0.001	0.8	1.00	0.317
Employment duration (in months)	82.11	88.965	-7.6	-6.12	0.000
Bank/insurance company	0.029	0.020	5.5	4.58	0.000
Entrepreneur	0.023	0.016	4.3	3.97	0.000
Foreign company	0.022	0.011	6.5	7.06	0.000
Private company	0.331	0.487	-34.2	-27.04	0.000
Public organization	0.215	0.182	8.3	6.99	0.000
Net monthly income	22585	24360	-12.4	-9.26	0.000
Divorced	0.171	0.201	-8.0	-6.57	0.000
Married	0.522	0.537	-2.9	-2.44	0.015
Partner	0.011	0.011	0.1	0.11	0.910
Single	0.266	0.225	9.0	8.01	0.000
Widow/er	0.020	0.023	-2.1	-1.96	0.050
Living with parents	0.114	0.101	3.9	3.66	0.000
Sharing property	0.028	0.009	10.6	11.53	0.000
Personal property	0.690	0.747	-11.8	-10.63	0.000
Renting	0.148	0.125	6.0	5.61	0.000

Summary of the distribution of |bias|					
	Pseudo R2	LR chi2	p>chi2	MeanB	MedB
	0.089	3488.96	0.000	8.7	5.5

Note: “Treated” and “Control” stands for purpose-loans and non-purpose loans, respectively.

Table 1.A.5: Common support – Default rate estimation

Treatment assignment	Common support		Total
	Off support	On support	
Untreated	0	91 297	91 297
Treated	294	14 160	14 454
Total	294	105 457	105 751

Note: “Treated” and “Control” stands for purpose-loans and non-purpose loans, respectively.

Table 1.A.6: Balancing hypothesis – Interest rate estimation

Application and loan term characteristics	Mean			t-test	
	Treated	Control	%bias	t	p>|t|
Risk-based pricing applied	0.342	0.336	1.2	0.98	0.326
Behavioral score	474.34	478.92	-2.3	-2.00	0.045
Credit bureau score	384.51	381.06	1.3	1.07	0.286
Loan maturity	2.740	2.735	0.8	0.87	0.387
Approved amount (in CZK)	2.717	2.725	-0.9	-1.09	0.276
Age	486.52	488.2	-1.2	-1.11	0.269
Female	0.436	0.444	-1.5	-1.32	0.188
Secondary (general)	0.037	0.037	0.1	0.06	0.950
Post-secondary (technical)	0.020	0.020	0.2	0.17	0.866
Secondary (vocational)	0.470	0.466	0.8	0.71	0.479
Post-secondary (vocational)	0.292	0.301	-1.8	-1.58	0.113
University	0.171	0.167	1.4	1.05	0.293
House wife	0.018	0.017	0.6	0.54	0.589
Pensioner	0.064	0.062	0.7	0.75	0.453
Student	0.001	0.001	0.0	-0.00	1.000
Employment duration (in months)	82.267	84.032	-2.0	-1.62	0.106
Bank/insurance company	0.028	0.028	0.0	0.04	0.972
Entrepreneur	0.023	0.021	1.3	1.13	0.259
Foreign company	0.022	0.021	0.5	0.49	0.624
Private company	0.330	0.333	-0.5	-0.41	0.680
Public organization	0.216	0.219	-0.8	-0.66	0.512
Net monthly income	22467	22253	1.5	1.15	0.250
Divorced	0.171	0.166	1.2	1.05	0.293
Married	0.525	0.529	-0.8	-0.71	0.480
Partner	0.011	0.012	-0.5	-0.38	0.702
Single	0.263	0.258	1.0	0.88	0.377
Widow/er	0.020	0.022	-1.3	-1.26	0.206
Living with parents	0.113	0.112	0.2	0.22	0.823
Sharing property	0.028	0.027	0.5	0.47	0.638
Personal property	0.693	0.690	0.5	0.45	0.656
Renting	0.147	0.149	-0.7	-0.66	0.508

Summary of the distribution of |bias|

	Pseudo R2	LR chi2	p>chi2	MeanB	MedB
	0.001	39.89	0.475	0.9	0.8

Note: “Treated” and “Control” stands for purpose-loans and non-purpose loans, respectively.

Table 1.A.7: Common support – Interest rate estimation

Treatment assignment	Common support		Total
	Off support	On support	
Untreated	0	91 297	91 297
Treated	2	14 452	14 454
Total	2	105 749	105 751

Note: “Treated” and “Control” stands for purpose-loans and non-purpose loans, respectively.

Table 1.A.8: Default rate by loan type

	Default = 30 days overdue		Default = 90 days overdue	
Loan type	No default	Default	No default	Default
Unspecified purpose	94.5%	5.5%	96.0%	4.0%
Specified purpose	98.6%	1.4%	99.2%	0.8%
Total	100 508	5 219	101 983	3 744

Note: Random sample of household loans, data from 2007-2013.

Chapter 2

Does Loan Maturity Matter in Risk-Based Pricing? Evidence from Household Loan Data

2.1 Introduction

Over recent decades, substantial increases in the number of household loans[24] have been observed worldwide. Lending to individuals to finance the purchase of goods or services has become particularly popular in emerging markets. Despite the initial difficulties related to the availability of only minimal credit history on borrowers and pioneering methods used to evaluate the creditworthiness of borrowers, lending institutions instituted extensive provision of household loans. The quantitative

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[24] The European Central Bank defines household loans in the following way: Credit for consumption (loans granted for mainly personal consumption of goods and services) includes loans to sole proprietors/unincorporated partnerships if the loan is predominantly used for personal consumption. Loans included in this category may or may not be collateralized by various forms of security or guarantee. Typical examples of loans in this category are loans granted for the financing of motor vehicles, furniture, domestic appliances and other consumer durables, holiday travel, etc. Loans to cover overdrafts and credit card loans also typically belong in this category. Lending for house purchase is excluded from this category.
Manual on Monetary Financial Institution balance sheet statistics, https://www.ecb.europa.eu/pub/pdf/other/manualmfibalancesheetstatistics201204en.pdf?426543c0dbb56bb78f5afd978b44db17

importance of household loans in emerging markets can be illustrated using the example of the Czech Republic, where between 2000 and 2012 the total volume of household loans rose from CZK 31.1bn to CZK 157.3bn. [25]

The rapid growth of the consumer credit market has drawn increased attention to the asymmetric information present between lenders and borrowers. Stiglitz and Weiss's 1981 paper shows that lenders who are imperfectly informed about the default probability of borrowers (henceforth referred to as a borrower's 'riskiness') may suffer from adverse selection when deciding to grant a loan or not. Adverse selection occurs when, being aware of their own riskiness, "low-risk" borrowers with low probability of default will not be willing to pay increased prices for loans in the form of higher interest rates, while "high-risk" borrowers with a high probability of default will accept them. To minimize this, lenders may choose to deny loans rather than raise interest rates. As the price fails to regain equilibrium in the market, market imperfection appears. Stiglitz and Weiss (1981) define the solution of limiting the amount of credit as credit rationing equilibrium, a situation when certain borrowers are refused funds even if they are willing to pay higher interest rates, as lenders are already maximizing profit. According to Jaffee and Stiglitz (1990) lenders can also react to adverse selection by offering multiple loan contract terms (i.e. loan packages with a distinct loan amount, interest rate and maturity).

Differentiating interest rates based on the borrowers' riskiness (i.e. applying risk-based pricing of interest rates) is one such attempt to mitigate asymmetric information on the household loan market. A number of studies (Edelberg, 2006; Einav, Jenkins, and Levin, 2012) argue that borrowers are highly responsive to interest rate variations. Specifically, they provide evidence that risk-based pricing raises the borrowing costs of "high-risk" applicants'; and hence restricts the level of their debt.

Addressing excess loan demand under imperfect information becomes more important in a loan market where borrowers have liquidity constraints. An individual with liquidity constraints does not have sufficient funds to finance present consumption

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[25] Czech Statistical Office - Statistical Yearbook of the Czech Republic, http://www.czso.cz/csu/.nsf/engpubl/10n1-04-2004

with income that will be accumulated in the future. Adams, Einav, and Levin (2009) show that this inability to reallocate funds over time can result in notable adverse selection (i.e. borrowers with a high probability of default increase their debt amount). Supporting the results of the previous literature, Adams et al. (2009) highlight that risk-based pricing can effectively diminish the severity of the information problem (i.e. “high-risk” borrowers receive lower loan amounts). Nevertheless, in identifying loan demand and loan repayment the authors did not consider an important aspect for borrowers with liquidity constraints, the role of loan maturity.

Although practitioners and policymakers consider interest rates as a key driver of loan demand, the sensitivity of loan demand to maturity might be equally crucial. Estimating the demand elasticity with respect to both interest rate and maturity, Attanasio, Goldberg, and Kyriazidou (2008) and Karlan and Zinman (2008) show that borrowers with low income are more responsive to maturity changes than to interest rate changes. Their finding is consistent with binding liquidity constraints, a situation when borrowers with limited available cash choose longer loan maturity in order to reduce monthly payments, rather than decreased interest rates. The authors shed light on the role of maturity on purchasing behavior; however, limited and inconclusive empirical evidence exists about its implications for loan performance or pricing decisions.

The current paper attempts to fill this gap by estimating loan demand and loan performance jointly and highlighting the implications of maturity choice for screening out risky borrowers. First, I derive the econometric specifications for loan granting and repayment. I use these to estimate the elasticity of loan demand and probability of default with respect to both interest rate and loan maturity. Specifically, I test the null hypothesis that loan interest rate and maturity have no role in loan demand, whether borrowers are liquidity constrained or not. Second, I point out the role of a risk-based maturity setting in decreasing the information asymmetries on the loan market. In particular, I test the null hypothesis that maturity choice after risk-based pricing has no impact on loan default. Third, I show that the time of default is maturity-dependent and differs across borrowers in the different risk categories. The key contribution of this paper is that it shows that by reflecting the borrower’s riskiness in the price of a loan, both loan maturity and loan defaults increase. Specifically, liquidity constrained "high-risk" borrowers are offered high interest rates and most often choose long-term loans. This eventually increases their probability of default. Hence, a risk-based maturity setting does not necessarily improve the quality of household loans granted or alleviate the adverse selection present on the lending market.

This paper utilizes a unique dataset of rejected and accepted household loans from a Czech commercial bank (hereafter, the "Bank").[26] These include loans granted for the purchase of goods and services, loans granted for the modernization/reconstruction of housing and loans without a stated purpose. The unique dataset contains extensive information on borrower application characteristics, loan contract terms, and loan performance information of over 220 000 individuals who applied for a household loan between 2007 and 2013. From January 2012, the Bank has applied risk-based pricing, which is reviewed and developed periodically.

2.2 The Lending Process

Altman (1980) defines the lending process as a sequence of activities involving two principal parties whose association spans from loan application to successful or unsuccessful loan repayment. Figure 2.1 illustrates the five key levels of the lending process.

Level 1

The individual enters the household loan market by submitting an application form for a loan.[27] The borrower discloses information about his/her socio-demographic characteristics such as age, marital status, education, etc. (application characteristics)

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[26] The Bank does not wish to be explicitly identified. The anonymized data is available for replication.

[27] On the household loan market, loan contract terms vary substantially across individual loan providers. Prior to loan application, the borrower has indicative information (for random loan amount and a minimum interest rate offer, each lender publishes a menu of maturities and annuity payments) about the lenders' offer from publicly available marketing materials. When entering the loan application process, the borrower uses this information to decide about his/her preferred loan maturity/amount given liquidity constraints – this requested loan amount and loan maturity can be considered the result of a searching process.

and information related to the requested loan such as the loan amount, loan maturity, etc. (loan term characteristics). The loan maturity is initially set by the applicant and is assumed to be driven by the long-term unemployment incidence of the region where the loan is requested.[28]

Level 2

The lender determines whether to grant the requested loan to the applicant. In order to assess the creditworthiness of their potential debtors, financial institutions use credit scoring techniques. The main purpose of these techniques is to estimate the probability that an applicant for credit will default by a given time in the future.[29] In its credit scoring model, the Bank estimates the default probability using 3 types of credit scores: behavioral score (derived from the applicant's repayment history), application score (derived from the applicant's descriptive socio-demographic characteristics) and credit bureau score (derived from information about the applicant's existing and prior debt). Using these scores the bank assigns each applicant a risk band (four groups of "very low-risk", "low-risk", "high-risk" and "very high-risk" borrowers). If the applicant's loan is pre-accepted (based on his/her aggregate credit score), the lender then assigns an interest rate for the requested loan maturity/amount. The interest rate is set primarily by the lender.[30] The lender offers loan contract terms that maximize its expected profit (taking into account the expected profit from an alternative investment of the loan amount). The interest rate is assumed to be driven by the applicant's risk margin, which is the price for the riskiness of the borrower and reflects the lender's risk aversion at the time of the loan request.

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[28] The change of loan maturity is subject to a new loan application.

[29] These are evaluated by analyzing a sample of customers who applied for loans in the past, where there is good information on subsequent loan performance history.

[30] The assumption that loan maturity is primarily set by the borrower and the approved loan amount/interest rate is set primarily by the lender is made based on the Bank's best practice applied in the household loan market. It is also in line with the related literature. In Karlan and Zinman (2008) the lender identifies the loan price based on the borrower's pre-approved riskiness; and Attanasio et al. (2008) argue that credit-constrained borrowers' loan maturity is driven by their liquidity.

Level 3

Given the approved loan amount, interest rate and maturity the applicant has a chance to accept (open the account) or reject the loan contract conditions (no loan is originated). The borrower's decision is driven by his/her risk awareness and by the amount of monthly annuity payment (especially if the applicant is liquidity constrained). A loan is considered to be approved if it is approved by both the lender and the applicant. A loan is considered to be rejected if it is rejected by either the lender or the applicant.

Level 4

Given that the lender and the borrower agree on loan contract terms[31] and the borrower is granted the loan, the borrower starts repaying the principal and interest in the form of monthly annuity payments. The borrower can either follow the agreed repayment schedule, or renegotiate the loan contract terms (e.g. early repayment).[32]

Level 5

The borrower either fully repays the loan or defaults. The borrower is considered to be in default if he/she is more than 90 days overdue with any payment connected with the loan.

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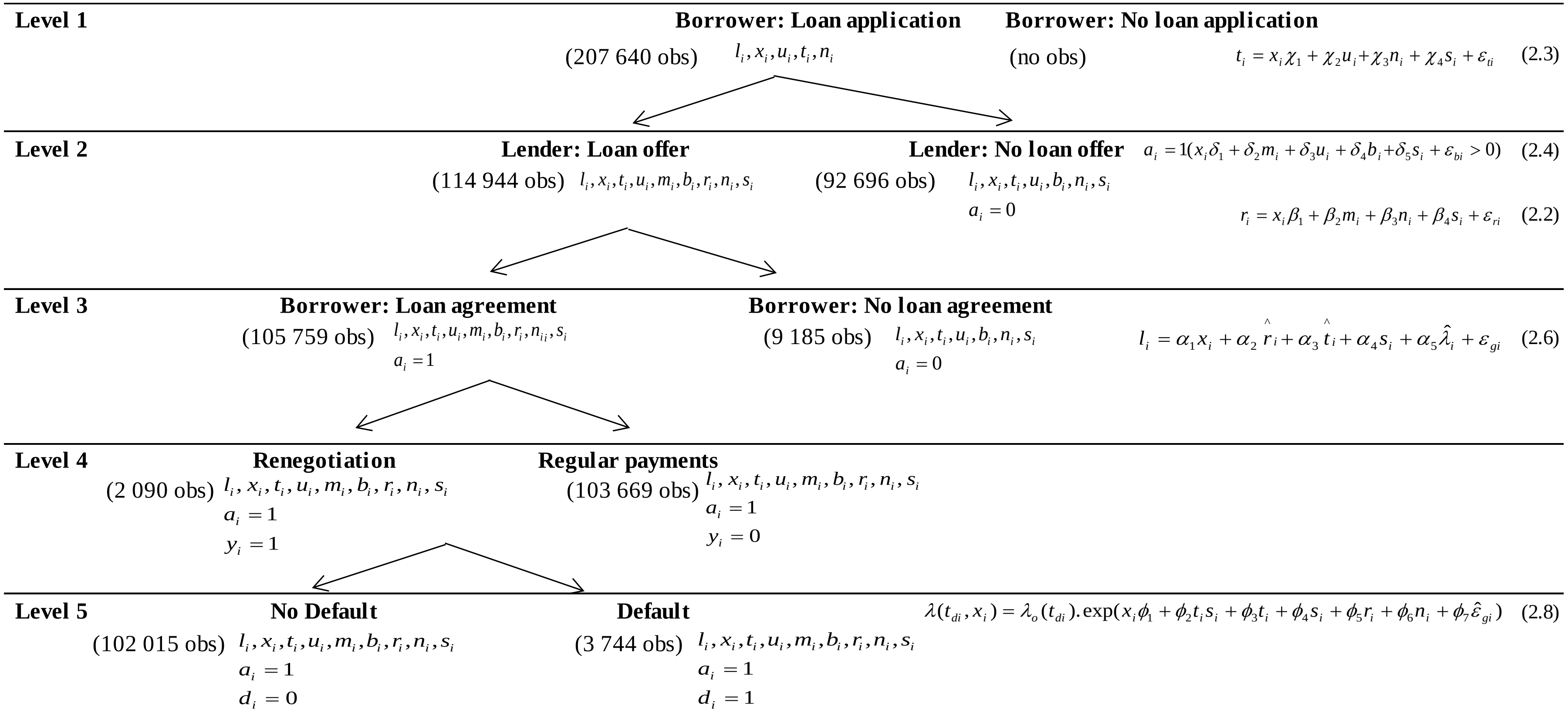
[31] The final loan contract terms are determined by the relative risk aversion across the borrower and the lender. The Bank's lending process is designed such that the lender reflects his/her risk aversion primarily through interest rate level and the borrower reflects its risk aversion primarily through maturity choice. In line with Adams et al. (2009) I assume that the competitive outcome is the contract that maximizes the borrowers' utility subject to lenders making non-negative profits.

[32] Early repayment might be more likely for "high-risk" borrowers, since they can have then better credit after successful payments. However, early repayment is connected with additional borrowing costs in the form of a prepayment penalty.

Figure 2.1: The lending process and data availability



Note: Author's illustration of the lending process based on the description of the Bank. For loan request *i* the following information is available: l_i - loan amount, r_i - loan interest rate, t_i - loan maturity, x_i - the borrower's application characteristics, n_i - the region in which is loan is requested, u_i - the region's long-term unemployment incidence, a_i - approved loan, b_i - number of debtors registered at the Czech Banking Credit Bureau at the time of loan request, m_i - risk margin, y_i - dummy for risk-based pricing, y_i - dummy for renegotiated loan, d_i - dummy for default, t_{di} - months until default. The individual equations of the econometric specification are described in Section 1.3 Methodology.

2.3 Methodology

Overall, the main objective of this paper is to develop an econometric model that demonstrates the role of risk-based pricing and loan maturity on a consumer credit market with asymmetric information. I start by estimating the loan demand elasticity with respect to maturity and interest rate. Then I highlight the time dependency of default and examine the maturity specific factors of loan performance.

The expected impact of selected variables and the predictions of the related literature are summarized in Table 2.A.1 in the Appendix.

2.3.1 Modeling Loan Demand

The loan demand estimation is complicated by the endogeneity of loan contract terms and sample selection (the non-random character) present in the household loan data. These can cause the parameter estimates to be biased. This section discusses how this paper deals with these two key issues in the loan demand estimation.

Loan Interest Rate

Interest rate endogeneity arises as lenders can change the loan price based on loan demand, and vice versa, the borrower can adjust his/her loan demand based on offered interest rates. In setting the price, the profit-maximizing lender aims to increase the interest rate, whereas the borrower aims to receive a loan at the lowest possible rate.

The literature deals with the endogeneity of interest rates in different ways. In Alessie, Weber, and Hochguertel (2005), the Italian usury law of 1997 (which limited interest rate charges) is used as an instrument for the identification of endogenous interest rate in loan demand estimation. The authors find evidence for the interest-rate elasticity of loan demand and argue that it is region specific. In Attanasio et al. (2008), the endogeneity of loan interest rate is addressed by exploiting data on the U.S. tax reform of 1986 (the change in interest deductibility affected the after-tax interest rate on the household loan market). Adams et al. (2009) identify loan demand on the car loan market by exploiting variation in list prices (i.e. catalogue car prices that differ from negotiated prices) and variation in the level of down payments.

Similarly to Karlan and Zinman (2008), this paper captures the variation in the interest rate by information on the applicant's risk category. Applicants are classified into risk bands based on their estimated riskiness. These bands are then translated into risk margins taking into account the (conservative or aggressive) loan granting strategy of the lender. The higher the lender's risk aversion, the higher the risk margin and the final loan interest rate. I assume that the lender sets the final interest rate based on the loan's risk margin (the lender's willingness to accept the expected risk of the borrower). The interest margin has no effect on the loan amount, as the borrower is not aware of the lender's (frequently changing) loan granting strategy when setting its preferences aiming to smooth consumption.

Loan Maturity

Endogeneity of maturity is a further issue if the borrower cares primarily about monthly borrowing costs rather than the ultimate price of the loan. If the borrower is credit constrained and offered monthly payments (as result of maturity chosen by the borrower and interest rate set by the lender) that s/he cannot afford, s/he can either apply for a lower loan amount (which might decrease the interest rate) or prolong the maturity of the initially requested loan (accepting the initial interest rate). I assume that setting loan maturity is primarily the decision of the borrower, who aims to decrease the cost of lending by choosing shorter loans. S/he is willing to prolong the length of the loan only to such an extent that the decreased monthly payments are acceptable for her expected future financial resources. The lender aims to prolong the loan maturity, as this is associated with higher interest income, while the higher riskiness of the borrower is implicitly reflected in the interest rate. It is questionable how successful the lender is in transferring the riskiness of borrower into the loan price or how significant the adverse selection is on the market. I discuss this issue in more detail in the next section.

The majority of studies neglect the effect of loan maturity on loan demand (Edelberg, 2006; Adams et al., 2009), and only limited empirical literature focuses on the role of loan maturity in borrowing behavior. In Attanasio et al. (2008) the endogeneity of loan maturity is addressed by using data on the increased durability of cars (due to slower car depreciation, the maturity of loans is prolonged). Karlan and Zinman (2008) cooperate with the lender to generate exogenous variation in loan maturity. Specifically, randomly assigned "maturity suggestions" (loan offers for different maturities) are used to identify the elasticity of loan demand with respect to maturity. The randomized trial was conducted by a microfinance institution in South Africa.

To identify loan maturity in the loan demand equation, this paper utilizes data on the region's unemployment duration. Specifically, I follow Jurajda and Munich (2002) and use the long-term unemployment incidence (hereafter, the "LTU incidence") as a measure of unemployment duration. The LTU incidence is defined as the share of persons unemployed for 12 months or more in the total number of unemployed persons, expressed as a percentage.[33] There are two reasons to use LTU incidence as a measure of unemployment duration. First, as opposed to the LTU rate (the share of the number of long-term unemployed to the size of the labor force), the definition of LTU incidence is more transparent in transition countries where the concept of labor-force participation has been adopted gradually. Second, LTU incidence allows a researcher to capture the specifics of the business cycle (during recession it first declines driven by the increase in short-term unemployed workers, then it rises driven by the difficulty of the short-term unemployed to find employment) with the required regional granularity.

Several studies emphasize the role of unemployment in determining the duration of household loans. Navratil (1981) is the first to highlight that in periods of high unemployment rates, the short-term lending for auto loans is likely to increase, thus decreasing loan maturity. A contrary finding is provided by the more recent paper by Chetty (2008), who shows that for the unemployed, the welfare gains of longer loans are much higher than the welfare gains of shorter loans. In particular, by prolonging the loan maturity, borrowers can decrease the monthly repayment amount and overcome

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[33] Eurostat, http://epp.eurostat.ec.europa.eu/tgm/table.do?tab=table&init=1&plugin=1&language=en&pcode=tgs00053

financial difficulties during longer periods of unemployment. Attanasio et al. (2008) and Stephens (2008) argue that liquidity constraints determine the length of loans.

Motivated by the above studies, this paper utilizes the incidence of regional unemployment for the identification of loan maturity. Higher unemployment is expected to prolong household loans, as obtaining loans with longer maturity enables borrowers to take precautions against the risk of a long period of unemployment. On the other hand, the region's long-term unemployment incidence does not influence the number of loans requested, because the requested loan is primarily the result of the borrower's preferences about smoothing his/her consumption. If the borrower prefers to borrow some amount (rather than to save over a period of time for an expenditure), s/he is not discouraged from borrowing because s/he lives in a region which has experienced an increase in its long-term unemployment incidence. What s/he primarily cares about in such a region are favorable loan contract terms.

Sample Selection

Sample selection arises for two reasons:

1) no information is available on those who did not wish to borrow;
2) information on rejected applicants is limited - loan contract terms are available only for those who were approved for a loan.

The related empirical literature acknowledges the difficulties in correcting for sample selection on the household loan market. Alessie et al. (2005) accept that the sample selection cannot be corrected, using Heckman's (1979) model, as the authors fail to find a variable that predicts loan approval but does not influence loan demand. They assume that a bank with a leading market position attracts applicants with good repayment behavior. Their solution is to estimate loan demand by controlling for the observable characteristics of the borrowers. Specifically, Alessie et al. (2005) correct for the composition effect connected to observable characteristics by p-score weighting the individual observations. Using data on auto loans, Attanasio et al. (2008) correct the sample selection in the loan demand equation through characteristics that have impact on buying a car, but do not necessarily affect loan amount (e.g. dummy for car ownership).

