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Are women more credit-constrained than men? – Evidence from a rising credit market

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Abstract

This study investigates whether gender discrimination is taking place in an innovative credit market known as peer-to-peer lending. Based on the data of the largest German peer-to-peer lending platform, we observe that female borrowers pay on average higher interest rates than males despite the fact that the two gender groups do not differ with respect to their credit risk. Our analysis shows however that this interest rate gap doesn't emerge because of discrimination against female borrowers. In all probability, female borrowers deliberately offer higher interest rates in anticipation that they would be otherwise discriminated.

Keywords: gender, financial constraints, peer-to-peer lending

JEL Classification: G21, J16

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1 Introduction

Numerous studies have investigated whether female borrowers' face higher barriers than male borrowers when lending from traditional financial institutions. However, very little research is done on gender discrimination in a specific type of credit market known as peer-to-peer lending. Although this form of lending is relatively new, its market share rapidly grows and peer-to-peer lending marketplaces become significant providers of financial resources.[1] So far only Pope & Sydnor (2008) study discrimination at a peer-to-peer lending marketplace. The paper provides novel evidence on the determinants of access to credit at *Prosper* – the largest marketplace for peer-to-peer lending in the USA. Although the main focus of the study is on the racial discrimination, an interesting finding with respect to borrowers' gender is revealed. In particular, lenders seem to discriminate in favor of female borrowers. The finding rises a range of questions. Is this pattern common to other peer-to-peer marketplaces because of the peculiar mechanism of funding by multiple lenders which acts as a correction mechanism of a possible taste-based discrimination in the sense of Becker (1957)? Or is the finding of Pope & Sydnor (2008) specific to one particular peer-to-peer lending platform studied in the paper? Are specific groups of female borrowers', e.g. entrepreneurs, favored over male borrowers in peer-to-peer credit markets? Answering this questions requires a detailed analysis of gender's role for credit access in different marketplaces for peer-to-peer lending.

This paper intends to shed more light on these questions. We investigate whether gender discrimination exists in the largest German peer-to-peer lending site *Smava*. In particular, we explore whether there are differences between male and female applicants in the probability of getting credit at *Smava*.

So far, the analysis of gender discrimination in the traditional credit markets is mostly based on household data which do not allow to observe financial constraints directly (e.g. Blanchflower & Oswald (1998) and Holtz-Eakin et al.

[1] The first marketplace for peer-to-peer lending, *Zopa*, was founded in 2005 in the UK. Since then, dozens of lending sites opened in the US and continental Europe. The total amount of outstanding peer-to-peer loans in the United States alone was estimated for $118 million in 2005, $269 million in 2006 and $647 million in 2009. Due to rapidly growing market share, the phenomenon attracts significant attention of general public (FTD 2009, Sviokla 2009, Kim 2009), financial industry professionals (Meyer 2009) and academics (Pope & Sydnor 2008, Freedman & Jin 2008, Garman et al. 2008, Duarte et al. 2009).

(1994)). Their existence has to be inferred from consequences of unexpected increase in wealth. Such approach doesn't allow to explore different dimensions of financial constraints, such as loan price, number of days to wait for the loan officer's decision or probability of getting a loan. Moreover, the data usually lacks information about borrowers' solvency and credit risk which renders it almost impossible to discriminate between the two possible sources for a distinct treatment of female and male entrepreneurs by capital providers. Data on peer-to-peer lending is free of limitations common to traditional data sets. Nevertheless, very few studies use these data to analyze gender differences in access to credit.

Lack of research on the role of gender in peer-to-peer credit markets is astonishing for several reasons. First, peer-to-peer lending may gain an ever increasing importance after the recent financial crisis. The new credit market can fill the gaps left by decreased lending capacity of ailing traditional financial institutions. Credit demand for peer-to-peer loans increases as more individuals seek for alternative finance sources. Credit supply at peer-to-peer lending marketplaces may rise as well, due to increasing capital injections from private investors who loose trust in financial institutions and instruments and look for alternative investment possibilities. Second, if the marketplaces are free of gender discrimination, female borrowers may benefit the most. More and more women are becoming interested in small business ownership and/or actually starting up a business (Global Entrepreneurship Monitor 200?), and respectively look for funds. Previous research shows that females, and especially female entrepreneurs, face more obstacles in obtaining credit at traditional lending institutions than males. Cavalluzzo et al. (2002) find evidence of credit excess gap between firms owned by males and females, while Alesina et al. (2009) show that female entrepreneurs have to pay more for the credit. Policy makers raise concerns that behavior of traditional financial institutions may impede creation of new businesses and survival of existing ones. Therefore, the question of whether peer-to-peer lending market is able to improve access to finance by women is important for assessing the effectiveness of policy programs aimed at supporting entrepreneurship via traditional lending channels.

Having said that, we feel that our data set takes us a few steps further. We employ lending and borrowing data from the German online peer-to-peer lending market *Smava*. The data includes key figures about borrowers, including an ex-ante measure of their riskiness and the ex-post default rates, details on loan applications, whether an application succeeded to raise funds or not, and terms on which a loan is provided. Hence, the data allows to directly observe different dimensions of constrained access to credit and to identify whether discrimination is taking place. Moreover, a distinguishing feature of peer-to-peer lending is that prospective borrowers offer the interest rate they are willing to pay. Lenders in contrast provide funds on "take it or leave it" bases, i.e. if they want to finance a loan they have to finance it on terms set by the borrower.

Our analysis of the data reveals that female borrowers pay on average higher interest rates than males despite the fact that the two gender groups do not differ with respect to credit risk. We find however that this interest rate gap is not caused by discrimination. In fact, we find no evidence for discrimination against female borrowers. Our model predicts that gender has no effect on the probability of getting credit. More likely, the interest rate gap emerges because female borrowers think they would be discriminated if they offered same interest rates as males and therefore offer unnecessarily high rates.

The rest of the paper is organized as follows. Section 2 provides a literature review and derives the hypothesis. Section 3 describes the lending at *Smava*. Section 4 investigates gender differences in loan- and borrower-specific characteristics. In section 5 we test the hypothesis whether there is discrimination at the market place. The last section concludes.

2 Financial constraints and gender

There is small but growing literature investigating whether financial constraints differ across demographic groups. Given the well-known importance of external finance for the creation and operation of businesses, some authors study whether the lower rates of self-employment and lower rates of business ownership among minority groups, which are widely documented, are driven by unequal access to external financing. A large group of these investigations focuses on the role of race, ethnicity and gender as determinants of credit applications, loan denials, interest rates charged, and other dimensions of restricted access to finance (see e.g. Bates (1991), Cavalluzzo & Cavalluzzo (1998), Bostic & Lampani (1999), Raturi & Swamy (1999), Cavalluzzo et al. (2002), Blanchflower et al.

