Journal of Business Ethics
https://doi.org/10.1007/s10551-024-05789-7

ORIGINAL PAPER

Does Soft Information Mitigate Gender Bias in Corporate Lending?

Udichibarna Bose[1] · Stefano Filomeni[1] · Elena Tabacco[2]

Received: 5 December 2023 / Accepted: 27 July 2024

Abstract
Gender bias in leadership and decision-making is a well-documented and pervasive topic that continues to garner significant attention in academic research and business literature. In this paper, by exploiting a unique proprietary dataset of 550 mid-corporate loan applications managed by a major European bank, we explore how the use of soft information influences lending decisions of female loan officers as compared to their male counterparts. We find that use of soft information reduces information asymmetry which helps female officers in making diligent lending decisions resulting in increased granted credit with a lower default probability. We also investigate gender affinity within the banking organisation and find that female loan approvers are more likely to be supportive of their subordinate female loan officers by approving more credit to the loan applications handled by female loan officers. Finally, we examine the possible mechanisms that can explain these results, and find that female loan officers are able to better collect and use soft information as they cultivate and maintain deeper firm-bank relationships with their clients due to higher threat of losing or being penalized in their jobs for any possible errors. We also rule out any other possible explanations such as differences in workload, work experience, loan officers' optimism, managerial ability, and screening capabilities between female and male loan officers. Our findings carry important policy implications, reflected in the optimal allocation of capital in the economy and the reduction of gender-related exclusion, which is vital in creating an equitable society and fostering a more ethical and inclusive workplace.

Keywords Soft information · Corporate lending · Female loan officers · Gender bias · Bank organization

JEL Classification D82 · G21 · J16 · M14

Introduction

The link between gender bias and business ethics literature is a complex and multifaceted issue that involves examining the ways in which gender-related biases can impact ethical decision-making, corporate culture, and overall business practices. Women are often underrepresented in top leadership positions, including executive roles and board seats. This phenomenon is commonly referred to as the "glass ceiling". Various studies highlight the challenges women face in ascending to leadership positions, despite comparable qualifications and capabilities (Cozarenco & Szafarz, 2018; Girardone et al., 2021; Malmström et al., 2024). Hence, addressing gender bias in business is not just an ethical imperative; it also makes good business sense. The concept of gender bias can also extend to how soft information, which refers to qualitative, non-financial information, is perceived and utilized in various contexts, including decision-making in business and finance. Soft information plays a role in investment and lending decisions, and gender biases may contribute to suboptimal outcomes and missed opportunities. Hence, addressing gender bias in the handling of soft information requires a commitment to fostering inclusion and transparent decision-making processes. In this paper, we dig deeper into this and explore how the use of soft information can reduce gender bias in bank lending decisions by using a unique proprietary loan-level dataset managed by a major European bank.

✉ Stefano Filomeni
stefano.filomeni@essex.ac.uk

Udichibarna Bose
ubose@essex.ac.uk

Elena Tabacco
elena.tabacco@yahoo.it

1 University of Essex, Essex Business School, Finance Group, Colchester CO4 3SQ, UK

2 Voghera (Pavia), Italy

Published online: 24 September 2024

The 2007–2008 global financial crisis (henceforth, GFC) exposed not only the inherent fragility of the system but also the costs that an excessive risk culture and a short-term focus can inflict on the society. More specifically, this led to important post-crisis developments towards reducing gender bias within organisations due to regulatory, social, and other forces, and improving gender diversity to gradually help place firms onto more stable ground (Girardone et al., 2021). This is also consistent with recent studies that show that diverse and inclusive businesses lead to better outcomes through lower market volatility, reduced fraud, better performance, and higher rates of innovation and productivity (e.g., Cumming et al., 2015; Erhardt et al., 2003; Østergaard et al., 2011). In this paper, we exploit a unique proprietary loan-level dataset of 550 mid-corporate loan applications managed by the Corporate and Investment Banking Division (CIB) of a major European bank in the post-GFC period from September 2011 to September 2012 to explore how the use of soft information can help female loan officers in making diligent lending decisions.

We focus on the aftermath of the 2007–2008 financial crisis, which was hardly a typical period in European banking history with increasing regulations aimed, among others, at breaking the glass ceiling faced by women in finance that even "doubles" in specific sectors, such as banking, where a strong masculine culture constraints them from advancing their career even if they have made it to middle management positions (the so-called "double glass ceiling") (Ryan et al., 2016). Moreover, the mid-corporate segment of the loan market is typically less plagued by problems of information opaqueness than SMEs. For this reason, lending to the mid-corporate segment should be less vulnerable to soft information-related problems across the bank's organizational structure.

The granularity of our dataset allows us to identify aspects related to both hard and soft information for each loan application. As for hard information, for each loan application, we observe borrower characteristics, loan characteristics, and loan officer characteristics including the gender of the loan officer in charge of monitoring the given credit relationship.[1] Any payment difficulties experienced by a borrower can therefore be directly linked to the specific loan officer in charge of the credit relationship, thus allowing us to investigate not only lending decisions but also lending outcomes. Furthermore, the dataset includes granular information about the gender of the loan approver, organisational distance between the bank's headquarters and the lending branch, operational distance between the lending branch and the borrower, and breadth and length of the firm–bank relationship.

As for soft information, since by assumption it is intangible and unobservable in practice, we exploit the opportunity of the loan officer to override final ratings by "hardening" the amount of (unobservable) soft information collected through repeated interactions with the same borrower over the course of their banking relationship. To study the role of "hardened" soft information in credit decisions by female loan officers, we therefore measure soft information as loan officers' use of discretion to override the credit score produced in the rating-assignment process that gives discretionary opportunity to loan officers to either upgrade or downgrade the credit rating of the borrowing firm based on a private algorithm of the bank. We refer to this type of discretion as "uncodified discretion", a type of "hardening" also documented by supervisors (BCBS, 2005; Federal Reserve, 2011) and in the academic literature (Brown et al., 2012, 2015; Filomeni et al., 2021; Gropp & Guettler, 2018; Montalvo & Reynal-Querol, 2020; Wang, 2020). Our setting is therefore, well suited to explore how the use of soft information by female loan officers influences their lending decisions as compared to their male counterparts.

Our paper contributes to the current literature in several ways. Firstly, we contribute to the studies exploring the nexus between gender bias and information sharing. Empirical works document mixed evidence as to whether men and women are different with respect to processing information and reaching more ethical decisions in businesses. The existing literature shows that men are more likely to behave unethically, and women are more likely to question certain acts as unethical (Beu et al., 2003; McCabe et al., 2006). In this respect, we focus on bank lending to investigate the ethics-related gender gap when using soft information in decision-making. Even though the role of gender bias in bank lending is well-explored by the extant literature (Beck et al., 2013; Bellucci et al., 2010; Cozarenco & Szafarz, 2018), existing studies neglect to specifically investigate how the use of soft information mitigates gender bias. To the best of our knowledge, this paper is the first one that aims to fill this gap in the literature by using proprietary mid-corporate loan-level data.

Efficient capital allocation is undoubtedly the primary role of financial institutions and generally believed to be far more relevant to economic growth than other factors (Stiglitz, 1989). The extant literature shows how better information processing and sharing within the banking organization can not only help in capital allocation (Collier & Mayer, 1989; Stiglitz, 1989) but also to better monitor and estimate the credit risk of borrowers. Our findings show that the use

[1] We were assured by the data providing bank that the assignment of applicants to loan officers (or the choice of applicants by loan officers) is random and mainly based on the availability of loan officers at the time the applicant appears at its closest bank's corporate branch. This random component in the data allows us to formally test and rule out that the borrower pools are different across male and female loan officers. More details regarding the identification strategy are provided in Sect. 3.2 of the paper.

of soft information helps female officers to reach accurate lending decisions that result in increased granted credit with a lower default probability. These results imply that the use of soft information reduces information asymmetry in lending and improves loan performance. The use of soft information helps female officers to accurately monitor the applicant's ongoing credit situation and repayment history throughout the credit relationship, leading to better quality and reduced default probability of the loans approved (Behr & Sonnekalb, 2012; Pagano & Jappelli, 1993).

Secondly, we dig into the extant literature on gender affinity which mainly focuses on the role of gender in lender–borrower positions within lending transactions (Agier & Szafarz, 2013; Aubert et al., 2009; Bellucci et al., 2010; Blanco-Oliver et al., 2021) and suggests that female loan officers are more likely to lend to female borrowers resulting in a reduction of default rate on granted loans. The gender affinity hypothesis is based on the presumption that loan granting rates are higher when credit officers and applicants have common experiential (social, economic, and cultural) backgrounds. However, in the banking industry where males are overrepresented in top management positions, there might be other challenges faced by women subordinates affecting their lending decisions. In this paper, we examine gender affinity between loan officer and the banking manager with loan approving authority involved in the lending process of a large banking organization. We find that female loan approvers at the managerial level are more likely to be supportive of their subordinate female loan officers by approving more credit to the loan applications which are handled by them. These results are in line with the empirical literature on organisational management that studies how women's interpersonal microsystem that includes colleagues, supervisors, mentors, and their families, can contribute to their career progression (Lau et al., 2023). The literature highlights that when there is an increase in the share of women in top management at the workplace, it benefits women in subordinate positions as they act as role models (Stojmenovska, 2019), provide critical feedback regarding their performance (Heilman & Alcott, 2001) aiding the development of women's leadership identity (Chen & Houser, 2019), and enhancing their likelihood of pursuing promotion and career advancement (Fernando et al., 2018). While gender affinity can lead to significant benefits in terms of mitigating gender bias and promoting women's support, it is also crucial to navigate its implications to ensure that it does not lead to exclusion and discrimination which are vital in creating a just and equitable society.

Lastly, we explore the various possible mechanisms that can explain the capability of female loan officers in processing soft information better. We find two potential explanations for this. Firstly, female loan officers are capable of cultivating deeper relationships with their clients that helps them to collect better soft information and improve their monitoring capabilities (Beck et al., 2013). Secondly, we provide evidence in support of the "mistake-punishment trade-off" argument highlighted by Montalvo and Reynal-Querol (2020). This argument shows that female loan officers may face a higher threat and penalty in terms of losing their job and can be more severely penalized in terms of career advancement as compared to their male counterparts. Female loan officers, therefore, have a higher incentive to better monitor their loan applications. Further, alternative explanations such as differences in workload, work experience, age, loan officers' optimism, managerial ability, and screening capabilities between female and male loan officers do not influence our main results.

Our findings carry important policy implications. They provide novel evidence to banks and regulators of the valuable human capital associated with female loan officers and their capability to build deeper firm–bank relationships by collecting valuable soft information on their clients. These results can also help banks and regulators to develop and implement ethically centred diversity and inclusion initiatives that go beyond mere compliance. These initiatives can help in fostering an inclusive workplace culture that values and celebrates gender diversity.

The remainder of this paper is structured as follows. In Sect. 2, we provide the literature review and hypothesis development, in Sect. 3 we present the bank's lending environment as well as details of its credit scoring mechanism. In Sect. 4, we present our data and provide some descriptive statistics. In Sect. 5, we describe our empirical methodology and present our main results. In Sect. 6, we test for different possible mechanisms underlying our main findings. In Sect. 7, we report several robustness tests, and we conclude the paper in Sect. 8.

Literature Review and Hypothesis Development

Soft Information and Gender Bias in Lending

This paper lies at the intersection of two extant streams of literature on soft information and gender bias in lending. The vast literature on soft information highlights its importance in lending decisions as it reflects different aspects of a borrower's creditworthiness that are not fully captured by hard information (Liberti, 2018; Michels, 2012; Qian et al., 2015). This literature suggests that cognitive constraints and behavioural biases of loan officers can influence the processing and interpretation of less salient, non-quantitative soft information, and this can affect their lending decisions. Other existing studies link the lending decisions to changes in loan officers' sentiments caused by the actual weather, outcomes of sports events, listening to TV shows (Agarwal et al., 2012; Cortes et al., 2016), negative shocks such as robberies (Morales-Acevedo & Ongena, 2020), and by their early career experiences as imprints a specific professional mind-set and attitude that affect their judgement and decision-making in the long-term (He et al., 2018; Schoar & Zuo, 2017). Other papers also focus on lenders' gender and behavioural biases in bank–firm relationships (e.g., Beck et al., 2013; Bellucci et al., 2010; Campbell et al., 2019). These empirical studies suggest that women generally perceive events as riskier and tend to be more risk averse and less self-confident than men, especially in the areas of financial decision-making and investments (Barber & Odean, 2001; Croson & Gneezy, 2009; Eckel & Grossman, 2008).

The other literature on gender bias and business ethics shows mixed evidence on how gender differences impact ethical behaviour in business. Some studies demonstrate that women tend to be more sensitive to ethical issues as women are associated with a better quality of financial reporting (Barua et al., 2010; Krishnan & Parsons, 2008) and accounting conservatism when a male CFO is replaced with a female CFO (Francis et al., 2015). These findings highlight women's cautiousness and their propensity to less expose themselves to risky corporate decisions. Eagly et al. (1981) suggest that women are more concerned about the quality of interpersonal relationships than men, and they are more prone to care for establishing and maintaining interpersonal social bonds. In contrast, the male gender role emphasizes independence and competitive behaviour, thus leading to a lower tendency to foster social relations. Moreover, Ridgeway and Diekema (1992) argue that women display more cooperative and group-oriented behaviour in group settings than men. Gilligan (1982) argues that men and women bring different values and traits to their work roles, which then influence their work-related decisions. Fletcher (1999) suggests that, due to their social role, women carry the relational responsibility and engage in relational practices in the workplace. Women engage in a relational practice called "creating a team", which refers to women's social interactions associated with building a collective identity. Cozarenco and Szafarz (2018) capture gender biases in banks' loan allocations using a natural experiment of a regulatory change in France. Other studies highlight the differences between men and women in handling money. Women are expected to be more risk averse, which impacts the types of investments they make, and men are thought to have more confidence with money matters (Barber & Odean, 2001; Bliss & Potter, 2002). Therefore, previous research has examined the characteristics of women in corporations and their favourable traits that may enhance decision-making, tasks, and roles, paying special attention to firm performance (Bear et al., 2010; Tanaka, 2014).

