# Sex and Credit:
# Do Gender Interactions Matter for Credit Market Outcomes?

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This version: September 2017

## Abstract

This paper studies the effects of gender interactions on the supply of and demand for credit using data from a large Albanian lender. We document that first-time borrowers assigned 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 also find that first-time borrowers matched with opposite-sex officers pay higher interest rates and receive smaller and shorter-maturity loans, but do not experience higher arrears. Our results are consistent with the existence of a gender bias and learning effects that lead to the disappearance of the bias.

JEL Classification: G21, G32, J16.
**Keywords:** Group identity, gender, credit supply, credit demand, loan officers.

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We are grateful to two anonymous referees, an anonymous Associate Editor, the Editor (Geert Bekaert), Santosh Anagol, Yuliya Demyanyk, Tore Ellingsen, Marcel Fafchamps, Paul Gertler, Eliana La Ferrara, Steven Poelhekke, Raghuram Rajan, Chris Woodruff, David Yanagizawa-Drott, and seminar participants at Barcelona Development Economics Workshop 2012, EBRD (London), EUDN (Paris), the Financial Intermediation Research Society's Conference 2013 (Dubrovnik), Goethe University Frankfurt, the NEUDC 2011 at Yale, the SITE conference on Institutional Challenges in Emerging Economies 2013 (Stockholm), Stockholm School of Economics, Tilburg University, the Development Economics Workshop in Bergen 2010, University of Göttingen, University of Mainz, and the World Bank.

# 1 Introduction

As credit transactions often rely on close (and repeated) interactions between the lender and the borrower, outcomes are likely to be influenced by whether a borrower is matched with a loan officer of the same or of the opposite gender. For instance, in many socioeconomic settings, including credit markets, people favor in-group over out-group members. Favoritism based on, for example, ethnic or gender identity can lead to misallocated credit and inefficiencies. Rather than taste-based, however, the resulting biases may be statistical if members of certain groups are more likely to default. In addition, dealing with own-group members can reduce transaction and monitoring costs and, ultimately, lower default. Being biased against out-group members may thus be an efficient outcome. However, there might also exist a dynamic dimension to such bias, as initial prejudices and/or the lack of knowledge result in inefficient transactions; learning about members of the other group, in turn, could mitigate if not eliminate the bias (Altonji and Pierret, 2001). While this latter hypothesis may be straightforward to derive theoretically, it is difficult to test empirically as it requires detailed data on the loan officer and borrower match as well as information on loan officer behavior over extended periods.

In this paper, we use unique data on loan officer and borrower matches and credit transactions of one specific financial institution to investigate how gender interactions in lending affect loan outcomes and the demand for credit. Specifically, we gauge whether the officer-borrower gender match influences the likelihood that first-time borrowers return to the same lender for further credit and whether this relationship varies with the experience of loan officers with borrowers of the opposite gender and the discretion loan officers face. We also assess whether interest rates, loan amounts, and loan maturity vary between borrowers assigned to same-gender loan officers and borrowers assigned to opposite-gender officers.

The setting of our study – a micro-lender in Albania – provides a unique opportunity to analyze the effects of the gender match on loan terms and loan demand, for several reasons. First, during the sample period the banking market in Albania was less regulated than in more developed economies, allowing us to study the causes of gender interactions in lending in a setting with limited government interference. Second, our sample is balanced in terms of the gender of loan officers and borrowers; specifically, 61% of all loan officers are female, while 82% of borrowers are male; 56% of all borrowers are assigned to a loan officer of a different gender when first taking out a loan.[1] Third, the loan transactions are individual, with the loan

[1] Male loan officers handle 36% of the transactions with female first-time borrowers, while female loan officers are assigned to male first-time clients in 61% of the cases.

officer being assigned to a specific borrower from the moment of screening, over monitoring during the life of the loan, to the full repayment. This makes the match between the loan officer and the borrower a close one, while also allowing learning by the loan officer from experience with borrowers from the same and the opposite gender.

In a framework, analogous to a difference-in-differences estimation, we exploit that first-time borrowers are assigned to their respective loan officers on a first-come first-served basis and compare the difference in credit market outcomes for male and female borrowers obtaining loans from male officers to the difference between male and female borrowers obtaining loans from female officers. The baseline specification includes officer fixed effects that control for all time-invariant effects across officers, branch fixed effects to account for constant differences across branches, sector fixed effects to absorb possible specialization in certain business sectors, and time (year, week, and day) fixed effects to control for changes over time across borrowers and officers that may influence the borrower-officer match. In addition, we add branch-by-year trends to control for secular variation that may affect other factors impacting supply of and demand for credit.

We find that the 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 10 percent less likely to apply for a second loan with the bank. We show that the effect originates with borrowers whose officers have below-median experience of the other gender. To investigate if officers' degree of discretion 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. We find that the effect of the gender interactions 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 42 percent less 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 contract terms, including interest rates, loan amount, and loan maturity, to explore one channel through which the gender match can affect credit demand. First-time borrowers assigned to officers of the other gender pay, on average, 38 basis points higher annual 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 of the opposite gender also receive loans with shorter maturity and somewhat smaller size than borrowers matched to officers of the same gender.

Establishing that officer exposure to opposite-sex borrowers matters helps us rule out the existence of a pure taste-based gender bias. However, it is not clear whether the effects we identify stem 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 maturities 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.

While we interpret our findings as supportive of the existence of an own-gender bias and important learning effects, we acknowledge that our results are consistent with several alternative explanations. First, unobservable borrower characteristics might drive our findings. Second, our results could be an indication of borrowers shopping around for loans, depending on the gender of the loan officer they are matched with. Third, it could also be that borrowers change their bargaining behavior depending on the gender of the loan officer they are matched with. Fourth, it is further possible that loan officers are better able to evaluate borrowers of the same gender. Our empirical setup does, unfortunately, not allow us to clearly distinguish between these alternative explanations of our findings.

This paper speaks to several literatures. First, while there are studies looking at own-race/ethnicity preferences in police behavior (Donohue and Levitt, 2001), in judicial sentencing (Abrams et al., 2012, Alesina and La Ferrara, 2014), in the workplace (Stoll et al., 2004), in lending (Fisman et al., 2017), and in sports (Price and Wolfers, 2010; Parsons et al., 2011) our paper is the first to gauge the effects of the borrower-loan officer gender match in the credit market.[2]

[2] There is also a broader literature documenting biases in lending, using U.S. data on either mortgage (Munnell et al., 1996; Berkovec et al., 1998; Ladd, 1998; Ross and Yinger, 2002; Han, 2004) or small business credit provision (Cavalluzzo and Cavalluzzo, 1998; Blanchflower et al., 2003, Blanchard et al., 2008). However, most of these studies are based on correlations that do not control for all the characteristics that lenders observe when setting the contract terms. Exceptions to this are the studies by Pope and Sydnor (2011) and Duarte et al. (2012). Bellucci et al. (2009) use Italian data showing that female entrepreneurs face tighter credit availability in branches with a lower share of female loan officers, but they do not investigate the borrower gender-loan officer gender match.

Second, we relate 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 can have important economic implications.

Third, we link to work showing that poor consumers are sensitive to changes in the loan terms. Attanasio et al. (2008) find that low-income U.S. households are very responsive to variation in loan maturity. Using experimental field data from a South African lender, 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 maturity and interest rate differential identified in our paper, these findings suggest that a gender match-induced maturity and price gap may be one important channel affecting credit demand.

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

The paper also relates to a small literature studying the importance of loan officers in lending stressing long-term relationships, compensation schemes, and officer rotation for loan performance (Hertzberg et al., 2010; Agarwal and Ben-David, forthcoming; Drexler and Schoar, 2013; Cole et al., 2014). We add to these studies by documenting the existence of effects of the gender match in lending and in emphasizing the importance of loan officers' prior exposure to opposite-sex borrowers.

Finally, this paper complements earlier work by Beck et al. (2013). Using a similar data set, they show that loans handled by female (as opposed to male) loan officers are less likely to go into arrears.[3] However, the current paper is interested in a distinctly different issue, namely if the officer-borrower gender match helps explain important credit market outcomes for a given set of officer attributes.[4]

[3] In particular, they find that female officers monitor more intensely while there is no difference across loan officer gender at the screening stage.

[4] While Beck et al. (2013) concentrate on differences across loan officers of different gender, thus the supply side of lending for a given set of demand-side factors, this paper controls for supply-side effects by including loan officer fixed effects and focuses on the impact on borrowers of different genders. That is, using officer fixed effects we evaluate the importance the gender match in lending independently of the quality of a particular banker.

In the next section, we provide institutional background information about the lender and the loan process, outline our methodology, and describe the data. Section three presents our findings on the relationship between the borrower-loan officer gender match and demand for a second loan, while section four discusses results for the relationship between the gender match and loan conditions. Section five investigates whether the effects we find are efficient while section six explores if they are 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 discusses 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 4,900 loans given by a commercial lender over the period January 1996 to July 2006. In terms of loan size, our lender can be compared to small U.S. or European commercial banks serving SMEs, adjusted for GNI per capita.[5] Hence, while our lender operates in a developing country, it does standard banking business that is comparable to the business of small commercial banks serving SMEs in the U.S. or other European countries. The data also contain information on 206 loan officers and cover 15 branches of the bank. While the lender clearly focuses on the low-income and microenterprise and very small business 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.[6] The population statistics report the total number of people living in each county during the same period.

[5] For instance, in 2006 the lender’s average loan size was 3,321 USD. If we standardize this figure with the ratio of the Albanian to the U.S. gross national income (GNI) per capita for that year, we get an average loan size of approximately 21,300 USD. This compares to an average loan size of 28,000 USD for SMEs in the U.S. as reported by the U.S. Small Business Administration per end of June 2007.

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

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 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. Specifically, first-time borrowers cannot choose a loan 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 and accompany applicants throughout the whole application process and the subsequent life of the loan. To account for the fact that officers can be distinctly different from one another besides gender, that branches can be influenced by local culture, that loan officers and borrowers potentially specialize in certain business sectors, and that the timing (year, week, and day) may influence the borrower-officer match, the baseline specification (discussed in detail below) includes loan officer, branch, sector, and time fixed effects. While this set of fixed effects allows us to rule out the importance of other officer traits, local culture, time, and sector-specific aspects it does not exclude the possibility that borrowers shop around or change their bargaining behavior depending on the gender of the loan officers.

### 2.2 Sample composition and summary statistics

When analyzing gender interaction differences we focus on the following five outcomes: (i) the likelihood that a borrower applies for a second loan with the lender; (ii) the annual interest rate paid; (iii) the loan maturity in days; (iv) the loan amount in U.S. Dollars (USD); and (v) the likelihood of going into arrears more than 30 days at any point during the loan cycle. 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 an effect of the gender match.[7] For our regression analysis, we restrict the data in three 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.[8] 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 terms. In addition, the fact that we find a reduced demand for a second loan introduces selection bias in the sample of repeat borrowers. Focusing on the first loan by each loan applicant yields the cleanest test of possible gender interaction effects. Second, we account 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 median time it takes until a second loan application of a first-time borrower is posted and use observations of first time borrowers with a loan that matured before July 21, 2006. [9] Finally, 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 gender. In total, this yields a dataset of 4,890 loan transactions.