(2003), Storey (2004), Cavalluzzo & Wolken (2005)). Essentially, these works raise an important question about discrimination against borrowers who belong to various demographic groups.

Discrimination in the credit market occurs when lenders' decisions on loan applications are influenced by personal characteristics - such as gender and race of the entrepreneurs - that are not relevant to the transaction. In the well-known model of discrimination by Becker (1957), discrimination arises due to the taste-based preferences of the lender so that he is willing to pay a price in order not to be associated with certain groups of borrowers. An alternative statistical model of discrimination suggests that, as long as borrowers' demographic characteristics are correlated with their creditworthiness, lenders may use the former as a proxy for the risk factor associated with loans. This occurs when lenders cannot observe the risk factors or do not collect relevant information due to the costs involved, see e.g. Phelps (1972) and Aigner & Cain (1977).[2]

Empirical testing for discrimination in the credit markets is usually implemented in a multivariate regression framework with dependent variables that characterize access to or cost of loans and independent variables that describe borrowers' characteristics, including demographics. In this framework, evidence of discrimination is found if the coefficients on the gender, race or ethnicity variables remain statistically significant after controlling for applicants' solvency and creditworthiness. Such an approach has several pitfalls. The major issue is the difficulty of controlling for all possible factors that are used by lenders in assessing the quality of borrowers and which are potentially correlated with the demographic characteristics of the latter. As a result, estimates may be biased due to omitted variables. There are also sample selection issues: dependent variables, such as loan denials, collateral requirements and interest rates, are not observed for all firms in a random sample. Some entrepreneurs may not need a loan and this may be related to the demographic factors. For example, there is evidence that risk attitude and risk tolerance may differ between the genders. Women are often found to be more risk averse than men (Jianakoplos & Bernasek (1998), Barber & Odean (2001), and (Dohmen et al. 2005)). As a result, female entrepreneurs may prefer to invest smaller amounts of personal

[2] Besides demographic characteristics, discrimination may be based on other factors, such as private versus public ownership of firms (Brandt & Li 2003).

wealth and to maintain lower debt-equity ratios in their businesses, possibly avoiding borrowing altogether.[3]

Most of the existing empirical studies provide some evidence of bankers' discrimination against entrepreneurs from different demographic groups. The strongest results are obtained for racial discrimination, especially for black entrepreneurs. For example, Bostic & Lampani (1999) report different approval rates for white-owned and black-owned firms, but no statistically significant differences between white-owned firms and firms owned by Asians and Hispanics. Blanchflower et al. (2003) also find that black-owned firms face obstacles in obtaining credit that are unrelated to their creditworthiness. The picture is less clear with respect to the gender-based discrimination. Cavalluzzo et al. (2002) find evidence of a credit access gap between firms owned by white males and white females with female denial rates increasing with lender concentration. In contrast, Cavalluzzo & Cavalluzzo (1998), Blanchflower et al. (2003), Storey (2004) and Cavalluzzo & Wolken (2005) find no statistically significant effect of gender. With the exception of Storey (2004), all the above-mentioned papers present evidence for the US; moreover, they use the same data set, the National Survey of Small Business Finances, though not necessarily the same waves. The studies differ, however, with respect to the indicators of restricted access to finance, sets of independent variables and econometric specifications. Few tackle the problem of omitted variables, e.g. Cavalluzzo et al. (2002) and Blanchflower et al. (2003). For example, Cavalluzzo & Wolken (2005) pay particular attention to the role of entrepreneurs' personal wealth in explaining loan denial rates.[4]

The above discussion suggests a scarcity of rigorous available evidence on gender-based discrimination against borrowers in general and for Peer to Peer Lending in particular. Most of the previous research has been implemented using the US data and little is known about other countries. Furthermore, the research concentrates of traditional lending and on business loans (see e.g. Mu-

[3]However, there are also contradictory results in the literature. E.g. Schubert et al. (1999) observed in experiments no gender differences in risk propensity when subjects face contextual decisions. This evidence is interpreted as a sign that male and female risk attitudes are comparable in the context of investment decisions.

[4]There is a related strand of literature that considers discrimination in the mortgage credit market (e.g., (Gilbert 1977), (Munnell et al. 1996) and (Ladd 1998)). (LaCour-Little 1999) and (Turner & Skidmore 1999) offer reviews of these studies.

ravyev et al. (2009)).[5] The virtual absence of evidence is remarkable and needs to be addressed.

3 Peer-to-Peer Lending at *Smava*

3.1 The Lending Mechanism

Peer-to-peer lending means direct lending and borrowing between individuals ("peers") without intermediation of a traditional financial institution. Historical forms of peer-to-peer lending include borrowing from friends, family members or business partners. Recent advances in the Internet-based technologies enabled lending transactions to be carried out at online marketplaces ("platforms") where people who need money are matched with those who are willing to lend money. The first online platform for peer-to-peer lending, *Zopa*, was founded in 2005 in the UK. Since then, several other lending sites were launched in the USA and continental Europe.[6] The platforms differ in business models, requirements to lenders and borrowers and lending mechanisms. They all, however, have one feature in common: Any particular loan request can be funded by multiple lenders.

The data used in this study are collected from the largest peer-to-peer lending platform in Germany – *Smava*. The platform was launched in March 2007. Since then, the number of originated loans and their volume has been continuously rising (Table 1). By March 2010, the platform procured 3,602 loans in total volume of more than € 26 million.

Lending at *Smava* functions in the following way. Prospective borrowers have to post a loan application on the platform's web page www.smava.de. Only individuals who comply with a number of requirements are eligible to apply for credit at the platform. Firstly, applicants have to be at least 18 years old and have a monthly income of min. € 1,000. Secondly, only those whose individual financial burden does not exceed 67 % are eligible to borrow at the

[5]There are many studies of the effect of gender on access and cost of external financing in the management literature, but most of them are purely descriptive and rarely based on representative samples.

[6]Other well known platforms are *Prosper* and *Kiva* in the USA; *Bobber* in the Netherlands; *Fairrates* in Denmark; *Elolly*, *Aux Money* and *SOS Money* in Germany.

platform. Financial burden is measured as a ratio of monthly payments on all outstanding consumer debts (including loans taken at *Smava*) to the borrower's personal monthly disposable income. Mortgage payments are treated as expenditures and subtracted from the disposable income. Income of other household members as well as household savings are not taken into account. Depending on the obtained ratio, borrowers are rated on a scale from 1 to 4 and assigned the so called KDF-indicator as described in Table 4. Finally, the platform accepts only applicants with Shufa-rating scores ranging from A to H. Schufa-rating is assigned to individuals by the German national credit bureau and measures borrowers' creditworthiness on a 12-point scale from A (the best) to M (the worst). Each rating score corresponds to an estimate of probability that a borrower defaults on his obligations within one year (see Table 3). Applicants' identity and compilation with the above mentioned requirements is verified via *postident* procedure: Each prospective borrower has to provide officers of the German Post in person with documents that prove his or her identity, place of residence, employment status, Shufa-rating, income and debts. The officers verify the documents and issue a certificate that is sent to the platform.

