Sex and Credit: Is There a Gender Bias in Lending?

Thorsten Beck[♣]
CentER, Dept. of Economics, Tilburg University, and CEPR

Patrick Behr[#]
EBAPE, Getulio Vargas Foundation

Andreas Madestam[*]
Department of Economics, Stockholm University

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Abstract

We exploit the quasi-random assignment of borrowers to loan officers using data from a large Albanian lender to show that own-gender preferences affect both credit supply and demand. Borrowers matched to officers of the opposite sex are less likely to return for a second loan. The effect is larger when officers have little prior exposure to borrowers of the other gender and when they have more discretion to act on their gender beliefs, as proxied by financial market competition and branch size. We examine one channel of influence, loan conditionality. Borrowers assigned to opposite-sex officers pay higher interest rates and receive lower loan amounts, but do not experience higher arrears. Our results imply that own-gender preferences in the credit market can have substantial negative welfare effects.

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[♣] Department of Economics and European Banking Center, Tilburg University, P.O. Box 90153, 5000 LE Tilburg, The Netherlands, and CEPR, Email: t.beck@uvt.nl.
[#] Brazilian School of Public and Business Administration, Getulio Vargas Foundation, Praia de Botafogo 190, 22253-900 Rio de Janeiro, Brazil, Email: patrick.behr@fgv.br.
[*] Department of Economics, Stockholm University, Universitetsvägen 10 A, 106 91 Stockholm, Sweden, Email: andreas.madestam@ne.su.se.

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1 Introduction

Group identity in the form of family, ethnicity, and gender is a powerful predictor of social preferences (Akerlof and Kranton, 2000; Chen and Li, 2009; Benjamin et al., 2010). In particular, people generally favor in-group over out-group members. Favoritism based on, for example, gender identity can lead to inefficient transactions and/or lost opportunities. However, gender similarity may also entail trust, reciprocity, and efficiency due to shared norms and understandings. In this paper, we examine one important form of group identity, gender, and the consequences of own-gender preferences for outcomes in the credit market.

Credit transactions rely heavily on the interaction between bank officers and borrowers. Microcredit is a case in point, with most clients being small and opaque, leaving the lending decision at the judgment of the loan officer.[1] If gender shapes business operations we need to understand how key determinants of officer behavior, such as human capital and officers' discretion to act on their beliefs, interact with gender. For example, how does prior experience with opposite-sex borrowers affect performance and do officers behave differently if they are more scrutinized? In addition, officers' decisions may not only impact loan conditionality but also subsequent demand for credit. Recent work shows that poor borrowers are sensitive to small changes in interest rates (Karlan and Zinman, 2008). If a gender bias in the relationship between officers and borrowers results in higher interest rates or smaller loan amounts, a bias can have negative repercussions not only for access to and cost of credit, but also for take up of loans. This is particularly harmful to borrowers in developing countries who already suffer from credit rationing because of weak legal institutions and a lack of collateral. Yet, despite its potential importance, an own-gender bias in lending has largely been overlooked by practitioners and academics.

Using a large dataset of loan transactions from a commercial microlender in Albania, we investigate whether the officer-borrower gender match influences the likelihood that borrowers return to the lender for additional credit. To understand if important officer attributes interact with gender identity, we examine if prior exposure to opposite-sex borrowers and a more competitive working environment with fewer possibilities for officers to act on their gender beliefs affect demand for credit. In addition, we explore a possible channel that may explain changes in demand–loan conditionality–by studying the impact of

[1] If officers and borrowers share gender identity, this could improve efficiency through a better understanding of the clients' particular circumstances. For example, female loan officers may better appreciate the ability of female entrepreneurs in terms of completing their project and/or repaying the debt. Conversely, a gender bias can also generate unfair loan conditionality.

the officer-borrower gender assignment on interest rates and approved loan amounts. Finally, the analysis allows us to test if the bias is taste based or related to lack of experience and whether it leads to more or less efficient loan transactions.

Estimating the effect of own-gender preferences presents two main challenges. First, if male or female borrowers with certain characteristics are more likely to be assigned to the same or opposite-sex loan officers, the true effect of loan officer gender would be biased. Second, if unobserved borrower traits are correlated with borrower gender, and if these can be observed by the loan officers but not by the researchers, it is not clear whether a significant coefficient on gender is due to a loan officer bias or the unobservable traits.

We address these issues by exploiting a quasi-random component of the institutional setting: the fact that first-time borrowers are arbitrarily assigned to their respective loan officer, with the sector of activity and time of application being the only factors driving the match with a specific officer. Conditional on sector and time, the random assignment of borrowers to officers ensures that unobservable borrower characteristics are the same across all officers, regardless of officer gender. In particular, we compare the difference in credit market outcomes for male and female borrowers obtaining loans from male loan officers to the difference between male and female borrowers obtaining loans from female loan officers.

We find that the random assignment of first-time borrowers to opposite-sex loan officers has a significant impact on the demand for credit. Borrowers matched with officers of the opposite gender are 15 percent less likely to apply for a second loan with the lender. To examine if gender-specific human capital traits matter, we explore the fact that our setting generates experimental variation in officers' experience with first-time borrowers of the opposite sex. We show that the effect originates with borrowers whose officers have below-median experience of the other gender. This indicates that officers learn about the other gender through professional experience and suggests that the bias is not taste based.

To investigate if officers' degree of discretion to act on their gender preferences is important, we use variation in financial market competition and in the number of officers employed in a given branch across bank branches and over time. The idea is as follows. In instances when it becomes costly for officers to express their gender beliefs, the incentives will be stronger to suppress the bias.[2] More competition offers borrowers better outside options inducing them to leave the bank if they are biased against. This lowers profits and

[2] The reasoning resembles the argument developed in Parsons et al. (2011), who show that an own-race bias associated with baseball referees is stronger in situations where it is less likely that the bias is discovered, in their context, in baseball arenas with cameras that document the decisions taken by the referees.

prompts the lender to monitor loan officers more carefully to detect mistreatment of their clients. Along the same lines, it may be easier to replace a given officer in large branches with many employees, leaving officers less discretion of indulging their own-gender preferences. The data confirm these predictions: the effect of the gender mismatch on credit demand occurs in areas where the competition from other financial institutions is weaker or where the branch size is smaller. The analysis further shows that officers' lack of opposite-sex experience and their degree of discretion are complements: the negative impact on demand for additional credit is most severe when officers have little experience with borrowers of the other gender and work in small branches or in areas with little outside competition. As an example, first-time borrowers are half as likely to apply for a second loan if they are matched with opposite-sex officers who have little prior experience of the other gender *and* work in smaller branches.

Next we study differences in loan conditionality to explore one channel through which an own-gender bias can affect credit demand. First-time borrowers assigned to officers of the other gender pay, on average, 35 basis points higher interest rates compared to borrowers assigned to same-gender officers. Again, these effects are more pronounced when officers have less opposite-sex experience and more discretion (weaker outside competition and smaller branches). Borrowers matched with officers with less exposure to the other gender and a large degree of discretion also receive between 10 to 20 percent lower loan amounts.[3]

Establishing that officer exposure to opposite-sex borrowers matters helps us rule out the existence of taste-based discrimination. However, it is not clear whether the bias we identify stems from a knowledge gap that leads officers to engage in more efficient transactions with own-gender borrowers at first—or if it reflects an initial prejudice. To test for this, we use data on the likelihood that borrowers enter into arrears during the loan. If information asymmetries between officers and borrowers were important, the variation observed in interest rates or loan amounts should be reflected in different arrear outcomes. However, we find that arrears do not depend on the interaction between officer and borrower gender, suggesting that the bias is inefficient.

Taken together, the results indicate that loan officers' gender preferences can have non-trivial welfare effects for consumers (higher interest rates, smaller loans, and lower demand) and providers of credit (lower long-run profits through diminished demand in the opposite-gender match). The findings are important as they inform us about the elasticities of

[3] In addition, we also find some support for opposite-gender borrowers offered a shorter maturity than what they applied for, implicitly increasing the monthly repayment burden.

a key group of marginal clients: first-time borrowers who are often the targets of microlenders looking to expand access. While our identification strategy bars us from making definite claims as to whether the bias stems from male or female loan officers favoring borrowers of their own gender, or disfavoring those of the other gender, we provide some suggestive evidence in support of own-gender preferences.[4]

This paper speaks to several literatures. First, using experimental field data from a South African lender, where the interest rate offers were randomized, Karlan and Zinman (2008) show that clients are sensitive to interest rate changes, in particular to increases in price above the lender's standard rates. In light of the interest rate differential identified in our paper, Karlan and Zinman's finding suggests that a gender bias-induced price gap may be one important channel affecting credit demand.[5]

Second, while there are studies looking at own-race preferences in police behavior (Donohue and Levitt, 2001), in judicial sentencing (Welch et al., 1988)[6], in the workplace (Stoll et al., 2004), and in sports (Price and Wolfers, 2010; Parsons et al., 2011), our paper is the first to gauge the existence of an own-gender bias in lending. There is also a broader literature documenting biases in credit markets, using US data on either mortgage (Munnell et al., 1996; Berkovec et al., 1998; Ladd, 1998; Ross and Yinger, 2002; Han, 2004) or small business lending (Cavalluzzo and Cavalluzzo, 1998; Blanchflower et al., 2003, Blanchard et al., 2008). More closely related, Fisman et al. (2012) report that shared ethnicity and religion between loan officers and borrowers in India improve credit allocation. Our paper differs from Fisman et al. by focusing on gender and on the combination of credit supply and demand, as well as in tracing the importance of prior exposure to opposite-sex borrowers.

With the exception of Fisman et al., the above studies on a minority/gender bias in the credit market are based on correlations that do not control for all the characteristics that lenders observe when setting the contract terms. As a consequence, any measured differences in outcomes could be attributed to these factors unobserved by the researcher. Our data and setting provide an opportunity to test for a gender bias more rigorously. Moreover, previous work does not combine a supply and a demand-side analysis.

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[4] In particular, running separate regressions at the loan officer level shows that the majority of male loan officers have a greater propensity to charge higher interest rates when lending to female borrowers than the majority of female loan officers and vice versa. Studying loan size and the demand for a second loan provides similar results.

[5] In this respect we also connect to work showing that poor consumers are highly sensitive to changes in the loan terms (see Attanasio et al's., 2008 study of the demand response to changes in loan maturity and in loan price).

[6] Similar in spirit to this paper, Abrams et al. (2012) use the random assignment of defendants to judges and find a racial bias in the incarceration rates but no evidence of an own-race bias.

Third, the paper relates to research documenting the impact of exposure to members of another group (Boisjoly et al., 2006; Beaman et al., 2009; Bagues and Esteve-Volart, 2010). While our data bar us from documenting changes in beliefs (unlike Boisjoly et al. and Beaman et al.), the results suggest that experience with the opposite gender has important economic implications.

Fourth, we connect to studies examining Becker's (1957) hypothesis on the link between discrimination and competition showing that US bank branch deregulations tightened the wage gap in the financial industry between male and female workers (Black and Strahan, 2001) and between white and black employees (Levine et al., 2011). We add to this literature by quantifying how financial market competition also reduces the impact of loan officers' own-gender bias.

Our findings further inform empirical work examining poor peoples' barriers to credit (Banerjee and Duflo, 2005; Karlan and Zinman, 2009). The setting of the current study, a for-profit lender in Albania, extending loans under individual liability also fits the pattern of the second generation of microcredit which has evolved in the direction of more traditional retail and small business lending (Armendáriz and Morduch, 2005; Karlan and Morduch, 2009).

Finally, the paper relates to a small literature studying the importance of loan officers in lending stressing long-term relationships, compensation schemes, officer rotation, and officer gender for loan performance (Hertzberg et al., 2010; Agarwal and Ben-David, 2011; Drexler and Schoar, 2011; Cole et al., 2012). We complement these studies by documenting the existence of an own-gender bias and in emphasizing the importance of loan officers' prior exposure to opposite-sex borrowers. This paper is also connected to but different from Beck, Behr and Guettler (forthcoming). Using a similar but smaller data set, Beck et al. (forthcoming) gauge the relative performance of female and male officers in terms of borrowers' default risk and find that loans given by female officers are less risky than loans provided by male officers. While it is important to identify how characteristics across loan officers help explain credit market outcomes, we are interested in a distinctly different question in this paper, namely how male and female borrowers succeed for a given set of officer attributes.[7] Our within-officer estimator investigates the interaction of officer and borrower gender allowing us to explore the importance of an own-gender bias in lending independently of the quality of a particular banker.