Table 1 presents summary statistics and shows that 65 percent of the first-time borrowers applied for a second loan. Opposite-sex officers manage 56 percent of the transactions and 61 percent of the loan officers are female.[10] Officers are, on average, 25 years old. For most officers, this is the first formal job after college.[11] Borrowers own assets with a value of 24,368 USD and earn a monthly business profit of 529 USD on average. Most loans require chattel collateral, while only 13 percent come with mortgage, and 22 percent with a personal guarantee. In terms of sector composition, 73 percent of all borrowers work in construction, while 12 percent work in production and 15 percent in transportation.[12]

### 2.3 Identification strategy

[7] In fact, using an approval indicator as the dependent variable shows no evidence of gender interaction effects (results are available on request).
[8] Focusing on first-time borrowers also makes it less likely that applicants know about any differences caused by the gender match when applying for a loan.
[9] The computation is based on the last two years of our data and represents the median time (163 days) until borrowers return to the bank for their second loan application.
[10] 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.
[11] This information was obtained through personal communication with the lender.
[12] The classifications incorporate a range of subsectors. For example, construction subsumes sectors such as carpentry, maintenance/service facilities, painting, other works, and construction work.

To study the impact of the interaction between officer and borrower gender on loan outcomes, we compare the difference in outcomes (demand for a second loan, interest rate, loan maturity, 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.

Our baseline estimates control for loan officer, branch, sector, and time fixed effects. Loan officer fixed effects allow us to compare male and female borrowers independent of the specific (time-invariant) characteristics of a given officer (besides gender). Branch fixed effects absorb time-invariant or slow-moving differences between branches, such as geographic differences or local culture outside and within the branch office.[13] Sector dummies control for any gender-specific business sector specialization. The time fixed effects include year, week, and day controls. Year fixed effects account for secular changes over time that affect all officers and borrowers similarly in a given year. To address the possibility that seasonality of loan demand differs between same- and opposite-loan officer borrower gender pairs we include week controls (at the time of the loan application). Finally, day dummies account for the concern that loan officers may work different days of the week, which could potentially affect the officer-borrower match. In addition, we add branch-by-year controls (interacting the branch dummies with a 0-1 variable for each year) to flexibly absorb unobservable trends in lending over the time period that may have affected 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.

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 handled by female loan officers, conditional on the baseline controls discussed above. 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. We do not take the identifying assumption as given, but formally gauge whether the borrower-loan officer gender match is uncorrelated with a number of important observable borrower and loan officer characteristics below. We also assess whether our effects are driven by an influential loan officer or bank branch, and run regressions where we drop each branch or officer.

[13] We can include branch fixed effects together with loan officer fixed effects as some loan 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.

Before we present the main results, we verify that male relative to female borrowers do not vary in some important characteristics depending on whether they are matched with an officer of their own or the opposite gender. In addition, we also show that time-variant loan officer traits of male relative to female officers are similar across borrower gender. Specifically, we utilize the following regression:

(1) $$y_{ijdwysb} = \beta gb_i gl_j + gb_i + \rho_j + \delta_d + \tau_w + \mu_y + \sigma_s + \varphi_b + \varphi_b \times \mu_y + \varepsilon_{ijyms},$$

where $y_{ijdwysb}$ is one of the relevant characteristics of borrower $i$ contracting with loan officer $j$ in day $d$ week $w$ year $y$ in sector $s$ and in branch $b$, $gb_i\, gl_j$ is a borrower-loan officer gender dummy taking the value 1 if borrower $i$ and loan officer $j$ are of the opposite sex, $gb_i$ is a borrower gender dummy, $\rho_j$ is a loan officer dummy, [14] $\delta_d$ is a day dummy, $\tau_w$ is a week dummy, $\mu_y$ is a year dummy, $\sigma_s$ is a sector dummy, $\varphi_b$ is a branch dummy, and $\varphi_b \times \mu_y$ are branch-specific time trends. The coefficient $\beta$ indicates whether there is a difference between male and female borrowers screened and monitored by male relative to female officers. Formally, the assumption is that $Cov(gb_i gl_j,\ u|\tilde{z}) = 0$, where $u$ is any other determinant of the outcome of interest $y_{ijdwysb}$ and $\tilde{z}$ is the vector of the relevant fixed effects. We test for differences in socio-demographic borrower information (age, total assets, and monthly profits in USD), loan officer information (age, experience with opposite gender, and opposite gender arrear experience), branch-level information (branch size as proxied by the number of loan officers and within county competition as measured by branches per 100,000 inhabitants per region), applied-for loan terms (applied loan size in USD, applied loan maturity in days, availability of a personal, mortgage, or chattel collateral guarantee), and the loan usage (working capital, fixed assets, housing improvement, consumption, and "other").[15] 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 in Table 2.

Table 2 shows that there are no systematic differences in important observable borrower characteristics between borrowers matched to same-gender officers and borrowers matched to opposite-gender loan officers prior to the loan transaction. The correlates across all tested characteristics enter insignificantly. Moreover, there is no discernable pattern as the sign of the

[14] The loan officer dummy absorbs the separate effect of $gl_j$.
[15] The results in this table and the rest of the paper are insensitive to rescaling the variables in logarithms.

reported coefficients change direction across the different variables. In addition, the F-test for joint significance of the borrower and loan officer variables that verifies the hypothesis that the coefficients are jointly equal to zero cannot be rejected (p-value= 0.943). This check supports the notion that the difference between male and female borrowers handled by male loan officers is, on average, the same as the difference between male and female borrowers handled by female officers along important observable traits that capture borrower quality. That is, there is no indication that male or female borrowers with certain characteristics are more likely to be assigned to the same or opposite-sex loan officers. The table also displays the tests across the subsamples used later in the analysis to understand some of the underlying mechanisms (above median loan officer experience, above median branch size, and above median competition). As before, all of the sample cuts enter insignificantly. While these tests reduce concerns of borrowers selecting into a lending relationship with certain loan officers, we cannot fully rule out that the borrowers differ along important unobservable dimensions which could, for example, result in borrowers shopping for better loan terms.

### 2.4 Main specification

To investigate whether loan demand and loan outcomes depend on the gender match, we use OLS to estimate the following specification

$$(2) \qquad O_{ijdwysb} = \beta gb_i gl_j + gb_i + \rho_j + \delta_d + \tau_w + \mu_y + \sigma_s + \varphi_b + \varphi_b \times \mu_y + X_{ijym} + \varepsilon_{O_{ijymsb}},$$

where $O$ is the outcome of interest (demand for a second loan, interest rate charged, loan maturity, loan amount, or arrear probability), $\rho, \delta, \tau, \mu, \sigma,$ and $\varphi$ are loan officer, day, week, year, sector, and branch fixed effects, respectively. As above, the specification also includes branch-by-year trends $\varphi_b \times \mu_y$. The coefficient $\beta$ 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.[16] Finally, the parameter $X_{ijym}$ is a vector that includes borrower and loan officer traits (those of Table 2). We use OLS regressions

[16] Our identification strategy does not strictly allow us to sort out which officer gender is responsible for the potential gender interaction effects. Hence, the interaction of $gb_i gl_j$ defined as female borrower(=1)×male loan officer(=1) and the separate terms, $gb_i$ and $gl_j$, yield an equivalent outcome to male borrower(=1)×female loan officer(=1). Including all (four) interactions between officer and borrower gender to capture differences across officer sex bars us from simultaneously including level differences between male and female borrowers, $gb_i$, or officer fixed effects, $gl_j$.

throughout the paper, including for the bi-variate dependent variables (demand for second loan and arrears) given that we saturate the model with fixed effects. Using a non-linear model would reduce the sample significantly, as we would lose many clusters with no variation in demand for second loans or arrears.[17]

# 3 Gender match and loan demand

## 3.1 Baseline findings

We first examine the effect of the gender match on the likelihood that borrowers apply for a second loan with the lender. Table 3 presents the results of estimating equation (2) with a dummy equal to one if a borrower applied for a second loan as the dependent variable. Column (1) includes loan officer, time, sector, and branch fixed effects. In column (2), we add loan officer and borrower specific covariates; column (3) includes branch-by-year fixed effects to control for branch-specific time trends; and column (4) includes the (potentially endogenous) loan characteristics (interest rate, loan maturity, and amount).

The coefficients on $gb_i gl_j$ are similar across the four specifications, statistically significant, and show that the interaction of loan officer and borrower gender is a significant determinant of demand for credit. The main estimate, column (3), implies that borrowers matched with opposite-sex officers are 6.68 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 65 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 10.3 percent higher relative to the fraction of borrowers teamed up with officers of the same gender. Note that column (3) accounts for any unobservable trend in lending over the time period. 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, not the gender mix of the workplace. In addition, to investigate if influential loan officers or bank branches drive the effect, we run regressions

[17] In non-reported regressions available on request, we test for the robustness of our main findings with Probit regressions and find that results are qualitatively and quantitatively unchanged. However, using this setup we lose more than 5% of observations in the loan demand regressions and more than 30% of the observations in the loan arrears regressions.

where we drop each branch or officer and find that the results are robust to omitting any particular branch or officer.[18]

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

Having established the existence of economically meaningful gender interaction effects, we now turn to exploring different explanations for the effects, as an important aim of this paper is to document how key determinants of loan officer behavior interact with the gender match. To do so, we study 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 loan officers' previous experience with borrowers of the other gender allows us to test whether the gender interaction effects are due to limited professional exposure to the opposite sex.

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 may influence gender interaction effects, 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, if the detected gender interaction effects are due to a pure taste-based bias on the side of the loan officers, as captured by a greater preference for own-gender borrowers (relative to opposite-gender borrowers), the gender interaction effects 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. We calculate the median of opposite-sex loan officer experience — 9 interactions with the opposite sex — and split the sample at this median. The regression models are analogous to the ones of columns (2) and (3) of Table 3.[19]

[18] Figure A1 in the Appendix plots the distribution of coefficients of our main outcomes (demand for a second loan, interest rate, loan maturity, and loan amount), and shows that the findings are not driven by any particular officer or branch.

[19] Note that this is a "within loan officer" test. We compare the likelihood of returning to the bank across borrowers of different genders for the same officer as officers' experience with opposite-gender borrowers changes. This implies that the findings are independent of the officer gender and, as such, our methodology does not allow us to gauge relative performance of male versus female loan officers as their opposite-borrower experience varies. This is different from Beck et al. (2013) who show that female loan officers, on average, seem to interact more efficiently with both their female and male borrowers.

The results in Table 4 show that the gender match affecting credit demand seems to be more pronounced for officers with less 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 loan officers have below-median experience with the other gender, while the coefficient in the above-median sample is insignificant and with different signs across the alternative specifications. A Wald test confirms that the difference between the two estimates in the first column pair is significant at the 10 percent level. In columns (3) and (4) we add branch-specific time trends; this does not alter the results. Finally, controlling for overall experience does not change the outcome, suggesting that the effect we capture is distinct from more general competence [columns (5) and (6)]. The treatment impact in column (1) implies a 17.3 percent (11.24 percentage points) decrease in the likelihood of demanding a second loan with the lender as compared to the overall mean of 65 percent, almost twice the size of the average effect estimated in Table 3. 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 gender interaction effects disappear relatively fast as loan officers gain additional professional experience with the opposite gender. Next, we turn to loan officers' degree of discretion.