After the successful verification, accepted applicants may post a loan application at the platforms' web page. An application specifies what amount of money the applicant wants to borrow, for how long and what nominal annual interest rate he is willing to pay. Two restrictions are imposed by the platform on loan requests: borrowers may not request less than € 500 or more than € 50,000, and loan duration may be either 36 or 60 months. In addition, applicants may provide a description of the loan purpose, of their own personality and upload a picture. These additional pieces of information are provided voluntarily and are not verified by the platform. All posted applications are made visible to all users of the platform: prospective lenders, other applicants and visitors of the platform. Users can browse through the list of applications and see information provided by the applicants. Each application is displayed for 14 days.

An important peculiarity of *Smava* is that, in contrast to many other peer-to-peer lending sites, loans are *not* auctioned. Lenders can not underbid offers of other lenders by offering a lower interest rate. Instead, lenders provide funds on "take it or leave it" basis: They may lend only on terms specified in loan applications, i.e. under the interest rate and for duration set by applicants. The amount of provided funds is the only parameter where lenders may deviate from the specified conditions. For instance, the lent amount may be smaller that the amount requested by an applicant. The minimal amount that a lender may lend is € 250. However, multiple lenders may lend money to one applicant. Multiple lending is an important feature of the most peer-to-peer lending platforms. In fact, the majority of loans at our platform are financed by several lenders with each of them providing only a fraction of the amount requested by applicants. Naturally, the number of lenders tends to increase with the amount of loan requested. So far, the average number of lenders per loan at the platform is 15.

It should be mentioned, that a lender who is willing to provide money to a particular applicant has to submit an electronic order. By submitting an order the lender "signs" a binding contract in which he commits to provide certain amount of money to the chosen applicant. Orders are submitted by lenders on the "first-come first-serve" basis, i.e. until the requested loan amount is covered to 100%. If however after 14 days from the moment when a loan application was posted, less than 25 % of the requested amount is raised, the application is canceled and the raised money (if any raised) is returned to lenders. In the case of cancelation, an applicant can post his application again, eventually, offering more attractive conditions, e.g. a higher nominal interest rate. In case of a successful brokerage, the platform charges borrowers with a fee of 2 – 2.5% depending on the loan amount. All loans procured at the platform are annuities repayed in fixed monthly installments.

3.2 Description of Loan Applications

The data collected for this study covers 3 years of lending at the platform – from March 2007 (when the first loan application was posted on the platform's web page) to March 2010. During the observation period, 3,401 individuals have applied for loans at the platform. 935 of them are females (27%) and 2,466 are males (73%). The total number of applications is 4,146: 1,114 (27%) applications are posted by female applicants and 3,032 (73%) are posted by male applicants. The total number of applications exceeds the number of applicants, because each individual may apply for multiple loans or resubmit an application once it was turned down. Resubmitted application are treated as new applications.

Not every application succeeds to raise funds. If an application hasn't received a single order during 14 days or received some orders but the amount provided by lenders makes less then 25 % of the requested sum then the application is canceled. We call such applications "failed applications". If an application raises at least 25 % of the requested sum, the applicant can receive the raised amount. Such applications are called "successful". Table 1 documents the distribution of applications by funding success. About 81% of applications succeeded to raise the total amount requested by applicants. About 6% of applications raised less than the applicants were asking for, however, still succeeded to surpass the threshold. About 13% of applications failed to raise the necessary 25%. Remarkably, within-group distributions of applications by applicants' gender indicate that the fraction of successful applications is somewhat higher for females than for males.

4 Gender Differences in Borrower- and Loan-Specific Attributes

4.1 Descriptive Evidence

We now turn to successful applicants, i.e. applicants that raised at least 25% of the requested amount and actually became borrowers. Proportions of males and females among borrowers are very close to those observed among all applicants. In particular, 2,612 (73%) loans are received by male borrowers and 990 (27%) are received by female borrowers. Table 2 summaries descriptive statistics of selected loan-specific variables by borrowers' gender. The figures reveal two important differences between loans taken by males and females. Firstly, females get on average smaller loans than males. This gap stems from the fact that females request smaller amounts then males. Secondly, females pay on average higher nominal interest rates than males. As shown in Figure 3, the form of gender specific distributions of interest rates is similar. However, the sample mean for females exceeds the mean for males by 0.3 percentage points. The difference is statistically significant at 0.01-level of significance.

Does the interest rate gap emerge because borrowers' gender is correlated with probability of default? The historical default rate observed at the platform during 3 years is about 5% for both male and female borrowers. Hence, none of the gender groups seems to be riskier than the other. But maybe female borrowers differ from male borrowers in some characteristics that are viewed by lenders as important predictors of credit risk? The main borrower-specific attribute that conveys the level of borrowers' riskiness is the Shufa rating score. Figure 4 plots distribution of male and female borrowers by the rating score. The distributions do not exhibit much difference. The sample mean and median rating for both gender groups is "D" corresponding to 4.41% probability of default.

There are however differences with respect to some borrower-specific characteristics that are summarized in Table 5. These characteristics include age, financial burden, employment status and place of residence (federal land). For instance, female borrowers are on average by 4 years older than males and are less numerous than males among self-employed borrowers, but more numerous in the group of retirees. We can't exclude that lenders take into account these differences when assessing borrowers' risk.

Furthermore, although information on the purpose of loan is not verified, lenders may consider this information too when making their decisions. We apply the classification of loan purpose suggested by the platform. Figure 2 plots distributions of loans by purpose separately for males and females. Gender differences can be observed in the categories where they are expected: Males prevail in the groups related to business, electronics and cars, while females dominate in categories related to housekeeping, education, family and health care.

Overall, a univariate analysis of loan- and borrower-specific characteristics shows that although male and female borrowers do not differ significantly in the expected probability of default, they do differ with respect to some attributes that may influence the cost of credit. An important question is whether these differences are responsible for the gender gap in the interest rate paid by borrowers at the platform.