In line with the literature, this paper could not account for individuals who did not apply for a loan. I assume that the probability that an individual will apply for a loan has no endogenous effect on the probability of default. An individual can apply for a loan regardless of his/her expectation of the default probability it will be granted, as credit bureaus collect only information on borrowers who were eventually provided a loan.[34] If a potential borrower is rejected by the credit scoring evaluation, this is recorded in the credit bureau system for a maximum of 12 months. Thus, unless the customer has a bad loan repayment/default history connected with a previously provided loan, being rejected has no direct impact on the quality of his future loans after 12 months. In such cases, the probability of being accepted is equal in all institutions with no rejection history. The only cost implied by loan application is the time cost.

On the other hand, this paper does take into account the limited information on those who applied, but did not ultimately sign the loan contract. This includes both cases when the Bank rejects the applicant or when the applicant does not accept the loan contract terms offered by the Bank. To solve this problem of missing data on rejected loans, I follow Heckman (1979) and first estimate the selection equation on the whole sample of applicants. Similarly to Haas, Ferreira, and Taci (2010) and Bicakova, Prelcova, and Pasalicova (2010), the level of information-sharing about the borrowers' indebtedness is used to capture the variation in loan approval. Specifically, in this paper the exclusion restriction for the selection equation is the number of debtors monitored by the Czech Banking Credit Bureau. Over the past ten years, the credit bureaus have achieved substantial development both in the quality of information and the coverage of debt in the financial sector. This allows the use of information about a varying number of debtors to identify loan approval. The more positive information that is available about the debt level of a borrower, the more likely it is that the borrower is reliable and will maintain regular monthly loan repayments. At the same time, the borrower's decision about the requested loan amount is independent of developments in credit

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[34] The CBCB - Czech Banking Credit Bureau was established in 2002 for the purpose of operating the Client Information Bank Register (CIBR). It contains data on contractual (loan) relations between banks and their clients

bureau information. His/her available credit history affects the decision of the prospective borrower to apply for a loan rather than the amount he/she applies for.

Model Specification

I specify the borrower's loan demand with respect to interest rate and maturity by the following econometric specification:

$$l_i = \log(L_i) = x_i\alpha_1 + \alpha_2 r_i + \alpha_3 t_i + \alpha_4 s_i + \varepsilon_{li}\,, \tag{2.1}$$

$$r_i = x_i\beta_1 + \beta_2 m_i + \beta_3 n_i + \beta_4 s_i + \varepsilon_{ri}\,, \tag{2.2}$$

$$t_i = x_i\chi_1 + \chi_2 u_i + \chi_3 n_i + \chi_4 s_i + \varepsilon_{ti}\,, \tag{2.3}$$

where for each loan application *i* = 1…N the following is known: L_i is the approved loan amount (takes logarithmic form as loans are non-negative) , x_i is the vector of the information on application characteristics, behavioral and credit bureau score; r_i is the loan interest rate set primarily by the lender, t_i is the loan maturity set primarily by the borrower, m_i is the borrower's risk margin, u_i is the long-term unemployment incidence in the borrower's region, n_i is the region where the application *I* was submitted to the lender, s_i is a dummy for risk-based pricing introduced by the Bank in January 2012; and $\varepsilon_{ri}, \varepsilon_{ti}, \varepsilon_{li}$ are the unobserved error terms. Consequently, using a loan repayment schedule with equal total payments, the lender charges the borrower a monthly annuity payment of $p_i(L_i) = (L_i * r_i)/(1-(1+r_i)^{-t_i})$.

To jointly account for both endogeneity and sample selection, I extend the sample selection model for endogenous explanatory variables suggested by Wooldridge (2002) and estimate the structural equation of interest (2.1) together with the two equations describing the endogenous interest rate (2.2) and maturity (2.3), and the selection equation (2.4):

$$a_i = 1(x_i\delta_1 + \delta_2 m_i + \delta_3 u_i + \delta_4 b_i + \delta_5 s_i + \varepsilon_{bi} > 0) \tag{2.4}$$

where a_i is a binary variable indicating whether the loan is accepted $(a_i = 1)$ or rejected $(a_i = 0)$ either by the borrower or the lender, m_i is the borrower's risk margin, u_i is the long-term unemployment incidence in the borrower's region, b_i is the number of debtors registered at the Czech Banking Credit Bureau at the time of the loan request and ε_{bi} is the unobserved error term.

The following assumptions are made:

(a) $(x_i, n_i, m_i, u_i, b_i, s_i)$ is always observed, (l_i, r_i, t_i) is observed when $a_i = 1$;

(b) $(\varepsilon_{li}, \varepsilon_{bi})$ is independent of $(x_i, n_i, m_i, u_i, b_i, s_i)$;

(c) ε_b ~ Normal (0, 1);

(d) $\mathrm{E}(\varepsilon_{li} \mid \varepsilon_{bi}) = \gamma_4 \varepsilon_{bi}$;

(e) $\mathrm{E}(z_1' \varepsilon_{ri}) = 0$ (where $z_1\beta = x_i\beta_1 + \beta_2 m_i + \beta_3 n_i + \beta_4 s_i$) and $\beta_2 \neq 0$;

$\mathrm{E}(z_2' \varepsilon_{ti}) = 0$ (where $z_2\chi = x_i\chi_1 + \chi_2 u_i + \chi_3 n_i + \chi_4 s_i$) and $\chi_2 \neq 0$.

Assumption (a) emphasizes the non-random nature of the sample. The exogeneity of application characteristics x_i and the two exogenous variables m_i, u_i is formalized by assumption (b). Assumption (c) states that the error term of the selection equation follows standard normal distribution. Linearity in the regression of ε_{li} on ε_{bi} is required by assumption (d). Lastly, assumption (e) results from the endogeneity of loan contract terms in the loan demand equation (2.1). It states that (i) the error terms $\varepsilon_{ri}, \varepsilon_{ti}$ have zero mean and are uncorrelated with the right-hand-side variables, and (ii), (β_2, χ_2) are non-zero, requiring that at least two exogenous variables (m_i, u_i) do not appear in the loan demand equation (the order condition). Under this assumption the parameters β_2 and χ_2 are identified.

The derived estimating equation has the following form:

$$l_i = \alpha_1 x_i + \alpha_2 r_i + \alpha_3 t_i + \alpha_4 s_i + g(x_i, n_i, m_i, u_i, b_i, s_i, a_i) + \varepsilon_{gi}, \qquad (2.5)$$

where $g(x_i, m_i, n_i, u_i, b_i, s_i, a_i) \equiv \mathrm{E}(\varepsilon_{li} \mid x_i, n_i, m_i, u_i, b_i, s_i, a_i)$ and $\varepsilon_{gi} \equiv \varepsilon_{li} - \mathrm{E}(\varepsilon_{li} | x_i, n_i, m_i, u_i, b_i, s_i, a_i)$. By definition the error term is uncorrelated with the exogenous variables: $\mathrm{E}(\varepsilon_{gi} \mid x_i, n_i, m_i, u_i, b_i, s_i, a_i) = 0$. Equation (2.5) is estimated by 3SLS on the sample of accepted loan applications $(a_i = 1)$ using the exogenous variables and the estimated inverse Mills ratio, where $\mathrm{E}(\varepsilon_{li} \mid x_i, m_i, u_i, b_i, s_i, a_i = 1) = \alpha_4 \lambda(x_i \delta_1 + \delta_2 m_i + \delta_3 u_i + \delta_4 b_i + \delta_5 s_i)$.

Specifically, the estimation is performed in two steps. First, using all observations the selection equation is estimated by probit and the estimated inverse Mills ratio $\overset{\wedge}{\lambda}_i$ is obtained. Second, using the subsample for which both (r_i, t_i) are observed, the equation

$$l_i = \alpha_1 x_i + \alpha_2 \hat{r}_i + \alpha_3 \hat{t}_i + \alpha_4 s_i + \alpha_5 \hat{\lambda}_i + \varepsilon_{gi} \tag{2.6}$$

is estimated by 3SLS, using the exogenous variables $(m_i, u_i, b_i, \overset{\wedge}{\lambda}_i)$.[35] In particular, I test the null hypothesis that interest rate and loan maturity have no effect on the approved loan amount: $(H_0 : \alpha_2 = 0)$ and $(H_0 : \alpha_3 = 0)$. The sensitivity of loan demand to loan contract terms is estimated both on the pooled sample (including all observations) and on the subsample of low-income borrowers (liquidity constrained borrowers[36] whose net monthly income at the time of loan application is below the sample's median net monthly income). Finally, the null hypothesis of no selection bias $(\mathrm{H}_0 : \alpha_5 = 0)$ is tested by exploiting the 3SLS t statistic for $\hat{\alpha}_5$; and the null hypothesis of no endogeneity is tested by estimating the structural model (2.1) that includes the residuals from the two equations describing the endogenous interest rate (2.2) and maturity (2.3).

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[35] The sample selection correction is also present in the equations for interest rate (2.2) and maturity (2.3) as these are estimated on approved loans.

[36] Borrowers with liquidity constrains cannot be easily identified. This paper utilizes the approach of Attanasio et al. (2008) who assume that low-income borrowers are liquidity constrained borrowers.

2.3.2 Modeling Default Probability

The goal of this section is to propose an econometric model that uses demand estimates for predicting default probability. The model should reflect how the different loan contract terms influencing consumer behavior affect the loan performance. Specifically, I focus on the time dependency of default (the length of time the borrower avoided default has an impact on the probability of default) and test for the significance of asymmetric information hidden in the maturity choice.[37]

To do this, I take advantage of the semi-parametric proportional hazard model, which relates the individual covariates and the time of event (or failure, as I refer to default) occurrence in multiplicate form. If $\lambda(t_{di}, x_i)$ is the probability that an individual defaults at time t_{di} (conditional on making regular payments until default), x_i are application characteristics, the relationship between the distribution of failure times and the vector of application characteristics can be expressed by the semi-parametric proportional hazard model developed by Cox (1972) as

$$\lambda(t_{di}, x_i) = \lambda_o(t_{di}).\exp(x_i\phi_1 + \phi_2 s_i y_i + \phi_3 t_i + \phi_4 s_i + \phi_5 r_i + \phi_6 n_i + \phi_7 y_i), \qquad (2.7)$$

where s_i is a dummy variable taking the value 1 if the application was evaluated using risk-based pricing, and y_i is a dummy variable taking the value 1 if the application renegotiated ex post. The advantage of proportional hazard models is that whereas parametric models use information over the whole time horizon (distributional assumption for baseline hazard $\lambda_0(t_{di})$; estimation of the cumulative hazard), semi-

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[37] Flannery (1986), Diamond (1991) and Berger, Espinosa-Vega, Frame, and Miller (2005) were the first to suggest that the size of asymmetric information between lenders and borrowers can significantly affect the choice of loan maturity. They focused on commercial and industrial loans.

parametric models use only the information at failure times (no distributional assumption for baseline hazard; estimation of the direct hazard).

The incomplete information on the occurrence of events during the observation period belongs among the specifics of duration time estimation. As the information about the loan performance after the end of the observation period is missing, I deal with right censored data. There are three possibilities of the event status: the event occurred by t_{di}^{*} (duration time), the event did not occur by the end of observation period or the event did not occur before loan completion (t_c). For each individual one observes t_{di}, where $t_{di} = \min(t_{di}^{*}, t_c)$.

Loan amount and default jointly are modelled jointly: [38]

$$\lambda(t_{di}, x_i) = \lambda_o(t_{di}).\exp(x_i\phi_1 + \phi_2 t_i s_i + \phi_3 t_i + \phi_4 s_i + \phi_5 r_i + \phi_6 n_i + \phi_7 \hat{\varepsilon}_{gi}), \qquad (2.8)$$

I test the null hypothesis that loan maturity choice after risk-based pricing has no impact on the loan default; formally I test $H_0 : \phi_2 = 0$. Similarly to Adams et al. (2009), the identification is through the two-stage control function approach – to estimate the loan default, the estimated residual $\hat{\varepsilon}_{gi}$ from loan demand estimation is used as a control variable. The main goal is to identify the borrowers' private information at the time of loan application that affects both loan amount and loan default. The models for loan demand (2.6) and the default probability (2.8) are also estimated for short-, medium- and long-term loans[39] and across borrowers in the different risk categories.

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[38] In line with Adams et al. (2009), the hazard model does not control for general macroeconomic conditions, as the loan amount and default are modeled jointly. Loan demand is assumed to reflect the macroeconomic development, as it is likely to decrease during recessions and grow during booms.

[39] Glennon and Nigro (2005) argue that the determinants of default are maturity-specific.

2.4 Data

2.4.1 Data Description

The data sample consists of the household loan information of over 220 000 individuals. The dataset includes application characteristics (e.g. age, marital status, education, etc.), loan contract information (e.g. interest rate, loan maturity, loan amount, etc.) and performance indicators (e.g. date of default, monthly outstanding balance, overdue payments, etc.). The consumers requested the loans between 2007 and 2013[40], where the last performance observation is from April 2013. Table 2.A.2 in the Appendix summarizes the list of available information on household loans. Table 2.A.3 in the Appendix, reporting the basic descriptive statistics, suggests that an average borrower is 40 years old, receives a net monthly income above CZK 17 000 and has been employed for more than 5 years.

In order to measure the performance of the loans, monthly data on repayment status are used. For each loan, one piece of the following information is available: the number of the months until default, the number of months until on-time repayment or the number of months until the end of the data observation interval (April 2013). That is, each loan has its survival time: either time to default or time to non-default (being repaid or censored data). This enables a more precise estimation of default, as the number of successful payments until default is also taken into account.

When monitored on 30th April 2013, 3.6% of those who had obtained a loan had defaulted and the rest of the borrowers had performed well. Although there are several different definitions of “defaulted” loans, the one of the Basel Committee on Banking Supervision (2004) is applied: a loan is in default if the borrower is more than 90 days overdue with any payment connected with the loan.

Rejected loans comprise 48.9% of the total number of household loans. These include those applications that were either rejected by the lender (due to application

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[40] The dataset differentiates between the date of loan request and loan opening. Year dummies are created based on the loan request date at which the Bank decided to accept or reject the applicant.

characteristics or credit history) or the borrower (due to unfavorable loan terms offered by the lender). Figure 2.1 illustrates the number of rejected loans by the lender (92 696 loans) and by the borrower (9 185 loans). Rejection by the borrower is not identified separately, as 90% of the applicants are rejected based on the information gained from the credit bureau.

In addition to information on interest rate, data on risk margin are also limited. Risk margin is observed only after risk-based pricing is implemented (January 2012). I solve this issue by multiple imputation (similar to Adams et al. 2009). For each approved loan application prior to January 2012, the missing risk margin is replaced with predicted values from a regression analysis of the complete data. The development of risk margin over the observation period is summarized in Table 2.A.4 in the Appendix. The sample statistics indicate that there is a gradual increase in the risk margin and lenders requested the highest risk margin during 2012.

The household loan data utilized in this paper is application-specific – for one application I observe only one outcome (loan contract terms, loan performance) and the change of loan contract terms is subject to a new unidentified loan application. Renegotiated loans were first signed with initial loan contract terms, and then during the loan repayment period the loan contract terms were renegotiated. As information on the renegotiated interest rates is not available, renegotiated loans cannot be used to study the incidence of change in loan maturity before and after the introduction of risk-based pricing.

Figure 2.1 summarizes how the data availability differs over the individual levels of lending process.

2.4.2 Data Analysis

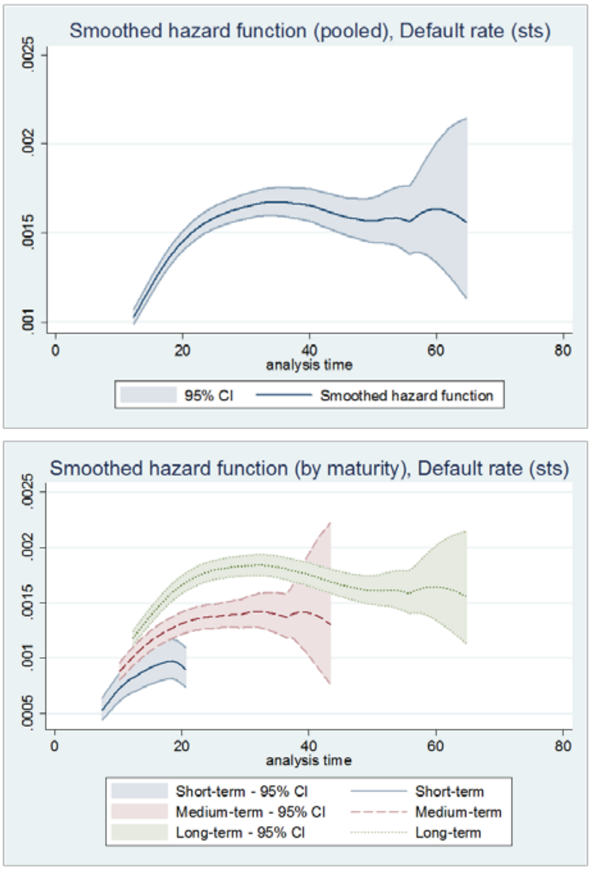
Although there are several estimation techniques of the survival functions, non-parametric methods are very useful for descriptive purposes in the first place. They illustrate the shape of the unconditional hazard and survival functions before introducing the covariates into the model. Specifically, the survivor and the hazard functions are easily interpretable and effective in describing the duration dependence.

Figure 2.A.1 in the Appendix depicts the cumulative hazard function (with 95% confidence intervals) estimated by the Nelson-Aalen method. It suggests that at the end of the household loan observation period, almost 90% of the sample remained without default. Figure 2.2 plots the estimated hazard rate (with 95% confidence intervals), which expresses the instantaneous probability of default conditional on making regular payments until a particular month during the time under analysis. According to the smoothed hazard function that treats all household loans equally and does not distinguish between maturity or risk bands (‘pooled’), defaults are most likely to occur around the 30th month from the date of loan provision. On the other hand, the smoothed hazard function by maturity suggests that default is not only time-dependent, but also maturity dependent.

Table 2.1 presents the preliminary sample statistics of average maturity (Panel A) and average default rate (Panel B) before/after the introduction of risk-based pricing. Due to the limited observation period after the introduction of risk-based pricing (January 2012), the before/after periods are represented only by one year (2011/2012). After the introduction of risk-based pricing, borrowers in all risk bands increase their average loan duration, but the “very high-risk” group remains almost unchanged. This is mostly likely driven by the low number of observations in the “very high-risk” group. The statistics from Table 2.1 (Panel A) are in line with Karlan and Zinman (2008), who show that by longer maturity the borrower can lower the amount of monthly payments and, hence, afford a higher loan amount. Panel B summarizes the observed average default rate for risk bands and loans with different maturities. One year before the introduction of risk-based pricing, “very high-risk” borrowers with medium-term loans (2-year to 5-year) have the highest incidence of default. One year after the introduction of risk-based pricing, borrowers with long-term loans (more than 5-year) default the most frequently.

Hence, the main focus of this paper is whether banks applying risk-based pricing are able to decrease the adverse selection (i.e. borrowers with high probability of default increase their debt amount) for liquidity constrained borrowers who are more sensitive to maturity changes (relative to interest rate changes).

Figure 2.2: Smoothed hazard function pooled and by maturity



Note: (1) The figure on the left depicts pooled data, i.e. treats all household loans equally and does not distinguish between maturity or risk bands. (2) The figure on the right depicts smoothed hazard functions for short-term loans with maturity up to 2 years, medium-term loans with maturity between 2 and 5 years and long-term loans with maturity more than 5 years.

Table 2.1: Sample statistics on before/after risk-based pricing

Panel A - Average maturity

	Average loan maturity		Number of observations	
Risk band	Before risk-based pricing	After risk-based pricing	Before risk-based pricing	After risk-based pricing
Very low-risk	4.4	4.6	8 667	9 902
Low-risk	4.5	4.7	6 443	6 624
High-risk	4.1	4.2	1 450	1 580
Very high-risk	3.5	3.5	551	454
Total	4.4	4.5	17 111	18 560

Panel B - Average default rate

Risk band	Before risk-based pricing	After risk-based pricing
Very low-risk	0.6%	0.1%
<2Y	0.1%	0.0%
2Y-5Y	0.4%	0.1%
>5Y	1.0%	0.2%
Low-risk	1.8%	0.4%
<2Y	1.0%	0.3%
2Y-5Y	1.8%	0.4%
>5Y	2.1%	0.4%
High-risk	3.9%	1.3%
<2Y	2.9%	1.0%
2Y-5Y	4.0%	1.3%
>5Y	4.2%	1.3%
Very high-risk	5.3%	4.0%
<2Y	3.1%	2.9%
2Y-5Y	6.2%	3.3%
>5Y	5.2%	6.4%
Total	1.5%	0.4%

Note: (1) The Bank classifies borrowers into risk bands based on the estimated riskiness. (2) Before risk-based pricing is represented by year 2011, and after risk-based pricing is represented by year 2012.

2.5 Results

This section starts with the estimation of the loan demand model that accounts for both the presence of sample selection and the issue of endogeneity. Then I discuss the estimates of default probability derived from the Cox proportional hazard model and highlight the implications of risk-based pricing on the quality of granted loans, i.e. on the probability of default. Both loan demand and loan performance are examined with respect to loan contract terms and with respect to the borrower's application characteristics. Finally, I illustrate the maturity-dependent default probability for borrowers in the different risk categories.

2.5.1 The Elasticity of Loan Demand to Interest Rate and Maturity

First, I correct for the non-random feature of the data, by estimating the probability of loan approval based on selection equation (2.6).[41] The non-random issue of the sample arises as there is no information available on those individuals who do not apply for a loan and limited information on those who apply but do not sign the loan contract. Therefore, I estimate the Heckman (1979) selection model that corrects for this type of incomplete information. The number of individuals monitored in the Czech Banking Credit Bureau at the time of loan application is used as an exclusion restriction.

Second, using the estimated inverse Mills ratio from the Heckman (1979) model I estimate the loan demand equation (2.1) with the two equations describing the endogenous interest rate (2.2) and loan maturity (2.3). The three equations are estimated using 3SLS, where the two exclusion restrictions are the borrower's risk margin and the average long-term unemployment incidence in the borrower's region.

I reject the null hypothesis that loan interest rate and maturity have no role in loan demand (Table 2.2). Consistent with Alessie et al. (2005), the results suggest that

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[41] I follow the variable (non-)categorization of the Bank. In all models the variables are used in the same manner as they enter the Bank's credit scoring model. The individual estimates refer to indicated changes in the dependent variable due to a change in the particular application characteristic compared to its reference group.

increasing interest rates discourage individuals from borrowing (loan demand decreases), whereas with longer maturity the loan amount increases (similar to Attanasio et al.’s 2008 study).

The test results suggest that both the null hypothesis of no-sample-selection and the null hypothesis of no-endogeneity can be rejected at 1%. First, I use the t statistic on the inverse Mills ratio (variable INVMILLS) as a test for the presence of sample selection $\mathrm{H}_0 : \alpha_4 = 0$. The z-value of 15.6 is strong evidence against the null hypothesis of no-sample-selection (Table 2.2, Column 2). Second, I test the endogeneity of interest rate and maturity jointly. Specifically, for both endogenous variables I obtain the reduced form residuals, and then I test the joint significance of these residuals in the structural equation using an F test. The F (2, 105723) being equal to 188.8 is well above the 1% critical value in the F distribution, so I reject the null hypothesis that interest rate and loan maturity have no effect on the approved loan amount. In addition, I reject the null hypothesis that risk margin has no effect on the loan interest rate (at 1% significance level) or that LTU incidence has no effect on the loan maturity (at 5% significance level). One percentage point increase in the risk margin leads to a 0.3 percentage point increase in the interest rate (similar to Karlan and Zinman’s2008 findings); and a one-year increase in the region’s long-term unemployment leads to a 0.4-year increase in the loan maturity rate (similar to Chetty’s 2008 findings).

In Table 2.2, I also compare the interest rate and maturity elasticity of loan demand for the pooled sample (Column 2) and for the subsample of low-income borrowers (Column 4). The results suggest that the loan amount of a low-income borrower increases with longer maturity (a one-month increase in the loan maturity results in a 2.1% increase in the loan amount), while the interest rate has statistically no significant effect for these borrowers. The increasing importance of loan maturity for low-income borrowers is in line with Karlan and Zinman’s 2008 findings. However, this paper goes further and uses the maturity elastic demand estimates to see the probability of default they imply (see the details in the next section).

Table 2.A.5 in the Appendix summarizes how the borrower’s application characteristics affect loan demand. The parameter estimates have the expected signs. If focusing on low-income borrowers, the results suggest that women, pensioners, students

Table 2.2: Estimation results of loan demand and default probability

Dependent variable	Loan demand		Default probability	
	Pooled sample	Low-income subsample	Pooled sample	Low-income subsample
	Coef.	Coef.	Haz. ratio	Haz. ratio
Interest rate	-0.035***	0.003	1.172***	1.084***
	(0.004)	(0.006)	(0.010)	(0.017)
Approved maturity	0.015***	0.021***	1.004***	1.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Credit bureau score	0.001***	-0.001***	0.999***	0.999***
	(0.000)	(0.001)	(0.001)	(0.000)
Behavioral score	0.001***	0.001***	0.998***	0.998***
	(0.000)	(0.001)	(0.001)	(0.000)
Inverse Mills ratio	0.326***	0.013		
	(0.028)	(0.037)		
Risk-based pricing	0.060***	0.020**	0.442***	0.328**
	(0.005)	(0.008)	(0.127)	(0.164)
Renegotiated loan			6.020***	6.671***
			(0.294)	(0.415)
Approved maturity *Risk-based pricing			1.009**	1.013
			(0.004)	(0.008)
Loan demand residual			0.819***	0.793***
			(0.024)	(0.032)
R^2	0.5093	0.4639		
N	105 759	46 598	105 759	46 598
Log likelihood			-38 221	-20 223
Prob> chi2			0.000	0.000
Loglikelihood ratio (LR) chi2			4 858	2 639

Note: (1) For loan demand estimation the logarithmic form of approved loan amount is used. (2) Estimation results presented only for variables that were statistically significant at least in one model. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parenthesis.

and borrowers who rent housing borrow less. Interestingly, married borrowers, with a university education who are employed in a banking/insurance company have the higher loan demand. The results are qualitatively comparable to the loan demand determinants derived by Attanasio et al. (2008) and Adams et al. (2009).