We examine 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). If the effects we have documented so far are due to a loan officer gender bias, it should be less costly to express such a bias in uncompetitive markets since borrowers have few outside options. As competition increases, however, such a bias can be more damaging to credit demand, inducing the lender to scrutinize loan officers with greater care to detect mistreatment.[20] 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 officer may be more difficult to replace, giving him or her more discretion of indulging his or her preferences.[21]

To measure financial market competition, we explore variation in the universe of registered bank branches across Albania's 12 counties over the years 2004-2006.[22] We map this information with population records for each county and year and merge both statistics with

[20] 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.
[21] 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 the provided intuition.
[22] We lack countrywide information on bank-branch establishments for the earlier years in our dataset.

our loan-level data. The final competition measure is defined as the number of bank branches per 100,000 inhabitants, by county and year.[23] 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 of 7.46. 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), which is 10. 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. It is important to point out that we effectively exploit within-branch variation, i.e., any differences in our coefficient estimates cannot be attributed to differences, for instance, across rural and urban or low- vs. high-income branches.

Table 5 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 or in the credit market. 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 more discretion.

Panel A reports the results on branch size and shows that borrowers assigned to opposite-sex loan officers are less likely to apply for a second loan in smaller branches. The point estimate on branch size implies that the likelihood of applying for a second loan decreases by approximately 15 percentage points or 24 percent for a borrower that ends up with an opposite-sex loan officer in a smaller branch. The coefficients are significantly different at least at the 10 percent level across the two column pairs and the point estimates are almost unchanged when we account for the trends.

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

In Panel B we investigate the joint relationship between loan officer discretion and prior opposite-sex exposure. It shows that the coefficient on the $gb_i gl_j$ variable is significant (p=0.003) only in smaller branches with loan officers that have little experience of opposite-gender borrowers, with an effect of 27 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 when we use the level of bank market competition as a proxy for loan officer discretion: demand for a second loan is reduced by 14 percentage points in less competitive counties, but there is no difference in counties with high competition. Again, the coefficients are significantly different at the five percent level. We get almost an identical result when we add branch-specific time trends in columns (3) and (4) of Panel C.

Finally, in Panel D, we combine competition with loan officer experience with the opposite gender. In counties with low competition, loan demand drops by 33 percentage points if the loan officer has little exposure to the opposite gender, reflecting a lower credit demand of about 50 percent. For all other combinations of competition and loan officer opposite-sex experience, the coefficient is not significant. The difference in coefficients is highly significant in all comparisons across these different combinations. 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-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.

## 4 Gender match and loan conditions

The assignment of borrowers to opposite-sex loan officers may hamper demand for credit through multiple channels. Loan officers interact with borrowers continuously over the lending relationship. A potential gender bias may lead 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. It could also affect the interpersonal relationship, making opposite-gender borrowers feel less comfortable with their respective loan officer. Alternatively, borrowers may adjust their bargaining behavior or shop around for loans depending on the gender of the loan officer they are matched with, which may result in different loan conditions. Finally, if loan officers are better able to evaluate borrowers of the same gender, they may charge opposite-sex borrowers inferior loan terms.

In this section, we explore one manifestation of gender interaction effects that is easy to capture, loan contract terms: interest paid, the maturity, and the loan amount borrowers receive.[24] We also estimate the average effect size across the three outcomes following Kling et al (2007). We again gauge whether opposite-sex experience and loan officer discretion remain important factors. We would like to stress that we cannot directly test for a formal link between loan contract terms in the first loan and subsequent demand for a second loan; rather we test whether the results on both outcomes are consistent with each other.

### 4.1 Loan conditions and officer experience

To investigate the effect of the gender match on loan conditions we replace the likelihood of applying for a second loan with the interest rate, loan maturity, and loan amount as the dependent variable and begin by studying the mean impact.[25] Overall, the results in Table 6 show that borrowers fare worse if matched with a loan officer of the opposite gender. Starting with the price, borrowers pay a significantly higher interest rate when paired with an opposite-sex officer. The coefficient in column (1) where we include the baseline controls and the covariates implies that a borrower pays, on average, a 38 basis points higher interest rate if matched with a loan officer of the other sex. This corresponds to an increase of about 3 percent overall (0.38 percentage points from the mean interest rate of 13.7 percent). The coefficient stays significant when we add branch-specific time trends [column (2)].

The results in columns (3) to (6) indicate that the effect seems to be concentrated in the sample of loan officers with below-median opposite-gender experience. Specifically, we find that officers with a below-median experience of opposite gender borrowers charge interest rates that are 58 basis points or 4.2 percent higher than those charged to same-sex borrowers with the difference between the below- and the above-median exposure being significant at least at the 10 percent level [p=0.0797 in column (6)].

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

[25] To economize on space, we omit the results estimated without borrower and officer covariates. The findings are similar when the model is run only with loan officer, time, sector, and branch fixed effects.

A shorter maturity increases the size of the monthly payments and allows for less flexibility on the part of the borrower, implying that loan maturities provide an additional measure of gender interaction effects. The findings to follow report on the effect of matching borrowers to opposite-sex officers on the maturity of loans as measured in days. Table 6 shows that borrowers receive shorter maturity loans if paired with other-gender officers, an effect that is driven by officers with below-median experience with opposite-sex borrowers. Columns (1) and (2) demonstrate that loans processed by a loan officer of the other gender have a maturity that is about 20 days or 4 percent shorter (compared to an average of 500 days). The result is significant at least at the 10 percent level across the two specifications that include the baseline controls, borrower and officer covariates, and the trends.

Columns (3) to (6) show evidence that officers with little opposite-sex experience grant loans with significantly shorter maturity if matched with borrowers of the other gender, while this is not the case for officers with above median opposite-gender experience. Specifically, loans granted by officers with low opposite-sex experience are almost a month or 55 days (11 percent) shorter in maturity if provided to borrowers of the other gender. The result is robust to controlling for overall experience and significantly different at the 1 percent level across the high/low experience sample cut.

The third row of Table 6 reports our findings on loan amount. While the negative sign suggests that borrowers interacting with opposite-sex officers receive smaller loans, the average effect is small and insignificant [Columns (1) and (2)]. However, similar to price and maturity we find evidence that borrowers matched with below-median experience opposite-gender officers receive significantly lower loan amounts. Compared with the mean approved loan size of 2,066 USD, the decrease of 196 USD indicates a 10 percent lower amount. In the case of loans given by officers with above-median exposure to the other gender, the coefficient enters positively and insignificantly in both instances [Columns (4) and (6)].

The last row of Table 6 reports the estimated average effect size (AES) for the three outcomes of interest (Kling et al., 2007). Let $\beta^k$ and $\sigma^k$ indicate the estimated opposite-gender coefficient and the standard deviation for outcome variable $k$, respectively. AES is equal to $\frac{1}{K}\sum_{k=1}^{K}\frac{\beta^k}{\sigma^k}$, where $K$ is the total number of outcomes variables (in our case, *K=3*). AES estimates help minimize the problem that a single finding is due to chance and reduce the risk of low statistical power.[26] The AES estimates confirm our findings that follow from the OLS estimates

[26] Similar to Alsan (2015), the sign of the interest rate is reversed in order to compute the index.

on each individual outcome. Being paired with an opposite-gender officer worsens the contractual terms by about 0.1 standard deviations on average (a finding significant at the 1-percent level). Similarly, in the subsample of below-median officer experience, the effect on the family of loan condition outcomes decreases by 0.18 standard deviations, a finding which is both economically and statistically significant. Overall, these findings lend credence to loan conditions being one possible channel explaining the drop in demand.

### 4.2 Loan conditions, branch size, and officer experience

Table 7 revisits the effect of branch size. For the interest rate, approved loan amount, and the AES estimate, the effects are qualitatively similar to those of demand for additional credit, that is, smaller branches yield higher interest rates and lower loan amounts for borrowers matched with opposite-sex loan officers, although only statistically different in the case of price. For loan maturity, the effect is reversed but it is not significantly different across branch size. The average impact combining all loan outcomes is of larger magnitude in small branches, with the coefficient being more than 30 percent bigger than the one in large branches.

Columns (3) to (6) combine loan officer opposite-sex experience and branch size. We find the effect to be strongest when officers have little experience with the other gender and work in small branches across all three contractual outcomes as well as the AES estimate. Borrowers matched with loan officers of the other sex that have little previous exposure to the opposite gender and work in smaller branches pay 94 basis points or 7 percent higher interest rates. While the coefficient is not significantly different from the point estimates in columns (4) and (5), it is significantly different from the coefficient estimate in the sample of large branches and high opposite-gender experience of loan officers [column (6)].

A similar pattern emerges for loan maturity and loan amount. The effect is most pronounced in small branches when officers have little experience with the opposite gender. Specifically, borrowers allocated to opposite-sex officers with little opposite-gender experience in small branches obtain loans that have a 74 days or 14 percent shorter maturity compared to borrowers matched with same-sex loan officers with low opposite-gender experience that also work in smaller branches. The point estimate is significantly different from the coefficient in the samples with high opposite gender experience in either small or large branches [columns (5) and (6)], but not from the estimate for low opposite-sex loan officer experience in large branches [column (4)]. For the loan amount, the effects are qualitatively similar. Ending up with a loan officer with less experience of the opposite gender in a small branch yields a loan size which is 430 USD smaller compared to a borrower paired with an inexperienced same-sex officer in the same location. The effect is marginally insignificant (p=0.101) and implies a 19 percent decrease from the mean loan size of 2,312 USD. When the three contractual outcomes are combined into a single measure, the AES estimate obtained for the intersection of below-median experience with the other gender and small branches yields a highly significant effect of 0.28 standard deviations. The impact is over 40 percent larger than the one found for officers with low opposite-gender experience in large branches.

Taken together, while the investigation of the association between loan conditions and officer discretion as proxied by branch size is weaker in a statistical sense, borrowers fare worse when low opposite-sex experience is combined with more loan officer discretion.

### 4.3 Loan conditions, bank competition, and officer experience

Table 8 displays the results when competition is used as the proxy for loan officer discretion. The findings for competition itself are less conclusive and overall mixed. As before, the effect for the interest rate is largest in magnitude in counties with little competition, but it is not statistically different from the effect for counties with high competition. Combining competition and loan officer opposite-sex experience in column (3) yields a significantly higher interest rate for borrowers matched to a loan officer from the other gender in counties with little competition and for loan officers with little prior exposure to the other sex. Borrowers paired with officers of the opposite gender with below-median experience and in a county with low competition pay a 154 basis points or 10 percent higher interest rate than borrowers matched to loan officers of the same gender (an effect which is significantly different from all the other combinations). By comparison, the magnitude is only half the size in the case of low-experienced officers in competitive counties.

For loan maturity, the signs are reversed but none of the estimates are significantly different from one another suggesting that credit market competition does not play a role when it comes to the length of the loan maturity. While the coefficient for the loan amount has the expected sign in column (3), it is not significantly different from the coefficients for officers with below median opposite-sex experience in competitive counties or from above-median experienced officers in low and high competition counties.

The AES estimates do, however, corroborate that the effect of ending up with an opposite-gender officer is the strongest when officers have little prior experience with borrowers of the other gender *and* work in counties with less bank competition. Interestingly, the effect size, 0.29 standard deviations, is almost identical to the effect found in Table 7 for the same sample cut using branch size as the proxy for loan officer discretion. The impact in column (3) of Table 8 is more than twice the size of any of the other sample combinations [columns (4) to (6)].