4.2 "Ceteris Paribus" Effect of Gender on the Interest Rate

To check whether differences in the interest rate result from discrepancies in the loan- and borrower-related attributes, we estimate a model describing the relationship between interest rate and the attributes:

$$I_{ij} = \alpha_1 + \beta_1 * Female_{ij} + \gamma_1 * \mathbf{X}_{ij} + \zeta_1 * \mathbf{W}_{ij} + \varepsilon_{ij}, \tag{4.1}$$

where I_{ij} is the interest rate that borrower j pays on loan i measured in percent. *Female* is a dummy-variable indicating borrower's gender (=1 for female, =0 for male). $\mathbf{X}_{ij}$ and $\mathbf{W}_{ij}$ are vectors of borrower- and loan-specific attributes respectively. These vectors include all information that can be used by lenders to make their decisions. ε_{ij} is the model's error. Since one borrower may take multiple loans, we allow for correlation in the error term over j.

The model is estimated on three different sample cuts. Firstly, we estimate parameters using the whole sample of loans. Then the model is estimated for a sub-sample of large loans. Large loans comprise the upper quartile of loan distribution by size. Finally, only the data on business loans are fitted to the model. All three estimations are done by means of OLS regression. Estimation results are summarized in Table 6. The obtained R^2 in all three cases is high suggesting that our model explains more than 70% of variation in the interest rates.

We firstly take a closer look at the coefficients estimated with the whole sample. The predicted effect of *Female* is positive and statistically significant at 10-percent level of significance. The value of the estimate suggests that interest rate payed by a female borrower is by 0.127 percentage points higher than the rate payed by a male borrower, all things being equal. Hence, our model predicts a gender interest rate gap even after we took into account all determinants of credit cost. As to the effects of other covariates, they are in line with expectations. For instance, the model predicts that interest rate increases with age. Obviously, lenders associate age with rising probability of default due to higher mortality risk. Financial burden is also an important predictor of credit cost: Highly financially burdened borrowers have to pay by 0.661 percentage points more for credit than their less burdened counterparts. The cost of credit seem to increase almost linearly with credit risk. Borrowers with the worst rating "H" pay 7 percentage points more than borrowers with the best rating "A". Due to higher background risk, self-employed also pay more compared to other borrowers. Furthermore, interest rate is predicted to increase with loan size. The positive relationship between these to factors is typical for lending business. Also loan duration has a typical effect on interest rate: loans with shorter duration cost by 0.254 percentage points less than loans with longer duration. Somewhat surprising are the effects of the two dummy variables indicating the purpose of loans. For instance, borrowers who take credit at *Smava* to consolidate or repay other debts or for business purposes seem to pay less than borrowers taking loans for usual consumer expenditures. How can we explain this finding? Probably, these two groups of borrowers are the most in need for cheep credit and set the lowest possible interest rate, just enough to meet lenders reservation rate.[7]

Results obtained for the sub-sample of large loans correspond by and large to those obtained for the whole sample of loans. One difference emerges with respect to the main covariate *Female*. For instance, gender seems now to have a much stronger effect in both economic and statistical terms. In particular, female borrowers are predicted to pay by 0.37 percentage points more than male borrowers, ceteris paribus. Hence, the results suggest that behavior of borrowers taking large loans differs somewhat from the behavior of borrowers with smaller loans. Finally, according to the model fitted on the sub-sample of business loans, there are no gender differences in the interest rates. The coefficient for Female is statistically insignificant. Effects of control variables are again as expected.

To summarize, results of a regression analysis show that females pay more for credit than their male counterparts. The effect is especially pronounced in a sub-sample of large loans. It disappears however when the analysis is restricted to business loans. If none of the considered loan and borrower-specific attributes help to explain the existing gender interest rate gap, does it mean that lenders discriminate against female borrowers? We address this question in the next section.

[7]Reservation rate is the minimal interest rate at which a lender is willing to lend money to a particular borrower.

5 Are Female Borrowers Discriminated?

5.1 Research Hypothesis and Testing Methodology

The observed gender gap in the interest rates suggests that peer-to-peer lenders might discriminate against female borrowers. Literature distinguishes between two types of discrimination: efficient statistical discrimination Phelps 1972, Arrow 1973) and inefficient taste-based discrimination (Becker (1957)). Statistical discrimination occurs for example when gender is correlated with credit risk and because of that lenders are less willing to lend money to female applicants or set tighter terms for loans to females than to males. Inefficient taste-based discrimination arises if probability of getting a loan or loan terms differ for men and women despite similar credit risk.

What type of discrimination is taking place in the considered peer-to-peer lending market? Statistical discrimination would emerge if female borrowers exhibited higher default rates than males. In this case it would be efficient for lenders to demand a higher risk premium from women as compensation for the higher credit risk. However, our data show that male and female borrowers exhibit equal historical default rates. Therefore, there is no reason for statistical discrimination. The interest rate gap might however stem from taste-based discrimination. Lenders may set higher reservation rates for loans to female borrowers than for loans to male borrowers even when the two groups have similar characteristics and gender per se is not correlated with probability of default. Therefore, if taste-based discrimination is really taking place, female borrowers should be less likely to get loans than males, ceteris paribus.

The research hypothesis that we shall test reads: *Female applicants are less likely to get loan than male applicants, ceteris paribus.* To test this hypothesis we suggest a model that predicts funding success. Let I_b denote the interest rate offered by applicant j who wants to borrow a specified amount of money. Let I_l denote the reservation rate that lenders set for applicant j given his credit risk. An applicant is likely to get credit, if there are lenders at the market whose reservation rate for the respective loan is at least as high as the interest rate set by the applicant, i.e. $I_b \geq I_l$. Hence, we define an indicator variable *Successful funding* equal 1 if $I_b - I_l \geq 0$, which means that an applicant succeeded to raise at least

25% of the requested sum, and 0 otherwise. Reservation rate depends on a number of factors. The main factor is the applicant's probability of default. Schufa rating score provides lenders with an estimate of probability of default. Besides rating, lenders may take into account other determinants of risk, e.g. applicants' employment status, financial burden and age. Further factors that may influence lenders' reservation rate is the purpose of loan, requested loan duration and amount, and possibly borrowers' gender.[8] Hence, our model relates probability of funding success to the factors that are important for determination of reservation rate:

$$Pr(\mathit{Successful\,funding}{=}1)_{ij} = \alpha_2 + \beta_2 * \text{Female}_{ij} + \gamma_2 * \mathbf{X}_{ij} + \zeta_2 * \mathbf{W}_{ij} + \varepsilon_{ij}, \quad (5.1)$$

where $\mathbf{X}_{ij}$ is vector of applicant's j individual characteristics and $\mathbf{W}_{ij}$ is vector of loan terms specified in application i. Because one applicant can submit multiple applications, we allow the model's errors ε_{ij} to be correlated over j.