However, an overlooked angle in existing studies is how the use of soft information that reduces asymmetric information can help to mitigate gender bias in lending decisions. The agency theory explains how asymmetric information can lead to adverse selection and moral hazard problems in credit markets due to lenders' inability to differentiate between safe and risky loan applicants, and to enforce safe use of granted funds leading to a market equilibrium with credit rationing and suboptimal allocation of capital (Stiglitz & Weiss, 1981). The empirical literature that studies the impact of information sharing on lending shows that the introduction of information sharing improves credit market performance and repayment behaviour. Overall, bank lending volume is found to be larger and credit risk to be lower in countries with more information sharing (Djankov et al., 2007; Jappelli & Pagano, 2002). Following these predictions, we expect that improved information sharing using soft information can help in reducing gender bias by improving credit access and reducing default rates among borrowing firms. Hence, we test the following hypothesis:

> ***Hypothesis 1:*** The use of soft information helps female loan officers to take better lending decisions resulting in increased granted credit with a lower default probability as compared to their male counterparts.

Gender Affinity in Lending Decisions

Another stream of literature shifts the focus to the role of economic agents who decide the loan approvals and the way in which their personality, experience, beliefs, and perceptions shape the credit relationships (Andersson, 2004; Hertzberg et al., 2010). Besides the separate impacts of gender on either side of the lending transaction, the particular gender pairing could have an impact on the lending decision. Empirical evidence shows that people's behaviour varies with the sex of the other party involved in the transaction. Eckel and Grossman (2001) highlight the effects of "chivalry" and "solidarity" to explain how in an ultimatum game the rate of acceptance by both males and females is higher when the proponent is a female. Gupta et al. (2009) show that both men and women perceive entrepreneurs to have predominantly masculine characteristics (masculine gender–role stereotype), while only women perceive entrepreneurs and females having similar characteristics (feminine gender–role stereotype). While Ben-Ner et al. (2004) document the existence of a gender-based envy which induces women to donate less to other women than to male recipients or recipients of unknown gender. Ravina (2008) advances the importance of gender-pairing in lending because "similarity breeds trust". In other words, lenders who share the same gender as the borrowers may experience a greater sense of solidarity with them, which could increase the likelihood of funding loans or granting larger credit amounts.

Kräft (2022) also suggests that getting women into leadership initiates a virtuous cycle. Consistent with the theory in organisational management, female leaders act as critical actors who bring about positive changes for women, which ultimately rebounds to their working conditions and labour force proportion. This argument especially holds for male-dominated industries. Thus, several studies such as Cardoso and Winter-Ebmer (2010) and Stojmenovska (2019) point out that an increase in the share of women in management at the workplace can, on average, benefit woman in subordinate positions because these employees have more role model managers who can support and mentor them. These represent relevant implications to rule out gender-related exclusion and discrimination, vital in creating an equitable society. Against the backdrop of the significance of female leaders in a male-dominated industry, there is no paper that studies the gender pairing between loan officers and loan approvers withing the banking organization. Hence, we aim to bridge this gap by testing the following hypothesis:

> ***Hypothesis 2:*** Female loan approvers are more likely to approve the loan applications managed by their subordinate female loan officers that incorporate soft information into their credit process.

Institutional Background

The Bank Lending Environment

The Corporate and Investment Banking Division (CIB) of our data-providing European bank, which is responsible for the mid-corporate loan applications that we analyse in this paper, is structured in the home country over 24 corporate branches in 12 different regions. These corporate branches are responsible for managing firm-bank relationships and submitting rating assessments and credit proposals to the bank's authorities. These corporate branches differ from traditional branches that mainly serve individuals and small firms. Hence, these corporate branches can be thought of *ad hoc* banking centres where all aspects of mid-corporate relations are managed and fostered. Within each corporate branch, loan officers are the ones accountable to develop credit relationships with the bank's mid-corporate clients. Corporate branches were established in recent years with the purpose to segregate relationships with mid-sized enterprises which are in need of specialized knowledge for sophisticated banking products and constant relationship monitoring and fostering. Specifically, these corporate branches reflect a new organizational structure of the bank established with the purpose of maintaining banking relationships with medium-large enterprises and keeping them separate from traditional banking associated with families and small firms.

Loan officers at CIB branches take charge of loan applicants from the beginning of the lending process, generating the rating and submitting a loan proposal to the relevant authority in the bank's hierarchy. The hierarchical level of approval is determined by a set of applicant and loan characteristics specified in the bank's credit policy manuals. The rules specifying approval delegation take into account the total exposure of the banking organization to the applicant company (or to the economic group to which the applicant company belongs in case of subsidiary corporations), the amount of credit for which the company applies, the applicant's credit score, and the strength of credit risk mitigation in the form of collateral and personal guarantees. Given that none of the corporate branches has been merged with another bank, we can reasonably assume that loan officers at these branches share the same corporate culture independent of their location. Finally, the compensation of loan officers includes, besides a fixed salary, a compensation component conditional on their individual performance in terms of loan volumes, which are distributed once a year at the discretion of the bank. Specifically, loan officers are assigned a personal loan budget each year in order to access minimum extra bonuses. Loan volumes above the budget threshold are then associated with greater bonuses.

Identification Strategy: Credit Scoring Mechanism

The bank uses a hybrid credit scoring process in which the borrower's final rating depends on both quantitative and qualitative information. Credit scoring information are computed and weighted based on an internal and proprietary rating algorithm that forecasts the firms' default probability. The credit scoring process is initiated by a loan officer at the local branch to which the company applies. Loan officers are assigned to applications randomly and according to a queuing system. When a loan officer starts the scoring process, the rating system of the bank automatically generates a statistical rating based on hard information that reflects the probability of default using the data mainly collected from the firm's financial statements. Statistical ratings are then corrected to consider the hard information collected from the national credit registry, giving rise to a modified statistical rating. At this stage of the credit scoring process, the loan officer must fill a qualitative questionnaire by answering several questions pre-defined by the bank, giving rise to an integrated rating that could confirm or deviate from the previously produced modified statistical rating. Even if some soft information may be captured by the integrated rating, the purpose of the qualitative questionnaire is to give loan officers the chance to inject non-verifiable hard information about their borrowers in credit scoring. To further illustrate

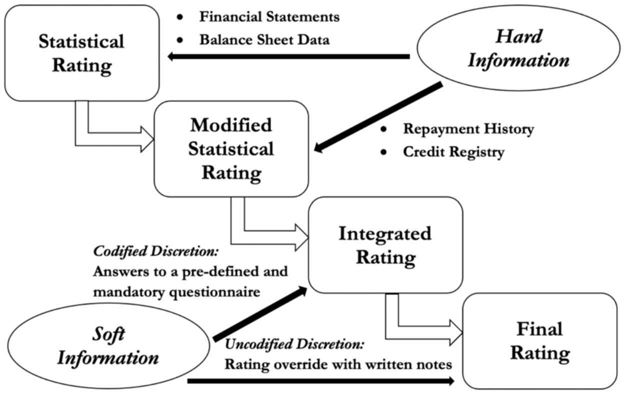

Fig. 1 The bank's credit rating process. Source: Credit rating policy adopted by our data provider

this point, we show the bank's credit scoring process (Fig. 1) and provide an example of the qualitative questionnaire in the Appendix.

In the final step of credit scoring, the loan officer could override the integrated rating, thus exploiting the soft information collected through interviews and frequent on-site visits throughout the course of the firm-bank relationship. The final output of the credit scoring process is therefore represented by the borrower's final rating.[2] These deviations of the final rating from the integrated rating reflects the exercise of uncodified discretion[3] and represents our proxy for the use of soft information. This measure is in line with Gropp and Guettler (2018) who proxy soft information with the deviations between financial (hard-based) and combined (hard- and soft-based) ratings. This approach is also supported by the findings in Degryse et al. (2013) who show that only non-verifiable soft information guide loan officer's discretion using detailed borrower information from one bank in Argentina.

The overrides of integrated ratings are closely monitored at the bank's headquarters. When using uncodified discretion, the loan officer must provide a written motivation to the senior management of the bank. Rating deviations may involve one or more rating notches resulting in rating upgrades or downgrades. The reasons for downgrading overrides range from commercial risks stemming from deterioration in the economic conditions in which the firm operates to marketing strategies not adequately defined, or even to regulatory changes that can compromise the value of the firm. Reasons for upgrading overrides can be related to factors that mitigate the applicant's credit risk such as penetration into markets with strong socio-economic development opportunities and expanding demand, participation in projects with strong creditworthy partners, or ongoing restructuring projects aimed at a reduction of the cost structure or a capital increase. The proposed rating upgrades need to be approved by the specialized *Rating Unit* located at the bank's headquarters. In contrast, downgrades are automatically approved within the system, even though the written notes produced by the loan officer are inspected by the loan reviewers at the headquarters. Hence, these rating overrides can result in possible reputational ramifications that can affect the future career prospects of loan officers. As the use of uncodified discretion by loan officers cannot be quantified into a well-specified objective metric (it can only be communicated within the banking organization by detailed explanatory notes), this type of non-mandatory subjective assessment of loan applications reflects the pure soft information "hardened" by loan officers.

Once loan officers generate final ratings, they cannot modify their rating assessments further. The given loan application, along with the generated final rating, then goes to the bank's manager with the loan approving authority. The hierarchical levels of approval depend on the client and loan characteristics as specified in the bank's credit policy manuals, as explained in Sect. 3.1.

Data and Summary Statistics

Data

The data used in this paper are collected from the credit files of mid-corporate loan applications (550 applications) managed (either eventually approved or denied) by the Corporate and Investment Banking (CIB) Division of a major European banking group spread over their home country from September 2011 to September 2012.[4] According to the bank policy rules, the mid-corporate segment is populated by firms with an annual turnover between EUR 150 million and EUR 1 billion. The European banking group is representative of the general population of banks in the Eurozone. The group has total assets of EUR 646 billion, a total market capitalization of about EUR 50 billion and subsidiaries in twelve central-eastern European and Mediterranean countries. Specifically, in the home country, the group is among the leading players with 14 affiliated banks and about 4500

[2] Specifically, the final rating varies from 1 to 15, where the fifteenth rating class represents the most creditworthy one and is equivalent to a S&P rating of AAA. Thus, the lower the numerical value, the riskier the borrower is.

[3] We use the terms "overrides" and "uncodified discretion" interchangeably throughout the paper.

[4] We acknowledge that the empirical analysis in this study covers a limited time-period; however, the literature has extensively used similar granular proprietary data with a limited time period (e.g., Beck et al., 2013; Filomeni et al., 2020; 2021; 2023; Liberti and Mian, 2009).

branches and covers a market share of about 15% in the loan and deposit markets. In particular, the lead bank (the data provider) operates in the home country (to which the data refer) with about 1,900 traditional branches located in 16 regions. Each credit application contains very granular information on the credit scoring process including the final and intermediate scores. In addition, each loan application contains detailed information on the applicant, loan characteristics, identity, and location of the loan officer in charge of the relationship, and the hierarchical level at which the loan was ultimately approved (or denied). We exclude applications related to borrower's intragroup-mergers and change in the bank managing the credit relationship within our given banking group. The definition of all the variables used in our empirical analysis, as well as their descriptive statistics, is provided in Table 1.

Summary Statistics

We report the detailed summary statistics in Table 1. As for the gender diversity dimension, female loan officers represent 22% of our sample and soft information use occurs in 19% of the cases.[5] Out of this 19%, the probabilities of upgrading and downgrading overrides are 13% and 6%, respectively. The average size of borrower's granted credit over total assets is 7.7%, while the average probability of default of the borrower is 7.9%. Further, the average loan officer in our bank is 49 years old with 21 years of work experience. The extant evidence on the influence of these variables on lending decisions is mixed. Agarwal and Wang (2009) and Agarwal and Ben-David (2014) document that older and more experienced loan officers have a higher loan approval rate, and their loans have a higher probability of defaulting, suggesting that risk aversion and career concerns are strongest at the beginning of their career. By contrast, Beck et al. (2013) find that loans underwritten and monitored by older officers have a lower probability of turning problematic, while Qian et al. (2015) show that loan officer's experience has no significant effect on loan prices and ex-post performance. Therefore, the expected impact of age and experience on the amount of credit granted and corporate default probability is a priori ambiguous.

[5] Out of this, 22% of the sample is represented by female loan officers. Female loan officers override ratings in 24% of the cases, as opposed to their male counterparts that override in 14% of the cases. In the remaining 76% of the cases, female loan officers confirm the integrated rating without overriding it.