Overall, while the results with respect to loan maturity and loan amount are less clear, our findings suggest that first-time borrowers assigned to opposite-sex loan officers fare worse in terms of the price they pay for credit. In line with our earlier results for credit demand, the AES estimates also suggest that loan officers' prior exposure to the other gender and their degree of discretion are complements: loan officers with little previous opposite-sex experience and more discretion offer borrowers of the other gender distinctly inferior loan terms. The consistent findings as to when the effects appear on the officer-borrower gender mismatch across applying for a second loan, interest rate, to some extent loan maturity and loan amount, and the AES estimates, indicate that the drop in demand for credit at least partly follows from the results on loan conditions.

### 4.4 Alternative interpretations

The results presented so far are consistent with the interpretation that loan officers engage in an own-gender bias and we provide several tests and arguments to validate our identification strategy supporting the explanations put forward. However, a number of other interpretations are also possible. For instance, while we show that important observable borrower characteristics that should be correlated with borrower outcomes are uncorrelated with loan officer gender (as documented by our orthogonality tests), we cannot rule out that differences in unobservable borrower characteristics across loan officer gender explain our results. Another alternative and related explanation for our findings is that borrowers matched with opposite-sex officers shop around for loan terms, which leads to different borrower populations ending up with same- versus opposite-sex loan officers. If same-gender officers provide better terms and same-gender borrowers are less likely to switch this also rationalizes the paper's findings. Borrowers may further adjust both their bargaining behavior and the behavior throughout the loan cycle depending on the gender of the loan officer which results in different contract terms and loan performance across same and opposite-gender loans.[27] In short, borrowers shopping around or changing their behavior depending on the officer gender may also explain why borrowers receive more favorable loan terms from own-gender loan officers and why opposite

[27] We thank a referee for highlighting these alternative explanations.

gender borrowers return less often to the bank. As our data do not allow us to observe either shopping around or gender-dependent behavior, we cannot exclude these alternative explanations.

## 5 Gender match and arrears occurrence

If the gender interaction effects we have documented so far are due to an own-gender bias, it is not clear whether such bias stems from a knowledge gap that leads 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, shorter maturity, and smaller 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 other-gender borrowers. 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. 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 9 and 10 report our findings with the results presented with the same sample cuts as in the case of loan conditions. Overall, there is little indication that borrowers of the same gender as their loan officer perform better in terms of a significantly lower likelihood of going into arrears. The results displayed in Table 9 show that, on average, the arrear probability of loans screened and monitored by opposite-gender loan officers is 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 and carries a negative sign in both specifications in columns (1) and (2). If anything, the negative sign is contrary to what we would expect if the behavior of loan officers matched to borrowers of the opposite gender was efficient, that is, if being matched with an *own*-gender officer rendered a lower likelihood of going into arrears. Dividing the sample by opposite-sex experience in columns (3) and (4) and in columns (5) and (6) does not alter this conclusion. The estimate on $gb_i gl_j$ is negative and insignificant above and below median opposite-gender experience and there is no significant difference between the two sub-samples.[28]

Table 10 examines the impact of the officer-borrower gender interaction on the arrear probability across the dimensions of branch size and financial market competition. Panel A shows no significant differences when we split the sample according to branch size, regardless of the specification used. We find one case where borrowers assigned to opposite-sex officers display a higher likelihood of going into arrears [column (5)] as well as one where they are less likely [column (6)] to go into arrears. The coefficient in the case of the positive impact is marginally significant and not statistically different from two of the three other cases (results not shown).

Similar null-results appear when we split the samples first by competition and then further by opposite-sex loan officer experience (Panel B). If transactions between borrowers and loan officers of the same gender were efficient, we would expect a positive and significant coefficient of the opposite-gender pairing in the case in which the loan officer has more discretion and where the bias documented above is strongest. We do not find this. Panel B shows that the effect of opposite-sex borrower-loan officer matching has no implications for the following arrear outcomes. Moreover, besides being insignificant, the coefficient is negative which works against the hypothesis that opposite-sex borrower-loan officer matches yield more inefficient loan transactions.

In unreported regressions, available on request, we focus on actual repayments rather than arrears. While we do not have recovery rates on defaulted loans (though we were assured by the bank that these are minimal given the small loan amounts, which do not justify going to the courts), we have no reason to believe that these small recovery rates vary systematically between same- and opposite-gender loan officers. Specifically, we can distinguish between capital repayments relative to the total loan amount as well as interest plus capital (re)payments relative to the total loan amount plus expected interest payment. Neither one of the two performance indicators are significantly different across the borrower-officer gender pairings, corroborating the arrear findings above.

These results suggest that the significant gender interaction effects found in the demand for a second loan or in terms of loan conditions are absent in the arrear outcomes. One possible explanation for the lack of any discernible pattern may be that officers change loan conditions

[28] This does not contradict the findings of Beck et al. (2013), as they compare arrear probabilities across loan officers of different gender (and find a lower arrear probability for female loan officers both vis-à-vis female and male borrowers), while we compare arrear probabilities for the same loan officer across different borrower genders.

*and* monitoring behavior simultaneously. For example, they could charge opposite-sex borrowers a higher interest rate, and offer shorter maturity and smaller loans 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.[29]

## 6 Are the gender interaction effects different for men or women?

To the extent that gender match is due to due to an own-gender bias, the question arises if such a 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 documented effects come from both sides by reanalyzing the average impact of $gb_i gl_j$ on the likelihood of applying for a second loan and loan conditions at the individual loan-officer level.

For each loan officer we regress the likelihood of returning for another loan, interest rates, loan maturity, loan amount, and the AES estimate on a female borrower dummy for officers with at least 20 observations using our baseline specification (replacing week and day dummies with month dummies as the former two result in too many female dummies dropping out).[30] We restrict the sample to loan officers with at least 20 observations in order to have the degrees of freedom needed to include all of the remaining fixed effects. As these regressions are estimated separately for each loan officer, they control for loan officer specific differences in monitoring, screening, and loan conditions.

Figure 1 plots the coefficient estimate on the probability of returning to the lender for the female borrower dummy for each loan officer, with the bars representing the 95 percent

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

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

confidence interval around the estimates. We find that female borrowers are 8.68 percentage points more likely (compared to male borrowers) to return to the lender if handled by female officers. Meanwhile female borrowers are 6.07 percentage less likely (compared to male borrowers) to come back if managed by a male officer. The figure also indicates that the gender interaction effects are prevalent for loan officers of both genders. Hence, a possible pro-male bias among male loan officers and a pro-female bias among female loan officers leads borrowers of the opposite sex to exit at a greater degree. While most of the coefficients are imprecisely estimated, quite a few yield point estimates that are statistically significantly different from zero.

Figures 2 to 5 investigate the same question with respect to loan conditions. For example, for interest charged we again find evidence of gender interaction effects: the average interest rate differential for female (as opposed to male) borrowers is –49 basis points in the case of female loan officers and 34 basis points in the case of male loan officers. That is, the majority of female borrowers have a greater propensity to pay higher interest rates when dealing with male loan officers than the majority of male borrowers. Figure 3 points to a qualitatively similar effect on loan maturity. The mean coefficient shows a similar symmetry across the genders as above: a female borrower handled by a male loan officer gets 16.7 days less (relative to male borrowers) in loan maturity while a female borrower is approved an extra 17.1 days (relative to male borrowers) in maturity if managed by a female officer.[31] Figures 4 and 5 point to quantitatively analogous results with smaller (bigger) loans offered to female borrowers by male (female) loan officers (figure 4) and overall better loan terms presented to own-gender borrowers (figure 5), where the latter is based on the standardized effect (expressed in standard deviations) across the family of loan condition outcomes (interest rates, loan amount, and loan maturity).

## 7 Conclusion

This paper provides evidence that the gender match between borrowers and loan officers significantly affects credit market outcomes. First-time borrowers matched with opposite-sex loan officers in a large Albanian bank are 10 percent less likely to demand additional credit from the lender. The detected effects originate with borrowers whose loan officers have little prior exposure to borrowers of the other gender or whose loan officers have weak incentives to

[31] The restricted sample is somewhat sensitive to outliers in the case of loan maturity. In the example presented, we exclude observations larger than 4 standard deviations above/below the mean.

suppress their beliefs given the lack of competition and outside discipline, which we proxy 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 higher interest rates, receive loans with shorter maturity, and obtain somewhat smaller loan amounts. These effects are larger for borrowers matched to loan officers of the opposite sex with limited opposite-gender experience and in settings where these loan officers have more discretion. On the other hand, we do not detect any gender interaction effects associated with arrear outcomes. This rules out an own-gender bias that is 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 gender interaction effects should be stronger and why demand for credit decreases in the opposite-gender match it is likely that other channels also are at work. Furthermore, our empirical setup does not allow us to distinguish between alternative explanations for our findings. Besides an own-gender bias, borrowers shopping around for loan terms, borrowers changing their behavior depending on the gender match, and loan officers being able to better evaluate borrowers of the same gender are all consistent with our findings.

A better understanding of gender interaction effects in lending 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 effects. Second, from a policy perspective, our findings point to the possibility that financial market competition can be a powerful tool in dampening the effects. Disentangling the exact causes of the gender interaction effects seem to be a fruitful avenue for future research.