Under taste-based discrimination, lenders should set a higher reservation rate for female borrowers, ceteris paribus. Respectively, for any specified interest rate, the riskier gender group should be less likely to get funds than the other gender group. This should lead to a negative effect of *Female* in model 5.1. Hence, a negative and statistically significant estimate of β_2 would indicate the existence of discrimination.

5.2 Results

We estimate the model by fitting data to a logit regression model. Estimation results are reported in Table 7. We use two specifications of the model: the first one includes only borrower-specific control variables, the second one additionally includes the attributes of requested loans. The second specification gives a better fit, the respective value of pseudo-R^2 is 0.445 and is twice as high as the

[8]Besides the relation between reservation and suggested interest rates, funding success may depend on trustworthiness of a prospective borrower. Lenders build their opinion about borrowers' trustworthiness upon various soft information voluntarily provided by applicants, e.g. description of loan purpose and applicant's personality, the content of pictures uploaded by applicants etc. Trustworthiness should have positive effect on the funding success. However, analysis of effects of trustworthiness goes beyond the scope of this study. We treat lenders' estimates of applicants' trustworthiness as unobservable random effects that are not correlated with observed characteristics.

pseudo-R^2 of the first specification. Remarkably, when only borrower-specific factors are taken into account, the model predicts a significant effect of applicants' gender on funding success. What's more, the effect is positive suggesting that female applicants are more likely to get credit than males, ceteris paribus. The effect disappears however when loan-specific factors are included in the model. Hence, there is no evidence that female applicants are less likely to surpass the threshold of 25% than male applicants.

To check robustness of the obtained result, we use an alternative specification of the dependent variable. Since we can observe the exact amount of money provided by lenders, we can use the financed fraction (in %) of the initially requested loan amount as a dependent variable. The new model is estimated by means of OLS regression. Results are reported Table 7. The estimated effects of gender are similar to those obtained previously. In particular, gender is predicted to have a positive statistically significant effect on the financed fraction in the reduced form model, but no significant effect when characteristics of loans are taken into account. Predicted effects of other control variables are by and large similar across specifications and are in line with expectations.

We also estimate our model for two alternative sample cuts: separately for individuals who apply for large loans and business loans. We distinguish these two groups because behavior of these applicants may differ from the rest, but also lenders may treat them in a different way. Estimation results for the subsample of applications for large loans are documented in Table 8. Effect of gender is statistically insignificant in all four specifications suggesting that male and female applicants have equal chances of getting funds. No effect of gender is also found in the sub-sample of business loans (see Table 9).

In sum, we can't confirm the hypothesis that borrowers' gender affects funding success. The result is robust across different model specifications and sample cuts. Hence, there is no evidence of gender discrimination at *Smava*.

6 Conclusions

Our analysis of peer-to-peer lending data reveals that female borrowers pay on average higher interest rates at the German market place *Smava* than males. The interest rate gap exists despite the fact that the two gender groups are similar with respect to the main default-relevant attributes and, what's more, are characterized by equal historical default rates. This observation led us to the hypothesis that there might be a taste-based discrimination against female borrowers at the considered market place. We test this hypothesis by means of a regression analysis. Our results however suggest that the observed gender interest rate gap is not caused by discrimination. In fact, our model predicts that males and females who offer equal interest rates have the same probability of getting credit, ceteris paribus. This finding is robust with respect to different model specifications and sample cuts.

If no discrimination is taking place, then why do female borrowers finance at higher cost? Our explanation is that female borrowers deliberately offer higher interest rates in anticipation that they would be otherwise discriminated. Especially in the case of large loans, where gender interest rate gap is the largest, female borrowers may think that lenders are more skeptical about the ability of a female to repay a large loan. In effect, female borrowers offer higher interest rates than it is necessarily given their risk profiles. This might also explain why we observe a slightly higher fraction of successful applications among female applicants. Lenders snatch more willingly at offers that promise higher returns.

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Appendix

Figure 1: Loans procured at *Smava*

This graph plots cumulative distribution of number and volume of loans procured at the platform between March, 2007 and March, 2010

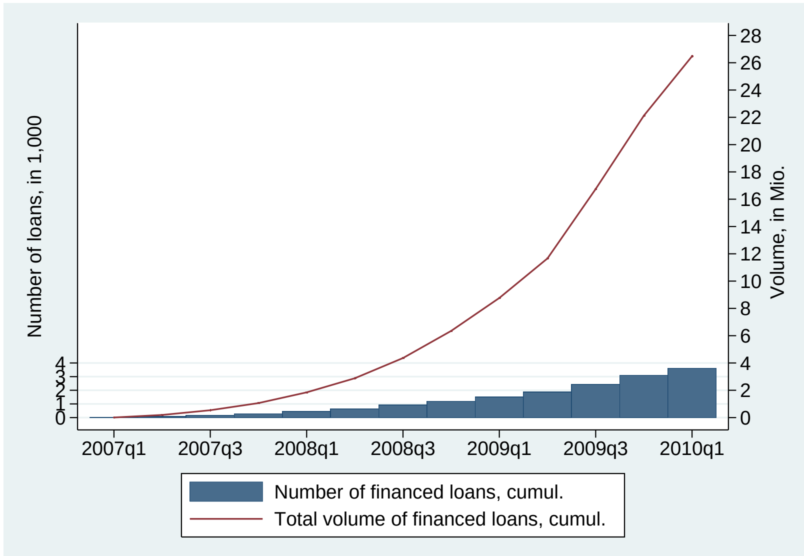

Table 1: Fraction of applications by funding success

	Fraction of posted applications, in %		
Amount of provided funds as a share of requested amount, in %	**by all applicants** N = 4,146	**by females** N = 1,114	**by males** N = 3,032
		Failed applications	
0 % raised (no bids submitted)	7.72	5.75	8.44
< 25 % raised	5.40	5.39	5.41
		Successful applications	
$\geq$ 25 but < 100 % raised	5.96	5.75	6.04
100 % raised	80.92	83.12	80.11
Total	100.00	100.00	100.00

Table 2: Summary statistics of selected loan parameters by borrowers' gender

	Male borrowers N=2,612		Female borrowers N=990			
Variable	Mean	St.Dev.	Mean	St.Dev.	t-Test	p-value
Obtained loan amount	7,520	6,011		6,901	5,401 2.97	0.00
Requested loan amount	7,832	6,171		7,222	5,630 2.83	0.00
Maturity = 36 months	0.41	0.49		0.40	0.49 0.53	0.59
Nominal interest rate, p.a.	9.91	3.32		10.22	3.34 -2.53	0.01
Number of lenders per loan	15	11		15	11 1.67	0.10