2.5.2 The Impact of Risk-Based Pricing on Loan Performance

The borrower's probability of default is estimated on the loan contract term and the borrower's application characteristics using the Cox proportional hazard model. In addition to the loan and application characteristics, the estimated residual from the loan demand equation is included in the model as a control variable. Table 2.2 summarizes the estimation results (hazard rates) for the pooled sample (Column 6) and for the subsample of low-income borrowers (Column 8). The Cox partial likelihood model provides a semi-parametric specification for the relationship between hazard rates and the application characteristics.[42] Column 6 and Column 8 in Table 2.2 quantify the hazard rate, $\exp(\beta)$, for the application characteristics as a percentage of the hazard rate for their reference groups. The results provide evidence of the effect of risk-based pricing (variable *RBPRICING*) introduced by the Bank over the observation time (in January 2012). As the elasticity of loan demand with respect to maturity has been shown to be statistically significant, I introduce an interaction term of risk-based pricing with approved maturity (*RBPRICING*AMATURITY*). The hazard ratio on this interaction term suggests that the null hypothesis that maturity choice after risk-based pricing has no impact on loan default can be rejected. Given risk-based pricing, prolonging loan maturity increases the probability of default for the pooled sample of borrowers by 1.3% (derived from coefficients in Table 2.2 Column 6) and for the sub-sample of low-income borrowers by 1.2%.[43] The time-dependence in default described below suggests that the negative impact of long-term loans is likely to increase as the observation period is extended (loan performance after introducing risk-based pricing is examined only over the fourteen-month period between January 2012 and April 2013). In other words, differentiating between borrowers solely through different interest rates causes borrowers to choose either to reduce the loan amount or to prolong maturity to compensate the lender for their riskiness. The latter then leads to higher default probability for both the liquidity constrained and liquidity unconstrained borrowers. Thus, banks seeking to mitigate adverse selection by developing risk-based pricing should also test for the increasing riskiness of the borrower pool with respect to loan duration. These results complement the findings of Adams et al. (2009), who quantify

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[42] The reference group for the application factor variables is always the one with the lowest coding. For the coding of variables refer to Table 3.A.3 in the Appendix.

[43] As a robustness check the simple probit of loan default was performed on all observations (with default occurring within 24 months after loan origination). This alternative specification yields similar conclusions as those derived from the Cox proportional hazard model.

the positive impact of risk-based pricing on loan performance without controlling for the endogeneity of loan maturity.

The effect of individual application characteristics on default probability presented in Table 2.A.5 in the Appendix is in line with the expectations. For instance, consistent with Kocenda and Vojtek (2009), the hazard ratio for low-income borrowers with a university education is only 56% of the hazard rate for those who have a secondary technical education. A longer survival time without default increases with a longer period of employment as in Bicakova (2007). Borrowers who own property are associated with a 43% lower risk of default than those who do not own property. These results are in line with the predictions of Einav et al. (2012).

Figure 2.A.2 in the Appendix plots the fitted Cox proportional hazards regression by loan maturity. It depicts the estimated default probability for the pooled sample and for the subsamples with different maturity: borrowers of short-term loans (maturity up to two years) are the most likely to be defaulted after the 18th month of granting; medium-term loans (maturity between two and five years) are the most likely to be defaulted at the 30th month, and long-term loans (more than five years maturity) are defaulted most frequently around the 34th month. Comparing the pooled proportional hazards and the proportional hazards by maturity, all achieve their peak before the end of the third year.[44] These results suggest that the timing of default is maturity-specific. While Glennon and Nigro (2005) find that between 1983 and 1998 the default most frequently occurs before the end of the second year after loan origination, Figure 2.A.2 shows that between 2007 and 2013 the default occurrence peaks around the third year. This can be explained by the overall prolongation of household loans.

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[44] It has to be highlighted that the results would be more precise by extending the observation period. Specifically, the timing of default might be influenced by the observed length of the loan (time span between loan origination and the date of default, maturity or the end of the observation period). At the time of monitoring (in April 2013), 64% of loans originated between 2007-2013 are right censored (did not reach default or maturity), with the average loan length for the observed loans being 29 months. Therefore, to see the sensitivity of loan performance, I estimate the Cox proportional hazards regression only for loans originating between 2007-2009 with an average loan length of 42 months. Compared to the findings derived based on the original sample the overall hazard rate increases, but the default for the pooled sample remains most likely around the 30th month from loan origination.

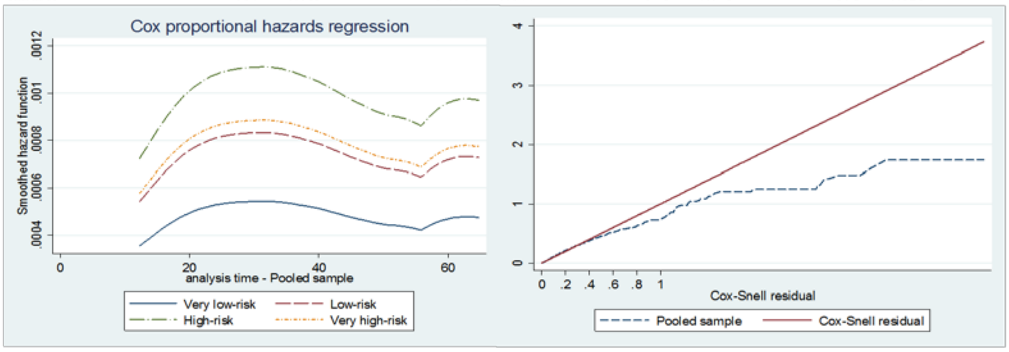
To see how significant the time-dependent default is across borrowers in the different risk categories, I also report the brief description of the data and plot the proportional hazard by maturity and by risk band (Figure 2.3). In line with expectations, the basic survival-time data statistics suggest that the default rate (i.e. number of failures per subject) increases with risk band for each sample. Nevertheless, after accounting for the application and loan contract characteristics in estimating the Cox model, "high-risk" borrowers prevail over "very high-risk" borrowers in default. This might be explained by the prudent loan granting strategy of the Bank, which aimed to closely monitor the quality and strictly limit the number of "very-high risk" households in the sample.

The overall model fit of the individual hazard regressions is assessed by computing the Cox-Snell residuals. If the model is correct, the real cumulative hazard function based on the covariate vector has an exponential distribution and a hazard rate of one. The default variation plotted in Figure 2.3 is the most significant for long-term loans. Comparing the dashed line with Cox-Snell residuals in Figure 2.3, it can be concluded that the maturity-specific models fit the data equally as well as the model for the pooled sample. The results suggest that in addition to risk-based household loan pricing, maturity-based credit scoring is also inevitable.

Figure 2.3: Cox proportional hazards regression pooled and by maturity/by risk bands

Pooled sample - survival-time data description

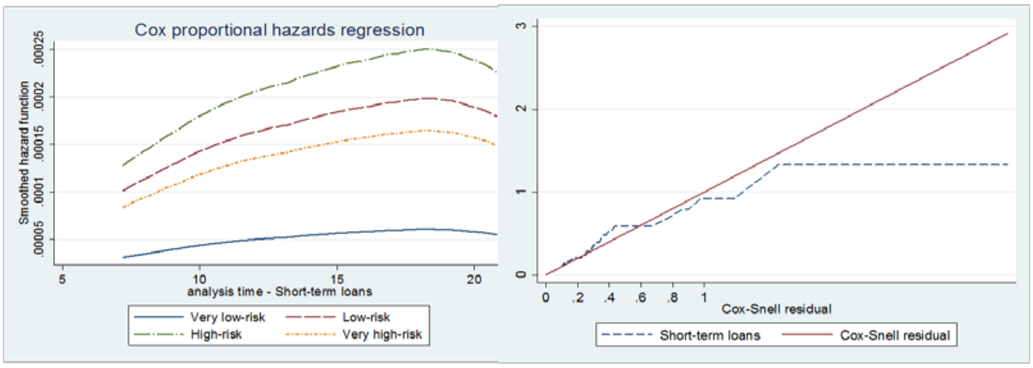
	Very low-risk			Low-risk			High-risk			Very high-risk		
		per subject			per subject			per subject			per subject	
	total	mean	median	total	mean	median	total	mean	median	total	mean	median
no. of subjects	51 591			38 251			12 862			3 055		
time at risk (in months)	1 487 877	28.8	25	1 133 415	29.6	26	398 925	31.0	32	92 072	30.1	26
failures	684	0.013		1 698	0.044		971	0.075		391	0.128	



(continued on next page)

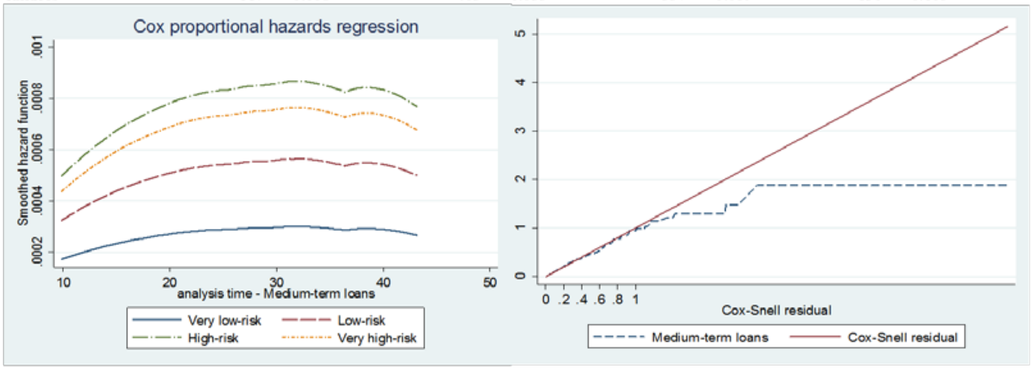
Short-term loans - survival-time data description

	Very low-risk			Low-risk			High-risk			Very high-risk		
		per subject			per subject			per subject			per subject	
	total	mean	median	total	mean	median	total	mean	median	total	mean	median
no. of subjects	11 069			7 103			2 124			488		
time at risk (in months)	184 314	16.7	16	124 354	17.5	20	39 932	18.8	24	8 083	16.5	17
failures	13	0.001		117	00.016		73	0.034		22	0.045	



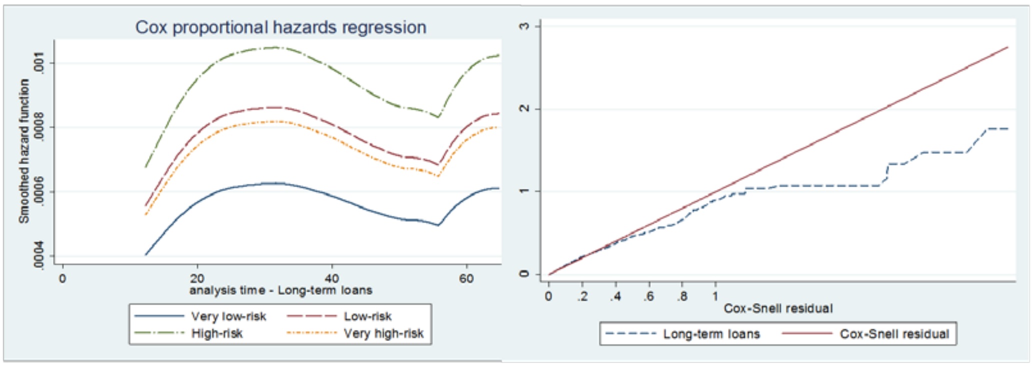
Medium-term loans - survival-time data description

	Very low-risk			Low-risk			High-risk			Very high-risk		
		per subject			per subject			per subject			per subject	
	total	mean	median	total	mean	median	total	mean	median	total	mean	median
no. of subjects	15 055			12 202			4 909			1 235		
time at risk (in months)	423 042	28.1	34	345 475	28.3	35	149 613	30.5	36	30 689	24.8	25
failures	117	0.008		403	0.033		337	0.069		130	0.105	



Long-term loans - survival-time data description

	Very low-risk			Low-risk			High-risk			Very high-risk		
		per subject			per subject			per subject			per subject	
	total	mean	median	total	mean	median	total	mean	median	total	mean	median
no. of subjects	25 467			18 946			5 829			1 332		
time at risk (in months)	880 521	34.6	35	663 586	35.0	35	209 380	35.9	34	53 300	40.0	43
failures	554	0.022		1 178	0.062		561	0.096		239	0.179	



Note: The model fit is evaluated by the comparison of the Cox cumulative hazard to the Cox Snell residual.

2.6 Conclusion

Driven by the sharp increase in household loan demand, the role of credit scoring methods in assessing a borrowers' creditworthiness is becoming more and more important. Thanks to the wide range of credit history collected by credit bureaus, lenders can screen out risky borrowers in their credit scoring models, not only based on application characteristics, but also on behavioral and credit history information. However, the ultimate effect of different loan contact terms on loan demand and loan performance has not yet been examined in the process of loan provision.

The aim of this paper is to present empirical evidence about whether a risk-based maturity setting improves the quality of granted household loans and alleviates the adverse selection present on the lending market. Taking advantage of a sample of both accepted and rejected household loans from a Czech commercial bank, this paper is the first to point out the importance of maturity in loan demand and loan performance.

This study contributes to the existing literature on household loan markets in several ways. First, it shows that low-income borrowers can be credit-constrained and thus have limited access to credit at market interest rates. Empirical evidence suggests that loan demand for low-income borrowers is more sensitive to available cash and loan maturity changes than to interest rate changes. This is consistent with the assumption that borrowers with liquidity constraints are likely to prolong the maturity of their loans in order to borrow the desired loan amount. Second, by reflecting the borrower's riskiness in the interest rate, lenders discourage risky borrowers from obtaining short-term loans. This then leads to higher default probability for both liquidity-constrained and liquidity-unconstrained borrowers. The finding is consistent with the theoretical prediction that reduced asymmetric information encourages "high-risk" borrowers to either demand lower loan amounts or to prolong their loan maturity to compensate the lender for their riskiness. Therefore, banks seeking to mitigate adverse selection by developing risk-based pricing should also test the increasing riskiness of borrower pool due to the sensitivity to loan duration. Finally, this paper provides evidence that the time of default is maturity-dependent and differs across borrowers in the different risk categories. Hazard models that differentiate between loan maturities and risk bands have an equally good model fit as one that treats all household loans as pooled and does not distinguish between these two factors. These results further advocate the necessity of maturity-based credit scoring.

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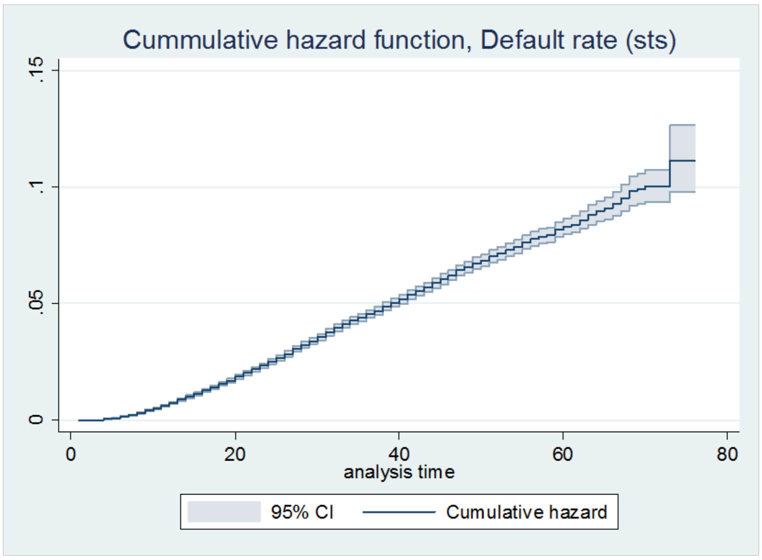
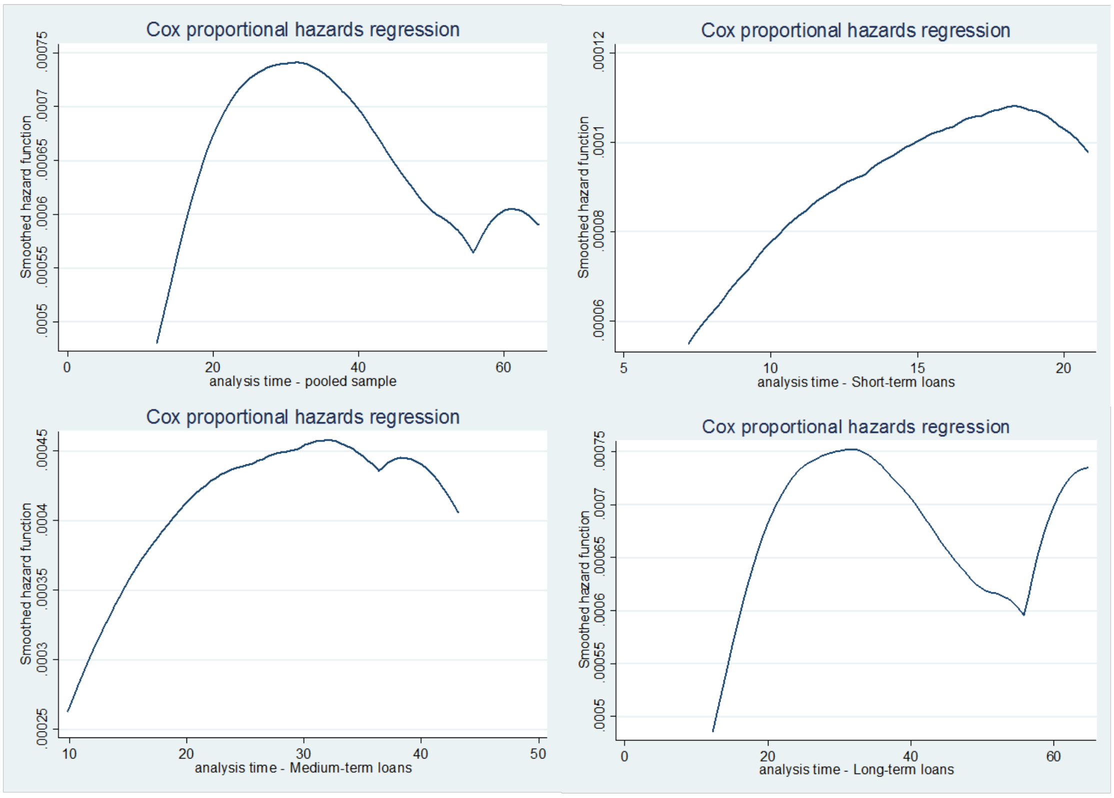
Appendix

Figure 2.A.1: Nelson-Aalen estimator of the cumulative hazard function



Note: Random sample of household loans, data from 2007-2013.

Figure 2.A.2: Cox proportional hazards regression pooled and by maturity



Note: The figure on the upper left corner depicts Cox proportional hazards for pooled data, i.e. treats all household loans equally and does not distinguish between maturity. The other three figures depict the Cox proportional hazards for short-term loans with maturity up to 2 years, medium-term loans with maturity between 2 and 5 years and long-term loans with maturity of more than 5 years.

Tables

Table 2.A.1: Expected relationship between selected dependent and independent variables

Dependent variable	Independent variable	Expected relationship	Literature
Loan approval	Car ownership	+	Alessie et al. (2005)
	Use of credit bureau information	+	Bicakova et al. (2010)
Loan demand	Interest rate	-	Alessie et al. (2005)
	Maturity	+	Attanasio et al. (2008)
Loan interest rate	Risk category	+	Karlan and Zinman (2008)
	Tax reform on phase out of interest deductibility	+	Attanasio et al. (2008)
	Usury law on max interest rate level	-	Alessie et al. (2005)
Loan maturity	Unemployment rate	+	Chetty et al. (2008)
	Durability of cars	+	Attanasio et al. (2008)
Default probability	Interest rate	+	Adams et al. (2009)
	Maturity	+	Adams et al. (2009)

Note: Author’s literature review.

Table 2.A.2: The list of personal loan information (Panel A)

Variable description	Variable name in dataset	Encoding
Application characteristics		
Age (in months)	AGE	continuous
Female	FEMALE	dummy
Marital status	MARITS	
Unspecified		1
Divorced		2
Married		3
Partner		4
Single		5
Widow/er		6
Education	EDU	
Secondary (technical)		1
Secondary (general)		2
Post-secondary (technical)		3
Secondary (vocational)		4
Post-secondary (vocational)		5
University		6
Housing status	HOUSE	
Unspecified		1
Living with parents		2
Sharing property		3
Personal property		4
Renting		5
Student dormitory		6
Employment status	EMPLOYS	
Employed		1
House wife		2
Pensioner		3
Student		4
Employment duration (in months)	EMPLOYY	continuous
Employment type	EMPLOYT	
Unspecified		1
Bank/insurance company		2
Entrepreneur		3
Foreign company		4
Private company		5
Public organization		6
Net monthly income (in CZK)	INCOME	continuous
Region (NUTS2)	REGION	dummy
Credit bureau score	CBSCORE	continuous
Application score	APPSCORE	continuous
Behavioral score	BEHAVSCORE	continuous

Note: Random sample of household loans, data from 2007-2013.

Table 2.A.2: The list of personal loan information (Panel B)

Variable description	Variable name in dataset	Encoding
Loan term characteristics		
Requested amount (in CZK)	RAMOUNT	continuous
Year of loan request	RYEAR	dummy
Loan approval indicator	APPROVED	dummy
Approved amount (in CZK)	AAMOUNT	continuous
Interest rate (in %)	IR	continuous
Risk margin (in %)	RM	continuous
Approved loan maturity (in months)	AMATURITY	continuous
Risk band	NRISK	
Very low-risk		1
Low-risk		2
High-risk		3
Very high-risk		4
Credit bureau information	CBINFO	dummy
Loan with specified purpose	PURPOSE	dummy
Number of individuals monitored in the CBCB (in mil.)	CBIND	continuous
Long-term unemployment rate (in %)	UNDUR	continuous
Risk-based pricing	RBPRICING	dummy
Default indicator	DEF	dummy
Renegotiated loan	RENEG	dummy
Number of months to default	DEFAULT	continuous

Note: Random sample of household loans, data from 2007-2013.

Table 2.A.3: Descriptive statistics (Panel A)

Variable name	Mean	Std. Dev.	Min	Max
Application characteristics	Accepted and rejected loans (N=207 640)			
Age (in months)	485	155	216	1 159
Female	0.479	0,500	0	1
Marital status				
Divorced	0.184	0.387	0	1
Married	0.418	0.493	0	1
Partner	0.012	0.107	0	1
Single	0.335	0.472	0	1
Widow/er	0.010	0.100	0	1
Education				
Secondary (general)	0.103	0.303	0	1
Post-secondary (technical)	0.015	0.120	0	1
Secondary (vocational)	0.400	0.490	0	1
Post-secondary (vocational)	0.387	0.487	0	1
University	0.084	0.278	0	1
Housing status				
Living with parents	0.170	0.375	0	1
Sharing property	0.033	0.180	0	1
Personal property	0.541	0.498	0	1
Renting	0.220	0.414	0	1
Student dormitory	0.000	0.009	0	1
Employment status				
House wife	0.030	0.172	0	1
Pensioner	0.142	0.349	0	1
Student	0.001	0.029	0	1
Employment duration (in months)	71	90	0	579
Employment type				
Bank/insurance company	0.017	0.129	0	1
Enterepreneur	0.027	0.161	0	1
Foreign company	0.032	0.176	0	1
Private company	0.261	0.439	0	1
Public organization	0.178	0.383	0	1
Net monthly income (in CZK)	17 451	11 861	1	500 000
Loan with specified purpose	0.102	0.303	0	1
Existence of credit bureau information	0.756	0.429	0	1
Risk band				
Low-risk	0.362	0.480	0	1
High-risk	0.122	0.327	0	1
Very high-risk	0.029	0.167	0	1
Loan approval indicator	0.510	0.500	0	1

Note: Loan characteristics are available only for approved loans.

Table 2.A.3: Descriptive statistics (Panel B)

Variable name	Mean	Std. Dev.	Min	Max
Loan term characteristics	Accepted loans (N=105 759)			
Approved amount (in CZK)	93 653	82 100	4 000	1 000 000
Approved loan maturity (in months)	54.0	26.5	1.0	134
Interest rate (in %)	13.4	2.8	3.7	25.9
Long-term unemployment rate (in %)	2.8	1.2	0.7	6.1
Risk margin (in %)	1.8	1.4	-5.2	10.6
Number of individuals monitored in the CBCB (in mil.)	4.9	0.3	4.2	5.3
Default indicator	0.04	0.19	0	1
Credit bureau score	318	269	-40	1 120
Application score	178	222	-4	998
Behavioral score	454	192	0	1 012

Note: Loan characteristics are available only for approved loans.

Table 2.A.4: Summary statistics of risk margin by year

Year of loan request	N	Mean	Standard deviation
2007	12 167	1.40	1.44
2008	16 567	1.52	1.38
2009	18 378	1.79	1.39
2010	17 784	1.88	1.39
2011	17 122	1.99	1.44
2012	36 866	2.65	2.32
2013	10 523	2.47	2.18
Total	129 407	2.06	1.84

Note: Prior to January 2012 the missing risk margin data is derived based on predicted value from a regression analysis of the complete data.