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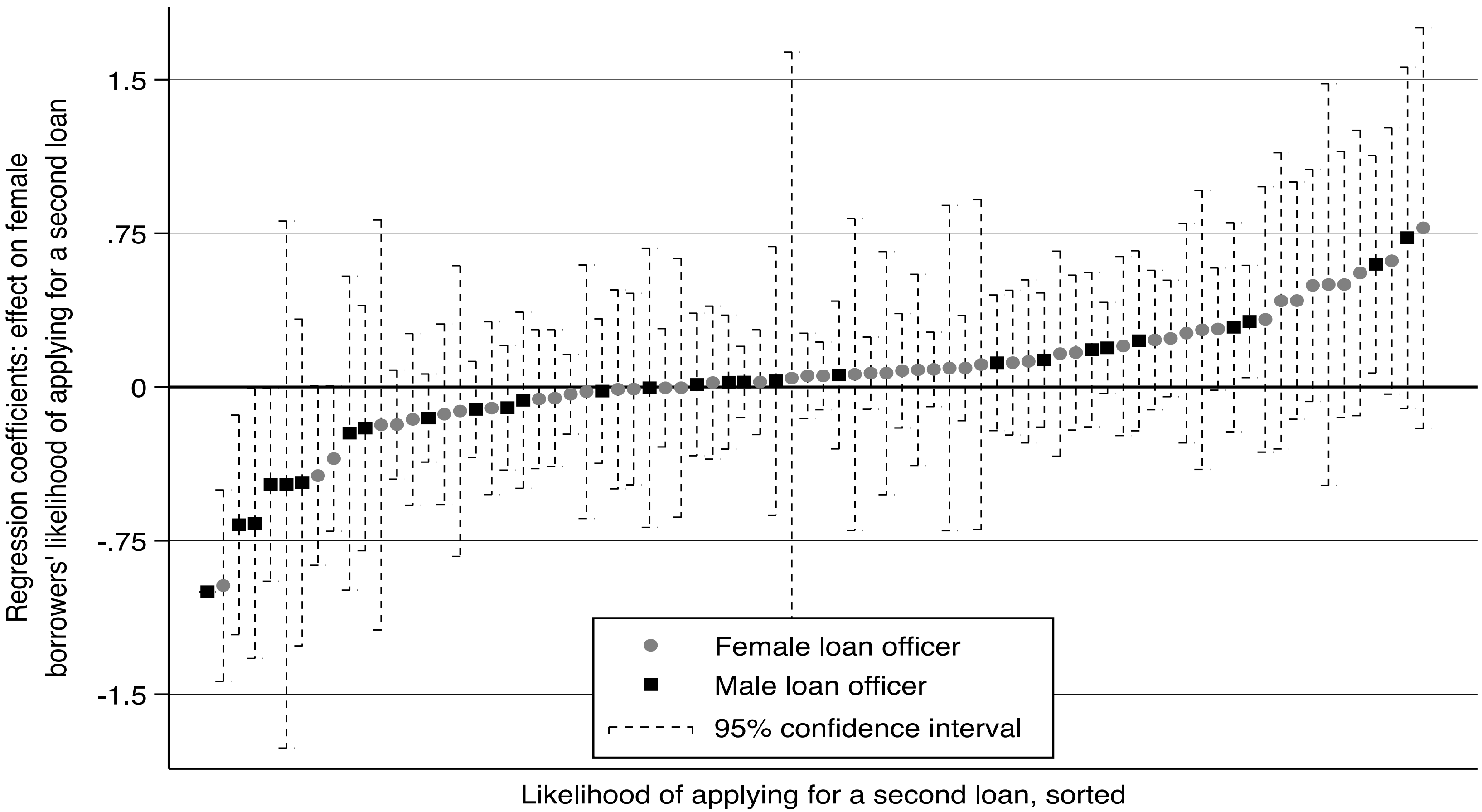


**Figure 1.** The figure shows the distribution of the bias on the likelihood of returning to the lender by officer gender. Each coefficient represents an estimate of the higher probability that a female versus a male borrower returns for additional funding.

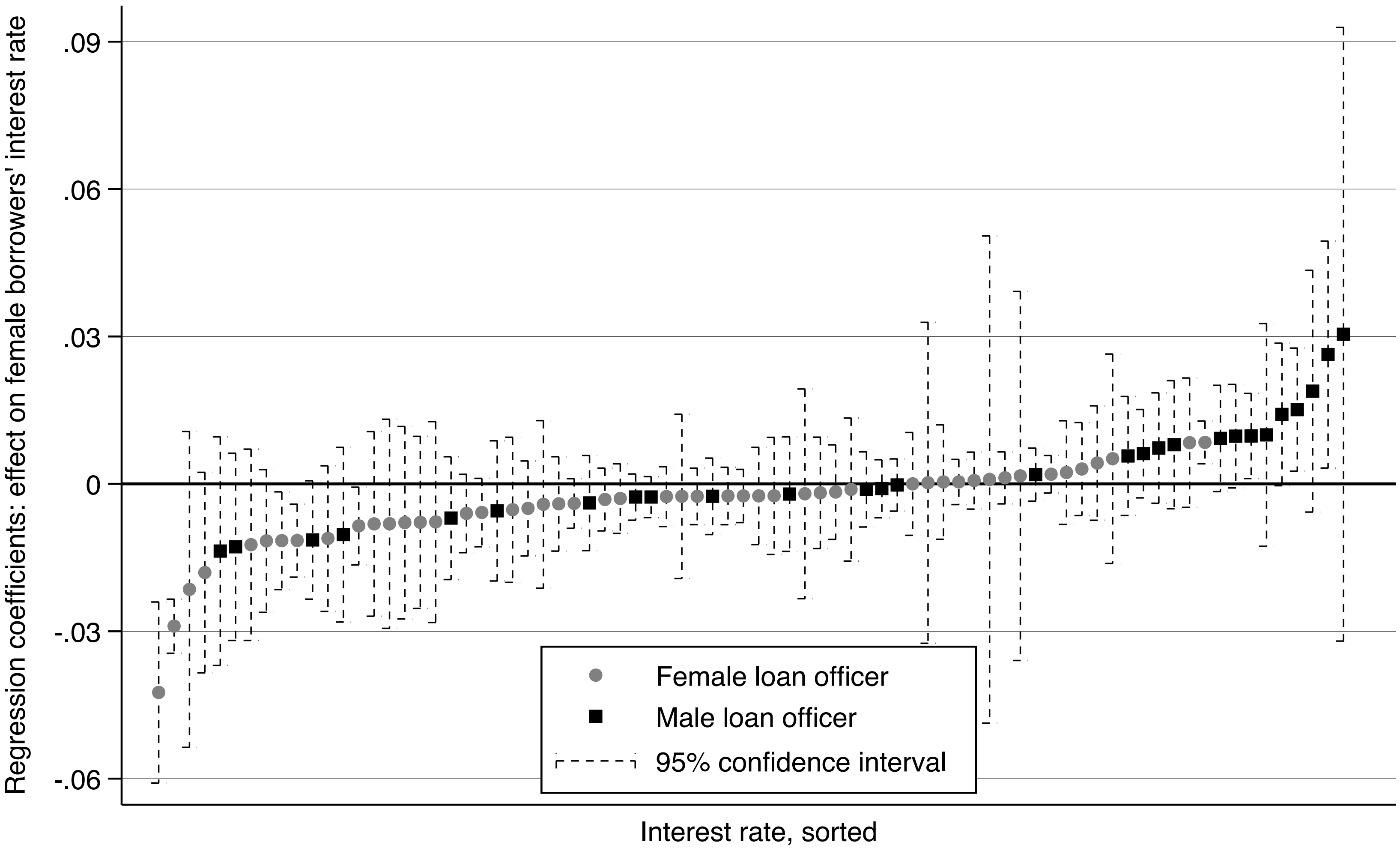


**Figure 2.** The figure shows the distribution of the bias on interest rates by officer gender. Each coefficient represents an estimate of the number of extra interest rate basis points an individual officer approves for female versus male borrowers.

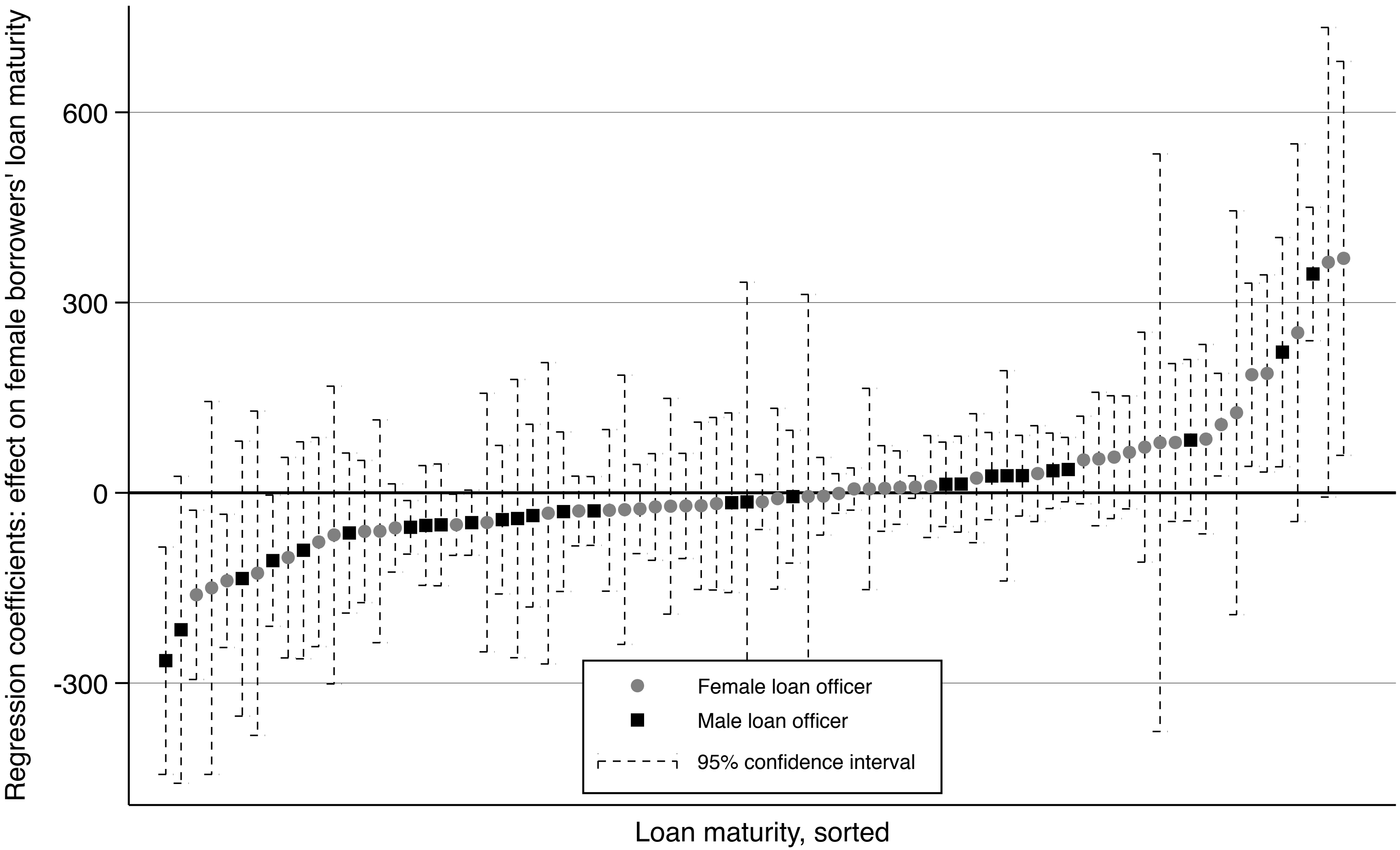


**Figure 3.** The figure shows the distribution of the bias on loan maturity by officer gender. Each coefficient represents an estimate of the number of extra days of loan maturity an individual officer approves for female versus male borrowers.