[7] Hence, the fact the female officers are more efficient does not provide an answer to whether female and male borrowers are treated differently per se.

In the next section we provide institutional background information about our lender and the loan process, outline our methodology, and describe the data. Section three presents our findings on the relationship between own-gender preferences and demand for a second loan, while section four discusses results for the relationship between own-gender preferences and loan conditionality. Section five investigates whether the bias is efficient while section six explores if the bias is more pronounced for male or female officers. Section seven concludes.

2 Data and identification strategy

This section describes our data, provides information about the lender, sample composition and summary statistics, and evidence on the validity of our identification strategy.

2.1 Sources of data and institutional background information of the lender

We rely on information from two sets of data. The loan-level data come from a large for-profit commercial lender serving individuals and small- and medium-sized enterprises in Albania while the population and the financial market competition data were obtained from the Bank of Albania.

The loan-transaction dataset includes nearly 7,300 loans given by a commercial lender over the period January 1996 to December 2006. The data also contain information on 274 loan officers and cover all 21 branches of the bank.[8] While the lender clearly focuses on the low-income and microenterprise segment, financial sustainability and therefore profitability is its primary goal. The financial market data include geographical information about the universe of Albania's formally registered banks and their respective branches at the county level (prefekturë) for the period 2004-2006.[9] The population statistics report the total number of people living in each county during the same period.

Loan officers working for the lender have discretion on the approval of a loan application, as well as setting the interest rate and other loan conditions including loan amount and maturity. The officer that originates a certain loan is also in charge of monitoring the repayment behavior of the borrower. If a loan is in arrears for more than 30 days, the officer intensifies monitoring, for instance, by calling or visiting the borrower to inquire about the reasons for repayment delay. When a loan is in arrears for more than 60 days, it is transferred to a special loan recovery department and, thus, a new loan officer. We can

[8] The data differ from the data used in Beck et al. (forthcoming) as it includes all of the lender's Albanian branches.

[9] The information was obtained through correspondence with the Bank of Albania.

therefore follow the relationship between a borrower and an officer from approval over loan condition setting to its performance in terms of arrears up to 60 days, but not beyond that point as we lack information about the gender of the officers working in the loan recovery department.

Assignment of borrowers to officers is based on the availability of officers in the respective branch when the borrower arrives.[10] Specifically, first-time borrowers cannot choose a bank officer, barring an assignment based on any observable (for example, gender) or unobservable characteristic (for example, ability). Similarly, loan officers are allocated to borrowers based on a first come first served basis. The officers, however, may specialize in certain business sectors. For instance, it is more likely that a borrower working in the transportation business ends up with an officer with previous experience in handling borrowers from this sector. Since male and female officers or borrowers potentially specialize in certain sectors, this needs to be accounted for. Below we outline our identification strategy and how we account for the potential loan officer and borrower specialization.

2.2 Sample composition and summary statistics

When analyzing treatment differences we focus on the following four outcomes: (i) the likelihood that a borrower applies for a second loan with the lender; (ii) the annual interest rate paid; (iii) the loan amount approved; and (iv) the likelihood of going into arrears more than 30 days at any point during the loan cycle.[11] While we have information on rejected loan applications, almost all first-time applicants are granted a loan following the lender's focus on targeting the low-income and microenterprise segment (customers otherwise shut out of the market). This policy leaves little room for loan officers to exercise any discretion in the approval stage, making it unlikely that we should detect a bias. (Table A1 in the Appendix confirms that 90 percent of all first-time loans are approved, with no evidence of loan officers treating the opposite gender differently.) For our regression analysis, we restrict the data in two ways. First, we focus on first-time borrowers. By studying the first loan application submitted by each borrower, we assume that borrowers and loan officers neither had a previous business relationship nor any knowledge of each other. In the case of repeat borrowers, loan officers have historic information, which they can use when granting and monitoring the loan and deciding on loan conditionality. In addition, the fact that we find a

[10] All loan officers work full time so it does not matter which day of the week a borrower arrives.
[11] We also analyze the impact of opposite-gender officers on the approved maturity (Tables A4 and A5 in the Appendix).

gender bias in the demand for a second loan introduces selection in the sample of repeat borrowers. Focusing on the first loan by each loan applicant yields the cleanest test of a possible bias. Second, we drop loans with missing gender information. For that purpose, we exclude loans by borrowers classified as legal entities in the database as we lack information on borrower sex. Together, this yields a dataset of 7,272 loan transactions.

In order to assess the gender bias across our four outcome variables, we work with two different samples. Specifically, we use the full sample of first-time borrowers as outlined above to study the relationship between gender assignment and loan conditionality: interest rate and loan amount approved, henceforth, the "loan-conditionality sample". To investigate the relationship between loan officer assignments and arrears on the first loan and demand for a second loan, we work with a smaller sample that accounts for the problem of right-censoring, that is, the fact that borrowers might not come back to the bank because the maturity of their first loan lies beyond the end of our sample period. Hence, we compute the average time it takes until a second loan application of a first-time borrower is posted and use only observations of first time borrowers with a loan that matured before June 16, 2006 (that is, December 31, 2006, less the average time of 198 days until a second loan application is posted) for the test.[12] This reduces the sample size from 7,272 to 4,589 observations, henceforth, the "credit-demand sample".[13]

Table 1 presents the summary statistics for the credit-demand sample, while Appendix Table A2 displays the same information for the loan-conditionality sample. The summary statistics in Table 1 show that 66 percent of the first-time borrowers applied for a second loan and 5 percent of all loans fell into arrears for more than 30 days. 18 percent of the borrowers are female, while 62 percent of the loan officers are female.[14] About 57 percent of the loans in the credit-demand sample are managed by an opposite-sex officer.[15] 61 percent among the male borrowers have a female officer and 36 percent of the female borrowers have a male officer. Loan officers are, on average, 25 years old, with male loan officers being two years older, which can be explained by compulsory military service for males in Albania. For most

[12] The computation is based on the last two years of our data. Results are insensitive to using the entire ten year period (or the last 5 or final year) when calculating the average time until the second loan application.
[13] We have also estimated the demand for a second loan using a duration model and find similar results to those reported in the paper.
[14] The relatively high share of female loan officers working for the bank is in line with labor market statistics published by the Statistical Institute of Albania (2007) and the recent Census, both showing that females are slightly overrepresented in financial institutions and in jobs similar to the job of a loan officer.
[15] This is simply $0.82 \times 0.61 + 0.18 \times 0.36$.

loan officers, this is the first formal job after college.[16] On average, loan officers have processed 19 loans with borrowers of the opposite gender (about 60 percent of all managed loans). Borrowers have a mean age of 41 with no significant difference between male and female borrowers or borrowers assigned to male or female loan officers. 87 percent of the borrowers are married, own assets with a value of 24,361 US Dollars (USD), and earn a monthly business profit of 528 USD. Almost all loans require chattel collateral, while only 14 percent come with mortgage and 23 percent with a personal guarantee. 73 percent of all borrowers work in construction, while 12 percent work in production and 15 percent in transportation.[17] 29 percent of the loans are used for fixed asset purchase, 37 percent for housing improvement, 24 percent for consumption, and 10 percent for working capital.

The summary statistics in the loan-conditionality sample, as reported in Appendix Table A2, show that the average interest rate is 14 percent, while the average loan size is 2,752 USD. All other variables are very similar to the credit-demand sample.

2.3 Identification strategy

To study the impact of the interaction between officer and borrower gender on borrower outcomes, we exploit the essentially random assignment of first-time borrowers to loan officers. In a framework analogous to a difference-in-differences estimation, we compare the difference in outcomes (demand for a second loan, interest rate, loan amount, and arrear probability) for male and female borrowers obtaining a loan from a male officer to the difference between male and female borrowers obtaining a loan from a female officer.

Table 2 illustrates the idea behind the identification strategy. It shows the demand for a second loan for male and female borrowers having had a male or female officer during the first loan cycle. Reading down the columns or across the rows suggests that male borrowers are more likely to return to the lender a second time if they had a male loan officer while female borrowers return to a greater extent when female officers handled their loan. The difference-in-differences analysis implies that a borrower is 7.4 percentage points less likely to demand additional credit when ending up with an opposite-sex officer than when dealing with an officer of the same gender.

[16] Personal communication with the lender.

[17] The classifications incorporate a range of subsectors. For example, construction subsumes sectors such as carpentry, maintenance/service facilities, painting, other works, and construction work. The inclusive definition explains the high share of female borrowers within the construction sector.

Although the symmetry across loan officer gender indicates that officers favor their own (or disfavor the other) borrower gender, the significant difference in this simple setting occurs only for male borrowers suggesting that the bias we document primarily affects men. However, the plain difference-in-differences relies on a number of simplifying assumptions, such as no differential effects of sector and time, and it does not account for the various borrower, branch, officer, and contract-specific characteristics that might influence subsequent credit demand. Before turning to the full-fledged analysis we discuss the underlying assumption of our econometric model in some detail.

The identifying assumption is that the difference between male and female borrowers screened and monitored by male loan officers is not significantly different from the difference between male and female borrowers screened and monitored by female loan officers, controlling for the respective sector of activity and time of application. Hence, while male and female borrowers may differ systematically due to any number of unobservable factors, identification of the gender effect will be robust as long as this difference is constant across male and female loan officers.[18] To address the possibility that it is not, we take two additional steps. First, we control for loan-officer fixed effects, allowing us to compare male and female borrowers independent of the specific (time-invariant) characteristics of a given loan officer (besides gender). Second, we also include a large number of observable contract-related, borrower, bank branch, and (time-varying) loan officer features.

To formally gauge whether borrower assignment is random with respect to officer gender, we use two complementary tests. First, we verify if male relative to female borrowers vary in their characteristics depending on whether they are matched with an officer of their own or the opposite gender. If the identifying assumption is correct, there should be no statistically significant difference-in-differences observed between male and female borrowers ending up with a male or female officer. We utilize the following regression:

(1) $$y_{ijyms} = \beta gb_i gl_j + gb_i + gl_j + \tau_m + \mu_y + \sigma_s + \varepsilon_{ijyms},$$

where y_{ijyms} is one of the relevant characteristics of borrower *i* contracting with loan officer *j* in month m year y in sector *s*, gb_i is a borrower-gender dummy taking the value 1 for female borrowers, gl_j is an officer-gender dummy taking the value 1 for male loan officers, μ_y is a year dummy, τ_m is a month dummy, and σ_s is a sector dummy. The coefficient β indicates whether there is a difference between male and female borrowers screened and monitored by

[18] That is, we only require that the unobservable characteristics are the same in the two differences. As an indirect test of this assumption, we show (Table 3) that the difference-in-differences in the observable traits are not significant.

male relative to female officers. The time fixed effects (τ and μ) account for the fact that the gender composition is idiosyncratic only within each month and year while the sector fixed effects (σ) control for any gender-specific business sector specialization.[19] The assumption is that $Cov(gb_i gl_j,\ u|\tilde{z}) = 0$, where u is any other determinant of the outcome of interest y_{ijyms} and $\tilde{z}$ is the vector of the relevant fixed effects. Specifically, we test for differences in socio-demographic borrower information (civil status, age), applied-for loan terms (applied loan size in USD, applied loan maturity in days, availability of a personal guarantee or of mortgage or chattel collateral), the loan usage (working capital, fixed assets, housing improvement, consumption, and "other"), and information on the financial status of the borrower's business (total assets and monthly profits in USD). We cluster the standard errors at the branch-sector-year level as borrowers in a given year, sector, and branch are likely to share background characteristics as well as be exposed to the same loan officer and environment. We present the results for the credit-demand sample in Table 3 and relegate the results for the loan-conditionality sample to the Appendix (Table A2).

Table 3 shows that there are no systematic differences in the observable borrower characteristics in the opposite gender match of borrowers and loan officers prior to the loan transaction. Specifically, columns (3) and (6) display the t-statistic of the relative difference across male and female borrowers for male and female officers, respectively. Finally, column (7) reports the t-statistic of the difference-in-differences estimate. While we find significant differences between male and female borrowers within the sub-groups of male and female loan officers, none of the differences in column (7) are significant. Moreover, there is no systematic pattern as the sign of the reported t-statistic changes direction across the different variables. (The same holds true for Table A2.)