Empirical Methodology and Results

Soft Information and Gender Bias in Lending

In this section, we study the impact of soft information used by female loan officers on their corporate lending decisions. We estimate the following OLS models on *granted credit/total assets* and *probability of default (PD)*:

$$\begin{aligned}\left(\frac{\text{Granted credit}}{\text{Total assets}}\right)_{ijk} = {} & \beta_0 + \beta_1 \text{female}_i * \text{soft information}_{ijk} \\ & + \beta_2 \text{female}_i + \beta_3 \text{soft information}_{ijk} \\ & + \beta_4 X_i + \beta_5 Y_j + \beta_6 Z_k \\ & + \text{D}_{area} + \text{D}_{industry} + \varepsilon_{ijk}\end{aligned} \tag{1}$$

$$\begin{aligned}\text{PD}_{ijk} = {} & \beta_0 + \beta_1 \text{female}_i * \text{soft information}_{ijk} \\ & + \beta_2 \text{female}_i + \beta_3 \text{soft information}_{ijk} \\ & + \beta_4 X_i + \beta_5 Y_j + \beta_6 Z_k + \text{D}_{area} + \text{D}_{industry} + \varepsilon_{ijk}\end{aligned} \tag{2}$$

where loan officer i grants a loan j to firm k. The dependent variables of *granted credit/total assets* is measured as the ratio of the amount of credit granted scaled by the borrowers' total assets and *PD* is the borrower's default probability computed by a private algorithm of the bank. We control for a set of loan officer (X_i), loan-level (Y_j), and borrower (Z_k) characteristics reflecting the firm's financial health and information transparency that influence the credit decisions of loan officers.

With respect to loan officer characteristics, we include the gender of the loan officer measured by the dummy variable *female*, in addition to other characteristics such as the *age* and *experience* of the given loan officer accountable for handling the loan application. Next, we include borrower's *total assets* which is a measure of firms' size and calculated as the logarithm of total assets. To reflect information opacity and capture financial risk, we include the *equity ratio* which is measured as the ratio of equity over total assets. We also include *collateral* and *global guarantee* as control variables. *Collateral* is a binary variable which takes the value of 1 if the credit line is collateralized and 0 otherwise, while *global guarantee* is a dummy variable that equals 1 if the credit line is backed by a guarantee of the parent company and 0 otherwise. Following the recent banking literature on reducing information asymmetries and monitoring costs (Petersen & Rajan, 2002; Degryse & Ongena, 2005; Agarwal and Hauswald 2010; Bellucci et al., 2013), we control for the *branch-to-borrower distance* measured as the geographical distance (in km) between the branch where the loan officer responsible for the bank-firm relationship operates and the headquarters of the applicant company, and for the *branch-to-headquarters distance* computed as the

Table 1 Descriptive statistics and variable description

Variable	Description	Obs	Mean	SD	Min	Max
Dependent variables						
Granted Credit/Tot. assets	Ratio of borrower's granted credit over total assets	455	0.077	0.12	0	0.87
Probability of default (PD)	Log of the probability of default of the borrower [%]	517	0.061 [7.9%]	0.16 [22.8%]	0 [0%]	0.69 [100%]
Default	Binary variable that equals 1 if the given borrower defaults (at the end of year 2012 or 2013) and 0 otherwise	550	0.050	0.21	0	1
Soft information variables						
Soft information	Binary variable equal to 1 if integrated rating ≠ final rating (override); 0 otherwise	483	0.19	0.39	0	1
Upgrading soft information	Binary variable equal to 1 if integrated rating < final rating (upward override); 0 otherwise	483	0.13	0.33	0	1
Downgrading soft information	Binary variable equal to 1 if integrated rating > final rating (downward override); 0 otherwise	483	0.06	0.23	0	1
Sentiment score	Binary variable equal to 1 if the sentiment score is below the 25th or above the 75th percentile of the distribution; 0 otherwise	550	0.48	0.49	0	1
Upward sentiment score	Binary variable equal to 1 if the sentiment score is above the 75th percentile of the distribution; 0 otherwise	550	0.25	0.43	0	1
Downward sentiment score	Binary variable equal to 1 if the sentiment score is below the 25th of the distribution; 0 otherwise	550	0.23	0.42	0	1
Firm-bank relationship variables						
Final rating	Final rating of a given borrowing firm	516	7.98	3.68	1	15
Scope of relationship	Binary variable equal to 1 if the borrower purchases at least one other banking product from the bank; 0 otherwise	550	0.52	0.50	0	1
Loan-level variables						
Exiting credit exposure	Credit amount that has already been granted to the borrowing firm	550	8,617,532	26,200,000	0	403,000,000
Approval level	Step variable taking values between 1 and 11 according to the hierarchical level with the power of loan approval	550	4.14	2.76	1	11
Collateral	Binary variable equal to 1 if the credit line is collateralized; 0 otherwise	550	0.39	0.49	0	1
Global guarantee	Binary variable equal to 1 if the credit line is backed by a guarantee from the parent company; 0 otherwise	550	0.15	0.35	0	1
Strength of covenants	Step variable equal to 0 if the strength of covenants attached to the loan application is low, 1 if medium, and 2 if high	550	1.24	0.62	0	2
Loan officer characteristics						
Female	Binary variable equal to 1 if the loan officer responsible for the credit relationship is a female; 0 otherwise	539	0.22	0.41	0	1

Table 1 (continued)

Variable	Description	Obs	Mean	SD	Min	Max
Age	Age in years of the loan officer responsible for the credit relationship	520	49	6	29	60
Experience	Years of experience of the loan officer within the bank	520	21	8	1	37
Branch % of female loan officers	Percentage of female loan officers in a given branch	550	0.21	0.21	0	0.8
LO-Approver gender	Binary variable equal to 1 if the loan officer and approver are of different gender, and 0 otherwise	352	0.29	0.45	0	1
Distance-related variables						
Branch-to-borrower distance (BBD)	Log of 1 + distance in kilometres between the branch in which the loan officer operates and the headquarters of the applicant company [km]	550	4.39 [795]	2.09 [2,523]	0.18 [0.2]	9.59 [14,753]
Branch-to-headquarters distance (BHD)	Log of 1 + distance in kilometres between the branch in which the loan officer operates and the bank's headquarters [km]	550	4.59 [290]	1.75 [390]	1.25 [2.5]	7.30 [1,482]
Borrower's characteristics						
Total assets	Logarithm of total assets [million euros]	472	18.01 [195]	1.78 [303]	12.32 [0.224]	21.59 [2370]
Total revenues	Logarithm of total revenues [million euros]	483	17.79 [201]	2.26 [346]	6.91 [0.001]	22.26 [4,660]
Leverage	Logarithm of long-term debt [million euros]	419	13.63 [37.2]	6.36 [77.9]	0 [0]	20.17 [573]
Capital ratio	Ratio of equity to total assets of the company	472	0.28	0.21	− 0.63	0.96
ROA	Ratio of net income to total assets	472	0.01	0.08	− 0.65	0.36
Liquidity	Ratio of cash liquidity to total assets	472	0.08	0.11	0	0.77
Share of long-term debt	Ratio of long-term debt to total debt	481	0.08	0.23	0	1
Group belonging	Binary variable equal to 1 if the borrower is part of an economic group; 0 if it is a stand-alone company	550	0.89	0.31	0	1

Source: The data are manually collected from our data provider

geographical distance (in km) between the lending branch and the bank's headquarters to account for possible frictions in transmitting soft information along the bank's hierarchy.

Further, to control for possible additional communication and organizational frictions with managers using the credit score to reach the lending decision, we control for the hierarchical design of our bank that involves eleven levels of approval at which the bank manager with loan approval authority might reside by including in all our regressions the step variable *approval level* which measures the distribution of loan approval authority within the banking organization. Moreover, as the delegation of loan approval authority is related to specific characteristics of loan applications and multiple hierarchical levels are located in the same branch/headquarters, this allows us to isolate the impact of information transmission problems related to physical distances between communicating parties.

We also control for whether the firm is part of a group using the dummy variable *group belonging* and for the breadth of the bank-firm relationship using *scope of relationship*, a binary variable that equals 1 if the borrower purchases at least one other banking product from the bank and 0 otherwise. Moreover, all estimated models control for the applicant's *final rating* to account for differences in the borrowers' risk profiles, for the borrower's *existing credit exposure*, and for the percentage of female loan officers in each branch (*branch % of female loan officers*) in line with Bellucci et al. (2010). Lastly, all regressions include four geographical area and industry dummies to control for

Table 2 Female loan officers and soft information

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default
Female	− 0.160**	0.031**
	(0.037)	(0.004)
Soft information	− 0.057	0.006*
	(0.067)	(0.002)
Female * Soft information	1.343**	− 0.043**
	(0.161)	(0.006)
Final rating	0.039	− 0.008**
	(0.016)	(0.001)
Age	− 0.243**	− 0.051**
	(0.044)	(0.006)
Experience	0.071***	− 0.003
	(0.003)	(0.002)
Collateral	− 0.006	− 0.013
	(0.013)	(0.005)
Global guarantee	− 0.301***	0.007
	(0.029)	(0.005)
Group belonging	0.046	0.004
	(0.021)	(0.002)
Approval level	0.170**	0.000
	(0.019)	(0.001)
Total assets	− 0.718***	0.004*
	(0.032)	(0.001)
Capital ratio	0.548**	− 0.011**
	(0.122)	(0.002)
Scope of relationship	0.149**	0.004
	(0.018)	(0.003)
Branch-to-borrower distance	0.023*	− 0.002**
	(0.007)	(0.001)
Branch-to-headquarters distance	− 0.140***	0.001
	(0.009)	(0.000)
Existing credit exposure	0.000***	0.000
	(0.000)	(0.000)
Branch % of female loan officers	− 0.230	− 0.037***
	(0.081)	(0.003)
Total revenues	0.152**	− 0.004***
	(0.016)	(0.000)
ROA	− 0.671**	− 0.114**
	(0.099)	(0.016)
Leverage	0.065***	− 0.000
	(0.004)	(0.000)
Strength of covenants	0.172***	0.002
	(0.006)	(0.002)
Liquidity	− 0.640***	0.044**
	(0.050)	(0.006)
Observations	326	322
R^2	0.20	0.39
Industry FE	Yes	Yes
Area FE	Yes	Yes

The table presents the results of the OLS regression analysis for the model of female loan officers and soft information where the dependent variables are the ratio *granted credit/total assets* (column 1) and the *probability of default* (column 2). The interaction term *female * soft information* captures the use of soft information by the female loan officer accountable for managing the firm-bank credit relationship. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively

unobserved characteristics of local credit market and credit demand that might be correlated with loan officer characteristics and discretion use. The standard errors are clustered at the industry level to control for heteroskedasticity and possible correlation of the error term within each industry.

We report the results of Eqs. (1) and (2) in Table 2. In column 1, we provide the results for *granted credit/total assets*, followed by the results for *PD* in column 2. The variable *female* captures the influence of gender bias in the absence of soft information. We find that, without the use of soft information, female loan officers have lower amounts of granted credit, followed by higher default rates. These results can be explained from the findings of behavioural and sociological research highlighted by Beck et al. (2013) and Doering (2018). Beck et al. (2013) highlight gender differences due to risk aversion between women and men, where a higher degree of risk aversion among female loan officers explains the restrictive behaviour in granting loans.[6] In addition, Doering (2018) and Blanco-Oliver et al. (2021) discuss the possibility that clients may be less compliant with female loan officers, based on sociological research, and find that female loan officers have more missed payments on their loans, thus increasing the riskiness of their loan portfolio compared to male loan officers.

However, when we focus on the main variable of interest *female * soft information* that captures the impact of soft information used by female officers in their corporate lending decisions as compared to their male counterparts, we find that female officers increase the amount of granted credit (coefficient of 1.343) and reduce the probability of corporate defaults (coefficient of − 0.043) in their lending

[6] Croson and Gneezy (2009) provide an excellent overview of the literature on differences in risk aversion between women and men, and other reasons for gender differences.

decisions. The economic magnitude of these coefficients suggests that a one standard deviation increase in soft information used by female loan officers (0.39) improves granted credit by 52.4% and reduces corporate defaults by 1.7% compared to male loan officers. Overall, these findings support our hypothesis 1 that when female loan officers use soft information that reduces asymmetric information, it helps them to more accurately assess the creditworthiness of borrowers which leads to better risk management, increases credit access, and reduces the likelihood of defaults.

Moving to the other control variables, we find that *older* loan officers grant less amount of credit and have lower default rates, and that *more experienced* loan officers are associated with a higher proportion of granted credit. These results further support the career concerns argument, suggesting that older and more experienced loan officers are less likely to exert effortcompared to their younger counterparts. Consequently, they approve less credit, which is associated with a lower probability of default (Agarwal & Ben-David, 2018; Agarwal & Wang, 2009). Furthermore, the presence of *collateral* is significantly associated with a reduced probability of corporate default (Cadot, 2013; Manove et al., 2001), *group belonging* of firms increases the amount of credit granted (Bae et al., 2012; Friedman et al., 2003; Lins et al., 2013), and larger credit applications are decided at higher *levels of approval*.