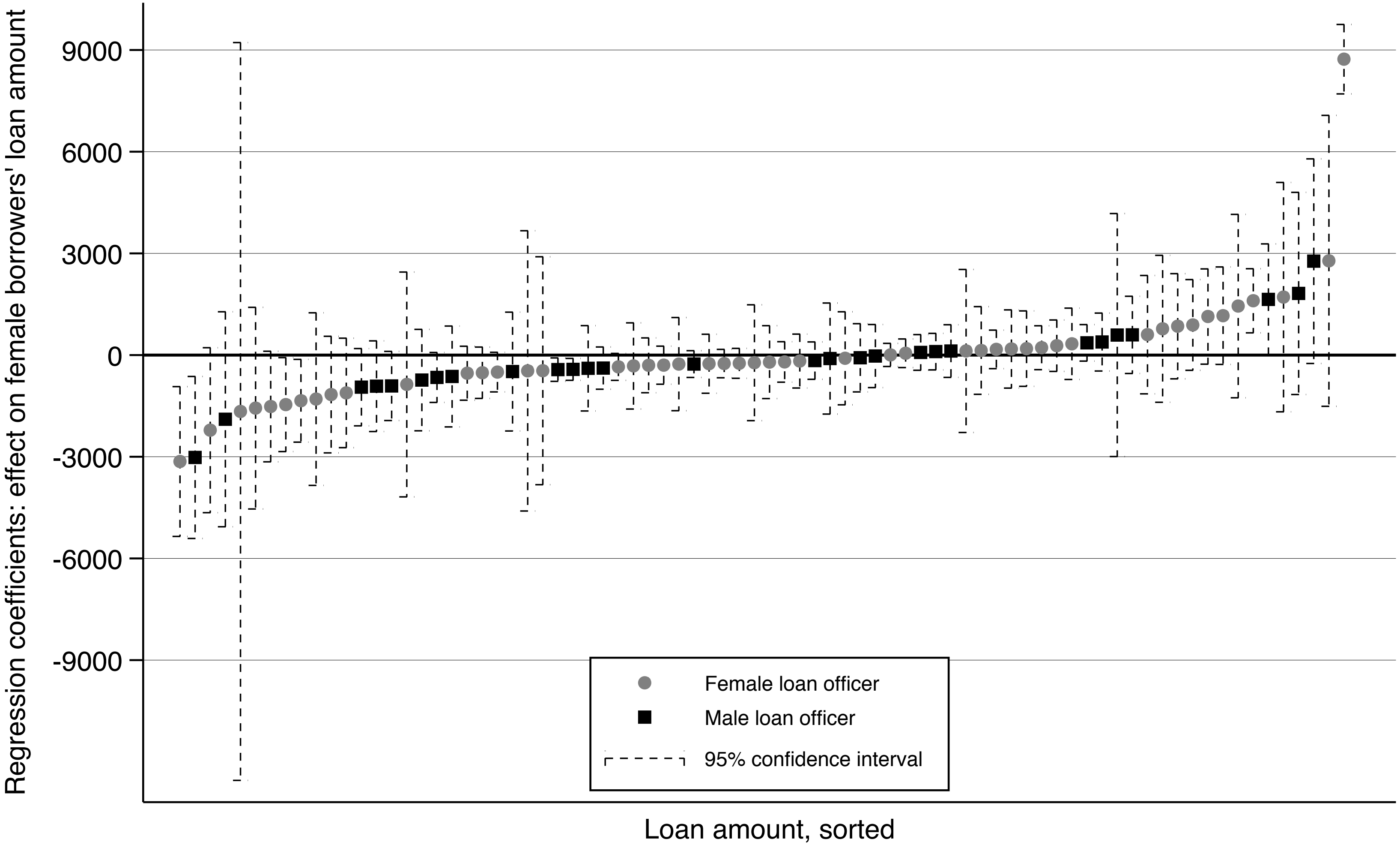


**Figure 4.** The figure shows the distribution of the bias on loan amount by officer gender. Each coefficient represents an estimate of the additional USD an individual officer approves for female versus male borrowers.

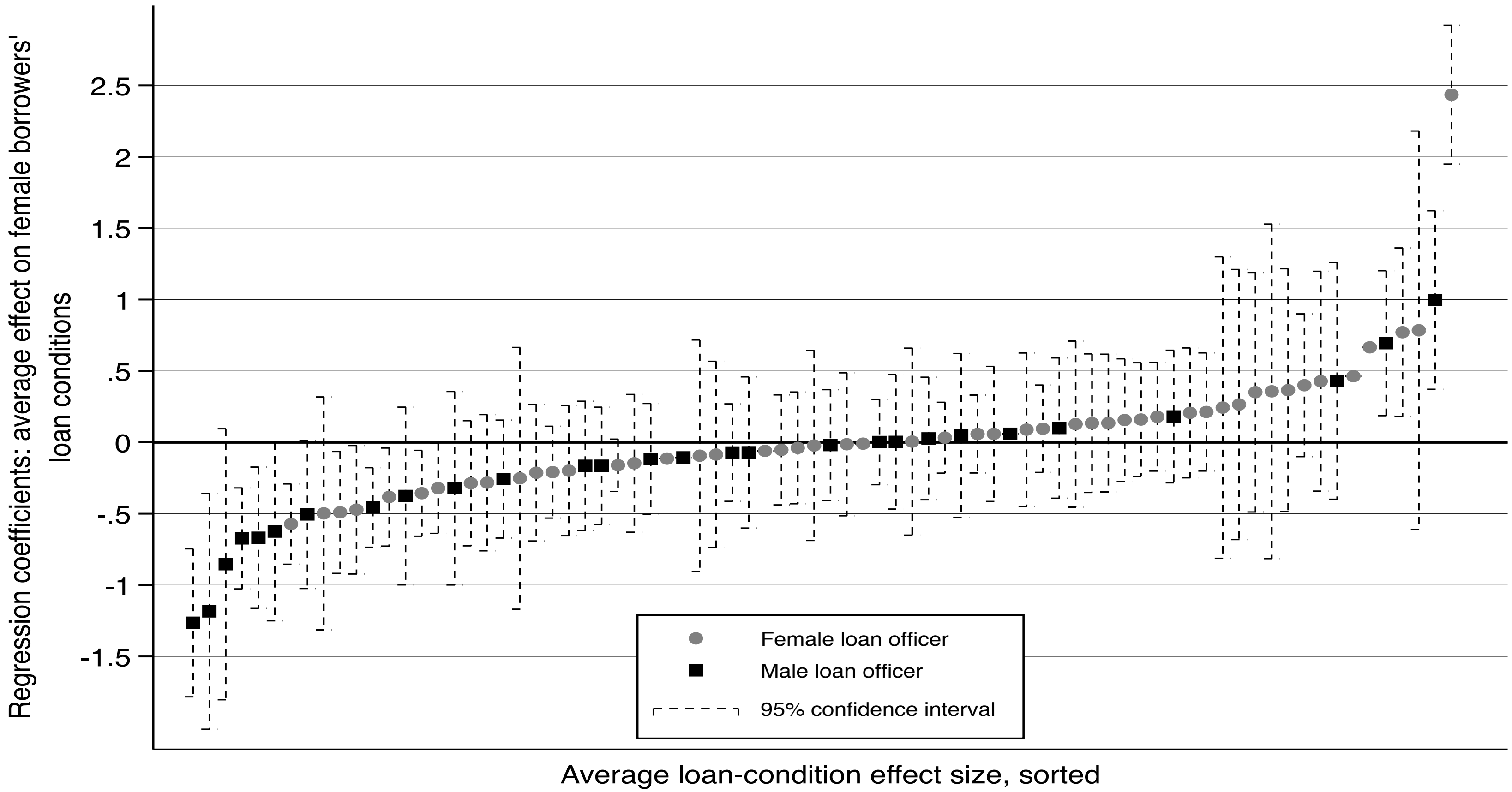


**Figure 5.** The figure shows the distribution of the bias on the loan conditions by officer gender. Each coefficient represents an estimate of the loan condition an individual officer approves for female versus male borrower.

**Table 1** Summary statistics

| Variable | Mean<br>(1) | SD<br>(2) | Median<br>(3) |
|---|---|---|---|
| Borrowers assigned to opposite sex loan officers | 0.561 | 0.496 | 1 |
| Likelihood of applying for a second loan | 0.651 | 0.477 | 1 |
| **Contract details** | | | |
| Interest rate | 0.137 | 0.0252 | 0.134 |
| Approved loan maturity (in days) | 501.7 | 205.0 | 480 |
| Approved loan amount (in USD) | 2,360 | 2,470 | 1,684 |
| **Loan performance variables** | | | |
| Likelihood of going into arrears > 30 days | 0.0513 | 0.221 | 0 |
| Likelihood of going into arrears > 1 day | 0.535 | 0.499 | 1 |
| **Borrower covariates** | | | |
| Female borrower | 0.183 | 0.386 | 0 |
| Age borrower | 40.89 | 10.18 | 40.94 |
| Total assets (in USD) | 24,368 | 44,593 | 15,277 |
| Monthly business profits (in USD) | 528.8 | 924.4 | 407.8 |
| Applied loan amount (in USD) | 2,713 | 2,676 | 1,990 |
| Applied loan maturity (in days) | 549.1 | 247.6 | 540 |
| Chattel guarantee | 0.951 | 0.217 | 1 |
| Mortgage guarantee | 0.132 | 0.163 | 0 |
| Personal guarantee | 0.219 | 0.413 | 0 |
| Destination Working Capital | 0.0928 | 0.290 | 0 |
| Destination Fixed Assets | 0.289 | 0.453 | 0 |
| Destination Housing Improvement | 0.368 | 0.482 | 0 |
| Destination Consumption | 0.237 | 0.426 | 0 |
| Destination Others | 0.0131 | 0.114 | 0 |
| Production | 0.120 | 0.325 | 0 |
| Transport | 0.148 | 0.355 | 0 |
| Construction | 0.732 | 0.443 | 1 |
| **Loan officer covariates** | | | |
| Female loan officer | 0.613 | 0.487 | 1 |
| Age loan officer | 25.29 | 4.185 | 23.73 |
| Overall loan officer experience (# of loans processed) | 29.42 | 29.27 | 20 |
| Opposite loan officer sex experience (# of loans processed) | 17.43 | 22.45 | 9 |
| Opposite loan officer arrear experience (# of loans in arrears) | 9.640 | 13.12 | 4 |
| Opposite loan officer experience above median (# of loans processed) | 0.501 | 0.500 | 1 |
| **Branch size and competition variables** | | | |
| Branch size of lender (# of loan officers) | 12.81 | 8.033 | 10 |
| Branch size of lender above median (# of loan officers) | 0.528 | 0.499 | 1 |
| Competition (# branches per 100,000 inhabitants) | 7.622 | 3.497 | 7.460 |
| Competition (# branches above median number of branches) | 0.514 | 0.500 | 1 |

This table reports summary statistics [mean, standard deviation (SD), and median].