In a second test, we regress loan officer gender on borrower gender to gauge whether there is systematic sorting of borrowers (officers) of a certain gender to loan officers (borrowers) of the same gender conditioning on time and on sector fixed effects. Specifically, we estimate

(2) $$gl_j = gb_i + \tau_m + \mu_y + \sigma_s + \varepsilon_{ijyms},$$

where the variables are defined in an analogous manner to equation (1). The assumption is that $Cov(gl_j, gb_i|z) = 0$ where z is a vector of the relevant fixed effects. Table 4 documents

[19] Month fixed effects also account for the possibility that the seasonality of loan demand differs between same- and opposite-gender pairs.

the results of this regression for both the credit demand [columns (1)-(3)] and the loan-conditionality sample [columns (4)-(6)].

The results in Table 4 show that conditional on time and on business sector, borrower gender cannot predict loan officer gender. In the first column, we estimate equation (2) without any fixed effects. In column (2) we add time dummies and in column (3) sector dummies. Columns (1)-(3) display a statistically insignificant and small effect of borrower gender on loan officer gender across all three specifications. Similarly, in columns (4)-(6), once we account for time fixed effects and sector specialization, borrower gender cannot explain loan officer gender. Together, the results of the tests (Tables 3, 4, and A2) lend credibility to our identification strategy.

2.4 Main specification

To investigate whether there is an own-gender bias in lending, we use OLS to estimate the following specification

$$(3) \quad O_{ijyms} = \alpha_0 + \beta gb_i gl_j + gb_i + gl_j + \tau_m + \mu_y + \sigma_s + \rho_j + \varphi_b + \varphi_b \times y + X_{ijym} + gb_i X_{ijym} + \varepsilon_{ijyms},$$

where O is the outcome of interest (demand for a second loan, interest rate charged, loan amount approved, or arrear probability), τ, μ, σ, ρ and φ are month, year, sector, loan officer, and branch fixed effects, respectively.[20] The specification also includes branch-by-year trends $\varphi_b \times y$. The coefficient β estimates the impact of opposite-sex officers on credit market outcomes (relative to own-gender officers). Put differently, it measures the differential effect of a female (male) borrower paired with a male (female) officer compared to a female (male) borrower matched with a female (male) officer.[21] The parameter X_{ijym} is a vector that includes borrower traits (those of Table 3) and loan officer traits (age and the number of loans processed with opposite-sex borrowers). Besides the time and the sector dummies, the loan-officer fixed effects (ρ) control for any time-invariant loan-officer specific determinant of credit demand, loan conditionality, or arrear probability.[22] The branch fixed effects (φ)

[20] The results are invariant to using a non-linear Probit model for the binary outcome variables. However, we lose the observations where the loan officers either have none of their borrowers return (or fall into arrears), or see all of their borrowers return (or all fall into arrears).

[21] As pointed out above, our identification strategy (which relies on random loan officer assignment) does not allow us to sort out which officer gender is responsible for the potential bias. Hence, the interaction of $gb_i gl_j$ defined as female borrower(=1)×male loan officer(=1) and the following direct terms yield an equivalent outcome to male borrower(=1)×female loan officer(=1). Including all (four) interactions between loan officer gender and borrower gender to capture differences across officer sex does not allow us to simultaneously include level differences between male and female borrowers or loan officer fixed effects.

[22] Note that the loan officer dummy makes gl_j redundant.

control for any time-invariant branch-level determinant of the relevant outcomes.[23] The branch-by-year control ($\varphi \times y$) interacts the branch dummies with a 0-1 variable for each year to flexibly absorb differential variation across time and space. Finally, we saturate the model by including an interaction ($gb_i X_{ijym}$) between borrower gender and the vector of our predetermined borrower and officer characteristics. This accounts for possible variation in borrower behavior between male and female borrowers depending on their socio-economic background, loan purpose, and the loan officers' age and gender experience.

3 Loan conditionality

3.1 Baseline findings

We first examine the effect of gender identity on the likelihood that borrowers apply for a second loan with the lender. Table 5 presents the results of estimating equation (3) with a dummy equal to one if a borrower applied for a second loan as the dependent variable. Column (1) is identical to the difference-in-differences specification presented in Table 2 except that it also includes sector and time-fixed effects. In the remaining columns (2) through (6) we gradually add loan officer fixed effects and (time-variant) loan officer covariates [column (2)], borrower specific covariates [column (3)], branch fixed effects and branch-by-year controls [column (4)], the interaction of borrower and officer covariates with the borrower gender dummy [column (5)], and the (potentially endogenous) loan characteristics (loan amount, maturity, and interest rate) [column (6)]. All of these variables are discussed above. We omit presenting results for the control variables to save space.

The coefficients on $gb_i gl_j$ are similar across the six specifications, statistically significant, and show that the interaction of loan officer and borrower gender identity is a significant determinant of demand for credit. The main estimate, column (5), implies that borrowers matched with opposite-sex officers are 10.32 percentage points less likely to apply for a second loan with the same lender as compared to borrowers assigned to same-sex officers. The impact of the gender mismatch is economically significant given that 66 percent of all first-time borrowers apply for a second loan. It implies that the fraction of borrowers paired with opposite-sex officers that do not return for a second loan is about 15 percent higher relative to the fraction of borrowers teamed up with officers of the same gender. Note

[23] We can include branch fixed effects together with officer fixed effects as some officers (roughly 20 percent of the sample) rotate across the different branches. The characteristics (for example, gender) of the rotating loan officers are very similar to the officers not moving around.

that column (5) accounts for any unobservable trend in lending over the time period that may have affected the overall demand for credit in a given branch or change in the lender's policy that differentially affects the allocation of employees or credit to a branch over time. As such it also absorbs changes in the share of female (or male) loan officers working in a branch, reflecting that it is the individual officer-borrower gender match that matters for the detected bias, not the gender mix of the workplace. For the remainder of the paper, we use the specification presented in column (5) that includes the full battery of fixed effects and all control variables, except for the loan characteristics.

3.2 Loan officers' opposite-gender experience and degree of discretion

An important aim of the paper besides establishing the existence of a bias is to document how key determinants of loan officer behavior interact with their gender preferences. To do so, we explore the impact of gender-specific human capital traits by investigating loan officers' prior exposure to opposite-sex borrowers. We also examine if loan officers' degree of discretion to act on their gender beliefs is important. Studying officers' previous experience with borrowers of the other gender allows us to test whether the gender bias is due to limited professional exposure to the opposite sex or if it is purely taste based. A better understanding of when loan officers find it in their interest to suppress their gender preferences tests if incentives matter. That is, do loan officers restrain their bias in situations where it potentially has negative consequences for their career prospective?

We first investigate the impact of prior exposure to opposite-sex borrowers. As mentioned above, most loan officers are first-time employees that may adjust their behavior through learning on the job. To the extent that more exposure lessens the bias, this may be due to an initial knowledge gap about the other gender which decreases with experience, allowing the loan officers to work more efficiently. Alternatively, they may have some initial prejudice that disappears as exposure creates "empathy" with the other gender that changes officers' preferences. On the other hand, a pure taste-based bias, as captured by a greater preference for own-gender borrowers (relative to opposite-gender borrowers) will be unchanged with additional opposite-sex experience.

Loan officer experience with opposite-sex borrowers is measured as the number of loans processed with first-time borrowers of the other gender. As these borrowers are matched arbitrarily across the officers, the number of interactions with the opposite sex is essentially random. We calculate the median of opposite-sex loan officer experience—nine interactions with the opposite sex—and split the credit-demand sample of 4,586 observations at this median.[24] The regression model is analogous to the one of column (5), Table 5, with the exception that we control for overall loan officer experience in some of the specifications.

The results in Table 6 show that the gender bias affecting credit demand is driven by loan officers with little previous exposure to borrowers of the opposite sex. We find a significant and negative coefficient estimate on $gb_i gl_j$ in the case where bank officers have below-median experience with the opposite gender, while the coefficient in the above-median sample is positive and insignificant. The Wald test shows that the difference between the two estimates in each column pair is significant at the 1 percent level. Controlling flexibly for overall experience does not change the outcomes, suggesting that the effect we capture is distinct from more general competence. The treatment impact in column (1) implies a 29 percent (19.4 percentage points) decrease in the likelihood of demanding a second loan with the lender as compared to the overall mean of 66 percent, twice the size of the average effect estimated in Table 5. The median number of 9 processed loans with opposite-sex borrowers corresponds to a median of 387 days (or average of 460 days). Although this is a non-trivial time period, it suggests that the bias disappears relatively fast as loan officers gain additional professional experience with the opposite gender.

Overall, the results provide support for a bias that fades away with gender-specific learning-on-the-job. The findings bear less credibility to the existence of a pure taste-based bias governing the loan officers' behavior and, ultimately, demand for a second loan by the borrowers. Next we turn to loan officers' degree of discretion.

Do loan officers act on a gender bias if it is potentially costly to do so? We examine this question by exploring how the effect of the opposite-gender match varies with situations that impact loan officers' discretion. We use two proxies for the degree of discretion: competition from other financial institutions and the number of loan officers employed in a branch (branch size). A gender bias should be less costly in uncompetitive markets since borrowers have few outside options. As competition increases, however, a bias can be more damaging to credit demand, inducing the lender to scrutinize loan officers with greater care to detect mistreatment.[25] Hence, less competition should increase loan officers' discretion to act on their gender beliefs. Similarly, when there are few employees in a branch, a given loan

[24] We ran the identification check of Table 3 for these two and all the other subsamples shown below. The tests show that our identifying assumption holds up also for the subsamples.

[25] Although loan officer wage is independent of whether borrowers return to the bank for a second loan, branch managers are likely to intervene (at a cost to the responsible loan officer) if a bias leads to a drop in demand.

officer may be more difficult to replace, giving him or her more discretion of indulging his or her preferences.[26]

To measure financial market competition we explore variation in the universe of formally registered bank branches across Albania's 12 counties (prefekturë) over the years 2004-2006.[27] We map this information with population records for each county and year and merge both statistics with our loan-level data. The final competition measure is defined as the number of bank branches per capita, by county and year.[28] We then divide the sample according to whether the loan observations belong to regions with a branch-per capita ratio below (weak competition) or above (strong competition) the median ratio. In effect, we explore variation in competition across branches and years (allowing us to keep the branch dummies). The impact of branch size is identified in a similar manner. We exploit changes in the number of loan officers employed per branch and year yielding within-branch variation for the entire period 1996-2006. For each year, we divide the sample into bank branches above or below the median number of loan officers (our proxy for branch size). While these measures involve stronger assumptions than our earlier analysis, it is unlikely that the results are driven by reverse causality, where lower demand at the level of the individual officer-borrower opposite-gender match leads to fewer branches locating in an area or to officers leaving a branch in a given year. Moreover, the branch-by-year controls should absorb any differential dynamic trend across branch and time both on the supply- and demand side that would potentially confound our findings.

Table 7 shows that demand for credit is affected by the officer-borrower gender mismatch only when loan officers have a sufficient degree of discretion as measured by the competition of the working environment. In addition, loan officer discretion and lack of exposure to the opposite sex are complements. The negative impact on credit demand is most severe in situations when bank officers have little experience with borrowers of the other gender and few incentives to suppress their gender bias.

Panel A reports the results on branch size and competition and shows that borrowers assigned to opposite-sex loan officers are less likely to apply for a second loan in smaller branches and in counties with less financial market competition. The point estimate on branch

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[26] Of course the tests do not provide direct support of changing gender preferences but only suggestive evidence consistent with the interpretation that the degree of discretion changes according to our intuition.

[27] We lack country-wide information on bank-branch establishments for the earlier years in our dataset. However, as most of the loan transactions take place in the latter period, the competition data still cover roughly 75 percent of all processed loans.

[28] The results on competition are invariant to including the total number of financial institutions (banks) per county and year.

size implies that the likelihood of applying for a second loan decreases by approximately 24 percentage points or over 30 percent for a borrower that ends up with an opposite-sex loan officer in a smaller branch (the median number of loan officers per branch over the entire period is 13). The effect of competition is also sizable; an opposite-gender match induces a 29 percent drop in demand in less competitive counties (the median number of branches per 100,000 people is 7.3 for the years 2004-2006). Meanwhile, larger branches or more competitive areas yield slightly negative point estimates that are significantly different from those of smaller branches and weak competition.

In Panels B and C we investigate the joint relationship between loan officer discretion and prior opposite-sex exposure. Panel B shows that the coefficient on the $gb_i gl_j$ variable is significant ($p<0.0001$) only in smaller branches with loan officers that have little experience of opposite-gender borrowers, with an effect of 40 percentage points. In the case of larger branches and with loan officers with more opposite-sex experience, there is no significant effect of the officer-borrower gender match. In Panel C we find a similar pattern: demand for a second loan is reduced by 38 percentage points if the loan officer in less competitive counties also has little prior exposure to borrowers of the other gender. If competition is high or the loan officer has more opposite-sex exposure the effect is insignificant. The results for the combination of exposure and competition are qualitatively and quantitatively similar to those obtained for the branch size and the exposure distinction. As noted above, the inclusion of branch-by-year trends implies that the findings are robust to variation in local credit demand or differential changes in employee assignments over time.