Table 2.A.5: Estimation results of loan demand and default probability

Dependent variable	Loan demand		Default probability	
	Pooled sample	Low-income sample	Pooled sample	Low-income sample
	Coef.	Coef.	Haz.ratio	Haz.ratio
Age	-0.001***	-0.001	1.000**	0.999
	(0.001)	(0.001)	(0.001)	(0.001)
Female	-0.125***	-0.053***	0.742***	0.710***
	(0.004)	(0.006)	(0.028)	(0.035)
Education				
Secondary (general)	-0.125***	-0.080***	1.762***	1.592**
	(0.178)	(0.023)	(0.216)	(0.253)
Post-secondary (techn.)	0.065***	0.016	0.607**	0.449**
	(0.021)	(0.031)	(0.127)	(0.158)
Secondary (voc.)	0.034***	0.001	0.751**	0.674**
	(0.016)	(0.022)	(0.088)	(0.105)
Post-secondary (voc.)	-0.054**	-0.048**	1.067	1.017
	(0.017)	(0.022)	(0.124)	(0.156)
University	0.130***	0.076***	0.396***	0.559**
	(0.173)	(0.026)	(0.059)	(0.134)
Employment status				
House wife	-0.129***	0.063***	1.050	0.956
	(0.015)	(0.017)	(0.121)	(0.125)
Pensioner	-0.160***	-0.023**	0.529***	0.573***
	0.010	(0.011)	(0.040)	(0.052)
Student	-0.257***	-0.119*	1.597	1.409
	(0.056)	(0.064)	(0.717)	(0.712)
Employment duration	-0.001*	-0.001***	0.996***	0.997***
	(0.001)	(0.000)	(0.001)	(0.001)
Employment type				
Bank/insurance company	-0.038**	0.157***	0.410**	0.635
	(0.018)	(0.040)	(0.111)	(0.243)
Entrepreneur	-0.013	0.021	1.180*	1.148
	(0.012)	(0.014)	(0.102)	(0.124)
Foreign company	0.060***	0.017	0.986	1.152
	(0.010)	(0.016)	(0.062)	(0.102)
Private company	0.010*	-0.017**	0.880**	1.129
	(0.005)	(0.009)	(0.046)	(0.085)
Public organization	-0.071***	-0.039***	0.691***	0.786**
	(0.006)	(0.010)	(0.042)	(0.066)

(continued on next page)

Table 2.A.5: Estimation results of loan demand and default probability

Dependent variable	Loan demand		Default probability	
	Pooled sample	Low-income sample	Pooled sample	Low-income sample
	Coef.	Coef.	Haz.ratio	Haz.ratio
Net monthly income	0.001***	0.001***	1.001	0.999***
	(0.001)	(0.001)	(0.001)	(0.001)
Marital status				
Divorced	0.022	-0.063***	1.013	0.984
	(0.019)	(0.023)	(0.144)	(0.173)
Married	0.116***	0.080***	0.793*	0.840
	(0.018)	(0.022)	(0.111)	(0.144)
Partner	0.091***	0.078**	0.929	0.928
	(0.026)	(0.033)	(0.188)	(0.243)
Single	0.098***	0.026	0.979	1.001
	(0.019)	(0.023)	(0.138)	(0.173)
Widow/er	0.072***	-0.012	0.908	1.001
	(0.021)	(0.024)	(0.159)	(0.213)
Housing status				
Living with parents	0.104***	0.093***	0.564***	0.564***
	(0.012)	(0.015)	(0.048)	(0.061)
Sharing property	0.030**	-0.031	0.616***	0.670**
	(0.014)	(0.019)	(0.066)	(0.094)
Personal property	0.035***	0.005	0.562***	0.574***
	(0.011)	(0.014)	(0.046)	(0.060)
Renting	0.030***	-0.026*	1.000	1.015
	(0.011)	(0.015)	(0.079)	(0.104)
Student dormitory	0.089***	0.067	1.812	1.685
	(0.199)	(0.234)	(1.294)	(1.213)
Region. Loan Purpose	Yes			
R^2	0,5093	0,4639		
N	105 759	46 598	105 759	46 598
Log likelihood			-38 221	-20 223
Prob> chi2			0.000	0.000
Loglikelihood ratio (LR) chi2			4 858	2 639

Note: (1) For loan demand estimation the logarithmic form of approved loan amount is used. (2) ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are in parenthesis.

Chapter 3

Credit Ratings and Their Information Value: Evidence from the Recent Financial Crisis

3.1 Introduction

The financial crisis in the early 2000s has underscored the financial markets' reliance on credit ratings. Credit ratings express rating agencies' opinion about the ability and willingness of debt issuers to meet their financial obligations in full and on time. They assist investors in evaluating the financial health of debt issuers and regulatory authorities in overseeing the financial market through rating-contingent policies.

Nevertheless, there are at least three issues financial market participants should consider when relying on credit ratings. First, inflated credit ratings failed to predict the recent financial crises. This has evoked widespread debate on the quality of credit ratings. Second, credit ratings are costly for companies. Although unrated companies may have financial difficulties they do not wish to reveal, the lack of a credit rating does not necessarily convey a negative signal about the company's creditworthiness in certain markets. Third, credit ratings can differ across the three rating agencies, Standard and Poor's (hereafter, S&P), Moody's Investor Services (hereafter, Moody's), and Fitch Ratings (hereafter, Fitch), depending on their prevailing rating methodology.

Inconsistency in credit ratings becomes essential when ratings are used to fulfil financial regulatory requirements. Although a debt issuer can be rated by more than one agency, financial market participants can only use one rating to evaluate the credit risk related to the issuer. For instance, the capital requirements of banks can substantially increase when banks use the more conservative (worse) rating. Recent empirical papers (Morgan, 2002; Livingston, Wei, and Zhou, 2010) find that disagreement in issuer ratings is substantial both in the case of financial and non-financial institutions. Livingston, Naranjo, and Zhou (2008) argue that rating splits (disagreement) between rating agencies might trigger subsequent rating changes. The authors show that rating splits can increase the probability of rating upgrade/downgrade within one year by up to 6%, and rating splits influence the pricing (credit spreads) of the issued debt. However, no study has tested which rating agency is consistently more prudent[45] within the individual industry sectors, crisis periods or rating grades. The information whether rating splits are industry-, time- and rating-dependent might be of high prominence for bond investors, as they often alter their behavior based on rating actions, and bond yields often rely on the rating of the more prudent agency (Livingston et al., 2010). The first hypothesis tested in this paper is that the distribution of credit ratings across the two major rating agencies[46] (Moody's and S&P) is identical for different industry sectors, crisis periods and rating grades.

Regulators and policymakers view increasing competition between credit rating providers as a fundamental driver of precise and prompt ratings. Nevertheless, rating agencies' reputational concerns and their costs of information acquisition vary over the business cycle. The theoretical model of Bar-Isaac and Shapiro (2013) suggests that the accuracy of ratings is determined by the extent of competition (the reputation losses) among rating agencies. Becker and Milbourn's (2011) empirical findings support this prediction and find that the rating quality (defined as 'the ability of rating to be informative about bond values and the ability to be accurate in predicting issuer default') of S&P and Moody's decreased after Fitch's market share increased. The

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[45] While more prudent rating agencies prefer to protect their reputational capital by assigning timely and accurate ratings; less prudent rating agencies prefer to increase their own profits (credit ratings are issuer-paid) by assigning favorable issuer ratings.

[46] Fitch was established in 1997 and over 2005 and 2014 it had a much smaller rating coverage than S&P and Moody's (established in the early 1900s). Thus, unless stated otherwise, this paper focuses on credit ratings assigned by the two incumbent rating agencies, S&P and Moody's. Fitch's credit ratings are only used to measure how competitive the rating market is (unless stated otherwise).

existence of a third rating opinion is highly relevant for regulatory rating classification, which accepts only one credit rating classification (the Basel Accord). If an issuer is rated by two or more rating agencies, the prevailing institutional rule is to use the 'second best' rating. In their recent paper, Bongaerts, Cremers, and Goetzmann (2012) find that gaining a third rating opinion results in regulatory rating improvement. Nevertheless, while the above studies focus on the ratings information value for investors and their accuracy in predicting default, no empirical evidence exists on how the incidence of rating split was affected by increased competition over the recent financial crises. The question is important due to the risk of 'rating shopping' (the hypothesis positing that issuers are prone to paying for a third rating opinion in the hope of enhancing their rating) that might result in more favorable 'second best' ratings. This paper tests the hypothesis that any disagreement between the issuer ratings of S&P and Moody's is independent of the competition between rating providers.

The recent financial crisis attracted the attention of the financial market to the severity of sovereign rating deterioration. This also has a direct effect on the private sector, as distressed economies often restrict the financial leverage of corporations (Borensztein, Cowan, and Valenzuela, 2013). Consequently, rating agencies may cap issuer ratings by the country rating in which they operate (henceforth referred to as 'ceiling effect'). Chen, Chen, Chang, and Yang (2013) emphasize that sovereign downgrades have a significant impact on declines in private investments. The influence of sovereign rating change is more substantial in low-rated economies (Ismailescu and Kazemi, 2010). Despite the broad empirical research on the effect of sovereign ratings on issuer ratings, no previous literature has explored its importance over the recent sovereign debt crisis for both financial and non-financial industry sector. The third hypothesis of this paper tests whether the sovereign ceilings cease to be restrictive for issuer ratings.

Rating agencies aim to provide timely information about the credit quality of issuers. When rating changes occur, they have extensive power to alter the decisions of financial market participants. Thus, identifying the rating agency that is consistently more prompt in capturing the changing creditworthiness of the issuers is of crucial importance. Although Hill, Brooks, and Faff (2010) and Alsakka and Gwilym (2010) find interdependence in sovereign rating actions, there is limited related research into the timeliness of rating actions for corporations. Thus, the final hypothesis tested in this paper is that there is no leader-follower relationship between rating agencies for financial and non-financial institutions.

The empirical results of this paper draw on extensive financial statement and credit rating data of over 2500 financial and non-financial institutions. Credit ratings assigned by Moody's, S&P and Fitch are available both for financial/non-financial institutions that issued debt (i.e. issuer company rating) and their country of domicile[47] (i.e. issuer sovereign rating). The panel data includes information about the companies from December 2005 to October 2014.

3.2 Credit Ratings

3.2.1 The Process of Credit Rating Assessment

Accurate and timely information is one of the key prerequisites of credit risk assessment and investment decisions. Information, however, is not evenly distributed among investors, borrowers, lenders and other market participants. Rating agencies, which assess the creditworthiness of debt issuers and issues (corporate or government financial obligation, such as a bond), aim to mitigate information asymmetry on the financial market by translating their credit risk assessment of issuers/issues into a rating grade from AAA to D. There are three major global rating agencies, each providing a comparable and independent credit risk assessment of debt issuers/issues. The rating assessment is based on publicly available methodologies, which creates a common comparison basis for all end users. Thus, rating agencies offer two pivotal benefits for financial markets in the form of credit rating: i) easy comparability of ratings in a global context, ii) favorable access to capital market funding for rated issuers.

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[47] The country of domicile (country in which the company has its headquarters) is a good proxy for 'country of risk' (International Organization for Standardization country code taking into account management location, country of primary listing, country of revenue and reporting currency of the issuer) – for 98% of the examined issuers, the country of domicile and the country of risk coincide.

Rating requests are assumed to be randomly ordered, as credit ratings are issuer-paid and one rating is sufficient to fulfill most rating-based regulations (Livingston et al. 2010). Nevertheless, as issuers pay for the rating, they have incentives to solicit positive bias in credit rating by switching between rating agencies or by paying for multiple rating assessments. The motivation of issuers to pay for multiple credit ratings can be interpreted by three hypotheses. First, according to the ‘information production’ hypothesis, multiple ratings reduce the market participants’ uncertainty about the creditworthiness and the default probability of the issuer (Güntay and Hackbarth, 2010). Second, according to the ‘rating shopping’ hypothesis, issuers will apply for an extra rating assessment if they anticipate an enhancement in average credit rating (Skreta and Veldkamp, 2009). Third, according to the ‘regulatory certification’ hypothesis, issuers rated close to the investment– non-investment grade boundary (i.e. with BBB and BB ratings) are often highly motivated to pay for two or more credit ratings. The main reason is that when an issuer is differently rated by two or more rating agencies, the prevailing institutional rule is to use the ‘second best’ rating. Thus, avoiding non-investment grade ‘second best’ rating might allow debt issuers to borrow at lower interest rates (Bongaerts et al., 2012). In general, most thorough issuers seek rating services from at least two agencies. This approach strengthens the issuer’s reliability compared to its peers who seek ratings by a single agency only, and appreciates its debt issuances (rated companies can issue debt/borrow at lower interest rates).

Based on the best practice of rating agencies, the process to obtain a rating takes approximately 90 days. In the first 30 days contracts are set up and signed. The issuer is then transferred to the analytical team within the rating agency, which collects the required documentation and sets meeting dates with the issuer over the next 30 days. During the meetings, the agencies’ analysts and the issuer’s representatives discuss all outstanding points required for credit rating assessment. After this rating visit, the analytical team has an additional 30 days to carry out the rating analysis, present the rating to an internal rating committee for approval[48] and announce the rating to the

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[48] A rating committee has at least 5 voting members: the lead analyst for the issuer, three other attendees with voting rights and a rating chair who is usually the most senior committee attendee. The chair casts his vote last so his opinion does not influence more junior voters.

issuer. Subsequently, depending on the timeliness of the issuer's publication consent, the credit rating is publicly released.

Once the rating is released to the market, the issuer is regularly monitored until the rating is withdrawn or, in the case of debt issue ratings, the debt matures. The rating agency's analytical team monitors the rated issuer regularly (reviews financial reports, industry development) and arranges a meeting with the issuer prior to the update of the rating analysis (usually annually). Nevertheless, the issuer's rating can be changed outside of the dates reserved for annual review. If the rating agency identifies material changes in the issuer's idiosyncratic risk profile or material shocks in exogenous factors (for instance, overall deterioration of the industry's performance or a change in the issuer's country rating), the rating is immediately adjusted. The rating action (rating downgrade, rating upgrade, change in rating outlook) can be released quickly, within days from the moment the rating agency learns the new information. In the case of issuers rated by multiple rating agencies, a rating change from one rating agency does not necessarily trigger a rating change by its competitor(s).

The building block of any rating assessment is an industry-specific methodology that describes in detail the rating scorecard used to derive the credit rating. The rating scorecard is comprised of quantitative and qualitative rating factors. In general, quantitative factors (financial profile) play a key role (70-90% weight on the final rating). The qualitative factor assessment (business profile) often rests on the subjective evaluation of the rating analysts (10-30% weight on final rating). [49] The rating derived based on the scorecard serves then as a basis for approval by the internal rating committee. If the rating committee members fail to reach mutual agreement, the assigned rating may deviate from that proposed by the scorecard.

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[49] Similarly to the existing research on credit ratings, this paper cannot fully control for the qualitative rating factors and thus considers the financial indicators essential to credit rating determinants.

3.2.2 Why Financial Institutions Are Different

Before examining the determinants and the quality of credit ratings, the specific features of the financial sector must be highlighted. Unlike non-financial corporations, the creditworthiness of financial institutions is particularly difficult to evaluate for at least two reasons. One is that their asset quality is determined mainly by their leading line of business. For instance, a bank mainly issues loans to different types of borrowers (e.g. individuals, corporations, and public organizations), so the financial strength of the institution stems from the quality of loans that it provides to borrowers with different levels of riskiness. Nevertheless, external market participants cannot accurately estimate the embedded riskiness of these loans. The second difficulty is that financial institutions are highly leveraged, and therefore the shareholders' equity (i.e. capital) at stake is low. Consequently, regulators and investors view the high (low) capital-to-asset ratio as a particularly useful signal of a financial institution's conservative (aggressive) business strategy, reflecting asset quality with low (high) risk. Recent research by Mehran and Thakor (2011) provides theoretical justification that higher capital has a positive impact on financial institutions' asset and liability structure. This view is supported by the empirical findings of Berger and Bouwman (2013), which show that companies with higher capital monitor their asset bases more strictly and focus on more conservative investment strategies.

The importance of capital in the performance of financial institutions has been highlighted over the recent financial crisis. To restrain risk and potential losses by the financial sector, the Basel Committee on Banking Supervision set out specific requirements regarding the capital of financial institutions. These regulatory capital requirements aim to strengthen the stability of the financial sector and define how much capital the financial institution must hold. The level of capital becomes a concern as soon as the assets of the company shrink due to losses in the company's business (e.g. defaults on granted loans). As the volume of assets drops, the volume of liabilities and shareholders' equity (capital) must also decrease on the balance sheet. In the first place, the shareholders' equity is used to cover the losses on the company's assets. If the level of capital is not sufficient, the financial institutions' liabilities must go down (e.g.

individuals lose their deposits). To protect the financial sector from such scenarios, capital must be at a level that absorbs the company's losses before depositors' funds must be tapped.

Although financial institutions must strictly follow the regulatory capital requirements, the recent financial crises have shown that these were insufficient to restore prudent risk-taking at the financial institutions. Hence, the determinants, the quality and the implications of credit ratings as important inputs for financial market regulations should be closely monitored.

3.3 Methodology

The four key hypotheses of this paper can be summarized as follows.

Hypothesis 1 (H1). The distribution of credit ratings across the two major rating agencies (Moody's and S&P) is identical for different industry sectors, crisis periods and rating grades.

The alternative hypothesis to H1 is that a significant disagreement exists between the credit rating of the two incumbent rating agencies. This would suggest that given the same public information, the ratings of S&P or Moody's are systematically different when compared for the same company. Rating splits across industry sectors, crisis periods and rating grades might appear for the following reasons: (i) Rating splits are likely to vary by the industry coverage of the rating agency (i.e. if the two agencies have different rating coverage in the given industry, the probability of rating split is higher); (ii) Rating disagreements are expected to deepen over time (i.e. as a result of improvements in the credit rating agencies' regulation during the recent financial crises[50], rating agencies are gradually forced to protect their reputational capital and to

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[50] For example, the Dodd-Frank Wall Street Reform and Consumer Protection Act (effective from July, 2010) increases the credit rating agencies' liability for issuing inaccurate ratings.

restrict ratings that follow the issuers' preferences or other rating agencies' actions); (iii) Rating splits are anticipated to be more frequent around the investment-non-investment grade boundary (i.e. as the difference in bond credit spreads is often the highest between investment-non-investment grade bonds).

In order to test for the null hypothesis that the distribution of credit ratings across rating agencies differ, the non-parametric Wilcoxon signed rank sum test is conducted. It tests the equality of matched pairs of observations ($H_0 : median_{Moody's} = median_{S\&P}$). As opposed to previous studies (Galil and Sofer, 2011), the distribution of credit ratings is also compared across industry sectors, crisis periods and rating grades.

Hypothesis 2 (H2). Any disagreement between the issuer ratings of S&P and Moody's is independent of the competition between rating providers.

The alternative hypothesis to H2 is that besides the analysts' different expert judgments, the rating disagreement (split) is affected by the increased competition on the credit rating market after the expansion of Fitch. If Fitch's issuer rating is different from the ratings assigned by S&P or Moody's, then Fitch's entry to the market might serve as a trigger for the two main rating agencies to reassess the creditworthiness of the issuer. This might then result in the rating split of S&P and Moody's issuer ratings.

To test whether competition on the credit rating market also contributes to rating disagreement, the probit model[51] is estimated with fixed effects controlling for average industry-, region- and time-characteristics:

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https://www.sec.gov/about/laws/wallstreetreform-cpa.pdf

[51] One of the drawbacks of the identification strategy is that it does not account for the selection having two ratings and does not consider the sequence of rating requests from the issuer.

$$
\begin{aligned}
& SPLIT^{*}_{i,j,c,t} = \delta_0 + INDUSTRY_j + REGION_c + PERIOD_t + \delta_1 FINANCIALS_{i,t} + \\
& + \delta_2 NIG\_SOVEREIGN_{c,t} + \delta_3 NIG\_ISSUER_{i,t} + \\
& + \delta_4 MARKET\_SHARE\_FIT_{j,t} + \mu_{i,j,c,t}
\end{aligned}
\qquad (3.1)
$$

where $SPLIT_{i,j,c,t}$ is a binary variable that takes the value of 1 if credit ratings (of issuer *i* from industry *j*, region *c*, at year *t*) assigned by Moody's and S&P are different, and takes the value of 0 if the credit ratings of the two agencies are consistent.[52]

$INDUSTRY_j, REGION_c, PERIOD_t$ are categorical variables for industry sector, geographical region and crisis period. The variable $FINANCIALS_{i,t}$ expresses the financial statement data[53], which is industry-specific. For financial institutions the choice of financial indicators is motivated by the CAMEL model (Caouette, Altman, Narayanan, and Nimmo, 2008; Golin and Delhaise, 2013), and for non-financial institutions it is motivated by the Altman Z score model (Altman, 1968; Altman and Rijken, 2004). Both are discussed in detail in a later section. Variables $NIG\_SOVEREIGN_{c,t}$ and $NIG\_ISSUER_{i,t}$ are dummy variables that take the value of 1 if the sovereign rating / issuer rating (assigned by S&P, as the rating agency with widest rating coverage) is non-investment grade. The error term $\mu_{i,j,c,t}$ is assumed to be normally distributed.

Similarly to Becker and Milbourn (2011), Fitch's market share is used as a measure of competition in the ratings industry. The variable $MARKET\_SHARE\_FIT_{j,t}$ denotes the share of debt issues rated by Fitch on the total number of debt issues rated by the three rating agencies (the ratio is derived based on

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[52] The rating split between the two main rating agencies is evaluated at year-ends. Rating updates on arrival of new information are disregarded in testing the effect of increased rating completion on the rating split. This paper focuses on the sequence of rating updates when studying the leader-followership between the rating agencies.

[53] The incorporation of financial statement data as determinant of rating split is motivated by Morgan (2002), who estimates the disagreement between rating agencies based on the banks' asset structure. The author suggests that disagreement between rating agencies is a gauge of uncertainty about the financial health of the company. He argues that banks with a high share of loans and trading assets might encompass risk that is difficult to assess (due to the unknown risk of borrowers and counterparties), and hence these banks might be rated differently.

Bloomberg's rated debt issue universe). Fitch's market share captures the variation in the competition between rating providers both across industry sectors and over time. This paper focuses on testing the null hypothesis that the increased competition of Fitch has no effect on the disagreement between ratings assigned by S&P and Moody's ($H_0 : \delta_4 = 0$).

Hypothesis 3 (H3). The sovereign ceilings cease to be restrictive for issuer ratings.

The alternative hypothesis to H3 is that the issuer's credit rating remains inherent to its operational or regulatory environment.

To estimate which predictors carry significant weight in explaining credit rating changes, the probit model is adopted. Motivated by the literature (Williams, Alsakka, and Gwilym, 2013) this paper explores the determinants of credit ratings separately for issuer rating upgrades and issuer rating downgrades:

$$\begin{aligned}\Delta R^{A}_{i,j,c,t} &= \beta_0 + INDUSTRY_j + REGION_c + YEAR_t + \\ &+ \beta_1 FINANCIALS_{i,t} + \beta_2 \Delta FINANCIALS_{i,t} + \beta_3 MACRO_{c,t} + \beta_4 \Delta MACRO_{c,t} + \\ &+ \beta_5 NIG\_SOVEREIGN_{c,t} + \beta_6 NIG\_ISSUER_{i,t} + \beta_7 MARKET\_SHARE^{A}_{j,t} + \\ &+ \beta_8 SOVEREIGN_{c,t} + \beta_9 \Delta SOVEREIGN_{c,t} + \beta_{10} \Delta R^{B}_{i,j,c,t} + \beta_{11} \Delta R^{C}_{i,j,c,t} + \varepsilon_{i,j,c,t}\end{aligned} \tag{3.2}$$

$$\begin{aligned}\Delta R^{B}_{i,j,c,t} &= \beta_0 + INDUSTRY_j + REGION_c + YEAR_t + \\ &+ \beta_1 FINANCIALS_{i,t} + \beta_2 \Delta FINANCIALS_{i,t} + \beta_3 MACRO_{c,t} + \beta_4 \Delta MACRO_{c,t} + \\ &+ \beta_5 NIG\_SOVEREIGN_{c,t} + \beta_6 NIG\_ISSUER_{i,t} + \beta_7 MARKET\_SHARE^{B}_{j,t} + \\ &+ \beta_8 SOVEREIGN_{c,t} + \beta_9 \Delta SOVEREIGN_{c,t} + \beta_{10} \Delta R^{A}_{i,j,c,t} + \beta_{11} \Delta R^{C}_{i,j,c,t} + \varepsilon_{i,j,c,t}\end{aligned} \tag{3.3}$$

where $\Delta R^{A}_{i,j,c,t}, \Delta R^{B}_{i,j,c,t}, \Delta R^{C}_{i,j,c,t}$ are binary variables of rating upgrade/downgrade originated by the rating agencies S&P, Moody's and Fitch (A, B, C, respectively).

Besides fluctuations in the issuer's financial ratios (defined by the Altman Z-score model for non-financial institutions and defined by the CAMEL model for financial institutions), the variable $FINANCIALS_{i,t}$ also considers the size of the company (Hau, Langfield, and Marques-Ibanez's 2013 study shows that larger banks are more highly rated) and the earnings per share (Ederington and Goh's 1998 empirical paper argues that a decline in earnings is a good proxy for market expectations and efficiently forecasts downgrades). As deteriorations in the macroeconomic conditions (in the issuer's country of domicile) might enhance the exposure of public and private debt and hence influence credit ratings, selected macroeconomic indicators ($MACRO_{c,t}$) are also incorporated in the model (similarly to Borensztein et al., 2013). Motivated by Ismailescu and Kazemi (2010), who show that rating changes are more severe in countries with low ratings, dummy variables for countries/issuers rated by non-investment grade ($NIG\_SOVEREIGN_{c,t}$ and $NIG\_ISSUER_{i,t}$) are part of the empirical specification.

$SOVEREIGN_{c,t}$ refers to the rating of the issuer's country of domicile. It is expected to be a significant determinant of issuer rating as negative fluctuations in sovereign ratings also have an adverse impact on the issuer's rating (Cantor and Packer, 1996; Hills et al., 2010; Borensztein et al., 2013 and Williams et al., 2013). On the other hand, the magnitude of sovereign risk on issuer rating might be fundamentally different before (pre-crises period, subprime lending crisis) and during the sovereign debt crisis. Using the above econometric specification, this paper tests the null hypothesis that sovereign ceilings cease to be restrictive for issuer ratings ($H_0 : \beta_9 = 0$).