Additional evidence shows that greater *scope of relationship* leads to more credit being granted and that applicants having stronger *equity ratios* are granted more credit and display a lower probability of default. In line with the presence of communications frictions in large banking organization, the results of *branch-to-headquarters distance* confirm that those credit applications approved "at distance" are of lower credit amounts (Filomeni et al., 2021; Stein, 2002) and that greater *branch-to-borrower* distance involves relatively less risky credit applications characterized by lower corporate defaults (Agarwal & Hauswald, 2010; Bellucci et al., 2013; Degryse & Ongena, 2005; Petersen & Rajan, 2002). Lastly, our findings corroborate the existing evidence provided by Bellucci et al. (2010) regarding the significance of branch gender composition in lending practices. Specifically, branches with a higher percentage of female loan officers (*branch % of female loan officers*) tend to grant less credit and exhibit a lower prabability of corporate default, consistent with a more risk-averse attitude of female loan officers.

Upgrading and Downgrading Soft Information

In this section we explore the effects of upgrading and downgrading soft information by female loan officers in their lending decisions. We do this by disentangling soft information into upgrading and downgrading overrides and estimating the following OLS models where loan officer *i* grants a loan *j* to firm *k*:

$$\begin{aligned}\left(\frac{\text{Granted credit}}{\text{Total assets}}\right)_{ijk} &= \beta_0 + \beta_1 \text{female}_i * \text{upgrading soft information}_{ijk} \\ &+ \beta_2 \text{female}_i * \text{downgrading soft information}_{ijk} \\ &+ \beta_3 \text{female}_i + \beta_4 \text{upgrading soft information}_{ijk} \\ &+ \beta_5 \text{downgrading soft information}_{ijk} \\ &+ \beta_6 X_i + \beta_7 Y_j + \beta_8 Z_k + \text{D}_{area} + \text{D}_{industry} + \varepsilon_{ijk}\end{aligned} \tag{3}$$

$$\begin{aligned}\text{PD}_{ijk} = \beta_0 &+ \beta_1 \text{female}_i * \text{upgrading soft information}_{ijk} \\ &+ \beta_2 \text{female}_i * \text{downgrading soft information}_{ijk} \\ &+ \beta_3 \text{female}_i + \beta_4 \text{upgrading soft information}_{ijk} \\ &+ \beta_5 \text{downgrading soft information}_{ijk} \\ &+ \beta_6 X_i + \beta_7 Y_j + \beta_8 Z_k + \text{D}_{area} + \text{D}_{industry} + \varepsilon_{ijk}\end{aligned} \tag{4}$$

We report the results of Eqs. (3) and (4) in Table 3. In column 1, we provide the results for *granted credit/total assets*, followed by the results for *PD* in column 2. We are interested in investigating the sign and significance of the coefficients associated with the interaction terms *female * upgrading soft information* and *female * downgrading soft information* that capture the impact of upgrading and downgrading soft information used by female loan officers in their lending decisions as compared to their male counterparts, respectively.

As for upgrades, we find a significant impact of *upgrading soft information* used by female loan officers with an increase in the amount of credit granted (coefficient of 2.872) and a reduction in the probability of corporate default (coefficient of − 0.043) relative to their male counterparts. The economic magnitude of the upgrade coefficients suggests that a one standard deviation increase in *upgrading soft information* (0.33) used by female officers improves the amount of granted credit by 94.8% and reduces the likelihood of corporate default by 1.4% compared to male loan officers. As for downgrades, we find a significant impact of *downgrading soft information* used by female loan officers with a decrease in the amount of credit granted (coefficient of − 0.324) and in the probability of corporate default (coefficient of − 0.049) relative to their male counterparts. The economic magnitude of the downgrade coefficients suggests that a one standard deviation increase in *downgrading soft information* (0.23) used by female officers reduces the amount of granted credit by 7.5% and the likelihood of corporate default by 1.1% in comparison to male loan officers.

These results confirm that when female loan officers use soft information, they are able to reduce default rates. Specifically, the negative and significant effect on

Table 3 Upgrading and downgrading soft information

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default
Female	− 0.296***	0.031**
	(0.017)	(0.004)
Upgrading soft information	− 0.178	− 0.003***
	(0.112)	(0.000)
Downgrading soft information	− 0.472*	0.017*
	(0.123)	(0.004)
Female * Upgrading soft information	2.872**	− 0.043**
	(0.450)	(0.008)
Female * Downgrading soft information	− 0.324**	− 0.049***
	(0.034)	(0.002)
Final rating	0.025	− 0.008**
	(0.021)	(0.001)
Age	− 0.213**	− 0.051**
	(0.044)	(0.006)
Experience	0.138**	− 0.003
	(0.028)	(0.002)
Collateral	0.086***	− 0.013
	(0.005)	(0.005)
Global guarantee	− 0.367***	0.007
	(0.022)	(0.005)
Group belonging	0.012	0.005*
	(0.010)	(0.002)
Approval level	0.200***	0.000
	(0.009)	(0.001)
Total assets	− 0.567***	0.004*
	(0.043)	(0.001)
Capital ratio	0.471	0.009*
	(0.259)	(0.003)
Scope of relationship	0.187***	0.004
	(0.009)	(0.003)
Branch-to-borrower distance	0.032*	− 0.002**
	(0.011)	(0.000)
Branch-to-headquarters distance	− 0.162***	0.001
	(0.001)	(0.000)
Existing credit exposure	0.000**	0.000
	(0.000)	(0.000)
Branch % of female loan officers	0.035	− 0.038***
	(0.036)	(0.003)
Total revenues	0.074	− 0.005***
	(0.079)	(0.000)
ROA	0.276*	− 0.115**
	(0.076)	(0.015)
Leverage	0.046***	− 0.000
	(0.001)	(0.000)
Strength of covenants	0.200***	0.002
	(0.004)	(0.002)
Liquidity	− 1.451**	0.045**
	(0.247)	(0.006)
Observations	326	322
R^2	0.24	0.39

Table 3 (continued)

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default
Industry FE	Yes	Yes
Area FE	Yes	Yes

The table presents the results of the OLS regression analysis for the model of female loan officers and upgrading/downgrading soft information where the dependent variables are the ratio *granted credit/total assets* (column 1) and the *probability of default* (column 2). The interaction term *female * upgrading soft information* (columns 1–2) captures the use of an upgrade by the female loan officer accountable for managing the firm-bank credit relationship. The interaction term *female * downgrading soft information* (columns 1–2) captures the use of a downgrade by the female loan officer accountable for managing the firm-bank credit relationship. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively

corporate default rate is significant for both upgrading and downgrading override decisions. On the one hand, the negative association between upgrading decisions and corporate default probability is more straightforward as it stems from the goodness and cautiousness of the assessment performed by female loan officers based on their positive soft information (subject to potential inspection by the bank's headquarters). On the other hand, the same negative association between downgrading decisions and corporate default probability can be explained by the more risk-averse attitude of female loan officers pushing them to downgrade a borrower at an early stage of financial distress. This notion is in line with the theory of less risk-taking behaviour of women as compared to men, especially in financial decision-making and investments (Barber & Odean, 2001; Byrnes et al., 1999; Croson & Gneezy, 2009; Eckel & Grossman, 2008; Powell & Ansic, 1997). Importantly, these results are supportive of responsible lending by female loan officers ensuring affordability, transparency of terms and conditions, and rule out any deceptive means to convince borrowers to accept a loan under unfair terms. Moreover, these results support the argument that female loan officers restrict credit availability to new and unestablished borrowers more than their male counterparts (Bellucci et al., 2010). Hence, loans screened and monitored by female loan officers have a lower likelihood to turn problematic than loans handled by male loan officers (Beck et al., 2013).

Among the other control variables, the variable *female* captures the influence of gender bias in the absence of soft information use. We find that, without the use of soft information, in either upgrading or downgrading decisions, female loan officers are associated with lower amounts of granted credit and with higher corporate default rates, consistent with our previous findings in Table 2. The control variables included in the estimated model behave as conjectured in the previous Sect. 4.1.

Gender Affinity in Lending Decisions

In this section, we examine the impact of soft information used by female loan officers on corporate lending decisions by considering the gender of the loan approver. Contributing to the existing studies investigating lender-borrower gender affinity in lending (Agier & Szafarz, 2013; Aubert et al., 2009; Bellucci et al., 2010; Blanco-Oliver et al., 2021), we explore the gender affinity between female loan officer and female loan approvers in the bank lending process. Gender affinity reinforces collaboration between women throughout the loan approval process which is likely to affect lending outcomes. Specifically, to capture the gender affinity between the loan officer and the loan approving authority of the bank, we construct the binary variable *LO-Approver gender* which takes the value of 1 if the loan officer and approver are of different genders and 0 otherwise. We then interact the dummy variable *LO-Approver gender* with our previous interaction term *female * soft information* used in Eqs. (1)–(2) which results in the triple interaction term *female * soft information * LO-Approver gender* that allows us to investigate the impact of soft information used by subordinate female loan officers on corporate lending decisions when the loan approver is a male. We estimate the following OLS models for *granted credit/total assets* and *PD* where loan officer i grants a loan j to firm k decided by the loan approver q:

Table 4 Gender affinity in lending decisions

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default
Female * Soft information * LO-Approver gender	− 0.077**	− 0.002
	(0.017)	(0.005)
Female	− 0.051**	0.006*
	(0.006)	(0.002)
Soft information	0.018	0.016**
	(0.009)	(0.003)
LO-Approver gender	− 0.018**	0.003
	(0.004)	(0.001)
Female * LO-Approver gender	0.040*	− 0.001
	(0.011)	(0.002)
Female * Soft Information	0.060***	− 0.021**
	(0.006)	(0.004)
Soft information * LO-Approver gender	0.089***	− 0.016**
	(0.009)	(0.002)
Final rating	0.007**	− 0.007***
	(0.001)	(0.000)
Age	− 0.076	− 0.004**
	(0.030)	(0.001)
Experience	− 0.012**	− 0.002
	(0.002)	(0.001)
Collateral	0.063***	− 0.005**
	(0.005)	(0.001)
Global guarantee	− 0.020*	0.006**
	(0.006)	(0.001)
Group belonging	− 0.099***	− 0.004***
	(0.007)	(0.000)
Approval level	0.000	0.000
	(0.000)	(0.000)
Total assets	− 0.102***	0.003***
	(0.004)	(0.000)
Capital ratio	− 0.033	0.014***
	(0.028)	(0.001)
Scope of relationship	0.031*	− 0.000
	(0.008)	(0.001)
Branch-to-borrower distance	− 0.009*	− 0.000
	(0.002)	(0.000)
Branch-to-headquarters distance	− 0.009**	0.000
	(0.002)	(0.001)
Existing credit exposure	0.000***	− 0.000***
	(0.000)	(0.000)
Branch % of female loan officers	0.022	0.004
	(0.015)	(0.003)
Total revenues	0.029***	− 0.002**
	(0.002)	(0.000)
ROA	− 0.046***	− 0.026***
	(0.003)	(0.001)
Leverage	0.004**	0.000
	(0.001)	(0.000)
Strength of covenants	0.022*	− 0.000

Table 4 (continued)

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default
	(0.007)	(0.001)
Liquidity	0.054***	0.039***
	(0.004)	(0.002)
Observations	282	324
R^2	0.39	0.58
Industry FE	Yes	Yes
Area FE	Yes	Yes

The table presents the results of the OLS regression analysis for the model of loan officer-approver gender matching where the dependent variables are the ratio *granted credit/total assets* (column 1) and the *probability of default* (column 2). The triple interaction term *female * soft information * LO-Approver gender* captures the use of soft information by the female loan officer accountable for managing the firm-bank credit relationship when the loan officer and approver are of different genders (i.e., male loan approver). All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively

$$\begin{aligned}\left(\frac{\text{Granted credit}}{\text{Total assets}}\right)_{ijkq} &= \beta_0 + \beta_1 \text{female}_i \\ &* \text{soft information}_{ijk} * \text{LO - Approver gender}_{iq} \\ &+ \beta_2 \text{female}_i * \text{soft information}_{ijk} \\ &+ \beta_3 \text{soft information}_{ijk} * \text{LO - Approver gender}_{iq} \\ &+ \beta_4 \text{female}_i * \text{LO - Approver gender}_{iq} \\ &+ \beta_5 \text{female}_i + \beta_6 \text{soft information}_{ijk} \\ &+ \beta_7 \text{LO - Approver gender}_{iq} + \beta_8 X_i + \beta_9 Y_j \\ &+ \beta_{10} Z_k + \text{D}_{area} + \text{D}_{industry} + \varepsilon_{ijk}\end{aligned} \tag{5}$$

$$\begin{aligned}\text{PD}_{ijkq} &= \beta_0 + \beta_1 \text{female}_i * \text{soft information}_{ijk} \\ &* \text{LO - Approver gender}_{iq} \\ &+ \beta_2 \text{female}_i * \text{soft information}_{ijk} \\ &+ \beta_3 \text{soft information}_{ijk} * \text{LO - Approver gender}_{iq} \\ &+ \beta_4 \text{female}_i * \text{LO - Approver gender}_{iq} \\ &+ \beta_5 \text{female}_i + \beta_6 \text{soft information}_{ijk} \\ &+ \beta_7 \text{LO - Approver gender}_{iq} + \beta_8 X_i \\ &+ \beta_9 Y_j + \beta_{10} Z_k + \text{D}_{area} + \text{D}_{industry} + \varepsilon_{ijk}\end{aligned} \tag{6}$$

We report the results of Eqs. (5) and (6) in Table 4. In column 1, we provide the results for *granted credit/total assets*, followed by the results for PD in column 2. We are interested in investigating the sign and significance of the coefficients associated with the triple interaction term *female * soft information * LO-Approver gender*. In column 1, we find a significant and negative coefficient (coefficient of − 0.077) associated with the triple interaction term implying that the positive effect of soft information used by female loan officers on the amount of granted credit diminishes when the loan is managed by a subordinate female loan officer but approved by a male officer, while no significant impact is found on the probability of corporate default in column 2. Hence, these results support our hypothesis 2 which suggests that female loan approvers are more likely to support the loan applications managed by their subordinate female loan officers in the credit process. These findings imply how the presence of managers of the same gender increases access to networks of power through which employees gain specific human capital relevant for the job and provides motivation that ultimately increases employees' aspirations or productive capacities (Stojmenovska, 2019). These traits are important to foster a sense of solidarity and empowerment among individuals of the same gender, promoting effective communication and collaboration especially in male-dominated industries.