Taken together, the results suggest that being assigned to an opposite-sex loan officer significantly reduces the likelihood that a first-time borrower applies for another loan. The effect appears when borrowers are matched to loan officers with little prior exposure to the opposite gender and when officers have more discretion as proxied by the degree of financial market competition and branch size. Having established that demand for credit is affected by the gender pairing of loan officers and borrowers, we turn to some possible channels of influence.

4 Loan conditionality

The assignment of borrowers to opposite-sex loan officers may have hampered demand for credit through multiple channels. Bank officers interact with borrowers continuously over the lending relationship. A gender bias may have led to excessive monitoring or even harassment of borrowers of the opposite sex or, alternatively, too little attention paid to them when advising on project-related matters.[29] It could also have affected the interpersonal relationship, making opposite-gender borrowers feel less comfortable with their respective loan officer. To the extent that these explanations have an impact on loan performance we will be able to assess whether the officer-borrower gender match affects the likelihood of going into arrears. Borrowers may also have adjusted their behavior depending on the gender of the loan officer, but it is not clear why this adjustment would have led to lower credit demand. If anything, borrowers would be motivated to lessen the effects of a potential bias making it more difficult to find any impact of a gender bias in the data.

In this section, we explore one channel in detail; loan conditionality. Less attractive contract terms is an explicit measure of a gender bias that is easy to capture.[30] We examine two essential parts of the loan contract, interest paid and the loan amount borrowers receive. As an indirect measure of their effect on the demand for additional credit, we gauge whether opposite-sex experience and loan officer discretion remain important factors.

4.1 Interest rates

The results in Table 8 show that borrowers pay a significantly higher interest rate if matched with a loan officer of the opposite gender. To investigate the effect of the gender mismatch on annual interest paid we use the loan-conditionality sample. We replace the likelihood of applying for a second loan with the interest rate as the dependent variable and begin by studying the mean impact. The result indicates that borrowers assigned to opposite-sex loan officers pay a higher price for credit compared to borrowers who end up with loan officers of the same gender. The coefficient in column (1) implies that a borrower pays, on average, a 35 basis points higher interest rate if matched with a loan officer of the opposite gender. This corresponds to an increase of about 2.5 percent overall (0.35 percentage points from the mean interest rate of 13.9 percent).

Columns (2) through (7) of Table 8 and Table 9 investigate the effect of loan officers' opposite-sex experience and degree of discretion. Overall the findings confirm our previous conclusions: little prior exposure to borrowers of the other gender and a larger degree of loan

[29] Below we report the outcomes of some results where we indirectly include controls for monitoring intensity. Overall there is no change in the outcomes when these controls are added.

[30] Gender-driven contract terms may, of course, also be an indication of the fact that other, less tangible, mistreatments are present.

officer discretion increase the impact of the bias. Specifically, columns (2)-(7) of Table 8 show that officers with a below-median experience of opposite gender borrowers charge interest rates that are 64 basis points or 4.6 percent higher than those charged to same-sex borrowers with the difference between the below- and the above-median exposure being significant at the 10 percent level [p=0.0667 for column (2)] (The median is defined as in Table 6.)

Panel A of Table 9 revisits the impact of financial market competition and of branch size. The effects are qualitatively similar to those of demand for additional credit, that is, smaller branches and lower levels of competition yield higher interest rates, but the coefficients are never significantly different across small and large branches or across counties with weak and strong competition. Finally, Panels B and C of Table 9 show that the complementarity between loan officer experience and degree of discretion as found with credit demand also holds for the interest rate. Borrowers matched with loan officers of the opposite sex that have little previous exposure to the opposite gender and work in smaller branches pay 114 basis points or 8 percent higher interest rates ($p<0.0001$). Similarly, an opposite-sex officer with little experience of the other gender who works in a weakly competitive market charges opposite-sex borrowers interest rates that are 105 basis points higher. The other respective cases (high experience and large branches/strong competition) have insignificant point estimates that are statistically different at least at the ten percent level in all but one case from the low experience-smaller branch/weaker competition outcome.

Finally, we explore a third proxy for the degree of discretion that loan officers can exercise: the age difference between officers and borrowers. The idea is as follows. Consistent with studies of cognitive behavior, there is a psychological cost involved in being biased that increases in cases where it is easier for the biased party to relate to the individual being biased against (Goodwin et al., 2000; Blair, 2002). For example, a male loan officer may have stereotype beliefs about women. However, if he interacts with a female borrower of similar age, he is more likely to identify with her and, hence, experience a higher cost coming from the bias. Meanwhile, mistreating someone of the opposite sex that is older (and, hence, quite different) could be associated with a smaller loss of utility. To sum up, loan officers' degree of discretion is larger when the psychological cost is lower, which–we conjecture–occurs when the age difference between loan officers and borrowers increases.

We implement this idea in Table 10 by dividing the sample according to the median loan officer age (24 years) and to the median borrower age (41 years). In addition, we split the sample according to the age difference, with the median difference being 16 years.[31] As predicted, the impact of the officer-borrower gender mismatch on interest rates is only significant among older borrowers [column (2)] and younger loan officers [column (3)]. Columns (5) and (6) bring the two measures together and quantify the age difference between loan officers and borrowers. When the age difference is above the median, the point estimate on $gb_i gl_j$ is 0.0054 (p=0.002). While the coefficient below the median age difference is 16 basis points, the difference between the two splits is significantly different at the ten percent level. The four last columns confirm that loan officer discretion as proxied by age difference and loan officer opposite-sex exposure are complements. Older borrowers assigned to younger opposite-sex loan officers with little exposure to the other gender pay 95 basis points higher interest. The point estimate is similar to the one obtained when investigating loan officer exposure and financial market competition [column (1), panel C, Table 9].[32]

4.2 Approved loan amount

Tables 11 and 12 report the effect of matching borrowers to opposite-sex loan officers on the loan amount they receive. As with the interest rate regressions, we use the loan-conditionality sample but now with loan amount as the dependent variable.[33] Starting with Table 11, it shows that borrowers receive smaller loans if matched with loan officers of the other gender. On average, the officer-borrower gender mismatch leads to a loan that is 282 USD or 10 percent smaller (p=0.015). When investigating the effect for loan officers with less experience with the other gender [column (2)], the effect more than doubles in size with a point estimate of -538 USD, significant at the one percent level. This can be compared with the mean approved loan amount of 3,677 USD, indicating a 17 percent decrease. In the case of loans given by loan officers with above-median exposure to the opposite gender, the coefficient enters positively and insignificantly in all three instances [columns (3), (5), and (7)]. The Wald tests further show that the point estimates are significantly different between the sample splits.

Table 12 reports the findings with respect to loan officer discretion and prior exposure to borrowers of the other gender. The results are qualitatively similar to those obtained when

[31] The results in Table 10 are invariant to excluding loan officers' opposite-sex experience suggesting that the age results are not driven by experience per se.
[32] We have also examined if the age difference affects the officer-borrower gender match with respect to approved loan size and applying for a second loan and find qualitatively similar results. However, the difference between some of the point estimates fails to be significant at conventional levels.
[33] As in all of the previously reported regressions, Tables 11 and 12 control for the amount of credit applied for.

examining credit demand and interest rates. Borrowers allocated to opposite-sex loan officers obtain less funding in smaller branches and when competition is lower (panel A) but the difference across the samples is not statistically significant. Panel B shows that low opposite-sex experience with the other gender and branch size are complements. The coefficient on $gb_i gl_j$ is negative and significant only in the sample of small branches with loan officers that are less experienced with the other gender. The estimate, -623 USD, is significant at the five percent level and implies a 21 percent decrease from the mean loan size of 2,995 USD. In larger branches or with loan officers that have more experience with opposite-gender borrowers, there is no significant impact and the coefficients are statistically different from the column (1) estimate except in the case of column (2). Finally, the results in panel C indicate, as before, that officers with little experience of opposite-sex borrowers that work in counties with less competition are more likely to act on their gender bias by granting smaller loans, specifically, 431 USD less.

We have also explored the impact of ending up with an opposite-gender officer on the approved contract maturity. Specifically, we assign a dummy variable the value of 1 if the approved maturity was shorter than the applied maturity and 0 otherwise.[34] As shorter maturity allows for less flexibility on the part of the borrower, this outcome yields an additional measure of mistreatment. The Appendix, Tables A4 and A5, show our findings. On average, the likelihood that the approved maturity falls short of the applied maturity increases by 6.85 percentage points or 22 percent overall for borrowers who face opposite-sex officers. We also find that this effect is stronger for officers with less opposite-gender experience, in smaller branches, and when competition decreases although the latter outcomes fail to be significantly different above and below the median.

Overall, first-time borrowers assigned to opposite-sex loan officers fare worse in terms of the price they pay for credit as well as the amount of credit they receive. In line with our earlier results for credit demand, we also find that loan officers' prior experience with the other gender and their degree of discretion are complements: loan officers with little previous opposite-sex exposure and more discretion offer borrowers of the other gender distinctly inferior loan terms. The consistent findings as to when the bias appears on the officer-borrower gender mismatch across applying for a second loan, interest rate, loan amount, and to some extent approved maturity, suggest that the drop in demand for credit at least partly follows from the results on loan conditionality. However, we recognize that moderately

[34] As loan maturity has a discrete distribution with focal points around 6, 12, 18, and 24 months a binary variable more efficiently captures differences across applied and approved maturity.

higher interest rates and smaller loans leave open the possibility that other channels of influence are at work as well.

5 Is the gender bias efficient?

The results so far point to a bias against borrowers of the other gender, a bias that decreases with exposure of loan officers to opposite-sex borrowers. Together these findings exclude the existence of pure taste-based bias. However, it is not clear whether the bias stems from a knowledge gap that leads loan officers to engage in more efficient transactions with own-gender borrowers at first or if it reflects initial prejudice. In order for the bias to be efficient in the former sense, the officer-borrower gender mismatch should also have an impact on the likelihood of ending up in arrears. Specifically, the higher interest rate and lower loan amount may indicate a higher riskiness attached by loan officers to borrowers of the opposite sex, especially if the loan officer has limited experience with borrowers of the other gender.

In this section we examine if loan officers initially have an information advantage with respect to borrowers of their own gender that is reflected in a lower level of ex-post risk as compared to borrowers of the opposite sex. We do this by exploring data on the likelihood that a loan is in arrears for more than 30 days. To allow for full loan cycles, we revert back to the credit-demand sample. All results reported in this section also go through with the loan-conditionality sample. The dependent variable is a dummy equal to one if a borrower has been in arrears more than 30 days during the duration of the contract.

Tables 13 and 14 report our findings. Overall, there is no indication that borrowers of the same gender as their loan officer perform better in terms of a significantly lower likelihood of going into arrears. Column (1) of Table 13 shows that, on average, the arrear probability of loans screened and monitored by opposite-gender loan officers are not significantly different from the arrear probability of loans screened and monitored by own-gender loan officers. The variable on the officer-borrower gender mismatch is insignificant, with an effect of -0.26 percentage points over the loan cycle. Dividing the sample by median opposite-sex experience [columns (2)-(7)], does not alter this conclusion. The estimate on $gb_i gl_j$ is close to zero for the below median sample and insignificant (p=0.92). For above-median opposite-gender experience, arrears are if anything (insignificantly) lower, not higher, for borrowers of the other gender.

Table 14 examines the impact of the officer-borrower gender interaction depending on branch size and financial market competition. Panel A shows (similar to Table 13) no significant differences when we split the sample according to branch size [columns (1) and (2), panel A], with a positive (negative) gender-interaction estimate in the small (large) branch subsample. This also holds true when investigating competition. Panels B and C unpack the joint relation between officer-borrower gender exposure and degree of discretion. Except for the pair of high exposure-small branches where the gender interaction term enters positively and significantly, there is little evidence for the conclusion that own-gender borrowers are less likely to go into arrears or, alternatively, that borrowers matched with opposite-sex loan officers are more likely to enter arrears during the life of their first loan.