Apart from financial statement data, macroeconomic indicators or sovereign ratings, rating actions of the competitors ($\Delta R^A_{i,j,c,t}, \Delta R^B_{i,j,c,t}, \Delta R^C_{i,j,c,t}$) might also contribute to the yearly changes in the issuer's credit assessment. As replicating the rating upgrades/downgrades of the competitor is less time- and cost-intensive than performing their own independent credit assessment, rating agencies tend to react to the competitors' behavior (Guttler and Wahrenburg, 2007). These prompted rating actions are then highly appreciated by investors, who after the downgrade/upgrade might experience loss/gain in the rating-driven borrowing costs.

Hypothesis 4 (H4). There is no leader-follower relationship between rating agencies.

The alternative hypothesis is that some rating agencies are systematically dependent on their competitors' rating actions, even though investors are highly sensitive to timely and accurate information about credit quality changes.

In order to quantify the effect of an issuer rating change (i.e. rating upgrade/downgrade) by rating agency A on an issuer rating change by rating agency B, the Granger-like ordered logit model[54] is utilized. The Granger-like model reflects the serial correlation in rating changes. It assumes that past rating changes influence the future rating changes, and past rating actions carry unique information about the future rating changes.[55] The ordinal model's key advantage is that it accounts for the ordinal scale of credit ratings. Similarly to Guttler and Wahrenburg (2007) and Alsakka and Gwilym (2010), the daily rating change is modelled for the two major rating agencies (S&P and Moody's) separately:

$$\Delta R^{*A}_{i,d} = \sum_{h'=1}^{4}\theta^{1}_{h}U^{B}_{i,h} + \sum_{h=1}^{4}\theta^{2}_{h}D^{B}_{i,h} + \sum_{h'=1}^{4}\theta^{3}_{h}U^{A}_{i,h} + \sum_{h=1}^{4}\theta^{4}_{h}D^{A}_{i,h} + \nu_{i} \qquad (3.4)$$

$$\Delta R^{*B}_{i,d} = \sum_{h'=1}^{4}\theta^{1}_{h}U^{A}_{i,h} + \sum_{h=1}^{4}\theta^{2}_{h}D^{A}_{i,h} + \sum_{h'=1}^{4}\theta^{3}_{h}U^{B}_{i,h} + \sum_{h=1}^{4}\theta^{4}_{h}D^{B}_{i,h} + \nu_{i} \qquad (3.5)$$

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[54] The model assumes that rating agencies have access to the same publicly available information, and past rating changes internalize any shocks affecting the rating.

[55] Rating changes indicate the speed of rating analysis required to re-assess the issuer's creditworthiness. They do not correspond to the sequence of the initial rating requests (as rating agencies are obliged to update the issuer's rating immediately after observing changes in its idiosyncratic risk profile or material shocks in exogenous factors), but might reflect the initial rating mistakes made by one of the rating agencies (rating changes could be faster for the agency that was more wrong in its previous rating).

where $\Delta R^{*A}_{i,d}$ and $\Delta R^{*B}_{i,d}$ are the unobserved latent variables of rating changes of issuer *i* at day *d* originated by the rating agencies A and B, respectively, while $\Delta R_{i,d}$ refers to the observed difference in the rating grades.

$$\Delta R_{i,d} = \begin{bmatrix} -2 \ \ (i.e.\ \ downgrade\ \ by\ \ two\ \ or\ \ more\ \ notches)\ \ if\ \ \Delta R^{*}_{i,d} \le \lambda_1 \\ -1 \ \ (i.e.\ \ downgrade\ \ by\ \ one\ \ notch)\ \ if\ \ \lambda_1 < \Delta R^{*}_{i,d} \le \lambda_2 \\ 1 \ \ (i.e.\ \ upgrade\ \ by\ \ one\ \ notch)\ \ if\ \ \lambda_2 < \Delta R^{*}_{i,d} \le \lambda_3 \\ 2 \ \ (i.e.\ \ upgrade\ \ by\ \ two\ \ or\ \ more\ \ notches)\ \ if\ \ \lambda_3 < \Delta R^{*}_{i,d} \end{bmatrix} \qquad (3.6)$$

The terms $U^{A}_{i,h}$ and $U^{B}_{i,h}$ are dummy variables for an issuer rating upgrade, $D^{A}_{i,h}$ and $D^{B}_{i,h}$ are dummy variables for an issuer rating downgrade.

The leader-follower relationship might take several forms. Specifically, as a result of one agency's rating action, the second agency might update the issuer's rating methodology (e.g. changing thresholds or weights that drive the rating change), review the issuer's credit quality or it might make a rating change release strategically dependent on the first-mover (Güttler and Wahrenburg, 2007). As any of these scenarios are equally likely, the leader/follower sequence is examined in time span ranging from 1 day to 180 days. Specifically, following Alsakka and Gwilym (2010) the rating changes of the potential follower (dependent variable) are examined in h time windows after the rating change by the potential leader: $h = 1$ denotes 1-15 days, $h = 2$ denotes 16-90 days, $h = 3$ denotes 91-180 days, and $h = 4$ denotes more than 180 days. Rating reaction within a few days might indicate that the rating agencies independently reacted to the same publicly available rating drivers, but the follower was either slow in processing the rating change or made its rating change strategically dependent on the leader's reaction. On the other hand, rating reaction after 180 days is expected to have no relation to the original rating changes and it can be considered as a result of a new fundamental event happening half a year late.

3.4 Data

The dataset is described in three steps. First, I outline how the sample of financial and non-financial companies was acquired. Next, separately for the financial and non-financial sectors, I describe the selected financial indicators and their expected impact on company performance. Finally, I illustrate the credit rating distribution of the companies across industry sectors and credit rating agencies.

3.4.1 Data Collection

Bloomberg, one of the largest market data providers, is the source of financial statement and credit rating data used. The data were collected in the following steps:

1) Index members of major equity indices create the basis of the sample of debt issuers. In particular, using Bloomberg's IMEN function, the list of 500 major equity indices traded on Bloomberg was gained. The equity indices are performance indicators of a particular equity market and are derived from the prices of selected stocks (most frequently using a weighted average). The index members are companies based in 65 countries worldwide.
2) The initial list of financial and non-financial institutions was defined using the constituents of these 500 major equity indices.
3) To enlarge the sample, Bloomberg's peer group assignment was utilized to identify competitive companies for the initial list of financial and non-financial institutions.
4) After eliminating duplicates of companies on several markets, the final list consists of over 2 500 financial and non-financial institutions.
5) For the final list of 600 financial and 1 900 non-financial institutions, comprehensive financial statement and credit rating data (observed at the end of years 2005 to 2013) were obtained. Specifically, the following information was

downloaded: (1) basic company information (industry sector[56], country of domicile, parent company), (2) financial statements and financial indicators, (3) long-term issuer company and sovereign ratings[57] assigned by S&P, Moody's and Fitch. Sovereign ratings are available for 61 countries (48% of issuers are from the USA) observed for 9 years (2005-2013). The dataset covers 10 regions (United States, Euro Area, Japan, Other Advanced Economies, Commonwealth of Independent States, Emerging and Developing Asia, Emerging and Developing Europe, Latin America and the Caribbean, the Middle East and North Africa and Sub-Saharan Africa).[58]

6) Finally, daily data on company and sovereign rating actions (over 14 000 downgrades, upgrades, and changes in rating outlook) were obtained. The rating changes were implemented by the three rating agencies from December 2005 to October 2014. In particular, for the sample of 2 500 financial and non-financial institutions both initial [59] and new ratings are observed along with the date of the rating change.

Bloomberg's rated universe is used for the derivation of the individual rating agencies' market share across industry sectors and over time. Specifically, the market share of S&P, Moody's and Fitch is derived for 9 industry sectors (Basic Materials, Communications, Consumer – Cyclical, Consumer – Non-cyclical, Diversified, Energy, Industrial, Technology and Utilities) and 9 years (2005-2013). The market share of a rating agency is determined as a portion of debt issues rated by this agency and the total

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[56] Table 3.A.1 (Panel A) in the Appendix summarizes the average issuer ratings by industry sector. It suggests that the ratings reflect the specifics of individual industry sectors. All three agencies agree that the highest average ratings (on average A-) are assigned in the financial sector (due to the presence of governmental or parental external support), while the lowest average ratings (on average BB+) are assigned in the sector of Cyclical Consumer Goods (as highly dependent on the economic cycle). The highest disagreement between the three agencies is in the case of sectors such as Industrial, Basic Materials and Communications.

[57] The issuer is attributed a sovereign rating based on its country of domicile.

[58] Table 3.A.1 (Panel B) in the Appendix presents the share of issuer ratings in the individual regions. The vast majority of debt issuers in the sample have their country of domicile in the United States (approximately 60 percent). Debt issuers from the Euro Area and Japan are represented in the sample only by 8-16 percent (depending on the rating agency).

[59] The issuer's first rating in the dataset is considered to be the initial rating.

number of debt issues rated by the three rating agencies in a given year and industry sector.

The World Bank, the database of World Development Indicators60, is the source of the macroeconomic indicator data. The downloaded dataset includes current account balance (% of GDP), GDP growth (annual %), GDP per capita (US$ of 2014) and inflation (GDP deflator, annual %).

3.4.2 Sample Statistics of Financial Indicators

A wide range of industry sectors is represented in the dataset. The data on the financial sector includes primarily banks, insurance companies and real estate investment trusts (REITS). The data on the non-financial sectors cover the following industry sectors (defined by Bloomberg Industry Classification System[61]): Basic Materials (e.g. Chemicals, Mining, Iron/Steel), Communications (e.g. Telecommunications, Media, Internet), Consumer – Cyclical (e.g. Retail, Entertainment, Auto Manufacturers), Consumer – Non-cyclical (e.g. Food, Commercial Services, Pharmaceuticals), Diversified (e.g. Holding Companies), Energy (e.g. Oil&Gas, Pipelines, Coal), Industrial (e.g. Transportation, Electronics, Building Materials), Technology (e.g. Semiconductors, Computers, Software) and Utilities (e.g. Electric, Gas, Water).

It is necessary to distinguish between the credit rating determinants based on industry sector. Caouette et al. (2008) and Golin and Delhaise (2013) suggest that financial institutions should be evaluated according to the Capital-Assets-Management-

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[60] The World Bank, http://data.worldbank.org/data-catalog/world-development-indicators

[61] The BICS (Bloomberg Industry Classification System) classification is based on the issuer's business characteristic and, similarly to GICS (Global Industry Classification Standard), it consists of 10 sectors. The classification of BICS (Basic Materials, Communications, Consumer - Cyclical, Consumer - Non-cyclical, Energy, Industrial, Utilities, Financial and Diversified) and GICS (Materials, Telecommunication Services, Consumer Discretionary, Consumer Staples, Energy, Industrials, Utilities, Financials and Health Care) are almost identical.

Earnings-Liquidity (CAMEL) model, which defines a set of financial indicators that capture capital adequacy, asset quality, profitability and liquidity assessment. [62]

Panel A in Table 3.A.2 in the Appendix shows the selected financial indicators for the credit rating prediction of financial institutions. In particular, the industry sub-sector of banks is used as an example to illustrate the mean values of these ratios across companies with different rating grades.

- ***Capital Adequacy –*** Basel III[63] requires that the Tier 1 Capital of banks must be at least 6.0% of risk-weighted assets. The Tier 1 ratio, calculated as the sum of core capital and disclosed reserves relative to risk-weighted assets, measures the company's financial strength. The higher the ratio, the higher the company's buffer against unexpected losses.
- ***Asset Quality –*** The non-performing Loans / Total Loans ratio indicates the severity of problems regarding the credit quality of the company's borrowers. A loan is considered to be non-performing if the borrower is more than 90 days overdue on any payment connected with the loan. Indeed, the higher the Non-performing Loans / Total Loans ratio, the worse the company's asset quality. The situation is even worse if the bank does not create enough Loan Loss Reserves to cover Non-Performing Loans (NPL), that is, it has low NPL coverage.
- ***Profitability –*** The profitability of banks is most frequently measured by the Return on Equity (ROE) and the Return on Assets (ROA). ROE expresses the profit generated from the shareholders' investments, while ROA shows how efficiently the management uses the company's assets to generate earnings. The rule of thumb in most markets is that an ROE of between 10 and 20 percent and an ROA of between 1 and 2 percent indicate acceptable performance. Companies below (above) these ranges have weak (very strong) profitability.

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[62] As management (corporate governance) quality is a qualitative factor and it is hard to find a proxy for that indicator, this paper had to neglect its impact on the company's rating.

[63] Third Basel Accord issued by the Bank for International Settlements, http://www.bis.org/publ/bcbs189.pdf

- ***Liquidity* –** The ratio between Total Loans and Total Deposits is a key measure of a company's liquidity. A ratio below 100 percent means that the company is funding its loan portfolio from core deposits, while a ratio above 100 percent signals that it also uses other types of market funding. The strength and stability of the bank's customer deposit base can be also measured by the Deposit to Funding ratio. If the ratio is high, it indicates that the company is less dependent on more volatile interbank or commercial sources of funding.

A broad set of control variables is also available for non-financial institutions. However, to avoid multicollinearity, only selected financial ratios are used to assess the credit quality of the company. Guided by Altman (1968) and Altman and Rijken (2004), non-financial institutions are evaluated based on the Z-score model. The model is comprised of five financial ratios that have the highest discriminating power in predicting corporate bankruptcy (Altman, 1968). These include proxies for liquidity (Working Capital / Total Assets), profitability (Retained Earnings / Total Assets, Earnings before Interest and Taxes / Total Assets), leverage (Total Equity / Total Liabilities) and the efficient use of assets (Sales / Total Assets).

Panel B in Table 3.A.2 in the Appendix presents descriptive statistics of selected financial ratios for the non-financial sector. Specifically, on the example of cyclical consumer goods the mean values of financial indicators are summarized by rating grades.

- ***Working Capital / Total Assets*** – The ratio is a measure of liquidity; the company's short-term financial health. Working Capital is calculated as the difference between Current Assets and Current Liabilities and expresses the ability of the company to cover its short-term obligations with short-term assets. Thus, the Working Capital / Total Assets ratio shows the percentage of remaining liquid assets (after repayment of current liabilities) on the total assets. As reported in Panel B of Table 3.A.2, this measure increases with the credit quality of the company.
- ***Retained Earnings / Total Assets*** - The ratio provides insight into the cumulative profitability of the company. Altman (1968) argues that the ratio effectively reflects the age of the company in terms of its probability of

bankruptcy: companies in their earlier years accumulate relatively low retained earnings and, accordingly, are more exposed to financial difficulties. As the company grows older, it should enhance its Retained Earnings / Total Assets ratio. The higher the ratio, the better the company's financial performance.

- ***Earnings before Interest and Taxes / Total Assets*** – The ratio expresses the general profitability of the company's assets. It considers the company's earnings before tax and leverage reductions are taken into account. As Panel B in Table 3.A.2 indicates, the Earnings before Interest and Taxes / Total Assets ratio can take negative values if the company generates losses and is close to default.
- ***Total Equity / Total Liabilities*** – The ratio is the measure of the company's leverage. It shows how much short-term and long-term debt the company can take and still be covered by its equity. The lower the Total Equity / Total Liabilities ratio, the lower the company's solvency.
- ***Net Sales / Total Assets*** – The ratio indicates how efficiently the company deploys its assets to generate net sales. Net sales (calculated as the difference between total revenue and any allowances or discounts provided to the customer) compared to total assets are heavily industry-specific. For instance, industries with low (high) assets and high (low) sales may have a ratio above 200 (below 50) percent. Panel B in Table 3.A.2 reports that the Net Sales / Total Assets ratio of cyclical consumer goods increases with higher credit ratings, but does not reach 100 percent.

3.4.3 Sample Statistics of Issuer Ratings

To express the forward-looking predictions of rating agencies about the credit risk of the individual financial and non-financial institution, long-term issuer credit ratings[64] assigned by three rating agencies (Moody's, S&P and Fitch) are utilized.

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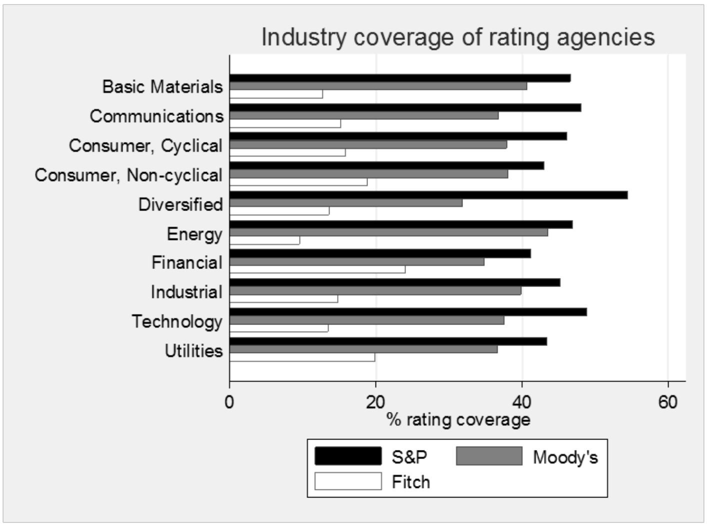
[64] "Credit ratings express the agency's opinion about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time. Credit ratings

Figure 3.1: Industry coverage by S&P, Moody's and Fitch



Note: The figure depicts the share of each agency on total number of issuer ratings within industry sectors. The total number of 3 955 issuer ratings is gained using the sample of 2 486 issuers. The rating coverage is evaluated at the end of 2013.

Credit ratings assessing the creditworthiness of obligors range from AAA (highest quality) to D (default). Nevertheless, S&P/Fitch and Moody's rating grades differ slightly. To make them comparable, the ratings need to be mapped into a common numeric scale. Table 3.A.3 in the Appendix summarizes the credit ratings together with their interpretation and the assigned rating grades on finer/wider scales.

The following sample statistics of issuer ratings guide the hypotheses formulated in this paper:

Figure 3.1 indicates that the rating coverage of rating agencies across the individual industry sectors (i.e. the share of each agency in the total number of issuer ratings within industry sectors) differs significantly. The sample statistics confirm the expectations that S&P and Moody's (both established in early 1900) have much higher rating coverage than Fitch (established in 1997). While in each industry sector both S&P and Moody's rate at least 40% of the issuer ratings, the rating coverage of Fitch is

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can also speak to the credit quality of an individual debt issue, such as a corporate note, a municipal bond or a mortgage-backed security, and the relative likelihood that the issue may default."
Standard & Poor's, http://www.standardandpoors.com/ratings/definitions-and-faqs/en/us

well below 20% (except in the financial industry sector). Therefore, this paper examines the credit ratings of S&P and Moody’s (if not stated otherwise), and the rating coverage of Fitch is only used as a measure of varying competition between rating agencies.

Table 3.1 suggests that the discrepancy in issuer ratings between these agencies is substantial. It summarizes the number of times Moody’s and S&P differently rated the issuer, given the issuer was rated by both agencies. The disagreement is measured in a sample of 2 486 issuers at the end of years 2005-2013. From a total amount of 22 374 observations, the two agencies assigned different rating to the issuers in 5 839 cases. [65] In the case of financial institutions, the two rating agencies significantly disagree when assigning ratings A and BBB. In the case of non-financial institutions, credit ratings across the two agencies also vary for issuers rated BBB and BB (i.e. at the investment–non-investment grade boundary).

From the early 2000s, rating agencies have gradually changed their approach to reflecting the country ratings in the issuer’s rating. The cases in which issuer ratings are higher than their country rating have become more frequent. Figure 3.2 provides some preliminary insight into the relationship of issuer and sovereign ratings during the pre-crisis period (2005-2007), during the subprime lending crisis (2008-2010) and during the sovereign debt crisis (2011-2013). It suggests that after the subprime lending crises, rating agencies ceased restricting company ratings by sovereign rating. When comparing the three rating agencies, Moody’s relaxes the sovereign cap most frequently.

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[65] Although the distance between the two ratings would provide a more precise measure of the rating split, this paper focuses only on the existence of a disagreement between Moody’s and S&P. In the examined sample, one notch rating difference constitutes 75 percent of total rating splits between the agencies.

Table 3.1: Disagreement between S&P and Moody’s in issuer ratings

(A) Financial institutions

Number of S&P Issuer Ratings Different from Moody's Issuer Ratings	Number of Moody's Issuer Ratings Different from S&P Issuer Ratings																			
	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	Total
AAA			1																	1
AA+			5																	5
AA	1	24		19	3															47
AA-	9	37	52		33	4		1												136
A+		12	28	81		53	9	3		3										**189**
A			10	51	138		42	18	5				2							**266**
A-			3	17	53	102		58	36	3	1									**273**
BBB+				2	17	51	64		88	31	2		1							**256**
BBB					1	10	30	80		71	13	1	4							**210**
BBB-						2	11	30	52		32	8	11	2	2					**150**
BB+								1	2	26		20	6	4						59
BB						2		1		7	19		36	16						81
BB-											5	8		42	9	2				66
B+											1	13	11		6	8	4			43
B											1		4	13		9	3			30
B-											1		2	4	2		7			16
CCC+																2		1	1	4
CCC													1	1	1	2	4			9
CCC-																	2			2
CC															1					1
Total	10	73	99	170	**245**	**224**	**156**	**192**	**183**	**141**	75	50	78	82	21	23	20	1	1	1844

(*continued on next page*)

(B) Non-financial institutions

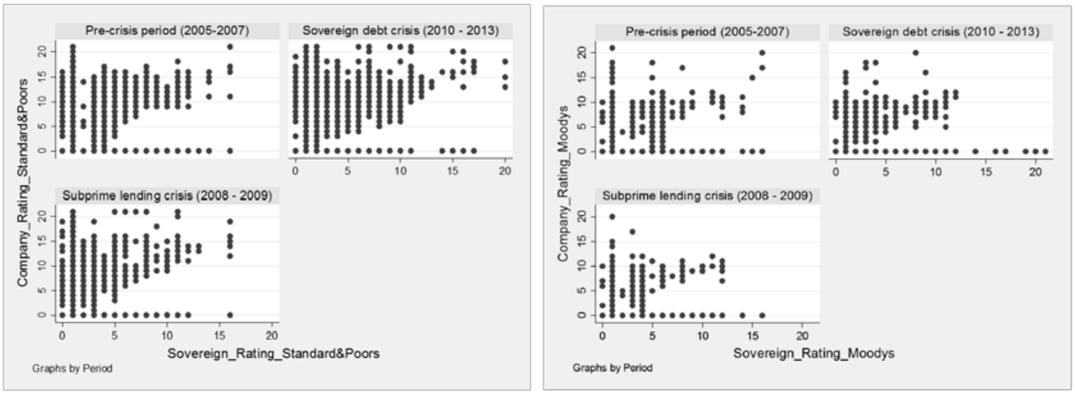
Number of Moody's Issuer Ratings Different from S&P Issuer Ratings

Number of S&P Issuer Ratings Different from Moody's Issuer Ratings

	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB	BBB-	BB+	BB	BB-	B+	B	B-	CCC+	CCC	CCC-	CC	Total
AAA		7																			7
AA+			7	2																	9
AA		53		13	21	1															88
AA-		17	37		44	24	4	2													128
A+			17	45		70	31	2													165
A			4	8	90		84	29	1												216
A-			1		29	90		174	63	9	12										378
BBB+					3	16	113		249	43	5										**429**
BBB	1				1	2	29	131		271	37	3					1				**476**
BBB-	2			5		2	2	6	147		157	41	9							1	**372**
BB+							2	2	15	47		142	33	2	1						**244**
BB							1		12	6	117		203	47	2	1				6	**395**
BB-									1	1	15	106		193	36	3				2	**357**
B+										1	1	10	106		139	20	5	1		2	285
B													12	83		115	23	5	2		240
B-													5	7	51		61	11	7	4	146
CCC+															3	16		5	2	4	30
CCC																2	2		5		9
CCC-																		1			1
CC																	1	2	4		7
D															3	1	1	1	3	4	13
Total	3	77	66	73	188	205	266	**346**	**488**	**378**	**344**	**302**	**368**	332	235	158	94	26	23	23	3995

Note: The table summarizes the number of times Moody’s and S&P differently rated the issuer, given the issuer was rated by both agencies. It is based on credit ratings of 2 486 issuers observed at the end of years 2005-2013 (i.e. over 9 years totaling 22 374 observations). While for financial institutions a rating disagreement is observed in 1 844 cases, for non-financial institutions the disagreement is observed in 3 995 cases.