**Table 2** Test for differences in borrower characteristics

| Variable | Coefficient (1) |
|---|---|
| Age borrower | -0.1741 |
| | (0.8291) |
| Total assets (in USD) | 166 |
| | (3,528) |
| Monthly business profits (in USD) | -7.50 |
| | (70.10) |
| Applied loan amount (in USD) | -29.21 |
| | (187.23) |
| Applied loan maturity (in days) | -15.35 |
| | (16.87) |
| Personal guarantee | -0.0111 |
| | (0.0309) |
| Mortgage guarantee | 0.0146 |
| | (0.0231) |
| Chattel guarantee | 0.0073 |
| | (0.0157) |
| Destination Working Capital | 0.0335 |
| | (0.0226) |
| Destination Fixed Assets | -0.0287 |
| | (0.0319) |
| Destination Housing Improvement | -0.0180 |
| | (0.0344) |
| Destination Consumption | 0.0195 |
| | (0.0292) |
| Destination Others | -0.0063 |
| | (0.0083) |
| Production | -0.0123 |
| | (0.0141) |
| Transport | -0.0089 |
| | (0.0252) |
| Construction | 0.0212 |
| | (0.0301) |
| Age loan officer | 0.0002 |
| | (0.0005) |
| Opposite loan officer sex experience (# of loans processed) | 0.4842 |
| | (0.7510) |
| Opposite loan officer arrear experience (# of loans in arrears) | 0.2843 |
| | (0.4455) |
| Opposite loan officer experience above median (# of loans processed) | 0.0330 |
| | (0.0221) |
| Branch size of lender above median (# of loan officers) | 0.0015 |
| | (0.0154) |
| Competition above median (# of branches per 100,000 inhabitants) | 0.0046 |
| | (0.0234) |
| P-value on joint null hypothesis | 0.9426 |

This table reports a test of difference in borrower and loan officer (time-variant) characteristics. Column (1) reports the coefficient from regressions of the respective characteristic on a dummy variable taking on the value of one if a borrower is matched with an opposite sex loan officer as described by equation (1) in the main text. The regressions are estimated conditioned on loan officer, branch, sector, and time fixed effects. The p-value reported at the bottom of column (1) is an F-test of the joint significance of the variables listed in the table. Each row of column (1) shows the coefficient from separate regressions of the predetermined variables. Standard errors are clustered at the branch-sector-year level. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

**Table 3** Gender match and credit demand

| Dependent variable | Likelihood of applying for a second loan | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Borrowers assigned to opposite-sex officers | -0.0633** | -0.0672** | -0.0668** | -0.0693** |
| | (0.0307) | (0.0310) | (0.0314) | (0.0316) |
| Adjusted R-squared | 0.0640 | 0.0758 | 0.0763 | 0.0786 |
| Observations | 4,890 | 4,887 | 4,887 | 4,887 |
| Mean dependent variable | 0.651 | 0.651 | 0.651 | 0.651 |
| Covariates | No | Yes | Yes | Yes |
| Trend | No | No | Yes | Yes |
| Contract details | No | No | No | Yes |

This table reports regression results with the likelihood of applying for a second loan as the dependent variable. Likelihood of applying for a second loan is a dummy variable that takes on the value of one if first-time borrowers apply for an additional loan. The regression in column (1) is estimated conditioned on loan officer, branch, sector, and time fixed effects. In column (2), borrower and loan officer covariates are added, in column (3) branch-year fixed effects are added, and in column (4) loan contract details are added. 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 4** 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) |
| Borrowers assigned to opposite-sex officers | -0.1124** | 0.0011 | -0.1205** | 0.0146 | -0.1193** | 0.0095 |
| | (0.0561) | (0.0332) | (0.0555) | (0.0343) | (0.0555) | (0.0329) |
| P-value of Wald test | 0.0974 | | 0.0538 | | 0.0621 | |
| Trend | No | No | Yes | Yes | Yes | Yes |
| Overall experience | No | No | No | No | Yes | Yes |
| Adjusted R-squared | 0.0766 | 0.0675 | 0.0806 | 0.0904 | 0.0827 | 0.0895 |
| Observations | 2,439 | 2,451 | 2,436 | 2,451 | 2,436 | 2,451 |
| Mean dependent variable | 0.651 | 0.656 | 0.646 | 0.655 | 0.646 | 0.655 |

This table reports regression results with the likelihood of applying for a second loan as the dependent variable. Likelihood of applying for a second loan is a dummy variable that takes on the value of 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 are estimated with the full set of fixed effects including loan officer, sector, time, and branch fixed effects as well as the covariates presented in Table 1. Further controls are added as indicated in the table. 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** Credit demand, branch size, competition, and loan officer experience

| Dependent variable | Likelihood of applying for a second loan | | | |
|---|---|---|---|---|
| | Small branches | Large branches | Small branches | Large branches |
| | (1) | (2) | (3) | (4) |
| **Panel A: Branch size** | | | | |
| Borrowers assigned to opposite-sex officers | -0.1445*** | -0.0391 | -0.1535*** | -0.0338 |
| | (0.0469) | (0.0351) | (0.0478) | (0.0333) |
| P-value of Wald test | 0.0587 | | 0.0299 | |
| Trend | No | No | Yes | Yes |
| Adjusted R-squared | 0.0470 | 0.0938 | 0.0499 | 0.0985 |
| Observations | 2,304 | 2,583 | 2,304 | 2,583 |
| Mean dependent variable | 0.630 | 0.674 | 0.630 | 0.674 |
| **Panel B: Experience and branch size** | Low experience | | High experience | |
| | Small branches | Large branches | Small branches | Large branches |
| Borrowers assigned to opposite-sex officers | -0.2662*** | -0.0408 | 0.0913 | -0.0384 |
| | (0.0870) | (0.0596) | (0.1133) | (0.0406) |
| P-value of Wald test | | 0.0183 | 0.0068 | 0.0083 |
| Trend | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.0834 | 0.0875 | 0.0550 | 0.1137 |
| Observations | 1,248 | 1,188 | 1,056 | 1,395 |
| Mean dependent variable | 0.630 | 0.688 | 0.620 | 0.656 |
| **Panel C: Competition** | Low competition | High competition | Low competition | High competition |
| Borrowers assigned to opposite-sex officers | -0.1403*** | 0.0082 | -0.1415*** | 0.0068 |
| | (0.0466) | (0.0583) | (0.0475) | (0.0591) |
| P-value of Wald test | 0.0441 | | 0.0451 | |
| Trend | No | No | Yes | Yes |
| Adjusted R-squared | 0.0742 | 0.0775 | 0.0761 | 0.0761 |
| Observations | 1,865 | 1,970 | 1,865 | 1,970 |
| Mean dependent variable | 0.625 | 0.658 | 0.625 | 0.658 |
| **Panel D: Experience and competition** | Low experience | | High experience | |
| | Low competition | High competition | Low competition | High competition |
| Borrowers assigned to opposite-sex officers | -0.3367*** | -0.0506 | -0.0012 | -0.0010 |
| | (0.0883) | (0.0847) | (0.0783) | (0.0475) |
| P-value of Wald test | | 0.0096 | 0.0026 | 0.0001 |
| Trend | Yes | Yes | Yes | Yes |
| Adjusted R-squared | 0.1221 | 0.0636 | 0.0586 | 0.0746 |
| Observations | 805 | 1,009 | 1,060 | 961 |
| Mean dependent variable | 0.625 | 0.641 | 0.661 | 0.671 |

This table reports regression results with the likelihood of applying for a second loan as the dependent variable. In Panel A we split the sample according to the median branch size measured as number of loan officers per branch. In Panel B we further split the samples according to the median loan officer experience with the opposite sex. In Panel C we split the sample according to the median branch ratio measured as number of bank branches per 100,000 inhabitants per region. In Panel D we further split the samples according to the median loan officer experience with the opposite sex. All regressions are estimated with the full set of fixed effects including loan officer, sector, time, and branch fixed effects as well as the covariates presented in Table 1. Further controls are added as indicated in the table. 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** Loan conditions and loan officer experience

| Dependent variable / Sample | All | | Low experience | High experience | Low experience | High experience |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Interest rate** | 0.0038*** | 0.0038*** | 0.0058*** | 0.0010 | 0.0060*** | 0.0018 |
| | (0.0013) | (0.0013) | (0.0019) | (0.0015) | (0.0020) | (0.0015) |
| P-value Wald test | | | | 0.0386 | | 0.0797 |
| Adjusted R-squared | 0.6086 | 0.5401 | 0.6601 | 0.6327 | 0.6622 | 0.6354 |
| Mean dependent variable | 0.137 | 0.137 | 0.137 | 0.137 | 0.137 | 0.137 |
| **Loan maturity** | -23.0375** | -21.8727* | -55.9443*** | 4.8330 | -54.5043*** | 2.5779 |
| | (11.3247) | (11.2403) | (18.5133) | (10.9866) | (18.6902) | (10.7376) |
| P-value Wald test | | | | 0.0039 | | 0.0072 |
| Adjusted R-squared | 0.7166 | 0.7223 | 0.7497 | 0.7132 | 0.7511 | 0.7135 |
| Mean dependent variable | 501.7 | 501.7 | 482.3 | 521.4 | 482.3 | 521.4 |
| **Loan amount** | -23.5618 | -18.6460 | -196.8326* | 92.1129 | -196.1799* | 63.1906 |
| | (69.8665) | (69.6279) | (117.6259) | (123.9916) | (117.5285) | (119.2544) |
| P-value Wald test | | | | 0.0922 | | 0.1224 |
| Adjusted R-squared | 0.7920 | 0.7919 | 0.7898 | 0.8058 | 0.7897 | 0.8062 |
| Mean dependent variable | 2,360 | 2,358 | 2,066 | 2,652 | 2,066 | 2,652 |
| **Average effect** | -0.1051*** | -0.0882*** | -0.1799*** | 0.0099 | -0.1803*** | -0.0100 |
| | (0.0332) | (0.0313) | (0.0385) | (0.0398) | (0.0383) | (0.0402) |
| Trend | No | Yes | Yes | Yes | Yes | Yes |
| Overall experience | No | No | No | No | Yes | Yes |
| Observations | 4,887 | 4,887 | 2,435 | 2,452 | 2,435 | 2,452 |

Each cell presents the result from a separate regression where the columns indicate different samples (all, low experience, and high experience) and the rows indicate different outcome variables (interest rate, loan maturity, loan amount, and the average effect size). All regressions are estimated with the full set of fixed effects including loan officer, time, sector, and branch fixed effects as well as the covariates presented in Table 1. Columns (5) and (6) also contain loan officers' overall 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** Loan conditions, branch size, and loan officer experience

| Dependent variable / Sample | Small branches | Large branches | Low experience | | High experience | |
|---|---|---|---|---|---|---|
| | | | Small branches | Large branches | Small branches | Large branches |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Interest rate** | 0.0069*** | 0.0030** | 0.0094*** | 0.0064** | 0.0041 | -0.0009 |
| | (0.0021) | (0.0014) | (0.0035) | (0.0026) | (0.0035) | (0.0012) |
| P-value Wald test | | 0.0873 | | 0.4055 | 0.2224 | 0.0008 |
| Adjusted R-squared | 0.6896 | 0.6136 | 0.7460 | 0.6194 | 0.6363 | 0.6648 |
| Mean dependent variable | 0.137 | 0.137 | 0.137 | 0.141 | 0.134 | 0.132 |
| **Loan maturity** | -14.3811 | -22.9386* | -73.7680*** | -49.9160* | 15.1128 | 4.9993 |
| | (15.4571) | (12.8028) | (26.3334) | (25.2552) | (18.4370) | (11.3726) |
| P-value Wald test | | 0.6175 | | 0.4460 | 0.0009 | 0.0016 |
| Adjusted R-squared | 0.7343 | 0.7311 | 0.7538 | 0.7658 | 0.7498 | 0.7088 |
| Mean dependent variable | 511.2 | 487.1 | 511.2 | 485.7 | 547.2 | 488.7 |
| **Loan amount** | -33.9747 | 1.0369 | -429.7324 | -81.1085 | -6.7459 | 58.1094 |
| | (118.0792) | (70.2179) | (260.0850) | (91.4396) | (178.0805) | (132.9163) |
| P-value Wald test | | 0.7699 | | 0.1285 | 0.1247 | 0.0508 |
| Adjusted R-squared | 0.8028 | 0.8118 | 0.7565 | 0.8735 | 0.8704 | 0.7590 |
| Mean dependent variable | 2,312 | 2,429 | 2,312 | 2,578 | 2,706 | 2,260 |
| **Average effect** | -0.1167*** | -0.0767*** | -0.2851*** | -0.1667*** | -0.0301 | 0.0322 |
| | (0.0419) | (0.0264) | (0.0681) | (0.0357) | (0.0565) | (0.0410) |
| Observations | 1,916 | 2,971 | 1,022 | 1,413 | 894 | 1,558 |