The results show that the significant gender bias found in the demand for a second loan or in terms of loan conditionality is more or less absent in the arrear outcomes. One possible explanation for the lack of any discernible pattern may be that officers change loan conditionality *and* monitoring behavior simultaneously. For example, they could charge opposite-sex borrowers a higher interest rate, lend them less, and offer shorter maturity together with increased monitoring. While we do not observe the actual steps taken by officers in their monitoring efforts, we can partially address this concern by deriving the number of outstanding loans that an officer is in charge of per unit of time. If opposite-sex borrowers are monitored more intensely, officers lending to the other gender should handle fewer loans per time unit. However, when we include the number of loans handled per month as an additional control variable the results on arrears remain essentially the same. Another possible explanation for our findings may be that the potential monitoring advantage officers have when interacting with borrowers of the same gender boils down to avoiding larger shocks. To explore this possibility, we repeated all the regressions using the 60-day arrear measure. Again, the results are similar to those reported above.[35]

Taken as a whole, this supports the existence of initial prejudice rather than the notion of an information hypothesis where loan officers are more efficient when transacting with own-gender as compared to opposite-gender borrowers.

6 The source of the bias

In our regression analysis, we rely on the quasi-random assignment of borrowers to loan officers controlling for sector and time fixed effects. While this ensures that our results are not

[35] The results including officer workload or using the 60-day arrear measure as an outcome variable are available on request.

driven by unobserved borrower characteristics correlated with the assignment of borrowers of one gender to loan officers of the other, it bars us from making inferences about the direction of the bias. That is, whether the bias is due to either male or female loan officers or both favoring borrowers of their own gender, or disfavoring those of the other gender. In this final section, we offer some suggestive evidence that the bias comes from both sides by reanalyzing the average impact of $gb_i gl_j$ on interest rates, the size of the approved loan, and on the likelihood of applying for a second loan at the individual loan-officer level.

Starting with loan conditionality, for each loan officer we regress the interest rate on a female borrower dummy for loan officers with at least 35 observations using our main specification (barring the interaction term $gb_i X_{ijym}$ as this results in too many female dummies dropping out).[36] We restrict the sample to at least 35 observations in order to have the degrees of freedom needed to include all of the relevant controls and fixed effects. Because these regressions are estimated separately for each loan officer, they control for loan officer specific differences in interest rate setting. Figure 1 plots the coefficient estimate on interest charged for the female borrower dummy for each loan officer, with the bars representing the 95 percent confidence interval around the estimates. We find that the average interest rate differential for female (as opposed to male) borrowers is –21 basis points in the case of female loan officers and 22 basis points in the case of male loan officers. While most of the coefficients are imprecisely estimated, quite a few yield point estimates that are statistically significantly different from zero. The figure indicates that the bias against the other gender is prevalent for loan officers of both genders. That is, the majority of male loan officers have a greater propensity to charge higher interest rates when lending to female borrowers than the majority of female loan officers. The reason for the smaller impact is that many of the loan officers in this sample have more experience with opposite-sex borrowers than the median officer. Figure 2 investigates the same question but for approved loan size. Again, we find evidence of an own-gender bias: the average loan size differential for female (as opposed to male) borrowers is 105 USD in the case of female loan officers and –42 USD in the case of male loan officers.

Finally, Figure 3 points to a qualitatively similar effect of the gender bias from both male and female loan officers on credit demand. Instead of using loan conditionality, we explore the probability of returning for a second loan as the dependent variable. The mean coefficient shows a similar symmetry across the genders as above although the estimated

[36] This analysis is similar in spirit to Price and Wolfers (2010).

coefficient is smaller in size: the female borrower dummy is –1.1 percentage points for male loan officers, whereas it is 3.4 percentage points for female loan officers.[37] The interpretation is again that there is a pro-male bias among male loan officers and a pro-female bias among female loan officers leading borrowers of the opposite sex to exit at a greater degree.

To sum up, Figures 1, 2, and 3 indicate that loan officers predominately engage in an own-gender bias when transacting with their clients. The results also show that the evidence of a gender bias to a large degree persists, even when the analysis is aggregated to the level of each loan officer.

7 Conclusion

Using loan-level data, we find that own-gender preferences affect credit market outcomes. First-time borrowers matched with opposite-sex loan officers in a large Albanian bank are 15 percent less likely to demand additional credit from the lender. The detected bias originates with borrowers whose loan officers have little prior exposure to borrowers of the other gender or whose loan officers have weak incentives to suppress their beliefs given the lack of competition and outside discipline, as proxied by financial market competition and branch size, respectively. These two factors are also complementary: the greatest impact of the officer-borrower match is found in instances when loan officers with little experience of the other gender are potentially less scrutinized.

The effects we identify are consistent with the explanation that opposite-sex borrowers receive inferior loan terms. To this end, we also show that borrowers assigned to loan officers of the other gender pay between 35 to 114 basis points higher interest rate and receive between 10 to 20 percent lower loan amounts, with the variation again depending on loan officers’ opposite-sex experience and degree of discretion.

The own-gender bias does not seem purely taste based nor is it consistent with loan officers initially treating borrowers of their own gender more efficiently, at least not as reflected in the level of ex-post risk as measured by the likelihood of entering into arrears.

While our findings provide answers to where the bias should be stronger and why demand for credit decreases in the opposite-gender match it is, of course, possible that other channels are at work. In addition, we have detected a gender bias in a relatively poor country,

[37] The credit-demand analysis is somewhat sensitive to outliers, which follows from the fact that these officers have a greater opposite-gender experience. In the example above, we exclude observations larger than 1 standard deviation above the mean.

Albania, where the level of gender discrimination is rather high, although women have made important strides into the labor market as shown by the high share of female loan officers employed by the lender. It is possible that the effect of a loan officer-borrower gender mismatch in a more developed setting would be different.

Finally, our paper is the first to gauge the existence of an own-gender bias in lending; a better understanding of in-group identity, in the form of own-gender preferences, has at least two implications for the functioning of the credit market. First, identity should affect firms' human-resource practices as loan officers' opposite-gender experience has repercussions for the size of the bias. Second, from a policy perspective, our findings point to the possibility that financial market competition can be a powerful tool in dampening the biases of loan officers, and, ultimately, banks, against borrowers of a certain gender.

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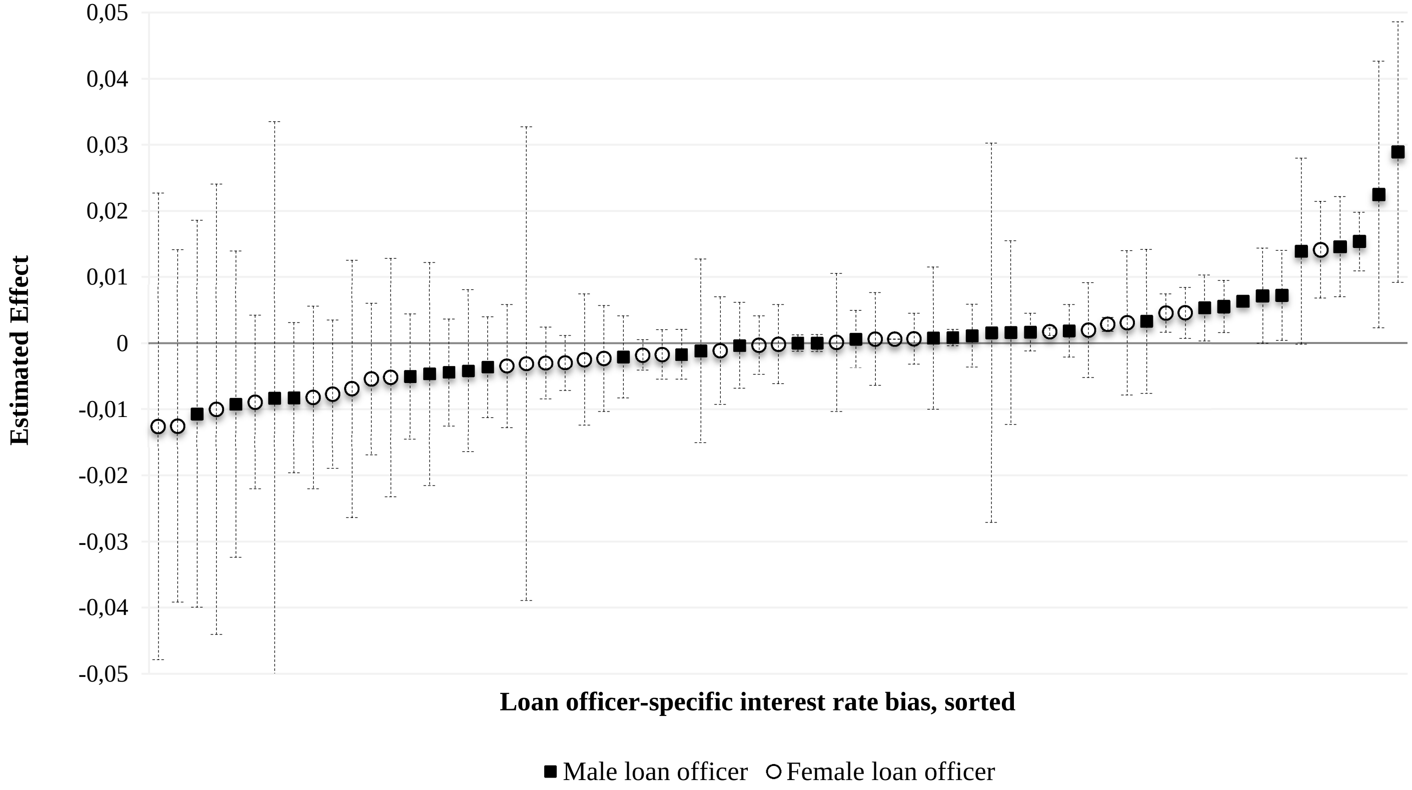