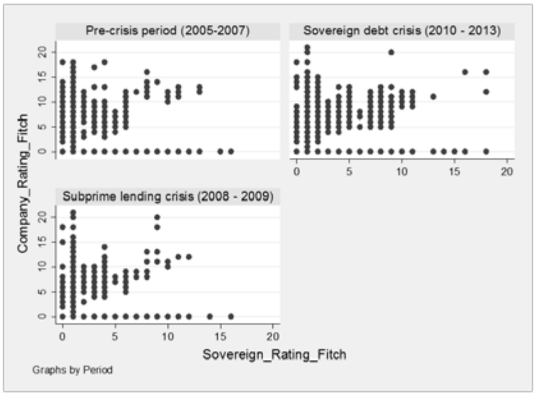
Figure 3.2: The relationship between company and sovereign ratings



(A) Ratings assigned by S&P

(B) Ratings assigned by Moody’s

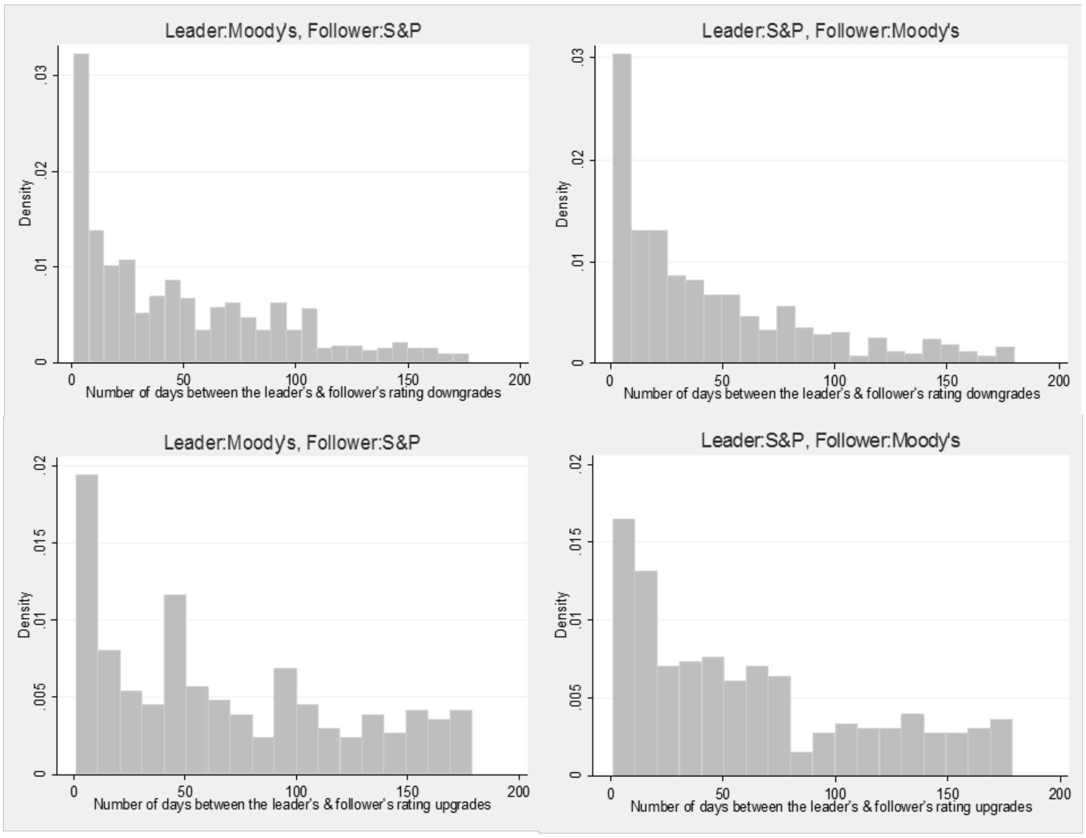
(C) Ratings assigned by Fitch



Note: (1) The figures illustrate the relationship between company and sovereign ratings using a sample of 2 486 issuer ratings and their sovereign ratings assigned by S&P, Moody’s and Fitch during three periods: pre-crisis period (2005-2007), subprime lending crisis (2008-2010) and sovereign debt crisis (2011-2013). It depicts to what extent issuer ratings are capped by sovereign ratings. (2) The numeric rating grades range from Aaa=1 to D=21.

To see whether there is a potential leader-follower relationship between S&P and Moody’s, daily information on rating actions are utilized. For the sample of rating actions observed for 2 486 issuers between December 2005 and October 2014, Figure 3.3 depicts the distribution of time elapsed between rating actions originated by Moody’s and S&P. Specifically, it illustrates the probability that the potential follower’s rating action is within a certain time window after the potential leader’s rating action. The figures suggest that while upgrades of the potential leader do not evoke immediate

Figure 3.3: The distribution of time between rating actions



Note: (1) The figures illustrate the distribution of time between S&P and Moody's rating changes observed in a sample of 2 486 issuers between December 2005 and October 2014. (2) The figures illustrate the probability that the potential follower's rating action is in a certain time window after the potential leader's rating action. (3) Only rating changes within 1-180 days are plotted.

actions by the potential follower, both agencies most likely react to the downgrade of the other agency within 50 days.

Table 3.2 summarizes the magnitude of the follower's rating change on the preceding rating change of the leader.[66] In particular, Panel A and B show what share of

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[66] Rating change refers only to a downgrade or an upgrade in the issuer's rating. New rating assignments (by an additional rating agency) or rating withdrawals are not considered in the analysis of leader-follower relationship, as these are driven by the decision of the issuer and there might be several reasons for them. For example, new rating assignments might correspond to the issuer asking for a second rating opinion either because the first agency assigned an unfavorable rating, or because the industry peers are strengthening their market position through an additional rating opinion. The opposite logic might motivate rating withdrawals.

S&P's rating change is a reaction to a prior rating change by Moody's, and Panel C and D present what share of Moody's rating change is a reaction to a prior rating change by S&P. Panel B for non-financial institutions suggests that if Moody's downgrades/upgrades at some point in time, on average 80% of these rating actions are followed by S&P within 90 days. Panel D for non-financial institutions shows that Moody's reaction to S&P's rating changes is lower, at 67% on average. The leader-follower relationship for financial institutions is slightly different. Considering the same time window, around 65% of Moody's downgrades/upgrades are followed by S&P (Panel A), while only 56% of S&P's rating actions are copied by Moody's (Panel C). These preliminary statistics suggest that S&P is likely to be the follower on the credit rating market.

3.5 Results

3.5.1 Disagreement in Rating Assessments across Industry, Time and Rating

As investors tend to differentiate between ratings, and bond yields often reflect the rating of the more prudent agency, the rating disagreement across industry sectors is of high prominence for the financial market participants. Based on the results of the Wilcoxon signed rank sum test summarized in Table 3.3 (Panel A), I reject the null hypothesis that the choice of rating agency has no effect on the credit rating of the issuer. Moody's is consistently more prudent in rating non-financial institutions. This finding is in line with Livingston et al. (2010) who on the sample non-financial U.S. corporations show that conservative ratings assigned by Moody's are also detected by the investors (when two ratings are available and Moody's rating is higher, bond yields are at a lower level than when S&P's rating is higher). Nevertheless, this paper extends the results of the recent literature by examining rating split also within the nonfinancial sector. Contrary to expectations, the results of the Wilcoxon signed rank sum test suggest that rating agencies agree in creditworthiness of issuers from the Technology and Communications industry sectors.

Table 3.2: The magnitude of the follower's rating change on the preceding rating change of the leader

Panel A - Leader: Moody's, Industry: Financial	Downgrade by Moody's in previous 1-15 days	Downgrade by Moody's in previous 16-90 days	Downgrade by Moody's in previous 91-180 days	Downgrade by Moody's in previous more than 180 days	Upgrade by Moody's in previous 1-15days	Upgrade by Moody's in previous 16-90 days	Upgrade by Moody's in previous 91-180 days	Upgrade by Moody's in previous more than 180 days	Total rating action by S&P
S&P downgrade by 2 or more notches	**28.2%**	**18.4%**	11.6%	5.8%	0.0%	0.0%	0.0%	0.0%	130
S&P downgrade by 1 notch	**43.6%**	**42.9%**	25.6%	43.5%	0.0%	4.2%	0.0%	13.0%	447
No rating change	28.2%	36.7%	53.5%	34.8%	40.0%	29.2%	14.8%	35.9%	2266
S&P upgrade by 1 notch	0.0%	2.0%	9.3%	15.9%	**60.0%**	**62.5%**	77.8%	50.0%	400
S&P upgrade by 2 or more notches	0.0%	0.0%	0.0%	0.0%	**0.0%**	**4.2%**	7.4%	1.1%	29
Grand Total	39	98	43	69	5	24	27	92	3272

Panel B -Leader: Moody's; Industry: Non-financial	Downgrade by Moody's in previous 1-15 days	Downgrade by Moody's in previous 16-90 days	Downgrade by Moody's in previous 91-180 days	Downgrade by Moody's in previous more than 180 days	Upgrade by Moody's in previous 1-15 days	Upgrade by Moody's in previous 16-90 days	Upgrade by Moody's in previous 91-180 days	Upgrade by Moody's in previous more than 180 days	Total rating action by S&P
S&P downgrade by 2 or more notches	**26.2%**	**18.3%**	8.0%	3.4%	0.0%	1.1%	1.5%	1.0%	427
S&P downgrade by 1 notch	**55.9%**	**54.3%**	45.0%	38.2%	3.0%	0.0%	3.0%	8.9%	1576
No rating change	16.6%	26.4%	43.0%	31.4%	16.7%	13.8%	22.4%	34.0%	7543
S&P upgrade by 1 notch	0.7%	0.0%	3.0%	25.0%	**63.6%**	**71.3%**	68.7%	53.6%	1593
S&P upgrade by 2 or more notches	0.7%	1.0%	1.0%	2.0%	**16.7%**	**13.8%**	4.5%	2.4%	227
Grand Total	145	197	100	204	66	87	67	291	11366

(*continued on next page*)

Panel C – Leader: S&P, Industry: Financial	Downgrade by S&P in previous 1-15 days	Downgrade by S&P in previous 16-90 days	Downgrade by S&P in previous 91-180 days	Downgrade by S&P in previous more than 180 days	Upgrade by S&P in previous 1-15 days	Upgrade by S&P in previous 16-90 days	Upgrade by S&P in previous 91-180 days	Upgrade by S&P in previous more than 180 days	Total rating action by Moody's
Moody's downgrade by 2 or more notches	**28.6%**	**31.4%**	16.7%	3.8%	0.0%	0.0%	0.0%	0.0%	142
Moody's downgrade by 1 notch	**20.4%**	**26.7%**	16.7%	37.7%	5.4%	0.0%	0.0%	4.9%	306
No rating change	51.0%	41.9%	66.7%	54.7%	21.6%	57.1%	55.6%	53.4%	2473
Moody's upgrade by 1 notch	0.0%	0.0%	0.0%	3.8%	**43.2%**	**14.3%**	38.9%	35.0%	285
Moody's upgrade by 2 or more notches	0.0%	0.0%	0.0%	0.0%	**29.7%**	**28.6%**	5.6%	6.8%	66
Grand Total	49	105	18	53	37	7	18	103	3272

Panel D – Leader: S&P, Industry: Non-financial	Downgrade by S&P in previous 1-15 days	Downgrade by S&P in previous 16-90 days	Downgrade by S&P in previous 91-180 days	Downgrade by S&P in previous more than 180 days	Upgrade by S&P in previous 1-15 days	Upgrade by S&P in previous 16-90 days	Upgrade by S&P in previous 91-180 days	Upgrade by S&P in previous more than 180 days	Total rating action by Moody's
Moody's downgrade by 2 or more notches	**23.2%**	**19.2%**	10.1%	2.7%	1.3%	2.5%	0.0%	0.0%	205
Moody's Downgrade by 1 notch	**46.4%**	**46.6%**	46.8%	28.7%	1.3%	2.5%	4.3%	6.7%	889
No rating change	29.8%	32.4%	43.0%	55.3%	34.8%	25.3%	21.3%	44.2%	9323
Moody's upgrade by 1 notch	0.7%	0.5%	0.0%	12.8%	**53.5%**	**55.7%**	66.0%	46.8%	838
Moody's upgrade by 2 or more notches	0.0%	1.4%	0.0%	0.5%	**9.0%**	**13.9%**	8.5%	2.2%	111
Grand Total	151	219	79	188	155	79	94	267	11366

Note: The table presents the magnitude of the rating changes of the follower (downgrade by more than 2 notches, downgrade by 1 notch, no rating change, upgrade by 1 notch, upgrade by 2 notches), given the leader's actions (downgrade, upgrade) in the previous 1-15 days, 16-90 days, 91-180 days or more than 180 days. For example, the first column of Panel C suggests that 15days after S&P downgraded the issuers; Moody's subsequently downgraded the issuers by more than 2 notches in 28.6% of cases, downgraded the issuers by 1 notch in 20.4% cases and did not change its rating in 51% of cases. The rating change statistics express the magnitude and the timing between subsequent rating updates (rating changes could be faster for the agency that was more wrong in its previous rating), where the initial rating is the first rating in the dataset. In total, the table covers 5 572 rating changes by Moody's and 9 066 rating changes by S&P observed on the sample of 2 236 issuers between January 2005 and October 2014 (for the remaining 250 issuers no rating changes were observed).

For the other non-financial industry sectors the numerical rating grades provided by S&P are lower (indicating a better rating) than the numerical rating grades provided by Moody's (Column 8 of Table 3.3, Panel A) and the disagreement is statistically significant at least at the 5% level (Column 5 of Table 3.3, Panel A).Interestingly, in the assessment of default risk for financial institutions S&P is the more conservative rating agency. These results might be explained by the difference in rating methodologies or the higher costs of overrating[67] financial institutions for S&P.

The difference between S&P and Moody's credit ratings deepens over time (Table 3.3, Panel B). During the pre-crisis period (2005-2007), it is statistically significant only at a 10% level, while during the subprime lending crisis (2008-2010), it is statistically significant at a 5% level and during the sovereign debt crisis (2011-2013), it is statistically significant at a 1% level.

According to Table 3.3 (Panel C), the two rating agencies also differ across rating grades divided into investment grade (ratings from AAA to BBB) and non-investment grade (ratings from BB to D). For investment grade ratings, the Wilcoxon sum rank test for the equality of median ratings is rejected at a 5% statistical significance level, while for non-investment grade ratings, the equality of median ratings between S&P and Moody's is already rejected at 1%.

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[67] Although credit ratings are issuer paid, rating agencies seek to protect their reputational capital by assigning timely and accurate ratings.

Table 3.3: Wilcoxon signed rank test of issuer ratings

Panel A

Industry sector	Rating agency	Complete sample	Sub-sample of issuers rated by both S&P & Moody's		Sub-sample of issuers with different rating from S&P & Moody's				
		N	N	Wilcoxon signed-rank p-value	N	Split % of Complete Sample	Mean	Median	Standard deviation
Basic Materials	S&P	1 728	792	0.016	330	19%	10.1	10.0	2.7
	Moody's						10.3	10.0	2.7
Communications	S&P	1 827	787	0.530	388	21%	10.9	11.0	3.7
	Moody's						10.8	11.0	3.7
Cyclical	S&P	2 853	1 298	0.000	661	23%	11.7	12.0	3.3
	Moody's						12.2	13.0	3.4
Non-cyclical	S&P	2 898	1 427	0.000	743	26%	9.2	9.0	3.6
	Moody's						9.7	10.0	3.6
Diversified	S&P	126	53	0.004	18	14%	10.4	11.0	1.8
	Moody's						11.4	12.5	2.5
Energy	S&P	1 620	947	0.000	449	28%	10.5	11.0	3.5
	Moody's						10.8	11.0	4.1
Financial	S&P	5 490	2 874	0.000	1 844	34%	8.0	8.0	3.0
	Moody's						7.6	7.0	3.5
Industrial	S&P	3 411	1 465	0.000	726	21%	10.0	10.0	3.5
	Moody's						10.6	11.0	3.8
Technology	S&P	1 008	308	0.764	161	16%	9.8	9.0	3.4
	Moody's						9.8	9.0	3.8
Utilities	S&P	1 413	883	0.000	519	37%	8.2	8.0	2.5
	Moody's						8.3	8.0	2.8
Total	S&P	22 374	10 834	0.000	5 839	26%	9.4	9.0	3.5
	Moody's						9.5	9.0	3.9

(*continued on next page*)

Panel B

Time period	Rating agency	Complete sample	Sub-sample of issuers rated by both S&P & Moody's		Sub-sample of issuers with different rating from S&P & Moody's				
		N	N	Wilcoxon signed-rank p-value	N	Split % of Complete Sample	Mean	Median	Standard deviation
Pre-crisis period (2005-2007)	S&P	7 458	3 179	0.073	1 705	23%	9.0	9.0	3.4
	Moody's						9.1	9.0	3.9
Subprime lending crisis (2008-2010)	S&P	7 458	3 686	0.025	2 055	28%	9.4	9.0	3.6
	Moody's						9.5	9.0	4.0
Sovereign debt crisis (2011-2013)	S&P	7 458	3 969	0.000	2 079	28%	9.6	9.0	3.4
	Moody's						9.9	10.0	3.7
Total	S&P	22 374	10 834	0.000	5 839	26%	9.4	9.0	3.5
	Moody's						9.5	9.0	3.9

Panel C

Rating grade	Rating agency	Complete sample	Sub-sample of issuers rated by both S&P & Moody's		Sub-sample of issuers with different rating from S&P & Moody's				
		N	N	Wilcoxon signed-rank p-value	N	Split % of Complete Sample	Mean	Median	Standard deviation
Investment grade (AAA to BBB-)	S&P	10 699	7 195	0.025	3 801	36%	7.3	7.0	2.0
	Moody's						7.3	8.0	2.6
Non-investment grade (BB+ to D)	S&P	11 675	3 639	0.000	2 038	17%	13.3	13.0	1.8
	Moody's						13.6	14.0	2.1
Total	S&P	22 374	10 834	0.000	5 839	26%	9.4	9.0	3.5
	Moody's						9.5	9.0	3.9

Note: (1) The table compares Moody's and S&P issuer ratings by industry sector (Panel A), by time period (Panel B) and by rating grade (Panel C). The first part of the table summarizes the *complete sample* that consists of credit ratings of 2 486 issuers observed at the end of years 2005-2013 (i.e. over 9 years totaling 22 374 observations). The second part of the table shows the results of Wilcoxon signed-rank test conducted on the *sub-sample of issuers rated by both S&P and Moody's* at year-ends. The third part of the table presents the descriptive statistics of credit ratings on the *sub-sample of issuers with different rating from S&P & Moody's.* (2) Cyclical denotes consumer goods industries that rely heavily on the business cycle and economic conditions. Non-cyclical denotes consumer goods industries that are immune to economic fluctuations.

3.5.2 Rating Split is Dependent on Competition between Rating Providers

A simple probit model was used to estimate the relationship between rating splits and selected rating determinants. The estimation results conducted separately for financial and non-financial institutions are summarized in Table 3.4. These show that Fitch's increasing market share has a positive and statistically significant (at a 5% level) effect on the rating split between S&P and Moody's in the non-financial sector (the impact in the financial sector is not statistically significant). These results extend the findings of Becker and Milbourn (2011), who show that the quality of issuer-paid credit ratings lowered (the rating's information value for investors and their accuracy in predicting default decreased) after Fitch entered the market.[68] Nevertheless, Fitch's increasing market share not only lowers the rating quality of S&P and Moody's, but it also increases the likelihood of rating split (as shown in Table 3.4). If Fitch's issuer rating is different from the ratings assigned by S&P or Moody's, then Fitch's entry to the market might serve as a trigger for the two main rating agencies to reassess the creditworthiness of the issuer. This might then result in the rating split of S&P and Moody's issuer ratings. Another possible explanation is that some rating agencies might prefer to protect their reputational capital by assigning timely and accurate ratings (i.e. likely to issue lower ratings); other rating agencies might prefer to increase their own profits (credit ratings are issuer-paid) by assigning favorable issuer ratings (i.e. likely to issue higher ratings). The results of this paper suggests that rating shopping (acquiring an additional rating opinion in the hope of rating improvement) fosters further disagreement between rating agencies, and hence reinforces the use of 'second best' issuer rating for regulatory purposes.

Other determinants of rating splits are also in line with expectations. The disagreement between issuer ratings deepens over time. During the sovereign debt crisis, the rating split is, on average, higher by 3.4 percentage points than during the pre-crisis period. Interestingly, for non-investment grade issuers, the rating split is less frequent. The results also suggest that rating disagreement is present even in relation to

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[68] Xia (2014) and Cornaggia and Cornaggia (2013) show that rating quality increases when investor-paid rating agencies are present on the credit rating market.

the key financial indicators (the choice of key financial indicators predicting the rating of financial and non-financial institution is in line with the literature - Altman, 1968; Altman and Rijken, 2004; Caouette et al., 2008; Golin and Delhaise, 2013; Hau et al., 2013). This can be partially explained by the different weights the rating agencies place on individual financial fundamentals.

A one-year change in the earnings-per-share (EPS), as the measure of performance volatility, does not influence rating splits. Although Ederington and Goh (1998) argue that a decline in earnings is a good proxy for market expectations and efficiently forecasts downgrades, the estimation results summarized in Table 3.4 suggest that the volatility of EPS has no statistically significant effect on the rating disagreement between Moody's and S&P.

3.5.3 Sovereign Ceilings Are Restrictive Only for Financial Institutions

Table 3.5 summarizes the key determinants of S&P and Moody's issuer rating changes estimated based on model (3.2) and (3.3). The regressions are run separately for financial and non-financial institutions. Panel A of Table 3.5 demonstrates that in the case of financial institutions, S&P increased the reliance of issuer rating on sovereign (i.e. country of domicile) rating over the observed period. Specifically, while during a pre-crisis period a one-notch sovereign upgrade has no impact on issuer rating (one notch sovereign downgrade decreases the likelihood of issuer rating downgrade - as the sovereign ceiling is most likely not low enough to imply a burden on the financial sector), over a sovereign debt crisis a one-notch sovereign upgrade leads to a 13.2% higher likelihood of issuer upgrade (a one-notch sovereign downgrade leads to an 8.6% higher likelihood of issuer downgrade). On the other hand, Panel C of Table 3.5 suggests that Moody's reflected the country ratings in its issuer ratings over all the examined periods, but the magnitude of sovereign effect is decreasing. Over the subprime lending crisis both agencies overhauled their rating methodologies with respect to their perceptions of government support, and slightly changed the weight of individual rating factors. In 2007, Moody's introduced the Joint Default Analysis

(JDA)[69], in which the issuer rating has no explicit country rating restrictions and government support depends on the bank's systemic importance. In 2011, S&P introduced the Banking Industry Country Risk Assessments (BICRA)[70], according to which the macroeconomic indicators and industrial/regulatory environment (determining country rating) might explicitly affect the stand-alone rating of the issuer. The change in the two agencies' approach underscores that there is no unique metric in measuring the systemic risk (the industrial, financial and economic environment) to which financial institutions are exposed.

Another explanation for the high reliance of financial sector on sovereign rating change is the dominant foreign ownership of financial institutions, where the high rating of the parent company is limited by the lower rating of the issuer's country. A recent contribution from Williams et al. (2013) similarly shows the importance of sovereign ratings for financial institutions in emerging markets for 1999-2009. Nevertheless, the findings in Table 3.5 suggest that the role of sovereign rating change is also essential in other than emerging markets and remains statistically significant at 1% in the sovereign debt crisis. Possessing a non-investment grade issuer/sovereign rating has no statistically significant impact on rating downgrade/upgrade.

The two major rating agencies put significantly less weight from sovereign ratings on the rating of non-financial institutions. In almost all time periods the sovereign rating change does not affect the issuer rating for S&P or Moody's (Panel B and D). Borensztein et al. (2013) analyze the relationship between sovereign and issuer ratings and find the same results for ratings assigned by S&P. This paper contributes to the literature with an important finding – throughout the recent financial crises, neither of the two incumbent rating agencies applied sovereign restriction on the rating of non-financial institutions.

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[69] Moody's Investors Services (2007): Incorporation of Joint-Default Analysis into Moody's Bank Ratings: A Refined Methodology, https://www.moodys.com/research/Moodys-Announces-Bank-Rating-Actions-Resulting-From-Implementation-Of-JDA--PR_128399

[70] Standard and Poor's (2011): Banking Industry Country Risk Assessment Methodology And Assumptions, http://www.standardandpoors.com/spf/upload/Ratings_EMEA/2011-11-09_CBEvent_CriteriaFIBankIndustryCountryRiskAssessment.pdf

Table 3.4: Determinant of rating disagreement between S&P and Moody's

Dependent variable – Rating disagreement	Financial institutions (Marginal effects)	Non-financial institutions (Marginal effects)
Sovereign debt crisis	0.003	0.034***
	(0.033)	(0.011)
Fitch market share	1.310	0.281**
	(2.152)	(0.127)
Non-investment grade issuer	-0.437***	-0.134***
	(0.031)	(0.009)
Non-investment grade sovereign	0.256***	-0.002
	(0.052)	(0.031)
Total asset	-0.000	-0.000***
	(0.000)	(0.000)
Volatility of Earnings per Share	-0.000	0.000***
	(0.000)	(0.000)
Net interest margin	0.000**	-
	(0.000)	-
Non-performing assets to total assets	0.016***	-
	(0.005)	-
Deposits to funding	-0.002***	-
	(0.001)	-
Retained Earnings / Total Assets	-	0.000**
	-	(0.000)
Total Equity / Total Liabilities	-	-0.001***
	-	(0.000)
Net Sales /Total Assets	-	-0.000***
	-	(0.000)
Euro Area	0.077	-0.097***
	(0.051)	(0.015)
Japan	-0.158***	-0.250***
	(0.055)	(0.014)
Other Advanced Economies	0.104**	-0.114***
	(0.041)	(0.013)
Commonwealth of Independent States	0.001	0.138***
	(0.125)	(0.051)
Emerging and Developing Asia	-0.138***	-0.081**
	(0.050)	(0.032)
Emerging and Developing Europe	0.304***	-0.125*
	(0.089)	(0.067)
Latin America and the Caribbean	-0.030	-0.105***
	(0.058)	(0.022)
Middle East, North Africa	0.180***	-
	(0.045)	
Materials	-	-0.055***
	-	(0.020)
Communications	-	-0.039**
	-	(0.019)
Industrials	-	-0.043***
	-	(0.016)
Technology	-	-0.060**
	-	(0.025)
Observations	1 553	10 238
R-squared	0.2001	0.0938

Note: (1) The results are derived using issuers that are rated by S&P or Moody's over 2005-2013. Estimation results presented only for variables that were statistically significant at least in one model. (2) For Sovereign debt crisis the reference value is the Pre-crisis period, for Region the reference value is USA, for Industry sector of non-financial institutions the reference value is the financial sector. (3) Standard errors are in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Turning to the other determinants of issuer rating change, Table 3.5 shows that competition is one of the key triggers of rating action. While the effect of the rating agencies' industry coverage is particularly strong in the case of financial institutions, for non-financial institutions the competitors' rating actions drive the rating update. When comparing the determinants of issuer rating change during pre-crisis and sovereign debt crisis periods, the reliance on the competitors' rating action weakens, but remains statistically significant. For instance, while for financial institutions a one-notch upgrade of Moody's (Fitch) issuer rating during a pre-crisis period increases the likelihood of an S&P upgrade by 25.6 percent (12.4 percent), this same change during the sovereign debt crisis increases the probability of an S&P upgrade by only 7.5 percent (8.7 percent). Although during a pre-crisis period a one-notch downgrade of Moody's (Fitch) issuer rating might even decrease the likelihood of an S&P downgrade, this same change increases the S&P downgrade during a subprime lending crisis by 8 percent (8.4 percent) and during a sovereign debt crisis by only 3.2 percent (2.5 percent). The competitors' impact on Moody's issuer rating change is similar, though much less significant. Overall, this diminishing influence of the competitors' behavior might be explained by the increased motivation of rating agencies to protect their reputational capital.