Exploring Possible Mechanisms

The results reported in the previous sections suggest a significant performance advantage of female loan officers in using soft information when making lending decisions. This section explores the possible mechanisms that can explain these findings. Specifically, we test whether our main results are driven by alternative explanations such as differences in workload, work experience, loan officers' optimism, managerial ability, and screening capabilities between female and male loan officers.

Table 5 Mechanisms: Stronger relationships with clients (Panels A and B) & Mistake-punishment trade-off (Panel C)

	(1)		(2)	
Dependent variables	Granted credit/Tot. assets		Probability of default	
Panel A:	Scope of relationship = 0	Scope of relationship = 1	Scope of relationship = 0	Scope of relationship = 1
Female * Soft Information	0.240	2.304***	− 0.035**	− 0.040***
	(0.443)	(0.072)	(0.011)	(0.001)
Observations	163	215	160	214
R^2	0.44	0.23	0.66	0.40
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Test of equality: p-value	0.000		0.071	
Panel B:	BBD = 0	BBD = 1	BBD = 0	BBD = 1
Female * Soft Information	1.443***	0.494	− 0.038***	0.010
	(0.086)	(0.401)	(0.003)	(0.013)
Observations	291	87	290	84
R^2	0.18	0.58	0.39	0.75
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Test of equality: p-value	0.001		0.099	
Panel C:	BHD = 0	BHD = 1	BHD = 0	BHD = 1
Female * Soft Information	2.451**	− 0.736***	− 0.032***	− 0.048*
	(0.185)	(0.061)	(0.000)	(0.012)
Observations	162	164	162	160
R^2	0.36	0.25	0.33	0.65
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes
Test of equality: p-value	0.098		0.075	

The table presents the results of the OLS regression analysis for the models investigating the possible mechanisms driving our findings regarding the performance advantage of female loan officers in using soft information and making lending decisions. The dependent variables are the ratio *granted credit/tot. assets* (column 1) and the *probability of default* (column 2). In Panel A, we segment the analysis by using *scope of relationship*, a dummy variable that assumes the value 1 if the borrower purchases at least one additional product/service from the bank besides the loan and 0 otherwise, and that reflects the breadth of firm–bank relationship. In Panel B, we segment the analysis by using *BBD*, measured as the logarithm of (1 + the geographical distance (in km) between the branch where the loan officer works and the headquarters of the applicant company). In Panel C, we segment the analysis by using *BHD*, measured as the logarithm of (1 + geographical distance (in km) between the branch in which the loan officer responsible for the credit score operates and the bank's headquarters). The interaction term *female * soft information* captures the use of soft information by the female loan officer accountable for managing the firm–bank credit relationship. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$, respectively

Stronger Relationships with Clients

The superior performance of female officers may be attributed to their ability to build deeper relationships with their clients helping them to better monitor their loan portfolios. To test this hypothesis, we use the breadth of firm–bank relationship, i.e., *scope of relationship*, and the *branch-to-borrower distance (BBD)*. The former is a dummy variable that takes the value of 1 if the borrower purchases at least one additional product/service from the bank besides the loan and 0 otherwise. The latter is measured as the logarithm of (1 + physical distance (in km)) between the branch where the loan officer works and the headquarters of the applicant company, which the recent banking literature views as reducing information asymmetries and monitoring costs (Agarwal & Hauswald, 2010; Bellucci et al., 2013; Degryse & Ongena, 2005; Petersen & Rajan, 2002).

We re-estimate the main models provided in Eqs. (1)–(4) by segmenting the sample into two groups based on the *scope of relationship* and *BBD* in Panels A and B of Table 5, respectively. The results show that female loan officers that have deeper credit relationships with their clients (greater *scope of relationship*) and work closely with the applicant company (lower *BBD*) have greater incentives and facilitated ease to collect and use soft information to perform better.[7] The former results provide empirical support to the fact that women loan officers are better at building credit relationships with their clients, which helps them to improve their monitoring skills. The latter results for *BBD* imply that local proximity between local loan officers and the headquarters of the applicant company facilitates interaction and, as such, the accumulation of qualitative and valuable soft information regarding the borrowing firm.

Mistake-Punishment Trade-Off

Empirical evidence shows that there is an asymmetric response to mistakes based on gender. Villanueva-Moya and Expósito (2022) show that women (vs. men) have a greater internalization of gender roles, which is associated with a higher fear of receiving negative evaluation. Further, Montalvo and Reynal-Querol (2020) argue that the higher degree of compliance among female loan officers is related to gender bias in the "mistake-punishment trade-off" as women's errors and careers are more severely penalized compared to men's, given their record of loan performance. Since our dataset lacks direct measures of penalties or rewards given to loan officers, following Filomeni et al. (2021) we indirectly explore this hypothesis by focusing on the branch-to-headquarters distance (*BHD*) measured as the logarithm of (1 + physical distance (in km)) between the branch in which the loan officer responsible for the credit score operates and the bank's headquarters. *BHD* reflects communication frictions due to spatial separation and lack of personal contact, cultural affinity, common languages, and mutual trust between loan officers at local branches and senior managers at the bank's headquarters that may inhibit the "hardening" and the transmission of soft information within the banking organization (Filomeni et al., 2021).

The results, presented in Panel C of Table 5, provide empirical support to the fact that female loan officers that are

[7] The segmentation between low and high *scope of relationship* borrowers has been performed using the 75th percentile of *BBD* distribution.

Table 6 Mechanisms: Better screening capabilities

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default
Female	– 0.168**	0.030**
	(0.031)	(0.004)
Soft information	0.009	0.008
	(0.029)	(0.003)
Female * Soft information	1.444***	– 0.041***
	(0.105)	(0.004)
Loan Officer's Ability	12.195***	– 0.356***
	(0.480)	(0.023)
Final rating	0.141**	– 0.005**
	(0.019)	(0.001)
Age	– 0.307***	– 0.053**
	(0.021)	(0.008)
Experience	0.078***	– 0.003
	(0.006)	(0.002)
Collateral	0.411***	– 0.001
	(0.013)	(0.004)
Global guarantee	0.004	0.015
	(0.014)	(0.006)
Group belonging	0.038	0.004
	(0.016)	(0.002)
Approval level	0.176***	0.000
	(0.016)	(0.001)
Total assets	– 0.725***	0.004**
	(0.015)	(0.001)
Capital ratio	0.416***	0.007*
	(0.029)	(0.002)
Scope of relationship	0.154***	0.004
	(0.010)	(0.004)
Branch-to-borrower distance	0.011	– 0.003**
	(0.011)	(0.000)
Branch-to-headquarters distance	– 0.142***	0.001
	(0.008)	(0.000)
Existing credit exposure	0.000***	0.000
	(0.000)	(0.000)
Branch % of female loan officers	– 0.178	– 0.035**
	(0.115)	(0.004)
Total revenues	0.129***	– 0.005***
	(0.008)	(0.000)
ROA	– 0.456	– 0.108**
	(0.236)	(0.020)
Leverage	0.066***	– 0.000
	(0.003)	(0.000)
Strength of covenants	0.259***	0.004
	(0.012)	(0.003)
Liquidity	– 0.631***	0.044**
	(0.043)	(0.007)

Table 6 (continued)

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default
Observations	326	322
R^2	0.21	0.40
Industry FE	Yes	Yes
Area FE	Yes	Yes

The table presents the results of the OLS regression analysis for the model of female loan officers and soft information when controlling for the loan officer's ability. The dependent variables are the ratio *granted credit/tot. assets* (column 1) and the *probability of default* (column 2). The interaction term *female * soft information* captures the use of soft information by the female loan officer accountable for managing the firm–bank credit relationship. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. $***p<0.01$, $**p<0.05$, $*p<0.1$, respectively

closer to higher levels of the bank's hierarchy have a higher incentive to perform better, leading to more credit being granted to applicants with a lower probability of corporate default.[8] This may occur due to female loan officers' threat of losing their jobs or being penalized in terms of career advancements (Qian et al., 2015). An alternative interpretation is that personal costs associated with overriding the integrated rating (e.g., reputational costs, among others) may be perceived as higher by female loan officers, possibly due to their greater risk aversion or actual penalties. This implies that female loan officers deviate from the integrated rating only when they are highly confident in their judgement. As a result, these loans are likely to be larger and safer, particularly when compared to loans where male loan officers override the integrated rating.

Better Screening Capabilities

To mitigate issues related to differential screening capabilities of loan officers affecting our main results, we now re-estimate our baseline model specifications of Eqs. (1) and (2) by controlling for the loan officer's ability in the regression models. Specifically, we follow the empirical approach proposed by Demerjian et al. (2012) and proxy the loan officer's ability using the residuals estimated by regressing *default*, a dummy variable that equals 1 if the given borrower defaults (at the end of year 2012 or 2013) and 0 otherwise, on several loan-level characteristics that are related to loan performance (i.e., final rating, soft information, collateral, global guarantee, and the strength of covenants) using a Tobit regression with industry fixed effects and clustering standard errors by industry. Overall, the new estimation results, reported in Table 6, show that that even after controlling for loan officers' capabilities (*loan officer's ability*), our main variable of interest *female * soft information* still has a significant impact on the amount of credit granted and on the probability of corporate default, thus ruling out the mechanism of differential screening capabilities between male and female loan officers. Moreover, *loan officer's ability* is significant in both model specifications (1) and (2) in Table 6 and associated with an increased amount of granted credit and a lower probability of default.

Differences in Workload

Differences in workload between female and male loan officers may also account for the superior performance observed among female loan officers. Indeed, if male loan officers are overworked than their female counterparts, the screening and monitoring intensity and efforts of the former might be affecting their lending performance. To rule out this explanation, we divide the dataset into two sub-samples, i.e., heavy/light workload, according to the median number of loan applications managed by loan officers and re-estimate our model specifications of Eqs. (1) and (2) on both subsamples. The results, shown in Table 7, confirm that the use of soft information effectively improves the quality of lending decisions performed by female loan officers resulting in an increased amount of granted credit and a lower probability of corporate default irrespective of workload size.[9] Based on this empirical evidence, we can confidently rule out that differences in the workloads of male and female loan officers influence our main empirical results.

Loan Officers' Optimism

To rule out overconfidence as one of the confounding factors influencing a loan officer's lending attitude (Huang et al., 2018), we now re-estimate the model specifications of Eqs. (1) and (2) in Table 8 by incorporating a measure for the loan officer's optimism (*optimistic*) as a control variable in our regression models. By referring to the word list provided by Loughran and McDonald (2011) and by drawing on the approach of Henry (2006), Price et al. (2012), and Henry and Leone (2015), we employ the following method to assess the degree of management optimism of loan officer i for loan j:

[8] The segmentation between close and distant loan officers (from the bank's headquarters) has been performed using the 75th percentile of *BHD* distribution.

[9] Moreover, as further confirmatory evidence, we have verified that the average number of loan applications managed by a female loan officer in our sample is 2.3, while that of a male loan officer is about 1.6, thus corroborating our results.