Figure 1 Distribution of the interest rate by loan officer gender

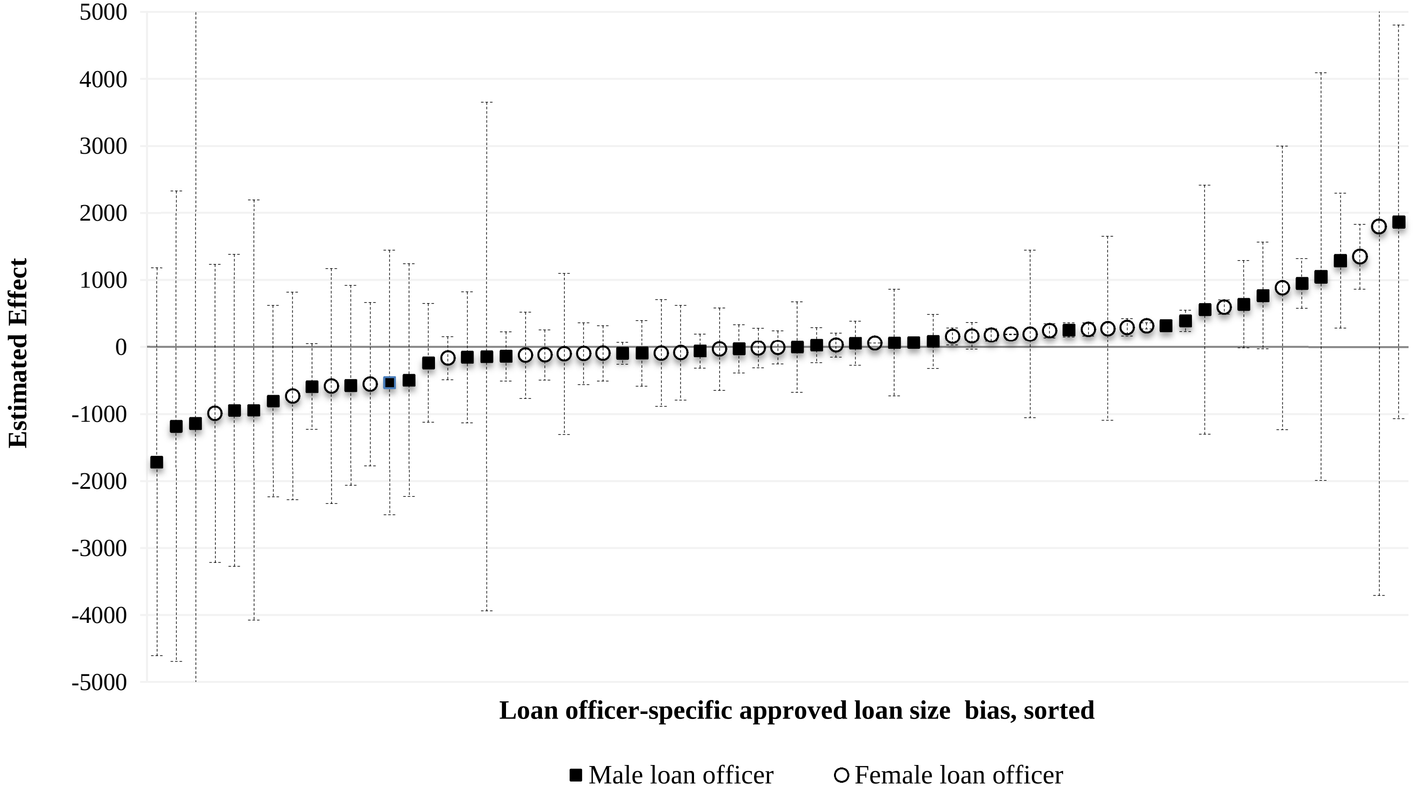

Figure 2 Distribution of the approved loan size by loan officer gender

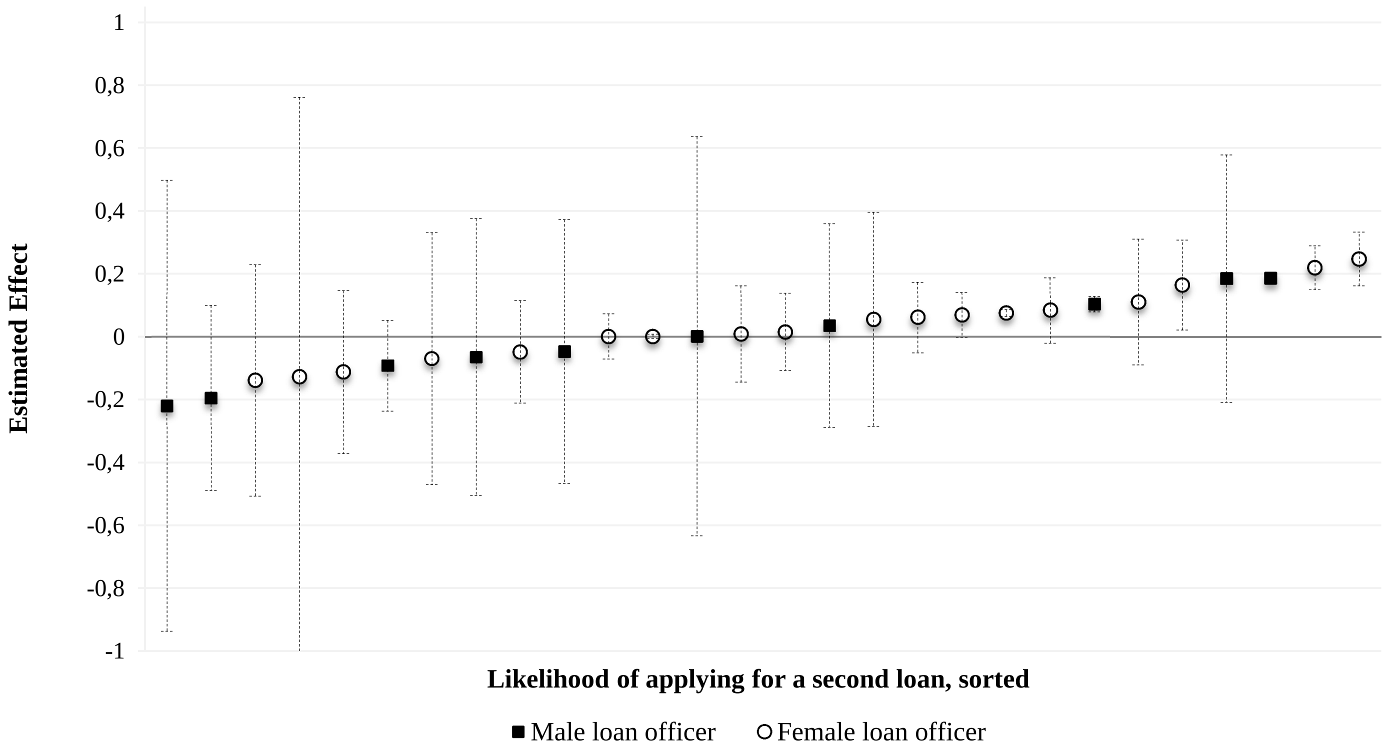

Figure 3 Distribution of the likelihood that borrowers apply for a second loan by loan officer gender

Table 1 Summary statistics for the credit-demand sample

Variable	Mean (1)	SD (2)	Median (3)	Male borrower (4)	Female borrower (5)	Male loan officer (6)	Female loan officer (7)
Likelihood of applying for a second loan	0.66	0.47	1.00	0.66	0.65	0.68	0.65
Arrears > 30 days	0.05	0.22	0.00	0.05	0.04	0.06	0.05
Female borrower	0.18	0.39	0.00	0.00	1.00	0.18	0.19
Civil status (married = 1)	0.87	0.34	1.00	0.90	0.74	0.87	0.86
Age applicant	40.87	10.10	40.94	40.75	41.44	40.86	40.88
Total assets (in USD)	24,361	45,536	15,108	24,700	22,862	25,299	23,778
Monthly business profits (in USD)	529	944	406	555	413	559	510
Applied loan amount (in USD)	2,726	2,692	1,993	2,801	2,392	2,625	2,788
Approved loan amount (in USD)	2,370	2,492	1,688	2,435	2,086	2,259	2,440
Approved maturity (in days)	501	205	480	501	498	478	515
Personal guarantee	0.23	0.42	0.00	0.23	0.22	0.20	0.24
Mortgage guarantee	0.14	0.35	0.00	0.14	0.13	0.11	0.16
Chattel guarantee	0.95	0.22	1.00	0.95	0.94	0.96	0.94
Destination Working Capital	0.10	0.29	0.00	0.10	0.06	0.11	0.09
Destination Fixed Assets	0.29	0.45	0.00	0.32	0.15	0.36	0.25
Destination Housing Improvement	0.37	0.48	0.00	0.36	0.45	0.30	0.42
Destination Consumption	0.24	0.43	0.00	0.21	0.35	0.22	0.25
Destination Others	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Production	0.12	0.32	0.00	0.14	0.04	0.20	0.07
Transport	0.15	0.35	0.00	0.17	0.04	0.16	0.14
Construction	0.73	0.44	1.00	0.69	0.92	0.65	0.79
Female loan officer	0.62	0.49	1.00	0.61	0.64	0.00	1.00
Age loan officer	25.28	4.17	23.75	25.32	25.11	26.33	24.63
Overall loan officer experience (# of loans processed)	32.10	35.95	21	31.05	36.74	26.64	35.49
Opposite loan officer sex experience (# of loans processed)	19.45	27.74	9.00	18.75	22.52	5.16	28.33
Branch size of lender (# of loan officers)	15.51	9.01	13.00	15.23	16.74	16.28	15.03
Branches per 100,000 inhabitants (all banks), county level	7.35	3.40	7.33	7.35	7.36	7.58	7.20
Monthly wage payment, city level (in USD)	276	71	285	275	281	286	269
Observations	4,589						

This table reports summary statistics [mean, standard deviation (SD), and median] for the credit-demand sample. Columns (1)-(3) show the values for the entire sample, columns (4) and (5) the means for male and female borrowers, and columns (6) and (7) the means for male and female loan officers.

Table 2 Difference-in-differences: likelihood of applying for a second loan

Loan officer gender / borrower gender	Male borrowers	Female borrowers	Difference across borrower gender
	(1)	(2)	(3)
Male loan officers	0.6912	0.6331	0.0581*
	(0.0167)	(0.0268)	(0.0329)
Female loan officers	0.6457	0.6617	-0.0160
	(0.0186)	(0.0248)	(0.0228)
Difference across loan officer gender	0.0455**	-0.0286	-0.0741**
	(0.0228)	(0.0277)	(0.0321)

This table reports the difference-in-differences estimate of the likelihood of applying for a second loan for the credit-demand sample. Credit demand is a dummy variable that takes the value one if first-time borrowers apply for an additional loan. Columns (1) and (2) show raw means for the credit demand of male and female borrowers matched with male (first row) and female loan officers (second row), respectively. The bottom rightmost cell displays the unconditional difference-in-differences estimate. Standard errors are clustered at the branch-sector-year level. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 3 Test for differences in borrower characteristics for the credit-demand sample

	Male loan officers			Female loan officers			
	Male borrowers	Female borrowers	t-statistic	Male borrowers	Female borrowers	t-statistic	t-statistic
Variable	(1)	(2)	(3) = (1) - (2)	(4)	(5)	(6) = (4) - (5)	(7) = (3) - (6)
Age applicant	40.81	41.12	0.78	40.70	41.63	2.16**	-0.36
Civil status (married = 1)	0.90	0.76	-4.74***	0.89	0.73	-9.92***	1.50
Applied loan amount (in USD)	2,686	2,336	-2.92***	2,874	2,424	-2.88***	0.33
Applied maturity (in days)	533	514	-1.98**	562	563	-1.05	-1.45
Total assets (in USD)	25,548	24,125	-1.67*	24,163	22,138	-2.63***	0.29
Monthly business profits (in USD)	578	469	-2.56**	540	381	-2.80***	1.44
Personal guarantee	0.21	0.20	-0.31	0.24	0.24	0.04	-0.32
Mortgage collateral	0.11	0.10	-0.98	0.16	0.14	-1.84*	0.18
Chattel collateral	0.96	0.95	0.32	0.94	0.93	-0.52	0.63
Working Capital	0.12	0.08	0.59	0.10	0.04	-2.99***	1.42
Fixed Assets	0.40	0.18	-4.92***	0.28	0.13	-3.84***	-1.47
Housing Improvement	0.28	0.37	1.10	0.40	0.49	2.09	-0.88
Consumption	0.20	0.36	4.18***	0.23	0.34	3.02***	1.03
Others	0.00	0.00	n.a.	0.00	0.00	n.a.	n.a.
Observations	1,451	308	1,759	2,292	538	2,830	4,589

This table reports a test of difference in borrower characteristics for the credit-demand sample. Columns (1) and (2) show raw means for the characteristics of male and female borrowers matched with male officers. Column (3) displays the t-statistic of a test of difference between male and female borrowers assigned to male officers. Columns (4), (5) and (6) show the analogous test for female officers. Column (7) reports the t-statistic of a test of difference-in-differences for the respective borrower characteristic. The t-statistics in columns (3), (6), and (7) are estimated conditioned on time and on sector fixed effects. Standard errors are clustered at the branch-sector-year level. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 4 Test of random officer-borrower assignment

Dependent variable	Loan officer gender (male=1)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Credit-demand sample			Loan-conditionality sample		
Borrower gender (female=1)	-0.0236	-0.0250	0.0097	-0.0979***	-0.0842**	-0.0267
	[0.0301]	[0.0276]	[0.0190]]	[0.0319]	[0.0346]	[0.0217]
Time fixed effects	No	Yes	Yes	No	Yes	Yes
Sector fixed effects	No	No	Yes	No	No	Yes
Observations	4,589	4,589	4,589	7,272	7,272	7,272
Mean dependent variable	0.383	0.383	0.383	0.417	0.417	0.417

This table reports the regression where loan officer gender is regressed on borrower gender. The dependent variable is a dummy that takes on value one if the loan officer is male. The main independent variable is a dummy that takes on value one if the borrower is female. Column (1) does not include any control variables. The column (2) regression adds time fixed effects and the column (3) regression further adds sector fixed effects. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 5 Own-gender bias and credit demand

Dependent variable	Likelihood of applying for a second loan					
	(1)	(2)	(3)	(4)	(5)	(6)
Gender×Gender	-0.0716**	-0.0706**	-0.0848***	-0.0796**	-0.1032***	-0.1047***
	[0.0322]	[0.0327]	[0.0318]	[0.0314]	[0.0379]	[0.0388]
Adjusted R-squared	0.015	0.060	0.080	0.082	0.087	0.087
Observations	4,589	4,589	4,586	4,586	4,586	4,586
Mean dependent variable	0.661	0.661	0.661	0.661	0.661	0.661
Time and sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan-officer fixed effects	No	Yes	Yes	Yes	Yes	Yes
Loan officer covariates	No	Yes	Yes	Yes	Yes	Yes
Borrower covariates	No	No	Yes	Yes	Yes	Yes
Branch fixed effects and branch-by-year trends	No	No	No	Yes	Yes	Yes
Borrower gender×borrower covariates and borrower gender×loan officer covariates	No	No	No	No	Yes	Yes
Loan characteristics	No	No	No	No	No	Yes