Figure 2: Distribution of male and female borrowers by loan purpose

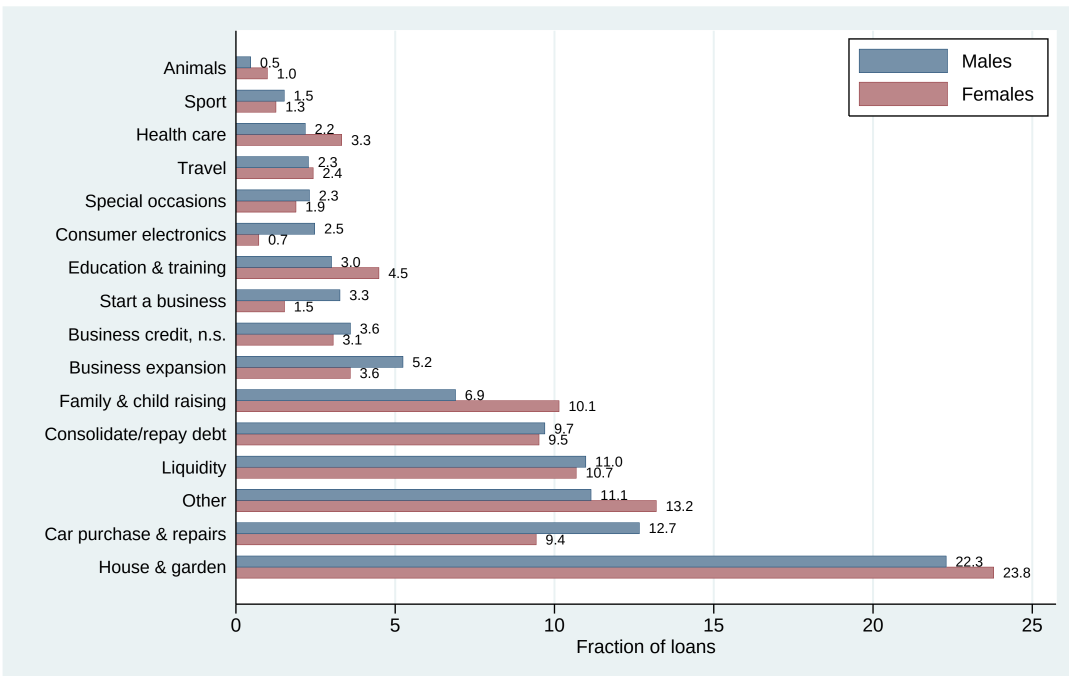

Figure 3: Distribution of interest rates

This graph plots distribution of interest rates that male and female borrowers pay at *Smava*. Mean interest rate paid by females is 10.22 and by males is 9.91. The difference is statistically significant at 0.01-level of significance.

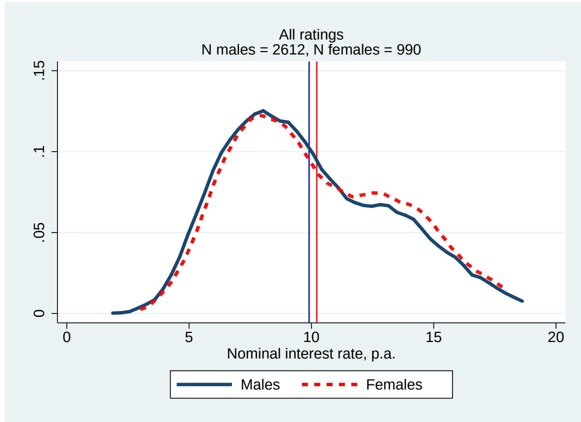

Table 3: Schufa rating scores

This table shows the Schufa rating scores that are accepted at *Smava*. The rating scores reflect probability of default and are assigned to each borrower by the German national credit bureau Schufa.

Rating score	A	B	C	D	E	F	G	H
Probability of default, in %	1.38	2.46	3.56	4.41	5.57	7.16	10.72	15.02

Figure 4: Distribution of borrowers by rating score

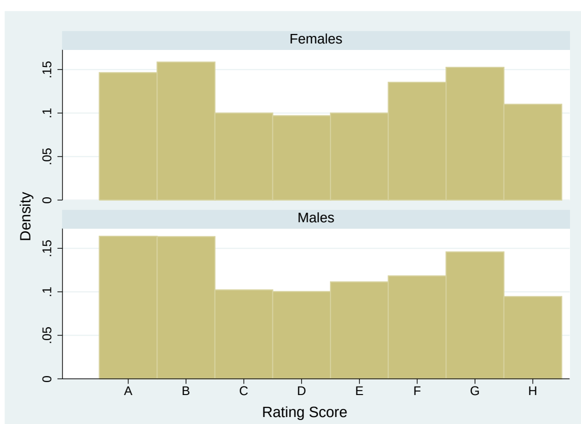

Table 4: KDF-Indicator as a measure of financial burden

Financial burden	KDF-Indikator	Debt-to-disposable income ratio
low	1	0 bis 20%
moderate	2	20 bis 40%
substantial	3	40 bis 60%
high	4	60 bis 67%

Table 5: Summary statistics of selected borrower characteristics by borrowers' gender

	Male borrowers N=2,612		Female borrowers N=990			
Variable	Mean	St.Dev.	Mean	St.Dev.	t-Test	p-value
Age	43.21	13.02	47.02	14.81	-7.57	0.00
Financial burden:						
low	0.13	0.33	0.11	0.31	1.66	0.10
moderate	0.22	0.42	0.25	0.43	-1.86	0.06
substantial	0.35	0.48	0.37	0.48	-1.05	0.30
high	0.30	0.46	0.27	0.45	1.64	0.10
Employment:						
Employee	0.52	0.50	0.54	0.50	-0.93	0.35
Civil servant	0.04	0.20	0.03	0.18	1.59	0.11
Freelancer	0.09	0.28	0.06	0.25	2.57	0.01
Managing partner	0.05	0.22	0.02	0.15	4.80	0.00
Sole proprietor	0.21	0.41	0.19	0.40	1.19	0.24
Retiree	0.08	0.27	0.14	0.35	-5.18	0.00
Other	0.00	0.04	0.00	0.06	-1.19	0.23
Place of residence:						
Baden-Württemberg	0.14	0.35	0.11	0.31	2.80	0.01
Bayern	0.16	0.37	0.17	0.38	-0.59	0.56
Berlin	0.07	0.25	0.10	0.30	-3.63	0.00
Brandenburg	0.03	0.17	0.04	0.18	-1.00	0.32
Bremen	0.01	0.09	0.01	0.08	0.46	0.65
Hamburg	0.03	0.17	0.03	0.18	-0.36	0.72
Hessen	0.09	0.28	0.09	0.28	-0.02	0.98
Mecklenburg-Vorpommern	0.01	0.11	0.02	0.14	-1.24	0.22
Niedersachsen	0.09	0.28	0.07	0.26	1.99	0.05
Nordrhein-Westfalen	0.20	0.40	0.19	0.39	1.08	0.28
Rheinland-Pfalz	0.05	0.21	0.05	0.22	-0.51	0.61
Saarland	0.01	0.10	0.01	0.08	1.11	0.27
Sachsen	0.04	0.19	0.05	0.21	-0.91	0.36
Sachsen-Anhalt	0.02	0.15	0.02	0.12	1.44	0.15
Schleswig-Holstein	0.03	0.18	0.03	0.18	0.21	0.83
Thüringen	0.02	0.14	0.03	0.17	-1.41	0.16