Each cell presents the result from a separate regression where the columns indicate different samples (small and large branches, low and high experience split by small and large branches) and the rows indicate different outcome variables (interest rate, loan maturity, loan amount, and the average effect size). All regressions are estimated with the full set of fixed effects including loan officer, time, sector, branch, and branch-by-year fixed effects as well as the covariates presented in Table 1. 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** Loan conditions, competition, and loan officer experience

| Dependent variable / Sample | Low competition | High competition | Low experience | | High experience | |
|---|---|---|---|---|---|---|
| | | | Low competition | High competition | Low competition | High competition |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Interest rate** | 0.0053* | 0.0039*** | 0.0154*** | 0.0080*** | -0.0005 | 0.0001 |
| | (0.0031) | (0.0010) | (0.0033) | (0.0021) | (0.0034) | (0.0011) |
| P-value Wald test | | 0.6369 | | 0.0273 | 0.0001 | <0.0001 |
| Adjusted R-squared | 0.7314 | 0.6721 | 0.8095 | 0.7046 | 0.7239 | 0.6615 |
| Mean dependent variable | 0.147 | 0.144 | 0.147 | 0.145 | 0.145 | 0.143 |
| **Loan maturity** | 13.3452 | -3.7738 | 2.2559 | 14.3168 | 30.6563*** | -13.0601** |
| | (12.3818) | (4.3181) | (24.2045) | (20.1232) | (10.8939) | (5.1821) |
| P-value Wald test | | 0.1601 | | 0.6516 | 0.2431 | 0.4677 |
| Adjusted R-squared | 0.7437 | 0.6959 | 0.7356 | 0.7190 | 0.7540 | 0.6846 |
| Mean dependent variable | 452.9 | 499.6 | 452.9 | 502.7 | 467.3 | 497.3 |
| **Loan amount** | -36.3000 | -51.1138 | -224.0528 | -256.2145 | 23.6368 | -60.6969 |
| | (49.2812) | (72.4783) | (179.7619) | (217.3959) | (77.4313) | (66.5890) |
| P-value Wald test | | 0.8550 | | 0.8931 | 0.1951 | 0.3194 |
| Adjusted R-squared | 0.8590 | 0.8481 | 0.8730 | 0.8263 | 0.8577 | 0.8718 |
| Mean dependent variable | 2,108 | 1,727 | 2,108 | 1,854 | 2,475 | 1,636 |
| **Average effect** | -0.0561 | -0.0804*** | -0.2929*** | -0.1363 | 0.0827 | -0.0500* |
| | (0.0700) | (0.0224) | (0.0814) | (0.0877) | (0.0511) | (0.0303) |
| Observations | 1,342 | 1,468 | 559 | 678 | 783 | 790 |

Each cell presents the result from a separate regression where the columns indicate different samples (low and high competition, low and high experience split by low and high competition) and the rows indicate different outcome variables (interest rate, loan maturity, loan amount, and the average effect size). All regressions are estimated with the full set of fixed effects including loan officer, time, sector, branch, and branch-by-year fixed effects as well as the covariates presented in Table 1. 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** Arrears > 30 days and loan officer experience

| Dependent variable/Sample | All | | Low experience | High experience | Low experience | High experience |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Borrowers assigned to opposite-sex officers | -0.0123 | -0.0143 | -0.0053 | -0.0251 | -0.0041 | -0.0279 |
| | (0.0177) | (0.0176) | (0.0261) | (0.0277) | (0.0256) | (0.0273) |
| P-value Wald test | | | | 0.5541 | | 0.4773 |
| Adjusted R-squared | 0.1120 | 0.1146 | 0.1603 | 0.0513 | 0.1610 | 0.0513 |
| Observations | 4,887 | 4,887 | 2,435 | 2,452 | 2,435 | 2,452 |
| Mean dependent variable | 0.0513 | 0.0512 | 0.0436 | 0.0587 | 0.0436 | 0.0587 |
| Trend | No | Yes | Yes | Yes | Yes | Yes |
| Overall experience | No | No | No | No | Yes | Yes |

This table reports regression results with the arrear occurrence > 30 days as the dependent variable. The variable takes on the value of one if a borrower was in arrears for more than 30 days anytime during the lifetime of the loan. Each cell presents the result from a separate regression where the columns indicate different samples (all, low experience, and high experience). All regressions are estimated with the full set of fixed effects including loan officer, time, sector, and branch fixed effects as well as the covariates presented in Table 1. Columns (5) and (6) also contain loan officers' overall 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 10** Arrears > 30 days, branch size, competition, and loan officer experience

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Experience and branch size** | | | Low experience | | High experience | |
| | Small branches | Large branches | Small branches | Large branches | Small branches | Large branches |
| Borrowers assigned to opposite-sex officers | -0.0053 | -0.0162 | -0.0161 | 0.0150 | 0.0716* | -0.0497** |
| | (0.0333) | (0.0219) | (0.0457) | (0.0412) | (0.0363) | (0.0214) |
| P-value Wald test | | 0.7657 | | 0.5484 | 0.0921 | 0.4389 |
| Adjusted R-squared | 0.1238 | 0.1152 | 0.1680 | 0.1675 | -0.0406 | 0.0633 |
| Observations | 1,916 | 2,971 | 1,022 | 1,413 | 894 | 1,558 |
| Mean dependent variable | 0.0646 | 0.0303 | 0.0646 | 0.0391 | 0.0729 | 0.0201 |
| **Panel B: Competition and branch size** | | | Low experience | | High experience | |
| | Low competition | High competition | Low competition | High competition | Low competition | High competition |
| Borrowers assigned to opposite-sex officers | -0.0123 | -0.0429 | -0.0329 | -0.0425 | 0.0006 | -0.0365 |
| | (0.0273) | (0.0275) | (0.0341) | (0.0318) | (0.0272) | (0.0336) |
| P-value Wald test | | 0.3927 | | 0.8095 | 0.0661 | 0.9328 |
| Adjusted R-squared | 0.0203 | 0.1109 | 0.0473 | 0.1454 | -0.0299 | 0.0484 |
| Observations | 1,342 | 1,468 | 559 | 678 | 783 | 790 |
| Mean dependent variable | 0.0203 | 0.1109 | 0.0858 | 0.0250 | 0.100 | 0.0268 |

This table reports regression results with the arrear occurrence > 30 days as the dependent variable. The variable takes on the value of one if a borrower was in arrears for more than 30 days anytime during the lifetime of the loan. In Panel A we split the sample according to the median branch size measured as number of loan officers per branch (columns 1 and 2) and further to the median loan officer experience with the opposite sex (columns 3 to 6). In Panel B we split the sample according to the median branch ratio measured as number of bank branches per 100,000 inhabitants per region (columns 1 and 2) further to the median loan officer experience with the opposite sex (columns 3 to 6). All regressions are estimated with the full set of fixed effects including loan officer, time, sector, branch, and branch-by-year fixed effects as well as the covariates presented in Table 1. Standard errors clustered at the branch-sector-year level are shown in parentheses. ***, **, * indicate significance at the 1, 5, and 10 percent level, respectively.

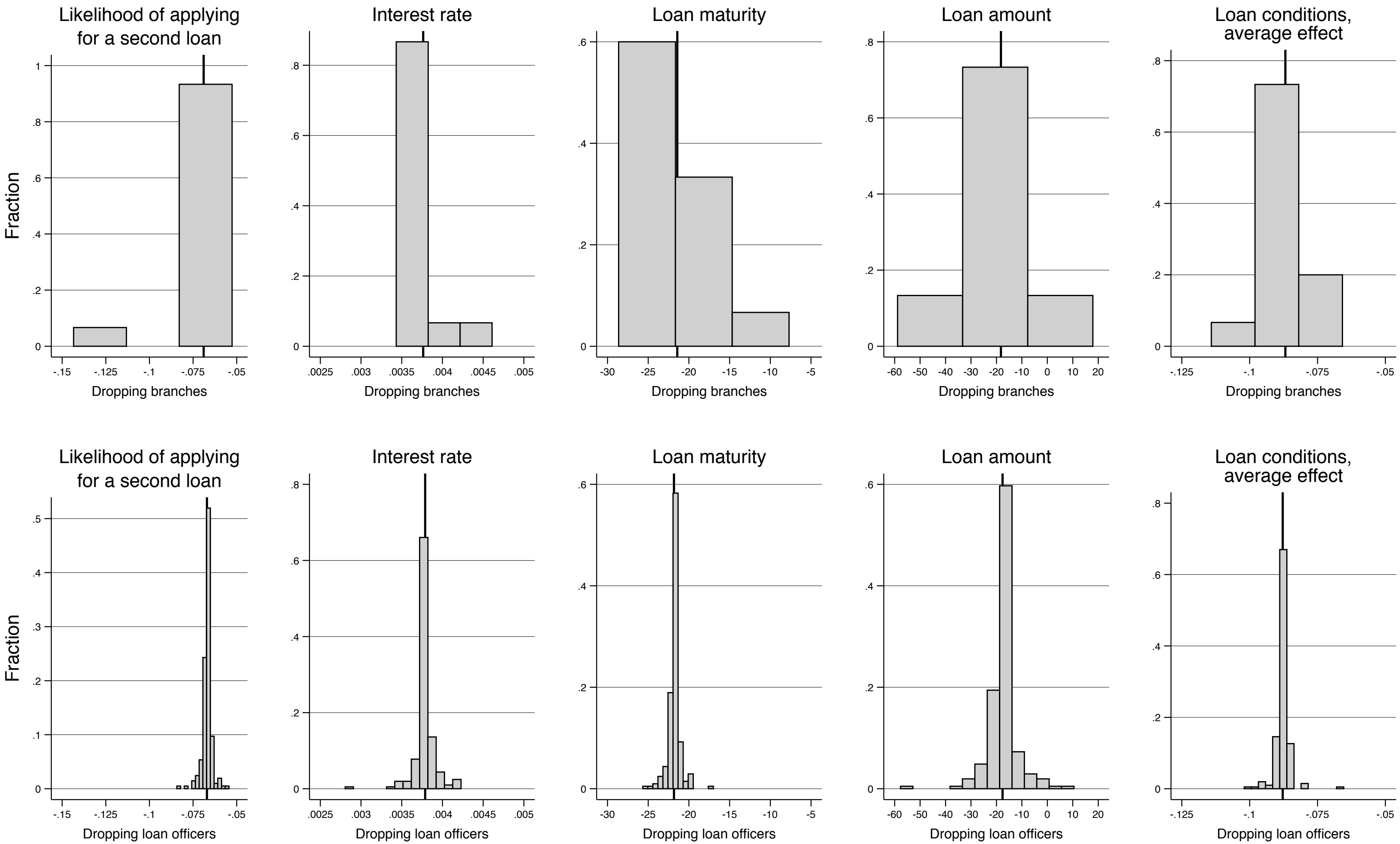


**Figure A1**. The histograms show the distribution of the effect of the officer-borrower gender match when branches (upper row) and officers (lower row) are dropped one by one. Black lines indicate the estimated coefficient using the full sample.