This table reports regression results with the likelihood of applying for a second loan as the dependent variable using the credit-demand sample. Credit demand is a dummy variable that takes the value one if first-time borrowers apply for an additional loan. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 6 Credit demand and loan officer experience

Dependent variable	Likelihood of applying for a second loan					
	Low experience (1)	High experience (2)	Low experience (3)	High experience (4)	Low experience (5)	High experience (6)
Gender×Gender	-0.1940***	0.0347	-0.1933***	0.0377	-0.1938***	0.0377
	[0.0623]	[0.0417]	[0.0621]	[0.0433]	[0.0623]	[0.0426]
P-value of Wald test	0.0037		0.0036		0.0034	
Overall experience	No	No	Yes	Yes	Yes	Yes
Overall experience, cubic polynomial	No	No	No	No	Yes	Yes
Adjusted R-squared	0.105	0.091	0.105	0.095	0.105	0.092
Observations	2,248	2,338	2,248	2,338	2,248	2,338
Mean dependent variable	0.662	0.660	0.662	0.660	0.662	0.660

This table reports regression results with the likelihood of applying for a second loan as the dependent variable using the credit-demand sample. Credit demand is a dummy variable that takes the value one if first-time borrowers apply for an additional loan. The sample is divided at the median first-time borrower opposite sex experience (median = 9 interactions with first-time borrowers of the opposite sex). All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. In columns (1) and (2), we do not control for any loan officer experience, in columns (3) and (4) we control for overall loan officer experience, and in columns (5) and (6) we control for a third-order polynomial in overall loan officer experience. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 7 Credit demand, branch size, competition, and loan officer experience

Dependent variable	Likelihood of applying for a second loan			
	Small branches	Large branches	Weak competition	Strong competition
	(1)	(2)	(3)	(4)
Panel A: Branch size and competition				
Gender×Gender	-0.2455***	-0.0478	-0.1895***	-0.0470
	[0.0671]	[0.0453]	[0.0561]	[0.0640]
P-value of Wald test	0.0100		0.0577	
Adjusted R-squared	0.063	0.116	0.094	0.083
Observations	2,275	2,311	1,798	1,736
Mean dependent variable	0.666	0.656	0.663	0.643
Panel B: Experience and branch size	Low experience		High experience	
	Small branches	Large branches	Small branches	Large branches
Gender×Gender	-0.4025***	-0.0987	0.0695	0.0122
	[0.0933]	[0.0879]	[0.0763]	[0.0461]
P-value of Wald test		0.0088	0.0002	<0.0001
Adjusted R-squared	0.103	0.116	0.056	0.109
Observations	1,197	1,051	1,078	1,260
Mean dependent variable	0.687	0.636	0.644	0.673
Panel C: Experience and competition	Low experience		High experience	
	Weak competition	Strong competition	Weak competition	Strong Competition
Gender×Gender	-0.3825***	-0.1523	-0.0483	0.1092
	[0.0916]	[0.1011]	[0.0740]	[0.0999]
P-value of Wald test		0.0479	0.0026	<0.0001
Adjusted R-squared	0.144	0.114	0.072	0.071
Observations	764	866	1,034	870
Mean dependent variable	0.645	0.674	0.676	0.613

This table reports regression results with the likelihood of applying for a second loan as the dependent variable using the credit-demand sample. Credit demand is a dummy variable that takes the value one if first-time borrowers apply for an additional loan. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. In columns (1) and (2) of Panel A we split the sample according to the median branch size, in columns (3) and (4) according to competition measured as the ratio of branches over population in a specific region and year for the time period 2004-2006. In Panels B and C, we further split the samples according to the median loan officer experience with the opposite sex. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 8 Interest rate and loan officer experience

Dependent variable	Interest rate						
	Mean effect (1)	Low experience (2)	High experience (3)	Low experience (4)	High experience (5)	Low experience (6)	High experience (7)
Gender×Gender	0.0035**	0.0064***	0.0013	0.0064***	0.0012	0.0064***	0.0013
	[0.0015]	[0.0021]	[0.0017]	[0.0021]	[0.0016]	[0.0021]	[0.0017]
P-value of Wald test		0.0667		0.0580		0.0667	
Overall experience	No	No	No	Yes	Yes	Yes	Yes
Overall experience, cubic polynomial	No	No	No	No	No	Yes	Yes
Adjusted R-squared	0.601	0.681	0.571	0.681	0.587	0.682	0.571
Observations	7,266	3,677	3,589	3,677	3,589	3,677	3,589
Mean dependent variable	0.139	0.138	0.140	0.138	0.140	0.138	0.140

This table reports regression results with the interest rate as the dependent variable using the loan-conditionality sample. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. In column (1) we show the average effect, in columns (2) to (7) we split the sample according to the median first-time borrower opposite sex experience (median = 8 interactions with first-time borrowers of the opposite sex). In columns (2) and (3), we do not control for any loan officer experience, in columns (4) and (5) we control for overall loan officer experience, and in columns (6) and (7) we control for a third-order polynomial in overall loan officer experience. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 9 Interest rate, branch size, competition, and loan officer experience

Dependent variable	Interest rate			
	Small branches	Large branches	Weak competition	Strong competition
	(1)	(2)	(3)	(4)
Panel A: Branch size and competition				
Gender×Gender	0.0043	0.0039*	0.0049**	0.0014
	[0.0027]	[0.0021]	[0.0021]	[0.0029]
P-value of Wald test	0.9180		0.3048	
Adjusted R-squared	0.670	0.555	0.668	0.567
Observations	3,964	3,302	3,365	1,720
Mean dependent variable	0.139	0.139	0.145	0.147
Panel B: Experience and branch size	Low experience		High experience	
	Small branches	Large branches	Small branches	Large branches
Gender×Gender	0.0114***	0.0019	-0.0022	0.0037**
	[0.0029]	[0.0019]	[0.0035]	[0.0016]
P-value of Wald test		0.0032	0.0025	0.0139
Adjusted R-squared	0.735	0.639	0.640	0.520
Observations	2,320	1,356	1,644	1,946
Mean dependent variable	0.141	0.134	0.137	0.142
Panel C: Experience and competition	Low experience		High experience	
	Weak competition	Strong competition	Weak competition	Strong Competition
Gender×Gender	0.0105***	0.0047	0.0012	0.0013
	[0.0030]	[0.0029]	[0.0028]	[0.0032]
P-value of Wald test		0.1327	0.0577	0.0273
Adjusted R-squared	0.709	0.646	0.690	0.578
Observations	1,527	879	1,838	841
Mean dependent variable	0.144	0.146	0.145	0.149

This table reports regression results with the interest rate as the dependent variable using the loan-conditionality sample. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. In columns (1) and (2) of Panel A we split the sample according to the median branch size, in columns (3) and (4) according to competition measured as the ratio of branches over population in a specific region and year for the time period 2004-2006. In Panels B and C, we further split the samples according to the median loan officer experience with the opposite sex. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 10 Interest rate and officer-borrower age difference

Dependent variable	Interest rate									
	Young borrowers	Old borrowers	Young loan officers	Old loan officers	Low age difference	High age difference	Low experience		High experience	
							Low age diff	High age diff	Low age diff	High age diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Gender×Gender	0.0017	0.0050***	0.0071***	-0.0002	0.0016	0.0054***	0.0011	0.0095***	0.0022	-0.0009
	[0.0019]	[0.0018]	[0.0018]	[0.0017]	[0.0017]	[0.0017]	[0.0032]	[0.0027]	[0.0023]	[0.0026]
P-value of Wald test	0.1031		0.0016		0.0752		0.0210		0.0426	0.0008
Adjusted R-squared	0.604	0.607	0.621	0.633	0.592	0.620	0.713	0.687	0.534	0.602
Observations	3,634	3,632	3,634	3,632	3,633	3,633	1,805	1,872	1,828	1,761
Mean dependent variable	0.139	0.139	0.140	0.138	0.140	0.138	0.139	0.137	0.140	0.140

This table reports regression results with interest rate as the dependent variable using the loan-conditionality sample. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. In columns (1) and (2), the sample is split according to median borrower age (41 years), In (3) and (4), the sample is split according to median officer age (24 years), in (5) and (6) according to median age difference between borrowers and officers (16 years), in (7) through (10) according to officer experience with the opposite sex (median = 8 interactions). Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 11 Approved loan amount and loan officer experience

Dependent variable	Approved loan amount (USD)						
	Mean effect	Low experience	High experience	Low experience	High experience	Low experience	High experience
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gender×Gender	-282.5759**	-538.7508***	31.6196	-540.2702***	32.7953	-538.5033***	33.6424
	[115.4648]	[167.8002]	[197.1225]	[167.7953]	[196.6621]	[167.7620]	[196.9911]
P-value of Wald test		0.0273		0.0268		0.0273	
Overall experience	No	No	No	Yes	Yes	Yes	Yes
Overall experience, cubic polynomial	No	No	No	No	No	Yes	Yes
Adjusted R-squared	0.712	0.656	0.712	0.656	0.712	0.656	0.712
Observations	7,266	3,677	3,589	3,677	3,589	3,677	3,589
Mean dependent variable	2749.825	3145.045	2344.692	3145.045	2344.692	3145.045	2344.692

This table reports regression results with the approved loan amount in USD as the dependent variable using the loan-conditionality sample. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. The sample is divided at the median first-time borrower opposite sex experience (median = 8 interactions). In column (1) we show the average effect, in columns (2) to (7) we split the sample according to median officer experience with the opposite sex. In columns (2) and (3), we do not control for any loan officer experience, in columns (4) and (5) we control for overall officer experience, and in columns (6) and (7) we control for a third-order polynomial in overall officer experience. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 12 Approved loan amount, branch size, competition, and loan officer experience

Dependent variable	Approved loan amount (USD)			
	Small branches	Large branches	Weak competition	Strong competition
	(1)	(2)	(3)	(4)
Panel A: Branch size and competition				
Gender×Gender	-373.2338*	-98.4964	-281.6156**	-56.9331
	[199.0192]	[157.2690]	[134.8653]	[225.4470]
P-value of Wald test	0.2574		0.3644	
Adjusted R-squared	0.726	0.675	0.747	0.751
Observations	3,964	3,302	3,365	1,720
Mean dependent variable	2782.762	2710.284	2483.456	2589.572
Panel B: Experience and branch size	Low experience		High experience	
	Small branches	Large branches	Small branches	Large branches
Gender×Gender	-623.9274**	-236.8823	282.0228	126.2358
	[254.6350]	[265.0792]	[218.4765]	[170.3197]
P-value of Wald test		0.2523	0.0057	0.0091
Adjusted R-squared	0.723	0.752	0.760	0.618
Observations	2,321	1,356	1,643	1,946
Mean dependent variable	2995.1	3403.512	2482.489	2227.233
Panel C: Experience and competition	Low experience		High experience	
	Weak competition	Strong competition	Weak competition	Strong Competition
Gender×Gender	-431.1513**	-334.1853	-44.1959	306.1979
	[208.1999]	[347.3017]	[78.6626]	[246.0570]
P-value of Wald test		0.7916	0.0517	0.0142
Adjusted R-squared	0.784	0.769	0.803	0.748
Observations	1,527	879	1,838	841
Mean dependent variable	2874.41	2974.092	2159.042	2187.678

This table reports regression results with the approved loan amount in USD as the dependent variable using the loan-conditionality sample. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. In columns (1) and (2) of Panel A, we split the sample according to the median branch size, in columns (3) and (4) according to competition measured as the ratio of branches over population in a specific region and year for the time period 2004-2006. In Panels B and C, we further split the samples according to the median loan officer experience with the opposite sex. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 13 Arrears > 30 days and loan officer experience

Dependent variable	Arrears > 30 days						
	Mean effect	Low experience	High experience	Low experience	High experience	Low experience	High experience
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gender×Gender	-0.0026	0.0035	-0.0351	0.0037	-0.0349	0.0035	-0.0348
	[0.0165]	[0.0288]	[0.0237]	[0.0288]	[0.0237]	[0.0288]	[0.0236]
P-value of Wald test		0.2787		0.2751		0.2787	
Overall experience	No	No	No	Yes	Yes	Yes	Yes
Overall experience, cubic polynomial	No	No	No	No	No	Yes	Yes
Adjusted R-squared	0.106	0.139	0.056	0.139	0.056	0.139	0.056
Observations	4,586	2,246	2,340	2,246	2,340	2,246	2,340
Mean dependent variable	0.051	0.059	0.043	0.059	0.043	0.059	0.043