Table 6: Effects of borrower- and loan-related characteristics on the interest rate of funded loans

This table reports estimated coefficients after OLS regression. Because of clustering of observations at borrower level, cluster robust standard errors are calculated for all four models. ***, ** and * indicate significance at 0.01, 0.05 and 0.1 levels respectively.

	All loans		**Large loans**		**Business loans**	
	Coefficient	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE
Female	0.127*	(0.073)	0.370***	(0.120)	-0.102	(0.130)
Age	0.014***	(0.003)	0.005	(0.004)	0.009*	(0.005)
Financial burden:						
low	base		base		base	
moderate	-0.035	(0.118)	-0.433**	(0.212)	-0.336	(0.233)
substantial	0.136	(0.115)	-0.308	(0.203)	-0.102	(0.218)
high	0.661***	(0.120)	0.313	(0.212)	0.452**	(0.224)
Rating:						
A	base		base		base	
B	0.727***	(0.101)	0.728***	(0.151)	0.758***	(0.152)
C	1.570***	(0.113)	1.709***	(0.172)	1.703***	(0.187)
D	2.242***	(0.115)	2.299***	(0.185)	2.220***	(0.193)
E	3.309***	(0.123)	3.292***	(0.170)	3.258***	(0.211)
F	4.199***	(0.122)	4.234***	(0.203)	4.187***	(0.192)
G	5.875***	(0.123)	5.830***	(0.199)	5.813***	(0.213)
H	7.332***	(0.144)	7.503***	(0.293)	7.417***	(0.279)
Self-employed	0.392***	(0.077)	0.461***	(0.122)	0.312**	(0.130)
Lives in East Germany	-0.089	(0.074)	-0.024	(0.118)	0.013	(0.130)
ln(Requested loan amount)	0.126**	(0.053)	0.616***	(0.168)	0.142*	(0.083)
36-months loan	-0.254***	(0.084)	-0.092	(0.147)	-0.146	(0.136)
Loan purpose:						
Consumer expenditures	base		base		No	
Consolidate/pay debt	-0.433***	(0.112)	-0.140	(0.254)	No	
Business loan	-0.231***	(0.072)	-0.345***	(0.117)	No	
Time effects	Yes		Yes		Yes	
R^2	0.736		0.752		0.735	
Number of obs.	3,602		1,023		1,008	

Table 7: Determinants of funding success: All applications

This table reports estimated effects of borrower- and loan-specific variables on the success of a loan funding. Columns (1) and (2) contain marginal effects after logit regression. The dependent variable is a dummy equal 1 if a loan application collected at least 25% of the initially requested loan amount and 0 otherwise. Columns (3) and (4) contain estimated coefficients after OLS regression. Here, the dependent variable is the fraction (in %) of initially requested sum funded by lenders. Because of clustering of observations at borrower level, cluster robust standard errors are calculated for all four models. ***, ** and * indicate significance at 0.01, 0.05 and 0.1 levels respectively.

	Probability of funding success				**Funded fraction**			
	(1)		**(2)**		**(3)**		**(4)**	
	Marg.eff.	Robust SE	Marg.eff.	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE
Female	0.026**	(0.127)	0.010	(0.148)	2.913***	(1.055)	1.634	(0.967)
Age	-0.001***	(0.004)	-0.001***	(0.005)	-0.172***	(0.037)	-0.200***	(0.035)
Financial burden:								
low	base		base		base		base	
moderate	0.177***	(0.137)	0.105***	(0.162)	19.471***	(2.047)	15.447***	(1.709)
substantial	0.259***	(0.150)	0.162***	(0.180)	27.068***	(1.878)	21.583***	(1.598)
high	0.309***	(0.214)	0.185***	(0.224)	34.002***	(1.852)	23.775***	(1.610)
Rating:								
A	base		base		base		base	
B	-0.020	(0.211)	-0.023***	(0.233)	-3.147**	(1.530)	-7.010***	(1.414)
C	0.020	(0.274)	-0.015	(0.303)	-0.035	(1.726)	-8.062***	(1.628)
D	-0.051***	(0.234)	-0.084***	(0.260)	-5.346***	(1.886)	-16.397***	(1.795)
E	-0.031*	(0.226)	-0.091***	(0.265)	-3.569**	(1.665)	-19.243***	(1.686)
F	-0.056***	(0.222)	-0.164***	(0.280)	-6.445***	(1.815)	-26.924***	(1.845)
G	-0.109***	(0.204)	-0.323***	(0.295)	-11.230***	(1.777)	-39.056***	(1.980)
H	-0.127***	(0.224)	-0.446***	(0.354)	-13.213***	(2.162)	-49.262***	(2.495)
Self-employed	-0.002	(0.119)	0.020**	(0.152)	-2.782***	(1.007)	1.294	(1.111)
Lives in East Germany	0.019	(0.135)	0.003	(0.157)	1.892*	(1.131)	0.993	(1.041)
ln(Requested loan amount)	No		-0.077***	(0.102)	No		-9.555***	(0.647)
36-months loan	No		0.045***	(0.185)	No		4.173***	(1.100)
Interest rate, in % p.a.	No		0.034***	(0.034)	No		4.912***	(0.227)
Loan purpose:								
Consumer expenditures	No		base		No		base	
Consolidate/pay debt	No		0.025	(0.279)	No		2.664*	(1.475)
Business loan	No		-0.005	(0.150)	No		0.207	(1.050)
Time effects	Yes		Yes		Yes		Yes	
R^2					0.225		0.374	
Pseudo-R^2	0.258		0.445					
Number of obs.	4,146		4,146		4,146		4,146	

Table 8: Determinants of funding success: Large loans

This table reports estimated effects of borrower- and loan-specific variables on the success of a loan funding when an applicant requests a large loan (larger than the 4th percentile of the overall distribution of loan requests). Proportion of females among applicants for large loans is ci. 23% and is roughly the same as the proportion of females in the whole population of applicants. Columns (1) and (2) contain marginal effects after logit regression. The dependent variable is a dummy equal 1 if a loan application collected at least 25% of the initially requested loan amount and 0 otherwise. Columns (3) and (4) contain estimated coefficients after OLS regression. Here, the dependent variable is the fraction (in %) of initially requested sum funded by lenders. Because of clustering of observations at borrower level, cluster robust standard errors are calculated for all four models. ***, ** and * indicate significance at 0.01, 0.05 and 0.1 levels respectively.