Table 7 Mechanisms: Differences in workload

	Light workload		Heavy workload	
	(1)	(2)	(3)	(4)
Dependent variables	Granted credit/Tot. Assets	Probability of default	Granted credit/Tot. Assets	Probability of default
Female	− 0.023*	0.001**	− 0.110*	0.010**
	(0.006)	(0.000)	(0.014)	(0.001)
Soft Information	0.046***	0.016***	0.058*	− 0.003
	(0.001)	(0.000)	(0.006)	(0.010)
Female * Soft Information	0.043*	− 0.027***	0.122*	− 0.018*
	(0.010)	(0.000)	(0.017)	(0.002)
Final rating	0.012***	− 0.005***	0.007**	− 0.011**
	(0.001)	(0.000)	(0.001)	(0.000)
Age	− 0.009	− 0.018***	− 0.070	0.032
	(0.005)	(0.000)	(0.020)	(0.014)
Experience	− 0.044**	0.002***	0.021	− 0.011***
	(0.006)	(0.000)	(0.004)	(0.000)
Collateral	0.103***	− 0.000	0.020	− 0.015
	(0.003)	(0.000)	(0.004)	(0.005)
Global guarantee	− 0.053**	0.001	0.093**	0.025**
	(0.006)	(0.001)	(0.003)	(0.001)
Group belonging	− 0.102***	− 0.001**	− 0.025*	− 0.002
	(0.001)	(0.000)	(0.004)	(0.001)
Approval level	0.004*	0.001***	0.004	− 0.002**
	(0.001)	(0.000)	(0.001)	(0.000)
Total assets	− 0.094***	0.001	− 0.068**	0.008
	(0.008)	(0.001)	(0.002)	(0.004)
Capital ratio	− 0.118**	0.008**	− 0.000	0.043
	(0.027)	(0.002)	(0.006)	(0.013)
Scope of relationship	0.056***	− 0.001	0.027	− 0.001
	(0.002)	(0.000)	(0.009)	(0.004)
Branch-to-borrower distance	− 0.017***	− 0.000	− 0.008*	− 0.003
	(0.001)	(0.000)	(0.001)	(0.001)
Branch-to-headquarters distance	0.012**	− 0.001**	− 0.007	0.003**
	(0.002)	(0.000)	(0.004)	(0.000)
Existing credit exposure	0.000***	− 0.000*	0.000**	− 0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Branch % of female loan officers	− 0.039**	0.001	− 0.005	0.013
	(0.009)	(0.002)	(0.019)	(0.011)
Total revenues	− 0.001	− 0.001	0.028	− 0.005
	(0.008)	(0.001)	(0.004)	(0.004)
ROA	− 0.191*	− 0.056***	0.131	− 0.058*
	(0.057)	(0.002)	(0.024)	(0.009)
Leverage	0.005***	− 0.000	− 0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Strength of covenants	0.053**	0.001	0.010**	− 0.005
	(0.007)	(0.000)	(0.001)	(0.002)
Liquidity	0.062	0.050***	0.096	0.076
	(0.025)	(0.000)	(0.049)	(0.021)
Observations	160	160	138	135
R^2	0.33	0.69	0.79	0.69
Industry FE	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes

The table presents the results of the OLS regression analysis for the model of female loan officers and soft information where the dependent variables are the ratio *granted credit/tot. assets* (column 1) and the *probability of default* (column 2). We divided the dataset into two sub-samples,

Table 7 (continued)

i.e., heavy/light workloads, according to the median number of loan applications managed by loan officers The interaction term *female * soft information* captures the use of soft information by the female loan officer accountable for managing the firm–bank credit relationship. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively

$$\text{Optimistic}_{ij} = \frac{\text{POS}_{ij} - \text{NEG}_{ij}}{\text{POS}_{ij} + \text{NEG}_{ij}}$$

The larger the value of *optimistic*, the higher the optimism of the loan officer in charge of the bank–firm relationship. POS is the number of times optimistic vocabulary appears in the loan officer's comments to the loan application and NEG is the number of pessimistic vocabulary occurrences in the loan officer's written notes attached to the loan application. Overall, incorporating the loan officer's optimism into our baseline models does not affect our main findings, further corroborating the novel evidence provided in this paper that the use of soft information effectively mitigates the gender bias by helping female loan officers to reach better lending decisions that result in increased granted credit with a lower default probability compared to their male counterparts.

Robustness Tests

In this section, we conduct a series of robustness tests to validate our main empirical findings.

Alternative Measure of Soft Information

In line with Campbell et al. (2019), we use an alternative measure of soft information based on the keywords mentioned by loan officers in their written notes in each loan application.[10] Specifically, we now measure soft information as the difference between positive and negative keywords divided by the total number of words contained in each loan application. Thus, we perform textual analysis using dictionaries specifically developed to analyse soft information, as outlined by Li (2010). To implement our dictionary-based approach, we adapt appropriate lists of positive and negative words using the Loughran McDonald (LM) dictionary sources, a list containing words of the LM dictionary, categorized by sentiment (Loughran & McDonald, 2011). The negative and positive keywords are translated and individually checked for potential spelling and construction mismatching. Moreover, dictionaries of positive and negative words are extended to enrich the algorithm capability to detect and classify words as positive or negative categories in the context of different languages (Chen & Skiena, 2014).

We start by calculating the sentiment score for each loan application where every positive word is given a score of + 1 and every negative word gets a score of − 1. We then construct the binary variable *sentiment score* that equals the value of 1 when the sentiment score is below the 25th or above the 75th percentile of the distribution and 0 otherwise. Next, we build the dummy variable *upward sentiment score* (or *downward sentiment score*) which takes the value of 1 if *sentiment score* is above the 75th (or below the 25th percentile) of the distribution and 0 otherwise. As a result, notes with greater sentiment scores reflect deeper bank-borrower relationship characterized by a greater amount of soft information collected by the loan officer throughout the duration of the firm-bank relationship.

Table 9 provides the results of these estimations. The results validate the superior performance of female loan officers in using soft information, leading to improved lending decisions compared to their male counterparts. Further, the findings also confirm the significant impacts of both upgrading and downgrading soft information used by female officers on the amount of credit granted and on the probability of corporate defaults, as compared to their male counterparts. Thus, our empirical findings are robust to an alternative measure of soft information.

Alternative Estimation Method

We re-estimate our main result on the probability of default using Cox proportional hazards regression models, firstly proposed by Cox (1972) and widely used in medical research and in the analysis of survival data in finance (Buehler et al., 2012; Henebry, 1997; Lane et al., 1986). In the context of this paper, we use this methodology to investigate the relationship between the survival time of borrowing firms after loan disbursement and the use of soft information by female loan officers.[11] In our analysis, survival time refers to the number of days a borrower survives in the marketplace after the loan is disbursed by the

[10] Due to confidentiality reasons, we are not allowed to disclose the word cloud of the keywords mostly recurring in the loan officers' comments to loan applications.

[11] For a more extensive discussion refer to Kalbfleisch and Prentice (2002) or Cox and Oakes (1984).

Table 8 Mechanisms: Loan Officers' Optimism

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default
Female	– 0.171**	0.031**
	(0.039)	(0.004)
Soft Information	– 0.078	0.006*
	(0.064)	(0.002)
Female * Soft Information	1.377**	– 0.044**
	(0.153)	(0.006)
Optimistic	2.692**	– 0.035*
	(0.448)	(0.011)
Final rating	0.042	– 0.008**
	(0.016)	(0.001)
Age	– 0.238**	– 0.051**
	(0.027)	(0.006)
Experience	0.070***	– 0.003
	(0.006)	(0.002)
Collateral	– 0.008	– 0.013
	(0.009)	(0.004)
Global guarantee	– 0.298**	0.007
	(0.044)	(0.005)
Group belonging	0.049	0.004
	(0.027)	(0.002)
Approval level	0.179**	0.000
	(0.021)	(0.001)
Total assets	– 0.724***	0.004*
	(0.051)	(0.001)
Capital ratio	0.445**	0.012**
	(0.060)	(0.002)
Scope of relationship	0.161***	0.004
	(0.013)	(0.003)
Branch-to-borrower distance	0.021	– 0.002*
	(0.012)	(0.001)
Branch-to-headquarters distance	– 0.142***	0.001
	(0.013)	(0.000)
Existing credit exposure	0.000***	– 0.000
	(0.000)	(0.000)
Branch % of female loan officers	– 0.230	– 0.037***
	(0.118)	(0.003)
Total revenues	0.148***	– 0.004***
	(0.005)	(0.000)
ROA	– 0.524*	– 0.116**
	(0.178)	(0.015)
Leverage	0.064***	– 0.000
	(0.004)	(0.000)
Strength of covenants	0.161***	0.002
	(0.006)	(0.002)
Liquidity	– 0.540**	0.042**
	(0.073)	(0.006)
Observations	326	322
R^2	0.20	0.39
Industry FE	Yes	Yes
Area FE	Yes	Yes

The table presents the results of the OLS regression robustness analysis for the model of female loan officers and soft information by controlling for the loan officer's optimism. The dependent variables are the ratio *granted credit/tot. assets* (column 1) and the *probability of default* (column 2). The interaction term *female * soft information* captures the use of soft information by the female loan officer accountable for managing the firm–bank credit relationship. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively

lending bank. In this respect, the Cox proportional hazards model allows us to simultaneously evaluate the effect of several factors on firms' survival. The dependent variable in our survival-time analysis is *default*, a binary variable that equals 1 if the given borrower defaults (at the end of year 2012 or 2013) and 0 otherwise.

The estimation results are provided in Table 10. We continue to find a significant negative effect of using soft information, including both upgrading and downgrading soft information, by female loan officers on corporate defaults, compared to male loan officers. Thus, our empirical findings on the probability of default are also robust to an alternative estimation method.

Alternative Measure of Credit

We now test the robustness of our empirical results by using an alternative measure of credit, represented by *approved share,* which is computed as the ratio of the borrower's granted credit to the amount of credit the borrowing firm is applying for. Using this alternative dependent variable allows us to rule out concerns related to further isolating the effect of female loan officers using soft information within the given credit application on the ratio of approved credit. Table 11 provides the results of these estimations. In column (1) we re-estimate the baseline model of Eq. (1), while in column (2) we present the estimation results of the model of Eq. (3) using *approved share* as the dependent variable. The findings validate the superior performance of female loan officers in using soft information, resulting in a higher share of approved credit. Further, the results also confirm the significant impacts of both upgrading and downgrading

Table 9 Robustness: Alternative measure of soft information

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default	(3) Granted credit/Tot. assets	(4) Probability of default
Female	− 0.477**	0.026***	− 0.484**	0.026***
	(0.061)	(0.002)	(0.062)	(0.002)
Sentiment score	0.081*	− 0.000		
	(0.023)	(0.000)		
Female * Sentiment score	0.599***	− 0.021**		
	(0.024)	(0.005)		
Upward sentiment score			0.073*	− 0.000
			(0.019)	(0.001)
Downward sentiment score			− 0.334***	− 0.001**
			(0.005)	(0.000)
Female * Upward sentiment score			0.471***	− 0.017*
			(0.022)	(0.005)
Female * Downward sentiment score			− 0.773***	− 0.026**
			(0.027)	(0.005)
Final rating	0.002	− 0.008***	0.005	− 0.008***
	(0.002)	(0.001)	(0.003)	(0.001)
Age	− 0.394	− 0.045**	− 0.380*	− 0.045**
	(0.135)	(0.005)	(0.123)	(0.005)
Experience	0.041*	− 0.000	0.036	− 0.000
	(0.012)	(0.002)	(0.013)	(0.002)
Collateral	0.015	− 0.011**	0.004	− 0.011***
	(0.026)	(0.001)	(0.021)	(0.001)
Global guarantee	− 0.272***	0.006*	− 0.282***	0.006*
	(0.010)	(0.002)	(0.017)	(0.002)
Group belonging	0.108***	− 0.002	0.123***	− 0.002
	(0.008)	(0.002)	(0.012)	(0.002)
Approval level	0.117***	− 0.001	0.124***	− 0.001
	(0.005)	(0.001)	(0.005)	(0.001)
Total assets	− 0.427***	0.004**	− 0.433***	0.005**
	(0.002)	(0.001)	(0.002)	(0.001)
Capital ratio	0.324	− 0.001*	0.292	− 0.002*
	(0.158)	(0.000)	(0.141)	(0.001)
Scope of relationship	0.130*	0.001	0.108*	0.002
	(0.037)	(0.001)	(0.034)	(0.001)
Branch-to-borrower distance	− 0.013*	− 0.002	0.007	− 0.002
	(0.003)	(0.001)	(0.004)	(0.001)
Branch-to-headquarters distance	− 0.093***	0.001**	− 0.095***	0.001**
	(0.006)	(0.000)	(0.005)	(0.000)
Existing credit exposure	0.000***	− 0.000	0.000***	− 0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Branch % of female loan officers	− 0.166*	− 0.018***	− 0.179**	− 0.018***
	(0.047)	(0.001)	(0.024)	(0.001)
Total revenues	0.094**	− 0.003	0.091**	− 0.003
	(0.017)	(0.001)	(0.017)	(0.001)
ROA	0.364**	− 0.059***	0.450**	− 0.059***
	(0.056)	(0.003)	(0.078)	(0.003)
Leverage	0.036**	0.000	0.045**	0.000
	(0.005)	(0.000)	(0.005)	(0.000)

Table 9 (continued)

Dependent variables	(1) Granted credit/Tot. assets	(2) Probability of default	(3) Granted credit/Tot. assets	(4) Probability of default
Strength of covenants	0.228***	− 0.001	0.247***	− 0.001
	(0.004)	(0.001)	(0.004)	(0.001)
Liquidity	− 1.025**	0.032***	− 0.940**	0.032***
	(0.117)	(0.001)	(0.151)	(0.001)
Observations	326	322	326	322
R^2	0.15	0.40	0.16	0.40
Industry FE	Yes	Yes	Yes	Yes
Area FE	Yes	Yes	Yes	Yes

The table presents the results of the OLS regression robustness analysis for the model of female loan officers and soft information by using an alternative measure of soft information. The dependent variables are the ratio *granted credit/tot. assets* (column 1) and the *probability of default* (column 2). The dummy variable *female* is interacted with (i) *sentiment score* (columns 1–2), a dummy variable that equals the value of 1 when the sentiment score is below the 25th or above the 75th percentile of the distribution and 0 otherwise; (ii) *upward sentiment score* (columns 3–4), a binary variable that takes the value of 1 if the sentiment score is above the 75th of the distribution and 0 otherwise; and (iii) *downward sentiment score* (columns 3–4), a binary variable that takes the value of 1 if the sentiment score is below the 25th percentile of the distribution and 0 otherwise. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively

soft information used by female officers on the amount of approved credit, compared to their male counterparts. Thus, our empirical findings remain robust to this alternative measure of credit.