This table reports regression results with the measure arrears > 30 days as the dependent variable using the credit-demand sample. Arrears > 30 days is a dummy variable that takes on value one if a borrower went into arrears for more than 30 days at any time during the lifetime of her loan. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. In column (1) we show the average effect on arrears > 30 days, in columns (2) to (7) we split the sample according to median loan officer experience with the opposite sex. In columns (2) and (3), we do not control for any loan officer experience, in columns (4) and (5) we control for overall loan officer experience, and in columns (6) and (7) we control for a third-order polynomial in overall loan officer experience. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Table 14 Arrears > 30 days, branch size, competition, and loan officer experience

Dependent variable	Arrears > 30 days			
	Small branches	Large branches	Weak competition	Strong competition
	(1)	(2)	(3)	(4)
Panel A: Branch size and competition				
Gender×Gender	0.0140	-0.0090	0.0200	-0.0095
	[0.0201]	[0.0267]	[0.0228]	[0.0321]
P-value of Wald test	0.4673		0.4463	
Adjusted R-squared	0.073	0.109	0.132	0.081
Observations	2,275	2,311	1,798	1,736
	0.030	0.072	0.029	0.071
Panel B: Experience and branch size	Low experience		High experience	
	Small branches	Large branches	Small branches	Large branches
Gender×Gender	-0.0026	0.0198	0.0458**	-0.0756***
	[0.0364]	[0.0465]	[0.0201]	[0.0222]
P-value of Wald test		0.6738	0.2585	0.0625
Adjusted R-squared	0.086	0.153	0.006	0.067
Observations	1,198	1,051	1,077	1,260
Mean dependent variable	0.034	0.087	0.025	0.059
Panel C: Experience and competition	Low experience		High experience	
	Weak competition	Strong competition	Weak competition	Strong competition
Gender×Gender	0.0407	0.0459	0.0143	-0.0683***
	[0.0379]	[0.0401]	[0.0419]	[0.0213]
P-value of Wald test		0.9232	0.5934	0.0052
Adjusted R-squared	0.156	0.112	0.060	0.023
Observations	764	866	1,034	870
	0.037	0.075	0.024	0.068

This table reports regression results with the measure arrears > 30 days as the dependent variable using the credit-demand sample. Arrears > 30 days is a dummy variable that takes on value one if a borrower went into arrears for more than 30 days at any time during the lifetime of her loan. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. In columns (1) and (2) of Panel A, we split the sample according to the median branch size, in columns (3) and (4) according to competition measured as the ratio of branches over population in a specific region and year for the time period 2004-2006. In Panels B and C, we further split the samples according to the median loan officer experience with the opposite sex. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

APPENDIX

Appendix Table A1 Summary statistics for the loan-conditionality sample

Variable	Mean (1)	SD (2)	Median (3)	Male borrower (4)	Female borrower (5)	Male loan officer (6)	Female loan officer (7)
Interest rate	0.14	0.03	0.14	0.14	0.14	0.14	0.14
Approved loan amount (in USD)	2,752	2,880	1,966	2,811	2,468	2,700	2,789
Female borrower	0.17	0.38	0.00	0.00	1.00	0.14	0.19
Civil status (married = 1)	0.87	0.34	1.00	0.90	0.74	0.89	0.86
Age applicant	41.08	10.25	41.07	40.97	41.64	41.19	41.00
Total assets (in USD)	27,790	85,099	17,028	27,974	26,897	27,495	28,001
Monthly business profits (in USD)	585	1,915	440	612	456	626	556
Applied loan amount (in USD)	3,078	2,986	2,116	3,143	2,760	3,024	3,116
Approved maturity (in days)	566	294	540	567	562	544	581
Personal guarantee	0.17	0.38	0.00	0.17	0.18	0.14	0.20
Mortgage guarantee	0.12	0.33	0.00	0.12	0.12	0.09	0.14
Chattel guarantee	0.96	0.20	1.00	0.96	0.95	0.97	0.95
Destination Working Capital	0.09	0.29	0.00	0.10	0.05	0.12	0.07
Destination Fixed Assets	0.36	0.48	0.00	0.40	0.18	0.52	0.25
Destination Housing Improvement	0.33	0.47	0.00	0.31	0.42	0.21	0.41
Destination Consumption	0.22	0.41	0.00	0.20	0.34	0.15	0.27
Destination Others	0.00	0.02	0.00	0.00	0.00	0.00	0.00
Production	0.16	0.37	0.00	0.19	0.06	0.29	0.07
Transport	0.14	0.35	0.00	0.16	0.04	0.16	0.13
Construction	0.69	0.46	1.00	0.65	0.90	0.55	0.80
Female loan officer	0.58	0.49	1.00	0.57	0.66	0.00	1.00
Age loan officer	25.38	4.33	23.79	25.44	25.10	26.53	24.56
Overall loan officer experience (# of loans processed)	42.15	48.15	26.00	40.63	49.51	32.48	49.05
Opposite loan officer sex experience (# of loans processed)	24.51	37.62	8.00	22.95	32.06	4.39	38.87
Branch size (number of loan officers)	14.15	8.53	12.00	13.79	15.86	13.50	14.61
Number of branches per 100,000 inhabitants (all banks), county level	5.75	2.69	5.47	5.76	5.74	5.90	5.63
Observations	7,272						

This table reports summary statistics [mean, standard deviation (SD), and median] for the loan-conditionality sample. Columns (1)-(3) show the values for the entire sample, columns (4) and (5) the means for male and female borrowers, and columns (6) and (7) the means for male and female loan officers.

Appendix Table A2 Test for differences in borrower characteristics for the loan-conditionality sample

	Male loan officers			Female loan officers			
	Male borrowers	Female borrowers	t-statistic	Male borrowers	Female borrowers	t-statistic	t-statistic
Variable	(1)	(2)	(3) = (1) - (2)	(4)	(5)	(6) = (4) - (5)	(7) = (3) - (6)
Age applicant	41.09	41.86	2.01**	40.88	41.52	1.88*	0.59
Civil status (married = 1)	0.90	0.77	-5.78***	0.89	0.73	-11.20***	1.54
Applied loan amount (in USD)	3,065	2,764	-2.67***	3,202	2,758	-2.76***	0.27
Applied maturity (in days)	589	582	-0.97	626	614	-1.90*	-0.40
Total assets (in USD)	27,259	28,978	0.06	28,521	25,842	-1.62	1.54
Monthly business profits (in USD)	642	523	-2.30**	589	422	-2.53**	1.45
Personal guarantee	0.13	0.17	0.23	0.20	0.18	-0.46	0.31
Mortgage collateral	0.09	0.11	-0.92	0.15	0.13	-1.92*	0.17
Chattel collateral	0.97	0.96	-0.12	0.95	0.94	-0.63	0.40
Working Capital	0.12	0.09	0.42	0.08	0.04	-3.07***	1.43
Fixed Assets	0.56	0.30	-6.62***	0.28	0.13	-4.48***	-1.07
Housing Improvement	0.19	0.32	1.80*	0.40	0.47	2.02**	-0.74
Consumption	0.13	0.29	4.60***	0.25	0.36	3.91***	0.75
Others	0.00	0.00	n.a.	0.00	0.00	1.18	-1.09
Observations	2,613	417	3,030	3,416	826	4,242	7,272

This table reports a test of difference in observable borrower characteristics for the loan-conditionality sample. Columns (1) and (2) show raw means for a set of borrower characteristics of male and female borrowers matched with male loan officers. Column (3) displays the t-statistic of a test of difference of the respective characteristic between male and female borrowers assigned to male loan officers. Columns (4) and (5) show raw means of male and female borrowers matched with female loan officers. Column (6) shows the t-statistic of a test of difference of the respective characteristic between male and female borrowers assigned to female loan officers. Column (7) reports the t-statistic of a test of difference-in-differences for the respective borrower characteristic. The t-statistics in columns (3), (6), and (7) are estimated conditioned on time and on sector fixed effects. Standard errors are clustered at the branch-sector-year level. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Appendix Table A3 First-loan approval

Dependent variable	Likelihood of approving the first loan				
	(1)	(2)	(3)	(4)	(5)
Gender×Gender	-0.0025	0.0032	-0.0002	-0.0015	-0.0038
	[0.0264]	[0.0153]	[0.0062]	[0.0062]	[0.0075]
Adjusted R-squared	0.036	0.204	0.137	0.161	0.167
Observations	8116	7996	7380	7380	7380
Mean dependent variable	0.896	0.910	0.985	0.985	0.985
Time and sector fixed effects	Yes	Yes	Yes	Yes	Yes
Loan-officer fixed effects	No	Yes	Yes	Yes	Yes
Loan officer covariates	No	Yes	Yes	Yes	Yes
Borrower covariates	No	No	Yes	Yes	Yes
Branch fixed effects and branch-by-year trends	No	No	No	Yes	Yes
Borrower gender×borrower covariates and borrower gender×loan officer covariates	No	No	No	No	Yes

This table reports regression results with the likelihood of approving the first loan as the dependent variable using the loan-conditionality sample. Likelihood of approving the first loan is a dummy variable that takes on value one if the borrower received a loan with the lender. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Appendix Table A4 Maturity

Dependent variable	Approved maturity < applied maturity (=1)						
	Mean effect	Low experience	High experience	Low experience	High experience	Low experience	High experience
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Gender×Gender	0.0685**	0.1199**	0.0185	0.1204**	0.0179	0.1200**	0.0176
	[0.0344]	[0.0520]	[0.0477]	[0.0524]	[0.0480]	[0.0520]	[0.0478]
P-value of Wald test		0.1802		0.1768		0.1768	
Overall experience	No	No	No	Yes	Yes	Yes	Yes
Overall experience, cubic polynomial	No	No	No	No	No	Yes	Yes
Adjusted R-squared	0.135	0.138	0.146	0.138	0.148	0.138	0.147
Observations	7,266	3,679	3,587	3,679	3,587	3,679	3,587
Mean dependent variable	0.298	0.302	0.293	0.302	0.293	0.302	0.293

This table reports regression results with approved maturity < applied maturity as the dependent variable using the credit-demand sample. Approved maturity < applied maturity is a dummy variable that takes on value one if the approved maturity was shorter than the applied maturity. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. The sample is divided at the median first-time borrower opposite sex experience (median = 8 interactions). In column (1) we show the average effect, in columns (2) to (7) we split the sample according to median officer experience with the opposite sex. In columns (2) and (3), we do not control for any loan officer experience, in columns (4) and (5) we control for overall officer experience, and in columns (6) and (7) we control for a third-order polynomial in overall officer experience. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

Appendix Table A5 Approved maturity < applied maturity, branch size, competition, and loan officer experience

Dependent variable	Approved maturity < applied maturity (=1)			
	Small branches	Large branches	Weak competition	Strong competition
	(1)	(2)	(3)	(4)
Panel A: Branch size and competition				
Gender×Gender	0.0708*	0.0598	0.0741**	0.0356
	[0.0426]	[0.0515]	[0.0356]	[0.1178]
P-value of Wald test	0.8671		0.7392	
Adjusted R-squared	0.138	0.125	0.130	0.078
Observations	3,964	3,302	3,365	1,720
Mean dependent variable	0.251	0.354	0.230	0.335
Panel B: Experience and branch size	Low experience		High experience	
	Small branches	Large branches	Small branches	Large branches
Gender×Gender	0.0889	0.1238	0.0294	0.0406
	[0.0711]	[0.0937]	[0.0745]	[0.0612]
P-value of Wald test		0.7463	0.5703	0.5848
Adjusted R-squared	0.137	0.151	0.145	0.124
Observations	2,322	1,357	1,642	1,945
Mean dependent variable	0.277	0.345	0.214	0.360
Panel C: Experience and competition	Low experience		High experience	
	Weak competition	Strong competition	Weak competition	Strong competition
Gender×Gender	0.0457	0.0134	0.0246	-0.0949
	[0.0713]	[0.1291]	[0.0321]	[0.1756]
P-value of Wald test		0.8091	0.7763	0.0102
Adjusted R-squared	0.134	0.096	0.136	0.4281
Observations	1,528	879	1,837	841
Mean dependent variable	0.231	0.302	0.228	0.371

This table reports regression results with approved maturity < applied maturity as the dependent variable using the credit-demand sample. Approved maturity < applied maturity is a dummy variable that takes on value one if the approved maturity was shorter than the applied maturity. All regressions include the control variables as specified in column (5) of Table 5, the results for these are omitted to save space. In columns (1) and (2) of Panel A, we split the sample according to the median branch size, in columns (3) and (4) according to competition measured as the ratio of branches over population in a specific region and year for the time period 2004-2006. In Panels B and C, we further split the samples according to the median loan officer experience with the opposite sex. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.