	Probability of funding success				**Funded fraction**			
	(1)		**(2)**		**(3)**		**(4)**	
	Marg.eff.	Robust SE	Marg.eff.	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE
Female	0.030	(0.213)	0.006	(0.244)	1.521	(1.956)	-0.655	(1.911)
Age	-0.002**	(0.007)	-0.002***	(0.009)	-0.156**	(0.074)	-0.183**	(0.074)
Financial burden:								
low	base		base		base		base	
moderate	0.266***	(0.233)	0.208***	(0.267)	29.378***	(3.646)	25.484***	(3.359)
substantial	0.416***	(0.271)	0.322***	(0.308)	43.328***	(3.165)	37.222***	(3.027)
high	0.435***	(0.338)	0.320***	(0.344)	45.442***	(3.234)	36.293***	(3.167)
Rating:								
A	base		base		base		base	
B	-0.052*	(0.339)	-0.052***	(0.370)	-5.516**	(2.614)	-8.594***	(2.563)
C	0.006	(0.450)	-0.028	(0.477)	1.353	(3.086)	-5.752*	(2.992)
D	-0.116***	(0.391)	-0.150***	(0.426)	-10.746***	(3.539)	-19.584***	(3.595)
E	-0.050	(0.396)	-0.124***	(0.436)	-2.516	(2.949)	-16.099***	(3.003)
F	-0.094***	(0.385)	-0.216***	(0.456)	-7.869**	(3.346)	-24.456***	(3.462)
G	-0.148***	(0.346)	-0.382***	(0.479)	-12.423***	(3.286)	-35.912***	(3.528)
H	-0.161***	(0.392)	-0.460***	(0.596)	-14.985***	(4.401)	-45.041***	(4.704)
Self-employed	0.045**	(0.189)	0.030*	(0.218)	3.227*	(1.780)	1.773	(1.924)
Lives in East Germany	0.003	(0.205)	-0.006	(0.235)	0.226	(1.893)	-0.059	(1.875)
ln(Requested loan amount)	No		-0.097***	(0.371)	No		-9.987***	(2.854)
36-months loan	No		0.040*	(0.310)	No		3.950	(2.567)
Interest rate, in % p.a.	No		0.038***	(0.055)	No		4.367***	(0.389)
Loan purpose:								
Consumer expenditures	No		base		No		base	
Consolidate/pay debt	No		0.019	(0.591)	No		4.123	(3.264)
Business loan	No		-0.020	(0.246)	No		-0.560	(1.845)
Time effects	Yes		Yes		Yes		Yes	
R^2					0.403		0.468	
Pseudo-R^2	0.392		0.494					
Number of obs.	1,275		1,275		1,275		1,275	

Table 9: Determinants of funding success: Business loans

This table reports estimated effects of borrower- and loan-specific variables on the funding success of applications for a business loan. Columns (1) and (2) contain marginal effects after logit regression. The dependent variable is a dummy equal 1 if a loan application collected at least 25% of the initially requested loan amount and 0 otherwise. Columns (3) and (4) contain estimated coefficients after OLS regression. Here, the dependent variable is the fraction (in %) of initially requested sum funded by lenders. Because of clustering of observations at borrower level, cluster robust standard errors are calculated for all four models. ***, ** and * indicate significance at 0.01, 0.05 and 0.1 levels respectively.

	Probability of funding success				**Funded fraction**			
	(1)		**(2)**		**(3)**		**(4)**	
	Marg.eff.	Robust SE	Marg.eff.	Robust SE	Coefficient	Robust SE	Coefficient	Robust SE
Female	0.009	(0.268)	0.018	(0.422)	0.837	(2.011)	1.716	(1.686)
Age	-0.002***	(0.010)	-0.002***	(0.015)	-0.123	(0.083)	-0.134*	(0.072)
Financial burden:								
low	base		base		base		base	
moderate	0.233***	(0.314)	0.098***	(0.418)	27.486***	(4.010)	19.346***	(3.274)
substantial	0.302***	(0.321)	0.140***	(0.469)	33.872***	(3.641)	24.189***	(3.082)
high	0.339***	(0.372)	0.137***	(0.550)	38.583***	(3.606)	24.263***	(3.148)
Rating:								
A	base		base		base		base	
B	-0.047*	(0.439)	-0.031***	(0.603)	-4.162	(2.630)	-8.692***	(2.340)
C	-0.001	(0.596)	-0.042***	(0.713)	-0.979	(3.018)	-11.176***	(2.602)
D	-0.102***	(0.494)	-0.100***	(0.644)	-8.460**	(3.405)	-20.221***	(3.017)
E	-0.057**	(0.486)	-0.133***	(0.781)	-2.228	(3.069)	-22.460***	(2.843)
F	-0.048	(0.510)	-0.220***	(0.786)	-3.089	(3.070)	-29.316***	(3.082)
G	-0.083***	(0.466)	-0.334***	(0.890)	-8.164***	(3.106)	-42.553***	(3.241)
H	-0.156***	(0.541)	-0.604***	(1.080)	-13.041***	(4.215)	-57.544***	(4.632)
Self-employed	0.024	(0.230)	0.015	(0.605)	1.025	(1.892)	2.590	(2.553)
ln(Requested loan amount)	No		-0.089***	(0.369)	No		-8.937***	(1.128)
36-months loan	No		0.041**	(0.476)	No		4.950**	(2.023)
Interest rate, in % p.a.	No		0.042***	(0.112)	No		6.400***	(0.436)
Loan purpose:								
Business credit, n.s.	No		base		No		base	
Start up	No		-0.059**	(0.725)	No		-2.048	(2.869)
Expansion	No		-0.023	(0.641)	No		1.984	(2.333)
Liquidity	No		-0.021	(0.679)	No		-0.588	(2.489)
Consolidate/pay debt	No		-0.030	(0.788)	No		-3.373	(2.960)
Place of residence	Yes		Yes		Yes		Yes	
Time effects	Yes		Yes		Yes		Yes	
R^2					0.308		0.490	
Pseudo-R^2	0.355		0.629					
Number of obs.	1,150		1,150		1,150		1,150	