Alternative Measures of Insolvency Risk

Following Roy (1952), Houston et al. (2010), Camara et al. (2013), and Filomeni (2023), we re-estimate the regression model in Eq. (2) using the *Z-score* and the volatility in the borrowing firm's return on assets (ROA) as further proxies for insolvency risk. Specifically, the *Z-score* equals (ROA + CAR)/σ(ROA), where ROA is the rate of return on assets, CAR is the ratio of equity to assets, and *σ(ROA)* is an estimate of the standard deviation of the rate of return on assets, all measured with accounting data. Intuitively, this measure represents the number of standard deviations below the mean by which ROA would have to fall so as to just deplete equity capital (Boyd et al., 2006; Hannan & Hanweck, 1988; Houston et al., 2010). Indeed, the basic principle behind the *Z-score* is to relate the capital ratio to the variability in the ROA so that one can know how much variability in returns can be absorbed by capital without the firm becoming insolvent (Hafeez et al., 2022). Default is expected to occur when losses consume capital (i.e., when $\text{ROA} + \text{Eq/TA} \leq 0$ or, equivalently, when $\text{ROA} \leq -\text{Eq/TA}$). As in the banking sector, equity serves as a buffer against unforeseen losses and is critical for a firm's ability to meet its obligations (Cummins et al., 2017). The *Z-score* therefore measures the distance from insolvency (Roy, 1952) where a higher *Z-score* implies that larger shocks to profitability are required to cause the losses to exceed equity and, hence, indicates greater stability. Because the *Z-score* is highly skewed, we follow Laeven and Levine (2009) and use the natural logarithm of the *Z-score*, which is normally distributed. The results are shown in Table 12.

Overall, the aforementioned analyses, conducted using alternative measures of insolvency risk, leave our main findings unaffected, further corroborating the significant impact of soft information used by female loan officers that leads, among other effects, to a reduced probability of corporate defaults compared to their male counterparts.

Lending Conditions to Borrowers with Upgraded Ratings

Consistent with the evidence provided by Qian and Strahan (2007), who show that non-price loan terms significantly affect firms' borrowing costs, we now provide additional insights into the female loan officers' discretionary decisions to upgrade or downgrade credit ratings by testing whether the bank offers attractive lending conditions to the borrowers with upgraded ratings. Specifically, we examine the mean values of the borrowing firm's share of long-term debt and granted credit, as well

Table 10 Robustness: Survival analysis

Dependent variable	(1) Default	(2) Default
Female	12.882***	12.013***
	(0.339)	(0.377)
Soft information	6.562***	
	(0.628)	
Female * Soft information	– 32.638***	
	(1.801)	
Upgrading soft information		– 37.400***
		(1.451)
Downgrading soft information		9.954***
		(0.924)
Female * Upgrading soft information		– 12.024***
		(0.138)
Female * Downgrading soft information		– 17.479***
		(0.450)
Final rating	– 2.276***	– 2.046***
	(0.115)	(0.147)
Age	– 6.243***	– 0.249
	(1.329)	(0.960)
Experience	– 5.783***	– 6.401***
	(0.647)	(0.760)
Collateral	– 52.941***	– 42.174***
	(6.876)	(0.784)
Global guarantee	– 54.476***	– 42.572***
	(7.061)	(0.848)
Group belonging	44.395***	43.892***
	(5.770)	(1.503)
Approval level	– 1.833***	– 2.115***
	(0.220)	(0.258)
Total assets	– 5.783***	– 6.360***
	(0.265)	(0.442)
Capital ratio	– 27.839***	– 21.493***
	(2.234)	(2.913)
Scope of relationship	4.184***	3.010***
	(0.417)	(0.280)
Branch-to-borrower distance	– 1.909***	– 1.526***
	(0.084)	(0.119)
Branch-to-headquarters distance	0.167***	0.153***
	(0.045)	(0.043)
Existing credit exposure	– 0.000***	– 0.000**
	(0.000)	(0.000)
Branch % of female loan officers	– 34.013***	– 30.649***
	(1.550)	(2.500)
Total revenues	5.268***	5.114***
	(0.226)	(0.357)
ROA	15.556***	7.024***
	(1.711)	(1.547)
Leverage	0.783***	1.156***
	(0.002)	(0.028)
Strength of covenants	– 0.730***	– 0.820***
	(0.153)	(0.140)
Liquidity	– 85.377***	– 100.379***
	(3.315)	(7.577)
Observations	322	322
Industry FE	Yes	Yes
Area FE	Yes	Yes

The table presents the results of the OLS regression robustness analysis for the model of female loan officers and soft information by using the Cox hazard regression models (i.e., survival analysis). The dependent variables is *default*, a dummy variable that equals 1 if the given borrower defaults (at the end of year 2012 or 2013) and 0 otherwise. The interaction term *female * soft information* (column 1) captures the use of soft information by the female loan officer accountable for managing the firm–bank credit relationship. The interaction term *female * upgrading soft information* (column 2) captures the use of an upgrade by the female loan officer accountable for managing the firm–bank credit relationship. The interaction term *female * downgrading soft information* (column 2) captures the use of a downgrade by the female loan officer accountable for managing the firm–bank credit relationship. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively

as firms with collateralized credit lines, firms backed by the parent company's guarantee, and the strength of covenants attached to loan applications. The results from this analysis, reported in Table 13, show that, on average, borrowers with upgraded ratings enjoy longer maturity terms (i.e., *share of long-term debt*), receive a greater amount of granted credit (i.e., *granted credit/total assets*), have more collateralized credit lines (i.e., *collateral*), and are less likely to be backed by the parent company's guarantee (i.e., *global guarantee*). Both upgraded and non-upgraded borrowing firms experience a similar strength of covenants overall (i.e., *strength of covenants*). The fact that upgraded borrowers' credit lines are more likely to be collateralized is consistent with the view that emphasizes collateral use as negatively correlated with observable risk. This "sorting-by-private information paradigm" suggests that safer borrowers are more willing to pledge collateral as a signal of their financial soundness and ability to repay loans (Besanko & Thakor, 1987; Bester, 1985; Boot et al., 1991; Chan & Thakor, 1987). Overall, these additional tests confirm that the bank offers attractive lending conditions to borrowers with upgraded ratings, further reinforcing our empirical results on female loan officers' discretionary decisions to upgrade or downgrade credit ratings.

Table 11 Robustness: Alternative measure of credit

Dependent variable	(1) Approved share	(2) Approved share
Female	− 0.008**	− 0.008***
	(0.002)	(0.002)
Soft information	0.003	
	(0.003)	
Female * Soft information	0.016***	
	(0.001)	
Upgrading soft information		0.000
		(0.003)
Downgrading soft information		− 0.008**
		(0.003)
Female * Upgrading soft information		0.021***
		(0.001)
Female * Downgrading soft information		− 0.005*
		(0.002)
Final rating	0.001*	0.001*
	(0.000)	(0.000)
Age	0.010	0.010
	(0.011)	(0.011)
Experience	0.003*	0.003*
	(0.002)	(0.002)
Collateral	0.011***	0.012***
	(0.003)	(0.003)
Global guarantee	0.007	0.007
	(0.003)	(0.003)
Group belonging	− 0.004***	− 0.004**
	(0.001)	(0.001)
Approval level	− 0.002***	− 0.002***
	(0.000)	(0.000)
Total revenues	0.001	0.001
	(0.001)	(0.001)
Capital ratio	− 0.015	− 0.016
	(0.011)	(0.011)
Scope of relationship	0.005*	0.005*
	(0.002)	(0.002)
Branch-to-borrower distance	− 0.002**	− 0.002**
	(0.001)	(0.001)
Branch-to-headquarters distance	− 0.004**	− 0.004**
	(0.001)	(0.001)
Existing credit exposure	− 0.000	− 0.000
	(0.000)	(0.000)
Branch % of female loan officers	− 0.027***	− 0.026***
	(0.005)	(0.005)
Leverage	0.001**	0.001**
	(0.000)	(0.000)
ROA	− 0.004	− 0.004
	(0.004)	(0.004)
Total assets	0.001	0.001
	(0.001)	(0.001)
Liquidity	0.015**	0.014**
	(0.005)	(0.005)
Strength of covenants	0.004	0.005*
	(0.002)	(0.002)
Observations	326	326
R^2	0.06	0.06
Industry FE	Yes	Yes
Area FE	Yes	Yes

The table presents the results of the OLS regression robustness analysis for the model of female loan officers and soft information by using an alternative measure of credit. The dependent variables is *approved share* computed as the ratio *granted credit/applied credit amount* for the model of female loan officers and soft information (column 1) and the model of upgrading and downgrading soft information (column 2). In column (1) the interaction term *female * soft information* captures the use of soft information by the female loan officer accountable for managing the firm–bank credit relationship. In column (2) the interaction term *female * upgrading soft information* captures the use of an upgrade by the female loan officer accountable for managing the firm–bank credit relationship. In column (2) the interaction term *female * downgrading soft information* captures the use of a downgrade by the female loan officer accountable for managing the firm–bank credit relationship. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively

Conclusions

This paper uses a unique, proprietary loan-level dataset comprising all the mid-corporate loan applications (550) managed by the Corporate and Investment Banking Division (CIB) of a major European bank in the post-GFC period from September 2011 to September 2012 to investigate whether soft information that reduces information asymmetry allows female loan officers to reach better lending decisions as compared to their male counterparts. Our empirical findings provide novel evidence that the use of soft information effectively improves the quality of lending decisions made by female loan officers as it helps to accurately assess the creditworthiness of borrowers, resulting in increased granted credit and lower corporate defaults. Moreover, when exploring gender affinity within the banking organisation, we find that female loan approvers are more likely to support their subordinate female loan officers by approving more credit to the loan applications handled by female loan officers. Next, we examine the possible mechanisms that can explain these results, and find that female loan

Table 12 Robustness: Alternative measures of default risk - Z-score and σ(ROA)

Dependent variables	(1) Z-score	(2) σ(ROA)
Female	− 0.236***	0.019***
	(0.009)	(0.003)
Soft information	− 0.053*	0.004*
	(0.016)	(0.002)
Female * Soft information	0.271***	− 0.038***
	(0.025)	(0.005)
Final rating	0.036***	− 0.002**
	(0.001)	(0.001)
Age	− 0.596***	− 0.017
	(0.045)	(0.010)
Experience	0.013*	0.007***
	(0.004)	(0.002)
Collateral	0.063	− 0.005**
	(0.034)	(0.002)
Global guarantee	0.098*	0.009***
	(0.025)	(0.001)
Group belonging	0.038**	− 0.039***
	(0.005)	(0.001)
Approval level	0.018***	0.000
	(0.000)	(0.000)
Total assets	− 0.028	0.018***
	(0.024)	(0.004)
Capital ratio	1.933***	− 0.065***
	(0.103)	(0.009)
Scope of relationship	− 0.052**	− 0.008***
	(0.008)	(0.000)
Branch-to-borrower distance	− 0.025*	0.003**
	(0.006)	(0.001)
Branch-to-headquarters distance	− 0.018***	0.002**
	(0.000)	(0.000)
Existing creditexposure	− 0.000*	− 0.000***
	(0.000)	(0.000)
Branch % of female loan officers	− 0.014	0.009
	(0.017)	(0.008)
Total revenues	0.037	− 0.021***
	(0.028)	(0.005)
ROA	0.522**	0.057**
	(0.108)	(0.021)
Leverage	0.004***	0.000
	(0.000)	(0.000)
Strength of covenants	0.067**	− 0.018
	(0.014)	(0.010)
Liquidity	− 1.010***	0.059***
	(0.023)	(0.002)
Observations	322	322
R^2	0.52	0.14
Industry FE	Yes	Yes
Area FE	Yes	Yes

Table 12 (continued)

The table presents the results of the OLS regression robustness analysis for the model of female loan officers and soft information by using the *Z-score* and *σ(ROA)* as alternative measures of insolvency risk. The dependent variables is *approved share* computed as the ratio *granted credit/applied credit amount* for the model of female loan officers and soft information (column 1) and the model of upgrading and downgrading soft information (column 2). In column (1) the interaction term *female * soft information* captures the use of soft information by the female loan officer accountable for managing the firm–bank credit relationship. In column (2) the interaction term *female* upgrading soft information* captures the use of an upgrade by the female loan officer accountable for managing the firm–bank credit relationship. In column (2) the interaction term *female* downgrading soft information* captures the use of a downgrade by the female loan officer accountable for managing the firm–bank credit relationship. All variables are defined in Table 1. Year and industry fixed effects are incorporated in regressions where indicated (not reported). Robust errors reported in parentheses are clustered at the industry level. ***$p<0.01$, **$p<0.05$, *$p<0.1$, respectively

officers are able to better collect and use soft information than their male counterparts as they cultivate and maintain deeper firm–bank relationships with their clients due to a higher threat of losing their job and being penalized in terms of career advancements. We also rule out any other possible explanations that can potentially drive our main results such as differences in workload, work experience, loan officers' optimism, managerial ability, and screening capabilities between female and male loan officers. Despite the granularity and the depth of our proprietary data that make our empirical setting unique, we acknowledge that the empirical analysis in this study covers a limited time period. Nonetheless, our empirical framework is consistent with other studies using very similar empirical settings, such as Liberti and Mian (2009), Beck et al. (2013), Filomeni et al., (2020, 2021, 2023), among others. Hence, despite this limitation, the empirical conclusions derived from this study provide important policy implications reflected in the optimal allocation of capital in the economy, the adoption of fairer banking practices, and the reduction of gender-related exclusion, which is vital in creating an equitable society and fostering a more ethical and inclusive workplace.