Table 3.A.4 in the Appendix reports the responses of rating agencies to macroeconomic, financial, geographical[71] and sectoral variables from models (3.2) and (3.3). In the case of financial institutions, the two agencies agree that a one-year change of macroeconomic indicators is statistically more significant than the fluctuation or the absolute level of the financial results. This also explains the importance of sovereign ceiling in this sector. For non-financial institutions, rating upgrades/downgrades are more influenced by changes in financial results, even though their magnitude and statistical significance are weak. For instance, a 1 percent improvement in Earnings before Interest and Taxes / Total Assets increases the likelihood of rating upgrade only by 0.7 percent. Moody's rating changes are less likely in geographical regions other than the United States. In the case of S&P the dependence of issuer rating change on

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[71] As the sample includes debt issuers from over 60 countries, dummy variables for geographical region are included among the determinants of issuer rating change.

geographical region is limited. The behavior of rating agencies for the individual non-financial industry sectors does not vary essentially. Nevertheless, during the subprime lending crisis and the sovereign debt crisis the probability of rating changes was higher for the majority of non-financial sectors (by around 10 percent) than for the financial sector.

3.5.4 S&P Tends to Be the Follower in Rating Actions

Having confirmed a close link between several rating actions, this sections turns to examining the leader-follower relationship of rating agencies. Table 3.6 presents the results of the ordered logit model for rating changes, where S&P (Moody's) is a potential follower and Moody's (S&P) is a potential leader. The estimation is conducted using daily rating changes between December 2005 and October 2014. The rating actions are analyzed in four time windows: the follower's rating action is 1-15 days[72], 16-90 days, 91-180 days or more than 180 days after the leader's rating action.

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[72] Rating changes within two days account for only 1% of the total number of rating actions.

Table 3.5: Determinants of issuer rating change

Panel A – Issuer rating: S&P, Industry: Financial

	Dependent variable - Issuer rating upgrade by S&P			Dependent variable - Issuer rating downgrade by S&P		
Rating change determinants	Pre-crisis: Financial inst. – Marg. effects	Subprime lending crisis: Financial inst. – Marg. effects	Sovereign debt crisis: Financial inst. – Marg. effects	Pre-crisis: Financial inst. – Marg. effects	Subprime lending crisis: Financial inst. – Marg. effects	Sovereign debt crisis: Financial inst. – Marg. effects
Upgrade of Sovereign by S&P	0.135	0.096***	0.132***			
	(0.086)	(0.032)	(0.040)			
Upgrade of Issuer by Moody's	0.256***	0.020	0.075*			
	(0.053)	(0.034)	(0.039)			
Upgrade of Issuer by Fitch	0.124*	0.051*	0.087**			
	(0.066)	(0.026)	(0.043)			
Downgrade of Sovereign by S&P				-0.144*	-0.034	0.086***
				(0.078)	(0.028)	(0.021)
Downgrade of Issuer by Moody's				-0.104***	0.080***	0.032*
				(0.040)	(0.021)	(0.018)
Downgrade of Issuer by Fitch				-0.016	0.084***	0.025
				(0.064)	(0.024)	(0.027)
Sovereign rating by S&P	0.018	-0.008*	-0.004	0.007	0.012*	0.004
	(0.014)	(0.005)	(0.005)	(0.016)	(0.007)	(0.007)
Non-investment grade issuer	-0.246***	-0.056**	-0.112***	-0.255***	-0.082**	-0.139***
	(0.092)	(0.025)	(0.029)	(0.095)	(0.038)	(0.041)
Non-investment grade sovereign	0.047	0.124***	0.012	0.144	0.141**	0.046
	(0.117)	(0.038)	(0.057)	(0.127)	(0.062)	(0.072)
S&P industry market share	21.359***	0.483	1.004*	13.223**	-15.778**	0.021
	(6.039)	(4.591)	(0.590)	(6.268)	(6.872)	(0.790)
Pseudo R2	0.2804	0.3506	0.3335	0.2172	0.3860	0.3197
Observations	293	496	638	293	631	638

(*continued on next page*)

Panel B – Issuer rating: S&P, Industry: Non-financial

	Dependent variable - Issuer rating upgrade by S&P			Dependent variable - Issuer rating downgrade by S&P		
Rating change determinants	Pre-crisis: Non-financial inst. – Marg. effects	Subprime lending crisis: Non-financial inst. – Marg. effects	Sovereign debt crisis: Non-financial inst. – Marg. effects	Pre-crisis: Non-financial inst. – Marg. effects	Subprime lending crisis: Non-financial inst. – Marg. effects	Sovereign debt crisis: Non-financial inst. – Marg. effects
Upgrade of Sovereign by S&P	0.088***	0.026	0.042			
	(0.025)	(0.026)	(0.032)			
Upgrade of Issuer by Moody's	0.185***	0.150***	0.152***			
	(0.019)	(0.013)	(0.014)			
Upgrade of Issuer by Fitch	0.143***	0.123***	0.099***			
	(0.028)	(0.022)	(0.022)			
Downgrade of Sovereign by S&P				-0.131***	-0.030	0.021**
				(0.032)	(0.025)	(0.010)
Downgrade of Issuer by Moody's				-0.029	0.048***	0.029*
				(0.022)	(0.013)	(0.015)
Downgrade of Issuer by Fitch				0.074***	0.039**	0.022
				(0.024)	(0.017)	(0.023)
Sovereign rating by S&P	0.001	-0.003	-0.006*	-0.015	0.006	0.004
	(0.007)	(0.005)	(0.004)	(0.009)	(0.007)	(0.005)
Non-investment grade issuer	-0.010	0.006	0.002	-0.053***	-0.021	-0.032**
	(0.014)	(0.009)	(0.010)	(0.018)	(0.014)	(0.014)
Non-investment grade sovereign	-0.002	0.034	-0.024	-0.046	0.034	-0.031
	(0.047)	(0.034)	(0.032)	(0.062)	(0.046)	(0.046)
S&P industry market share	0.144	0.149	-0.243	0.074	-0.021	-0.234
	(0.320)	(0.121)	(0.165)	(0.427)	(0.183)	(0.218)
Pseudo R2	0.1342	0.1728	0.1573	0.0575	0.0910	0.0742
Observations	2 595	4 057	3 889	2 595	4 060	3 908

(*continued on next page*)

Panel C – Issuer rating: Moody’s, Industry: Financial

	Dependent variable - Issuer rating upgrade by Moody's			Dependent variable - Issuer rating downgrade by Moody's		
Rating change determinants	Pre-crisis: Financial inst. – Marg. effects	Subprime lending crisis: Financial inst. – Marg. effects	Sovereign debt crisis: Financial inst. – Marg. effects	Pre-crisis: Financial inst. – Marg. effects	Subprime lending crisis: Financial inst. – Marg. effects	Sovereign debt crisis: Financial inst. – Marg. effects
Upgrade of Sovereign by Moody's	0.458***	0.607***	0.201***			
	(0.082)	(0.118)	(0.033)			
Upgrade of Issuer by S&P	0.192***	0.015	0.037			
	(0.039)	(0.023)	(0.024)			
Upgrade of Issuer by Fitch	0.097	0.303***	0.050*			
	(0.061)	(0.069)	(0.027)			
Downgrade of Sovereign by Moody's				-0.485***	-0.081***	-0.010
				(0.084)	(0.028)	(0.020)
Downgrade of Issuer by S&P				-0.189***	0.052**	0.045*
				(0.039)	(0.024)	(0.025)
Downgrade of Issuer by Fitch				-0.041	0.028	0.033
				(0.048)	(0.029)	(0.030)
Sovereign rating by Moody's	-0.018	0.003	0.009*	-0.012	0.015**	-0.008
	(0.014)	(0.006)	(0.005)	(0.014)	(0.006)	(0.007)
Non-investment grade issuer	-0.353**	-0.011	0.029	-0.390**	-0.135***	0.092**
	(0.159)	(0.025)	(0.024)	(0.157)	(0.045)	(0.039)
Non-investment grade sovereign	0.474***	0.067	0.033	0.517***	0.054	0.063
	(0.141)	(0.047)	(0.037)	(0.149)	(0.072)	(0.069)
Moody's industry market share	89.031***	-43.147***	-1.052	86.166***	18.423***	5.150***
	(16.600)	(13.377)	(1.023)	(17.831)	(6.938)	(1.702)
Pseudo R2	0.4823	0.8019	0.5575	0.476	0.3835	0.2809
Observations	289	411	575	289	631	632

(*continued on next page*)

Panel D – Issuer rating: Moody’s, Industry: Non-financial

	Dependent variable - Issuer rating upgrade by Moody's			Dependent variable - Issuer rating downgrade by Moody's		
Rating change determinants	Pre-crisis: Non-financial inst. – Marg. effects	Subprime lending crisis: Non-financial inst. – Marg. effects	Sovereign debt crisis: Non-financial inst. – Marg. effects	Pre-crisis: Non-financial inst. – Marg. effects	Subprime lending crisis: Non-financial inst. – Marg. effects	Sovereign debt crisis: Non-financial inst. – Marg. effects
Upgrade of Sovereign by Moody's	-0.012	0.026	0.042*			
	(0.025)	(0.017)	(0.023)			
Upgrade of Issuer by S&P	0.093***	0.075***	0.087***			
	(0.010)	(0.007)	(0.008)			
Upgrade of Issuer by Fitch	0.087***	0.068***	0.057***			
	(0.017)	(0.012)	(0.015)			
Downgrade of Sovereign by Moody's				0.014	-0.022*	0.005
				(0.039)	(0.013)	(0.009)
Downgrade of Issuer by S&P				-0.016	0.029***	0.008
				(0.012)	(0.007)	(0.009)
Downgrade of Issuer by Fitch				0.043**	0.003	0.007
				(0.019)	(0.013)	(0.020)
Sovereign rating by Moody's	0.006	-0.003	0.001	-0.006	0.016**	0.010***
	(0.006)	(0.004)	(0.003)	(0.009)	(0.006)	(0.004)
Non-investment grade issuer	-0.006	0.003	0.014*	-0.046***	-0.027**	0.003
	(0.009)	(0.007)	(0.009)	(0.014)	(0.011)	(0.012)
Non-investment grade sovereign	-0.068**	0.005	0.007	-0.017	-0.058	-0.076**
	(0.032)	(0.021)	(0.024)	(0.045)	(0.044)	(0.036)
Moody's industry market share	0.175	-0.043	0.666**	0.171	-0.328**	0.705*
	(0.259)	(0.108)	(0.285)	(0.350)	(0.162)	(0.390)
Pseudo R2	0.1906	0.2386	0.1930	0.0599	0.0791	0.0680
Observations	2 567	3 994	3 882	2 567	4 060	3 908

Note: (1) The table presents the results of probit estimation (Eq. (3.2) and Eq. (3.3)) with robust standard errors. It reports the impact of own/other agency’s sovereign/issuer ratings on the probability of the issuer rating change (marginal effects) originated by S&P and Moody’s. The dependent variable is a binary variable for rating upgrade/downgrade observed at the end of years 2005-2013 for a sample of 2 486 financial and non-financial institutions. Rating downgrades and upgrades are examined separately due to their different determinants. The determinants of issuer rating changes are presented for three different periods: pre-crisis period (2005-2007), subprime lending crisis (2008-2010) and sovereign debt crisis (2011-2013). The impact of financial and macroeconomic data on issuer rating change is presented in Table 3.A.4. (2) Standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The rating downgrade/upgrade of the competitor is statistically significant at the 1% level in all examined time windows. In line with expectations, the more time that has passed after the leader's rating action, the less likely it is that the follower will downgrade/upgrade its rating (i.e. the impact of a 1-notch rating change is more substantial in magnitude than a 2-notch rating change). Comparing the reaction of one rating agency 1-15 days after the other agency's downgrade/upgrade, the following can be concluded: (1) Moody's issuer downgrade/upgrade increases the likelihood of S&P's issuer downgrade/upgrade by 25-30% on average (Panel A and Panel B); (2) S&P's issuer downgrade/upgrade increases the likelihood of Moody's issuer downgrade/upgrade by only 15-19% on average (Panel C and Panel D). This suggests that S&P is more likely to be the follower in rating actions when compared to Moody's. The results do not vary substantially for financial and non-financial institutions. Overall, rating actions are less likely to be affected by the agency's own previous rating downgrades/upgrades. The result is qualitatively similar to the findings of Alsakka and Gwilym (2010), which show that Moody's is the first mover on the sovereign credit rating market.

After measuring market reaction (stock return movement) to rating outlook[73] changes, Bannier and Hirsch (2010) argue that outlooks have not only an informative role, but serve as early warning indicators. As a robustness check, a model utilizing rating outlook changes was also estimated. However, the results of model (3.4) and (3.5) with rating outlook are very similar to those predicted using credit rating changes; the findings are not presented in this paper.

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[73] "A rating outlook assesses the potential direction of a long-term credit rating over the intermediate term (typically six months to two years). In determining a rating outlook, consideration is given to any changes in the economic and/or fundamental business conditions. An outlook is not necessarily a precursor of a rating change."
Standard & Poor's,
https://www.standardandpoors.com/ratings/articles/en/us/?articleType=HTML&assetID=1245378053126

Table 3.6: Leader-follower relationship between S&P and Moody's

Panel A - Follower: S&P, Industry: Financial

	Financial institutions (Marginal effects)			
Dependent variable	S&P upgrade by 1 notch	S&P upgrade by more than 2 notches	S&P downgrade by 1 notch	S&P downgrade by more than 2 notches
Downgrade by Moody's in previous 1-15days	-0.245***	-0.015***	0.283***	0.071***
	(0.025)	(0.003)	(0.030)	(0.008)
Downgrade by Moody's in previous 16-90days	-0.204***	-0.012***	0.235***	0.059***
	(0.017)	(0.003)	(0.021)	(0.006)
Downgrade by Moody's in previous 91-180days	-0.121***	-0.007***	0.140***	0.035***
	(0.029)	(0.002)	(0.034)	(0.009)
Downgrade by Moody's in previous 180 and more days	-0.126***	-0.008***	0.145***	0.036***
	(0.025)	(0.002)	(0.029)	(0.007)
Upgrade by Moody's in previous 1-15days	0.249***	0.015***	-0.288***	-0.072***
	(0.048)	(0.004)	(0.056)	(0.015)
Upgrade by Moody's in previous 16-90days	0.239***	0.015***	-0.277***	-0.069***
	(0.030)	(0.003)	(0.035)	(0.010)
Upgrade by Moody's in previous 91-180days	0.275***	0.017***	-0.318***	-0.079***
	(0.032)	(0.003)	(0.036)	(0.012)
Upgrade by Moody's in previous more than 180 days	0.162***	0.010***	-0.188***	-0.047***
	(0.021)	(0.002)	(0.024)	(0.007)
Downgrade by S&P in previous 1-15days	-0.135***	-0.008***	0.156***	0.039***
	(0.046)	(0.003)	(0.053)	(0.014)
Downgrade by S&P in previous 16-90days	-0.177***	-0.011***	0.204***	0.051***
	(0.023)	(0.002)	(0.027)	(0.008)
Downgrade by S&P in previous 91-180days	-0.172***	-0.010***	0.199***	0.049***
	(0.027)	(0.003)	(0.032)	(0.009)
Downgrade by S&P in previous more than 180 days	-0.107***	-0.006***	0.123***	0.031***
	(0.024)	(0.002)	(0.030)	(0.008)
Upgrade by S&P in previous 1-15days	0.033	0.002	-0.038	-0.010
	(0.027)	(0.002)	(0.031)	(0.008)
Upgrade by S&P in previous 16-90days	-	-	-	-
	-	-	-	-
Upgrade by S&P in previous 91-180days	0.153***	0.009***	-0.177***	-0.044***
	(0.039)	(0.003)	(0.046)	(0.012)
Upgrade by S&P in previous more than 180 days	0.065**	0.004**	-0.075**	-0.019**
	(0.031)	(0.002)	(0.035)	(0.009)
Observations	3 766			
Pseudo R2	0.0862			

(*continued on next page*)

Panel B - Follower: S&P, Industry: Non-financial

Dependent variable	Non-financial institutions (Marginal effects)			
	S&P upgrade by 1 notch	S&P upgrade by more than 2 notches	S&P downgrade by 1 notch	S&P downgrade by more than 2 notches
Downgrade by Moody's in previous 1-15days	-0.305***	-0.041***	0.296***	0.075***
	(0.015)	(0.004)	(0.015)	(0.005)
Downgrade by Moody's in previous 16-90days	-0.262***	-0.035***	0.254***	0.065***
	(0.014)	(0.003)	(0.014)	(0.004)
Downgrade by Moody's in previous 91-180days	-0.179***	-0.024***	0.173***	0.044***
	(0.020)	(0.003)	(0.019)	(0.005)
Downgrade by Moody's in previous more than 180 days	-0.063**	-0.008**	0.061**	0.016**
	(0.027)	(0.004)	(0.027)	(0.007)
Upgrade by Moody's in previous 1-15days	0.309***	0.041***	-0.299***	-0.076***
	(0.024)	(0.004)	(0.023)	(0.007)
Upgrade by Moody's in previous 16-90days	0.319***	0.043***	-0.309***	-0.079***
	(0.019)	(0.003)	(0.018)	(0.006)
Upgrade by Moody's in previous 91-180days	0.265***	0.035***	-0.256***	-0.065***
	(0.019)	(0.003)	(0.019)	(0.006)
Upgrade by Moody's in previous more than 180 days	0.186***	0.025***	-0.180***	-0.046***
	(0.014)	(0.002)	(0.013)	(0.004)
Downgrade by S&P in previous 1-15days	0.121*	0.016*	-0.117*	-0.030*
	(0.065)	(0.009)	(0.063)	(0.016)
Downgrade by S&P in previous 16-90days	-0.193***	-0.026***	0.187***	0.047***
	(0.016)	(0.003)	(0.016)	(0.004)
Downgrade by S&P in previous 91-180days	-0.174***	-0.023***	0.168***	0.043***
	(0.018)	(0.003)	(0.017)	(0.005)
Downgrade by S&P in previous more than 180 days	-0.030**	-0.004**	0.029**	0.007**
	(0.015)	(0.002)	(0.014)	(0.004)
Upgrade by S&P in previous 1-15days	-0.008	-0.001	0.007	0.002
	(0.012)	(0.002)	(0.011)	(0.003)
Upgrade by S&P in previous 16-90days	-	-	-	-
	-	-	-	-
Upgrade by S&P in previous 91-180days	0.075**	0.010**	-0.073**	-0.018**
	(0.035)	(0.005)	(0.034)	(0.009)
Upgrade by S&P in previous more than 180 days	0.097***	0.013***	-0.094***	-0.024***
	(0.011)	(0.002)	(0.010)	(0.003)
Observations	10 872			
Pseudo R2	0.0748			

(*continued on next page*)

Panel C - Follower: Moody’s, Industry: Financial

	Financial institutions (Marginal effects)			
Dependent variable	Moody's upgrade by 1 notch	Moody's upgrade by more than 2 notches	Moody's downgrade by 1 notch	Moody's downgrade by more than 2 notches
Downgrade by S&P in previous 1-15days	-0.140***	-0.029***	0.156***	0.062***
	(0.019)	(0.005)	(0.021)	(0.009)
Downgrade by S&P in previous 16-90days	-0.153***	-0.032***	0.171***	0.068***
	(0.014)	(0.005)	(0.016)	(0.007)
Downgrade by S&P in previous 91-180days	-0.102***	-0.021***	0.113***	0.045***
	(0.025)	(0.006)	(0.027)	(0.011)
Downgrade by S&P in previous more than 180 days	-0.095***	-0.020***	0.106***	0.043***
	(0.016)	(0.004)	(0.018)	(0.007)
Upgrade by S&P in previous 1-15days	0.186***	0.039***	-0.207***	-0.083***
	(0.064)	(0.014)	(0.071)	(0.029)
Upgrade by S&P in previous 16-90days	0.218***	0.046***	-0.243***	-0.097***
	(0.022)	(0.006)	(0.024)	(0.012)
Upgrade by S&P in previous 91-180days	0.142***	0.030***	-0.158***	-0.063***
	(0.027)	(0.006)	(0.030)	(0.013)
Upgrade by S&P in previous more than 180 days	0.125***	0.026***	-0.140***	-0.056***
	(0.013)	(0.004)	(0.015)	(0.007)
Downgrade by Moody's in previous 1-15days	-0.149**	-0.032**	0.166**	0.067**
	(0.059)	(0.013)	(0.066)	(0.027)
Downgrade by Moody's in previous 16-90days	-0.132***	-0.028***	0.147***	0.059***
	(0.021)	(0.005)	(0.023)	(0.010)
Downgrade by Moody's in previous 91-180days	-0.134***	-0.028***	0.149***	0.060***
	(0.019)	(0.005)	(0.021)	(0.008)
Downgrade by Moody's in previous more than 180 days	0.004	0.001	-0.005	-0.002
	(0.024)	(0.005)	(0.027)	(0.011)
Upgrade by Moody's in previous 1-15days	0.045	0.009	-0.050	-0.020
	(0.139)	(0.029)	(0.154)	(0.062)
Upgrade by Moody's in previous 16-90days	0.010***	0.002***	-0.011***	-0.004***
	(0.002)	(0.001)	(0.003)	(0.001)
Upgrade by Moody's in previous 91-180days	0.061	0.013	-0.068	-0.027
	(0.075)	(0.016)	(0.084)	(0.034)
Upgrade by Moody's in previous more than 180 days	0.105***	0.022***	-0.117***	-0.047***
	(0.013)	(0.003)	(0.015)	(0.007)
Observations	3 766			
Pseudo R2	0.0973			

(*continued on next page*)

Panel D - Follower: Moody’s, Industry: Non-financial

	Non-financial institutions (Marginal effects)			
Dependent variable	Moody's upgrade by 1 notch	Moody's upgrade by more than 2 notches	Moody's downgrade by 1 notch	Moody's downgrade by more than 2 notches
Downgrade by S&P in previous 1-15days	-0.175***	-0.015***	0.190***	0.031***
	(0.010)	(0.002)	(0.011)	(0.003)
Downgrade by S&P in previous 16-90days	-0.166***	-0.014***	0.180***	0.030***
	(0.009)	(0.002)	(0.009)	(0.002)
Downgrade by S&P in previous 91-180days	-0.143***	-0.012***	0.155***	0.025***
	(0.012)	(0.002)	(0.012)	(0.003)
Downgrade by S&P in previous more than 180 days	-0.064***	-0.006***	0.069***	0.011***
	(0.014)	(0.001)	(0.015)	(0.003)
Upgrade by S&P in previous 1-15days	0.178***	0.015***	-0.194***	-0.032***
	(0.013)	(0.002)	(0.014)	(0.003)
Upgrade by S&P in previous 16-90days	0.160***	0.014***	-0.174***	-0.029***
	(0.009)	(0.002)	(0.010)	(0.003)
Upgrade by S&P in previous 91-180days	0.181***	0.016***	-0.197***	-0.032***
	(0.011)	(0.002)	(0.012)	(0.003)
Upgrade by S&P in previous more than 180 days	0.128***	0.011***	-0.140***	-0.023***
	(0.008)	(0.001)	(0.009)	(0.002)
Downgrade by Moody's in previous 1-15days	-0.022	-0.002	0.024	0.004
	(0.044)	(0.004)	(0.048)	(0.008)
Downgrade by Moody's in previous 16-90days	-0.128***	-0.011***	0.139***	0.023***
	(0.014)	(0.002)	(0.015)	(0.003)
Downgrade by Moody's in previous 91-180days	-0.148***	-0.013***	0.161***	0.026***
	(0.014)	(0.002)	(0.015)	(0.003)
Downgrade by Moody's in previous more than 180 days	0.012	0.001	-0.013	-0.002
	(0.030)	(0.003)	(0.033)	(0.005)
Upgrade by Moody's in previous 1-15days	-	-	-	-
	-	-	-	-
Upgrade by Moody's in previous 16-90days	0.087***	0.008***	-0.094***	-0.015***
	(0.032)	(0.003)	(0.034)	(0.006)
Upgrade by Moody's in previous 91-180days	0.129***	0.011***	-0.140***	-0.023***
	(0.033)	(0.003)	(0.036)	(0.006)
Upgrade by Moody's in previous more than 180 days	0.092***	0.008***	-0.100***	-0.016***
	(0.013)	(0.001)	(0.014)	(0.003)
Observations		10 872		
Pseudo R2		0.1500		

Note: (1) The table presents the results of ordered logit estimation (Eq. (4) and Eq. (5)) with robust standard errors. It reports the impact of potential leader’s/follower’s rating action on the probability of the follower’s rating upgrade/downgrade (marginal effects). The results are based on the sample of daily rating changes between December 2005 and October 2014 originated by S&P and Moody’s. The dependent variable is a binary variable taking the value of 1 if the follower upgraded/downgraded the issuer by one/two or more notches. The independent variables are dummy variables taking the value of 1 if the issuer is upgraded/ downgraded by the potential leader/follower in four previous time windows (1-15 days, 16-90 days, 91-180 days, more than 180 days). (2) Standard errors are in parenthesis. ***, **, and * denotes significance at the 1%, 5%, and 10% levels, respectively.

3.6 Conclusion

The recent financial crisis has prompted increased analysis of the quality of credit ratings. Several issues focused the attention of the financial market on credit ratings: (1) significant but slow credit rating fluctuations over the past decades, (2) Basel III continuing to give high prominence to ratings in bank capital requirements, (3) excessive power of ratings to influence market expectations.

This paper contributes to the recent related literature in several ways. First, empirical evidence suggests that there is a statistically significant difference in the rating evaluations of the two incumbent credit rating agencies. While Moody’s is consistently more conservative in its assessment of default risk for non-financial institutions, S&P is consistently more conservative in its assessment of default risk for financial institutions. The two rating agencies systematically agree in credit ratings only in the Communications and Technology industry sectors. The difference between S&P and Moody’s credit ratings has deepened over time, becoming the most substantial during the sovereign debt crisis from 2011 to 2013.

Second, empirical evidence indicates that Fitch’s increasing market share has a positive and statistically significant effect on the rating split between S&P and Moody’s in the non-financial sectors. This might be because some rating agencies might prefer to protect their reputational capital by assigning timely and accurate ratings; other rating agencies might prefer to increase their own profits (ratings are issuer-paid) by assigning more favorable ratings. Thus, instead of promoting rating competition, the reporting requirements about financial data should be vastly enhanced to reduce sole reliance on credit ratings. The findings of this paper also imply that rating shopping (acquiring an additional rating opinion) fosters further disagreement between rating agencies, and hence reinforces the use of ‘second best’ issuer rating for regulatory purposes.

Third, this paper confirms that sovereign ratings remain significant determinants of issuer ratings in the case of financial institutions, even though S&P gradually increases and Moody’s gradually relaxes its weight. For non-financial institutions, the approach of rating agencies is exactly the opposite. While S&P issuer ratings reflect sovereign ceilings, Moody’s does not constrain the rating of non-financial institutions by the issuer's country rating. The findings suggest that sovereign ceilings constitute a potential source of negative externality for financial institutions in low- rated countries, given that the financial health (rating) of the issuer is much stronger than of the parent company.

Lastly, the empirical results of this paper strongly support the idea that the rating actions of one agency are considerably influenced by the prior ratings of other agencies. When compared to Moody's, S&P is a follower in its rating actions for both financial and non-financial institutions. Further research should examine at what point financial market participants internalize this fact in their investment decisions.

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Appendix

Table 3.A.1: Descriptive statistics by rating agency

Panel A – Average rating by industry sector

Industry sector	S&P	Moody's	Fitch
Financial	8.4	8.6	7.6
Basic Materials	10.1	9.8	8.8
Communications	11.0	10.7	9.4
Consumer, Cyclical	11.0	11.6	11.1
Consumer, Non-cyclical	9.5	9.7	8.3
Diversified	9.3	9.1	7.7
Energy	10.9	10.9	9.4
Industrial	9.8	10.2	8.6
Technology	9.6	9.3	8.2
Utilities	8.8	8.8	8.3

Panel B – Geographical coverage by rating agency

Region	S&P	Moody's	Fitch
United States	57%	60%	63%
Euro Area	16%	15%	15%
Japan	8%	8%	14%
Other Advanced Economies	6%	4%	1%
Commonwealth of Independent States	6%	5%	2%
Emerging and Developing Asia	4%	5%	3%
Emerging and Developing Europe	1%	1%	0%
Latin America and the Caribbean	1%	1%	2%
Middle East, North Africa, Afghanistan and Pakistan	1%	1%	0%
Sub-Saharan Africa	0%	0%	0%

Note: The descriptive statistics are based on the sample of 2 486 issuer ratings assigned as at the end of 2013. The credit ratings in Panel A are mapped into 21 numerical values, where AAA is the best rating category and SD/D (semi-default/default) is the worst rating category. In particular, A- = 7, BBB+ = 8, BBB = 9, BBB- = 10, BB+ = 11.

Table 3.A.2: Mean financial statistics per rating grade

Panel A – Financial sector: Banks

in %

Rating grade	Tier 1	Common Equity / Total Assets	Loan Loss Reserves / Non-performing Assets	Non-performing Assets / Total Assets	Return on Assets	Return on Equity	Total Loans / Total Deposits	Deposits / Funding
AAA	N/A	2.0	N/A	1.0	0.3	7.3	61.4	59.9
AA	12.0	30.0	104.3	1.2	0.6	10.8	131.1	60.3
A	11.4	111.0	77.2	2.4	0.6	5.8	108.4	68.2
BBB	12.3	62.0	134.5	3.2	0.5	5.7	94.8	80.0
BB	12.8	26.0	93.1	3.0	0.6	5.0	94.1	76.6
B	14.7	10.0	97.1	5.4	0.7	4.1	109.1	72.1
CCC	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
C	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
NR	11.4	59.0	117.4	2.1	0.6	6.4	82.8	88.0

Panel B – Non-financial sector: Consumer-Cyclical

in %

Rating grade	Working capital / Total Assets	Retained Earnings / Total Assets	Earnings before Interest and Taxes / Total Assets	Total Equity / Total Liabilities	Net Sales / Total Assets
AAA	N/A	N/A	N/A	N/A	N/A
AA	16.9	36.4	1.7	99.7	82.2
A	10.6	20.9	1.6	54.2	78.9
BBB	10.3	12.6	1.7	63.8	84.6
BB	14.1	4.9	1.6	53.7	77.9
B	9.8	-12.6	1.3	26.6	99.5
CCC	4.2	-19.7	0.0	29.1	71.8
C	-127.9	-52.0	-0.7	-29.5	67.4
NR	18.9	13.8	1.7	127.0	103.2

Note: (1) The summary statistics are based on financial statement data from the end of 2009 credit rating assigned by S&P. As several indicators provide meaningful interpretation only if evaluated within the same sector, the table summarizes the financial ratios of only two industry sub-sectors. Based on the total number of observations in the dataset, the industry sub-sectors of banks and cyclical consumer goods were chosen to illustrate the financial indicators of the financial and non-financial sectors. (2) NR denotes issuers not rated by S&P, N/A stands for missing observations.

Table 3.A.3: Credit rating interpretation and numeric scales

Original rating grades		Interpretation	New rating grades			
S&P/ Fitch	Moody's		Fine scale		Wide scale	
			Numeric	Letter	Numeric	Letter
		Investment grades				
AAA	AAA	Extremely strong capacity to meet financial commitments	1	AAA	1	AAA
AA+	Aa1	Very strong capacity to meet financial commitments	2	AA+	2	AA
AA	Aa2		3	AA	2	AA
AA-	Aa3		4	AA-	2	AA
A+	A1	Strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances.	5	A+	3	A
A	A2		6	A	3	A
A-	A3		7	A-	3	A
BBB+	Baa1	Adequate capacity to meet financial commitments, but more subject to adverse economic conditions	8	BBB+	4	BBB
BBB	Baa2		9	BBB	4	BBB
BBB-	Baa3	Considered lowest investment grade by market participants	10	BBB-	4	BBB
		Non- investment (speculative) grades				
BB+	Ba1	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions	11	BB+	5	BB
BB	Ba2		12	BB	5	BB
BB-	Ba3		13	BB-	5	BB
B+	B1	More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments	14	B+	6	B
B	B2		15	B	6	B
B-	B3		16	B-	6	B
CCC+	Caa1	Currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments.	17	CCC+	7	CCC
CCC	Caa2		18	CCC	7	CCC
CCC-	Caa3		19	CCC-	7	CCC
CC	Ca	Currently highly vulnerable	20	CC	8	CC
C	C	Currently highly vulnerable obligations and other defined circumstances	21	C	9	C
SD/D		Payment default on financial commitments	21		9	D

Note: (1) The credit ratings are mapped into 21 numerical values, where AAA is the best rating category and SD/D (semi-default/default) is the worst rating category. (2) The interpretation of credit ratings is defined by S&P, http://www.standardandpoors.com/ratings/definitions-and-faqs/en/us

Table 3.A.4: Determinants of issuer rating change

Panel A – Issuer rating: S&P, Industry: Financial

	Dependent variable - Issuer rating upgrade by S&P			Dependent variable - Issuer rating downgrade by S&P		
Rating change determinants	Pre-crisis: Financial institutions - Marginal effects	Subprime lending crisis: Financial institutions - Marginal effects	Sovereign debt crisis: Financial institutions - Marginal effects	Pre-crisis: Financial institutions - Marginal effects	Subprime lending crisis: Financial institutions - Marginal effects	Sovereign debt crisis: Financial institutions - Marginal effects
Total asset	-0.000*	0.000**	-0.000	-0.000**	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return on assets	-0.023	-0.007	0.019**	-0.003	-0.023	0.006
	(0.033)	(0.009)	(0.009)	(0.036)	(0.014)	(0.014)
Common equity to total assets	-0.015*	0.003	-0.000	-0.021**	0.002	0.003
	(0.008)	(0.002)	(0.003)	(0.009)	(0.003)	(0.004)
Total loans to total deposits	0.000	0.000	0.000	0.000	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Deposits to funding	-0.003*	0.001**	0.000	-0.003*	-0.000	-0.002**
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
1Y change in Return on assets	0.019*	0.000	-0.003***	-0.013	0.001***	-0.002***
	(0.011)	(0.000)	(0.001)	(0.012)	(0.000)	(0.001)
1Y change in Net interest margin	0.065	0.024**	0.071	0.072	0.092***	0.096
	(0.054)	(0.011)	(0.043)	(0.059)	(0.032)	(0.069)
1Y change in Common equity to total assets	-0.143	-0.044	0.004	0.076	-0.041	0.059***
	(0.137)	(0.060)	(0.005)	(0.128)	(0.073)	(0.022)
1Y change in Loan loss reserves to non-performing assets	-0.012	-0.066	-0.023	-0.004	0.000***	-0.026
	(0.011)	(0.044)	(0.025)	(0.008)	(0.000)	(0.047)
1Y change in Non-performing assets to total assets	0.026	-0.037	-0.016	0.038*	-0.001	-0.033
	(0.021)	(0.025)	(0.031)	(0.022)	(0.007)	(0.040)

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1Y change in Total loans to total deposits	-0.031	-0.003	0.060	0.111	0.127	-0.306*
	(0.211)	(0.081)	(0.124)	(0.194)	(0.130)	(0.176)
1Y change in Deposits to funding	0.462**	-0.149	0.097	0.602***	0.155	-0.125
	(0.202)	(0.114)	(0.120)	(0.185)	(0.140)	(0.176)
Current account to GDP	-0.014***	-0.001	0.000	-0.011***	-0.006**	-0.000
	(0.003)	(0.001)	(0.002)	(0.004)	(0.002)	(0.003)
GDP per capita	-0.000	-0.000	-0.000**	-0.000	0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1Y change in Current account to GDP	-0.022***	-0.004	-0.001	-0.024***	-0.010**	0.013
	(0.006)	(0.003)	(0.007)	(0.009)	(0.005)	(0.021)
1Y GPD growth	-0.013	-0.002	-0.024***	-0.016	-0.010**	-0.042***
	(0.009)	(0.004)	(0.006)	(0.013)	(0.004)	(0.008)
1Y change in GDP per capita	0.536	0.406***	1.176***	0.729	0.436**	1.430***
	(0.685)	(0.141)	(0.288)	(0.765)	(0.211)	(0.293)
1Y change in Inflation	0.002	0.001	-0.008*	0.004	-0.000	-0.007
	(0.013)	(0.002)	(0.005)	(0.015)	(0.004)	(0.005)
Euro Area	-0.251***	0.059	-0.068	-0.240**	-0.037	-0.002
	(0.088)	(0.048)	(0.087)	(0.100)	(0.058)	(0.078)
Emerging and Developing Europe	0.066	0.028	0.046	-0.032	-0.082	0.249**
	(0.186)	(0.040)	(0.074)	(0.207)	(0.102)	(0.111)
Middle East, North Africa, Afghanistan and Pakistan	0.241*	0.019	-0.027	0.236	0.036	-0.067
	(0.125)	(0.044)	(0.054)	(0.146)	(0.060)	(0.074)
Pseudo R2	0.2804	0.3506	0.3335	0.2172	0.3860	0.3197
Observations	293	496	638	293	631	638

(*continued on next page)*

Panel B – Issuer rating: S&P, Industry: Non-financial

	Dependent variable – Issuer rating upgrade by S&P			Dependent variable – Issuer rating downgrade by S&P		
Rating change determinants	Pre-crisis: Non-financial institutions - Marginal effects	Subprime lending crisis: Non-financial institutions - Marginal effects	Sovereign debt crisis: Non-financial institutions - Marginal effects	Pre-crisis: Non-financial institutions - Marginal effects	Subprime lending crisis: Non-financial institutions - Marginal effects	Sovereign debt crisis: Non-financial institutions - Marginal effects
Total asset	-0.000	-0.000	-0.000	-0.000	0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Earnings per Share	-0.000	0.000	0.000***	-0.000**	-0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Retained Earnings /Total Assets	-0.000**	0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Earnings before Interest and Taxes /Total Assets	0.007***	0.005**	-0.000	0.003	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Total Equity / Total Liabilities	-0.000***	-0.000	-0.000	-0.001***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net Sales /Total Assets	0.000	0.000**	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1Y change in Working capital / Total Assets	0.001	0.000**	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
1Y change in Retained Earnings / Total Assets	-0.000	-0.000	-0.001***	-0.002	-0.000	-0.001***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
1Y change in Earnings before Interest and Taxes / Total Assets	0.001	0.000	0.002**	0.001	0.000	0.002
	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	(0.001)
1Y change in Total Equity / Total Liabilities	-0.001	0.000	-0.001	-0.001	0.001	-0.002*
	(0.002)	(0.000)	(0.001)	(0.003)	(0.001)	(0.001)
Current account to GDP	0.005**	0.001	0.003*	0.007***	-0.000	0.003
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)

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GDP per capita	-0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Inflation	0.001	-0.004	0.006	0.009	-0.003	-0.001
	(0.006)	(0.003)	(0.004)	(0.008)	(0.004)	(0.005)
1Y change in Current account to GDP	-0.002	-0.001	0.019**	-0.006	0.000	0.008
	(0.004)	(0.001)	(0.009)	(0.004)	(0.001)	(0.007)
1Y GPD growth	-0.008	0.002	-0.006	-0.017	-0.002	-0.009
	(0.008)	(0.002)	(0.004)	(0.011)	(0.003)	(0.005)
1Y change in GDP per capita	0.312	0.218**	0.114	0.436	0.023	0.084
	(0.221)	(0.085)	(0.124)	(0.300)	(0.123)	(0.122)
1Y change in Inflation	0.003	-0.006**	0.000	-0.003	-0.006	-0.000
	(0.006)	(0.002)	(0.000)	(0.007)	(0.004)	(0.001)
Japan	-0.039	-0.095***	-0.151***	-0.127**	-0.258***	-0.211***
	(0.041)	(0.025)	(0.029)	(0.054)	(0.037)	(0.029)
Other Advanced Economies	-0.088***	-0.044***	-0.053***	-0.102***	-0.040*	-0.049**
	(0.032)	(0.015)	(0.016)	(0.038)	(0.022)	(0.019)
Emerging and Developing Asia	-0.166*	-0.032	0.043	-0.148	-0.103*	-0.002
	(0.086)	(0.039)	(0.038)	(0.109)	(0.061)	(0.052)
Emerging and Developing Europe	0.055	-0.048		0.275**	-0.113	-0.076
	(0.078)	(0.073)		(0.113)	(0.111)	(0.098)
Latin America and the Caribbean	-0.082	0.004	0.006	-0.144*	-0.005	-0.004
	(0.061)	(0.030)	(0.032)	(0.082)	(0.045)	(0.041)
Basic Materials	-0.021	0.005	0.025	-0.001	0.102***	0.037
	(0.045)	(0.025)	(0.035)	(0.060)	(0.039)	(0.045)
Communications	-0.059**	0.014	0.027	-0.004	0.085***	0.021
	(0.028)	(0.020)	(0.031)	(0.035)	(0.031)	(0.042)
Consumer, Cyclical	-0.027	-0.004	0.057*	0.020	0.142***	0.079*
	(0.027)	(0.021)	(0.030)	(0.035)	(0.031)	(0.041)
Consumer, Non-cyclical	-0.086*	-0.012	0.004	-0.030	0.019	-0.005
	(0.046)	(0.019)	(0.030)	(0.060)	(0.028)	(0.039)
Pseudo R2	0.1342	0.1728	0.1573	0.0575	0.0910	0.0742
Observations	2 595	4 057	3 889	2 595	4 060	3 908

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Panel C – Issuer rating: Moody’s, Industry: Financial

	Dependent variable – Issuer rating upgrade by Moody's			Dependent variable – Issuer rating downgrade by Moody's		
Rating change determinants	Pre-crisis: Financial institutions - Marginal effects	Subprime lending crisis: Financial institutions - Marginal effects	Sovereign debt crisis: Financial institutions - Marginal effects	Pre-crisis: Financial institutions - Marginal effects	Subprime lending crisis: Financial institutions - Marginal effects	Sovereign debt crisis: Financial institutions - Marginal effects
Total asset	-0.000	0.000**	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Earnings per Share	0.000	0.000***	-0.000	0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return on assets	0.039	0.046**	-0.002	0.047	-0.019	-0.016
	(0.030)	(0.018)	(0.007)	(0.031)	(0.015)	(0.019)
Net interest margin	-0.000	0.000***	-0.000	-0.000	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Common equity to total assets	-0.005	0.024***	-0.005**	-0.012*	-0.018***	0.001
	(0.007)	(0.006)	(0.002)	(0.007)	(0.005)	(0.005)
Loan loss reserves /Non-performing assets	-0.000	-0.000**	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Non-performing assets / Total assets	-0.004	0.031**	0.008*	-0.002	0.013*	-0.007
	(0.016)	(0.012)	(0.005)	(0.016)	(0.007)	(0.006)
Total loans to total deposits	0.000	0.000**	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Deposits to funding	0.003*	0.000	-0.002**	0.003*	-0.003***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
1Y change in Return on assets	-0.017	-0.009**	-0.000	-0.058***	0.000*	0.002
	(0.013)	(0.004)	(0.000)	(0.014)	(0.000)	(0.002)
1Y change in Net interest margin	0.008	0.010	-0.061	0.022	0.014	-0.171*
	(0.052)	(0.018)	(0.043)	(0.056)	(0.031)	(0.103)
1Y change in Common equity / Total Assets	0.060	0.037	-0.007	0.057	0.083	-0.022*
	(0.132)	(0.034)	(0.007)	(0.149)	(0.067)	(0.012)
1Y change in Loan loss reserves to non-performing assets	-0.008	-0.075**	0.054**	-0.004	0.000***	0.061
	(0.048)	(0.032)	(0.025)	(0.052)	(0.000)	(0.046)

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1Y change in Non-performing assets to total assets	-0.015	-0.158**	-0.012	-0.013	-0.002	-0.005
	(0.019)	(0.063)	(0.053)	(0.021)	(0.008)	(0.039)
1Y change in Deposits to funding	0.049	-0.310**	0.136	0.185	-0.120	-0.298
	(0.192)	(0.143)	(0.102)	(0.172)	(0.152)	(0.205)
Current account to GDP	0.001	0.008***	-0.008**	0.001	0.002	-0.001
	(0.004)	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)
GDP per capita	0.000	-0.000**	-0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Inflation	-0.005	0.004	-0.003	-0.007	0.004*	-0.011*
	(0.010)	(0.003)	(0.005)	(0.011)	(0.003)	(0.007)
1Y change in Current account to GDP	-0.002	0.003***	-0.004	-0.002	0.004***	-0.022**
	(0.005)	(0.001)	(0.003)	(0.006)	(0.001)	(0.009)
1Y GPD growth	-0.020*	0.045***	-0.004	-0.020*	-0.001	-0.025***
	(0.011)	(0.010)	(0.005)	(0.011)	(0.004)	(0.009)
1Y change in GDP per capita	3.778***	0.201	-0.037	3.895***	-0.238	0.899**
	(0.739)	(0.197)	(0.141)	(0.735)	(0.211)	(0.359)
1Y change in Inflation	-0.020	0.025***	0.007***	-0.016	-0.011***	-0.002
	(0.018)	(0.006)	(0.003)	(0.016)	(0.004)	(0.003)
Euro Area	-0.095		-0.624***	-0.132	-0.023	0.105
	(0.090)		(0.186)	(0.089)	(0.053)	(0.084)
Other Advanced Economies	-0.357***	0.056	-0.061	-0.412***	-0.037	-0.007
	(0.098)	(0.053)	(0.041)	(0.102)	(0.060)	(0.071)
Emerging and Developing Asia	-0.344*	-0.363***	-0.175***	-0.427**	-0.150*	0.137*
	(0.192)	(0.123)	(0.067)	(0.201)	(0.084)	(0.078)
Latin America and the Caribbean	-0.421***	-0.304***	-0.171***	-0.522***	-0.135*	-0.054
	(0.152)	(0.104)	(0.056)	(0.162)	(0.079)	(0.084)
Pseudo R2	0.4823	0.8019	0.5575	0.476	0.3835	0.2809
Observations	289	411	575	289	631	632

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Panel D – Issuer rating: Moody’s, Industry: Non-financial

	Dependent variable – Issuer rating upgrade by Moody's			Dependent variable – Issuer rating downgrade by Moody's		
Rating change determinants	Pre-crisis: Non-financial institutions - Marginal effects	Subprime lending crisis: Non-financial institutions - Marginal effects	Sovereign debt crisis: Non-financial institutions - Marginal effects	Pre-crisis: Non-financial institutions - Marginal effects	Subprime lending crisis: Non-financial institutions - Marginal effects	Sovereign debt crisis: Non-financial institutions - Marginal effects
Total asset	0.000	0.000	-0.000*	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Earnings before Interest and Taxes / Total Assets	0.004***	0.000	0.003**	0.002	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Total Equity / Total Liabilities	-0.000*	-0.000	-0.000	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Net Sales / Total Assets	0.000	-0.000	-0.000	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1Y change in Earnings per Share/ Total Assets	0.001*	-0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
1Y change in Retained Earnings / Total Assets	0.000	-0.000	0.002**	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
1Y change in Earnings before Interest and Taxes / Total Assets	-0.000	0.000	-0.000	0.000	0.000**	0.000
	(0.001)	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)
1Y change in Total Equity / Total Liabilities	-0.002	-0.000	-0.001*	0.002	-0.000	-0.002**
	(0.001)	(0.000)	(0.001)	(0.003)	(0.000)	(0.001)
1Y change in Net Sales /Total Assets	0.017**	0.001	-0.012	0.005	-0.002	-0.007
	(0.008)	(0.001)	(0.015)	(0.015)	(0.004)	(0.028)
Current account to GDP	0.004**	-0.000	-0.002	0.004*	0.002	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Inflation	-0.001	-0.007**	-0.004	-0.009	-0.007**	-0.007
	(0.004)	(0.003)	(0.004)	(0.006)	(0.003)	(0.005)

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1Y GPD growth	-0.005	0.001	-0.000	-0.001	-0.003	-0.013***
	(0.006)	(0.002)	(0.004)	(0.008)	(0.003)	(0.005)
1Y change in GDP per capita	-0.077	0.260**	0.050	0.295	0.052	0.163*
	(0.160)	(0.104)	(0.093)	(0.224)	(0.109)	(0.094)
1Y change in Inflation	0.003	0.004*	0.000	-0.000	0.001	0.001
	(0.005)	(0.002)	(0.001)	(0.006)	(0.004)	(0.001)
Euro Area	-0.062**	-0.026**	-0.043**	-0.087***	-0.023	-0.028
	(0.025)	(0.013)	(0.017)	(0.032)	(0.018)	(0.024)
Japan	-0.073***	-0.082***	-0.109***	-0.160***	-0.147***	-0.129***
	(0.028)	(0.021)	(0.024)	(0.037)	(0.028)	(0.024)
Other Advanced Economies	-0.053**	-0.029*	-0.027**	-0.089***	-0.049***	-0.049***
	(0.025)	(0.015)	(0.013)	(0.031)	(0.019)	(0.017)
Emerging and Developing Asia	-0.073	-0.057	-0.079**	-0.060	-0.156**	0.012
	(0.059)	(0.035)	(0.036)	(0.085)	(0.061)	(0.050)
Latin America and the Caribbean	-0.062	-0.043	-0.026	-0.036	-0.131**	-0.032
	(0.049)	(0.036)	(0.027)	(0.069)	(0.051)	(0.041)
Basic Materials	-0.005	0.012	0.099**	-0.003	0.039*	0.086
	(0.019)	(0.015)	(0.047)	(0.028)	(0.024)	(0.063)
Communications	-0.005	0.013	0.074*	0.003	0.021	0.074
	(0.019)	(0.015)	(0.045)	(0.026)	(0.023)	(0.060)
Consumer, Cyclical	-0.036*	0.014	0.099***	-0.013	0.083***	0.081
	(0.020)	(0.015)	(0.036)	(0.025)	(0.022)	(0.050)
Consumer, Non-cyclical	-0.046**	0.015	0.102**	-0.013	0.009	0.085
	(0.023)	(0.016)	(0.046)	(0.032)	(0.023)	(0.063)
Energy	-0.013	0.025*	0.092**	0.001	0.044**	0.079
	(0.022)	(0.013)	(0.038)	(0.029)	(0.021)	(0.052)
Industrial	-0.048	0.006	0.075**	-0.065	0.030	0.041
	(0.039)	(0.014)	(0.035)	(0.052)	(0.020)	(0.047)
Pseudo R2	0.1906	0.2386	0.1930	0.0599	0.0791	0.0680
Observations	2 567	3 994	3 882	2 567	4 060	3 908

Note: (1) The table presents the impact of financial and macroeconomic data on the probability of the issuer rating change (marginal effects) from the probit estimation (Eq. (3.2) and Eq. (3.3)). It summarizes the remaining (statistically significant) determinants of issuer rating change not presented in Table 3.5. The dependent variable is a binary variable for rating upgrade/downgrade observed at the end of years 2005-2013 for the sample of 2 486 financial and non-financial institutions. (2) The reference for regions is the United States, and the reference for the industry sector is the Financial sector. (3) Standard errors are in parenthesis. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.