Table 13 Robustness: Lending conditions to borrowers with upgraded ratings

Upgrade	Share of long-term debt	Granted credit/ Tot. assets	Collateral	Global guarantee	Strength of cov-enants
Yes	0.187	0.111	0.548	0.097	1.258
No	0.098	0.079	0.342	0.147	1.249
p-value	0.0368	0.0957	0.0016	0.2868	0.9173

Summary statistics represented by the mean of the variables reported, while the group variable is *upgrade*, a dummy equal to 1 if integrated rating < final rating (upward override) and 0 otherwise. The p-values provide test of equality for mean differences between the two groups. All variables are defined in Table 1

Appendix

Qualitative questionnaire (corporate).

Section A—Industry analysis and competitive position

A1—Current industry cycle

a. recession b. expansion c. stability d. stagnation

A2—Expected industry cycle

a. recession b. expansion c. stability d. stagnation

A3—Market type

a. non-cyclical b. cyclical c. volatile

A4—Market structure

a. low competitive b. highly competitive c. competitive

A5—Competitive position

a. leader b. competitor

A6—Investment requirements

a. low b. high c. medium

A7—Market share and margins

a. below the average b. above the average c. average

A8—Investment requirements

a. stable b. growing c. declining

A9—Specific risk

a. none b. raw materials, energy, currency c. suppliers, distribution d. more than one

A10—Specific risk exposure

a. null b. low-medium c. high d. very high

A11—Operative leverage

a. below the average b. above the average c. average d. high

Section B—Corporate specific

B1—Geographic diversification

a. local b. national c. multinational d. international

B2—Client diversification

a. diversification b. concentration

B3—Product diversification

a. low b. high c. medium

B4—Past strategy–management track record

a. satisfactory b. successful

B5—Future strategy

a. external growth b. internal growth c. debt reduction

B6—Stock performance

a. low value b. high c. low growth d. high growth e. non listed

B7—Financial flexibility

a. low b. medium c. high d. very high

B8—Source of financing available

a. credit lines wide and diversified b. committed credit lines c. banks, bond, equity d. information not available

B9—Existence of risk of legal cases pending and tax/social and welfare disputes

a. no b. yes, there are minor legal proceedings (value < 10% of partners equity) c. information not available

B10—Environmental risks: the business exposes the company/group to environmental problems (use of harmful substance, pollution, workplace safety)

a. no b. yes, there but the company/group operates in compliance with regulations by adopting protective measures c. information not available

B11—Recourse to C.I.G. (redundancy fund) in the past 2 years

a. no b. yes

B12—Judgment of the auditors and the statutory boards on the quality of the financial statements

a. judgement without exception b. judgement with exception

B13—Criteria for the evaluation of financial statement items

a. prudential b. market-based

Section C—Group influence

C1—Does the company belong to a group?

a. no b. yes c. yes, it belongs to a creditworthy group with low probability of counterpart's insolvency

Acknowledgements We are grateful to the Editor Hao Liang and to two anonymous referees for their valuable insights and suggestions.

Declarations

Conflict of interest No conflict of interest is disclosed by the authors.

References

Agarwal, S., & Ben-David, I. (2014). Do loan officers' incentives lead to lax lending standards?, NBER Working Papers No. 19945.

Agarwal, S., & Ben-David, I. (2018). Loan prospecting and the loss of soft information. *Journal of Financial Economics, 129*, 608–628.

Agarwal, S., Duchin, R., Sosyura, D. (2012). In the mood for a loan: The causal effect of sentiment on credit origination (Working paper).

Agarwal, S., & Hauswald, R. (2010). Distance and private information in lending. *Review of Financial Studies, 23*(7), 2757–2788.

Agarwal, S., & Wang, F. H. (2009). Perverse incentives at the banks? Evidence from a Natural Experiment, Working paper, Federal Reserve Bank of Chicago.

Agier, I., & Szafarz, A. (2013). Microfinance and gender: Is there a glass ceiling on loan size? *World Development, 42*(February), 165–181.

Andersson, P. (2004). Does experience matter in lending? A process-tracing study on experienced loan officers' and novices' decision behavior. *Journal of Economic Psychology, 25*, 471–492.

Aubert, C., de Janvry, A., & Sadoulet, E. (2009). Designing credit agent incentives to prevent mission drift in pro-poor microfinance institutions. *Journal of Development Economics, 90*(1), 153–162.

Bae, K. H., Baek, J. S., Kang, J. K., & Liu, W. L. (2012). Do controlling shareholders' expropriation incentives imply a link between corporate governance and firm value? Theory and evidence. *Journal of Financial Economics, 105*, 412–435.

Barber, B. M., & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *Quarterly Journal of Economics, 116*, 261–292.

Barua, A., Davidson, L. F., Rama, D. V., & Thiruvadi, S. (2010). CFO gender and accruals quality. *Accounting Horizons, 24*(1), 25–39.

Basel Committee on Banking Supervision (BCBS). (2005). Studies on the Validation of Internal Rating Systems. *BCBS Working Paper No. 14*.

Bear, S., Rahman, N., & Post, C. (2010). The impact of board diversity and gender composition on corporate social responsibility and firm reputation. *Journal of Business Ethics, 97*, 207–221.

Beck, T., Behr, P., & Guettler, A. (2013). Gender and banking: are women better loan officers? *Review of Finance, 17*, 1279–1321.

Behr, P., & Sonnekalb, S. (2012). The effect of information sharing between lenders on access to credit, cost of credit, and loan performance—evidence from a credit registry introduction. *Journal of Banking & Finance, 36*, 3017–3032.

Bellucci, A., Borisov, A., & Zazzaro, A. (2010). Does gender matter in bank–firm relationships? Evidence from small business lending. *Journal of Banking & Finance, 34*(12), 2968–2984.

Bellucci, A., Borisov, A., & Zazzaro, A. (2013). Do banks price discriminate spatially? Evidence from small business lending in local credit markets. *Journal of Banking and Finance, 37*(11), 4183–4197.

Ben-Ner, A., Kon, F., & Putterman, L. (2004). Share and share alike?Share and share alike? Gender-pairing, personality, and cognitive ability as determinants of giving *Journal of Economic Psychology, 25*, 581–589.

Besanko, D., & Thakor, A. (1987). Collateral and rationing: Sorting equilibria in monopolistic and competitive credit markets. *International Economic Review, 28*, 671–689.

Bester, H. (1985). Screening vs. rationing in credit markets with imperfect information. *American Economic Review, 75*, 850–855.

Beu, D. S., Ronald, M. B., & Harvey, M. G. (2003). Ethical decision-making: A multidimensional construct. *Business Ethics: A European Review, 12*(1), 88–197.

Blanco-Oliver, A., Alvarado, N. R., & Veronesi, G. (2021). Credit risk in the microfinance industry: The role of gender affinity. *Journal of Small Business Management, 59*(2), 280–311.

Bliss, R., & Potter, M. (2002). Mutual fund managers: Does gender matter? *The Journal of Business and Economic Studies, 8*, 1–17.

Boot, A., Thakor, A. V., & Udell, G. (1991). Secured lending and default risk: Equilibrium analysis and monetary policy implications. *Economic Journal, 101*, 458–472.

Boyd, J., De Nicolò, G., & Al Jalal, A. (2006). Bank risk taking and competition revisited: new theory and new evidence, IMF Working Paper No. 06/297.

Byrnes, J. P., Miller, D. C., & Schafer, W. D. (1999). Gender differences in risk taking: A meta analysis. *Psychological Bulletin, 125*, 367–383.

Brown, M., Schaller, M., Westerfeld, S., & Heusler, M. (2012). Information or Insurance? On the Role of Loan Officer Discretion in Credit Assessment, *MoFiR Working Paper* No. 67.

Brown, M., Schaller, M., Westerfeld, S., & Heusler, M. (2015). Internal control and strategic communication within firms—evidence from Bank Lending. *University of St. Gallen Working Papers on Finance* No. 1504.

Buehler, S., Kaiser, C., & Jaeger, F. (2012). The geographic determinants of bankruptcy: Evidence from Switzerland. *Small Business Economics, 39*(1), 231–251.

Cadot, J. (2013). Collateral, bank monitoring and firm performance: The case of newly established wine farmers. *Australian Journal of Agricultural and Resource Economics, 57*(3), 344–358.

Camara, B., Lepetit, L., & Tarazi, A. (2013). Ex ante capital position, changes in the different components of regulatory capital and bank risk. *Applied Economics, 45*(34), 4831–4856.

Campbell, D., Loumioti, M., & Wittenberg-Moerman, R. (2019). Making sense of soft information: Interpretation bias and loan quality. *Journal of Accounting and Economics, 68*, 101240.

Cardoso, A. R., & Winter-Ebmer, R. (2010). Female-led firms and gender wage policies. *ILR Review, 64*, 143–163.

Chan, Y., & Thakor, A. V. (1987). Collateral and competitive equilibria with moral hazard and private information. *Journal of Finance, 42*, 345–363.

Chen, J., & Houser, D. (2019). When are women willing to lead? The effect of team gender composition and gendered tasks. *The Leadership Quarterly, 30*, 101340.

Chen, Y., & Skiena, S. (2014). *Building Sentiment Lexicons for All Major Languages*. In: Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), 383–389.

Collier, P., & Mayer, C. (1989). The assessment: Financial liberalization, financial systems, and economic growth. *Oxford Review of Economic Policy, 5*(4), 1–12.

Cortes, K., Duchin, R., & Sosyura, D. (2016). Clouded judgment: The role of sentiment in credit origination. *Journal of Financial Economics, 121*(2), 392–413.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society Series B (Methodological), 34*(2), 187–220.

Cox, D., & Oakes, D. (1984). *Analysis of Survival Data*. Chapman and Hall.

Cozarenco, A., & Szafarz, A. (2018). Gender biases in bank lending: Lessons from microcredit in France. *Journal of Business Ethics, 147*, 631–650.

Croson, R., & Gneezy, U. (2009). Gender differences in preferences. *Journal of Economic Literature, 47*, 448–474.

Cumming, D. J., Leung, T. Y., & Rui, O. M. (2015). Gender diversity and securities fraud. *Academy of Management Journal, 58*(5), 1572–1593.

Cummins, J.D., Rubio-Misas, M., & Vencappa, D. (2017). Competition, efficiency and soundness in European life insurance markets, *Journal of Financial Stability*, 28.

Degryse, H., & Ongena, S. (2005). Distance, lending relationships, and competition. *Journal of Finance, 60*(1), 231–266.

Degryse, H., Liberti, J., Mosk, T., & Ongena, S. (2013). Is Loan Officer Discretion Advised When Viewing Soft Information? *Working paper, Northwestern University*.

Demerjian, P., Lev, B., & McVay, S. (2012). Quantifying managerial ability: A new measure and validity tests. *Management Science, 58*(7), 1229–1248.

Doering, L. (2018). Risks, returns, and relational lending: personal ties in microfinance. *American Journal of Sociology, 123*(5), 1341–1381.

Djankov, S., McLiesh, C., & Shleifer, A. (2007). Private credit in 129 countries. *Journal of Financial Economics, 84*, 299–329.

Eagly, A. H., Wood, W., & Fishbaugh, L. (1981). Sex differences in conformity: Surveillance by the group as a determinant of male nonconformity. *Journal of Personality and Social Psychology, 40*(2), 384–394.

Eckel, C., & Grossman, P. J. (2001). Chivalry and solidarity in ultimatum games. *Economic Inquiry, 39*, 171–188.

Eckel, C., & Grossman, P. J. (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior and Organization, 68*, 1–17.

Erhardt, N. L., Werbel, J. D., & Shrader, C. B. (2003). Board of director diversity and firm financial performance. *Corporate Governance: An International Review 11*(2), 102–111.

Federal Reserve. (2011). *Supervisory Guidance on Model Risk Management*. Board of Governors of the Federal Reserve System, Office of the Comptroller of the Currency, SR Letter 11–7.

Fernando, D., Cohen, L., & Duberley, J. (2018). What helps? Women engineers' accounts of staying on. *Human Resource Management Journal, 28*, 479–495.

Filomeni, S., Udell, G. F., & Zazzaro, A. (2020). Communication frictions in banking organizations: Evidence from credit score lending. *Economics Letters, 195C*, 109412. https://doi.org/10.1016/j.econlet.2020.109412

Filomeni, S., Udell, G. F., & Zazzaro, A. (2021). Hardening soft information: Does organizational distance matter? *The European Journal of Finance, 27*(9), 897–927. https://doi.org/10.1080/1351847X.2020.1857812

Filomeni, S., Bose, U., Megaritis, A., & Triantafyllou, A. (2023). Can market information outperform hard and soft information in predicting corporate defaults?, *International Journal of Finance & Economics*, pp 1–26. https://doi.org/10.1002/ijfe.2840.

Filomeni, S. (2023). The impact of the Paycheck Protection Program on the risk-taking behaviour of US banks. *Review of Quantitative Finance and Accounting, Online First.* https://doi.org/10.1007/s11156-023-01223-7

Fletcher, J. K. (1999). *Disappearing acts: Gender, power, and relational practice at work*. MIT Press.

Francis, B., Hasan, I., Park, J. C., & Wu, Q. (2015). Gender differences in financial reporting decision making: Evidence from accounting conservatism. *Contemporary Accounting Research, 32*, 1285–1318.

Friedman, E., Johnson, S., & Mitton, T. (2003). Propping and tunneling. *Journal of Comparative Economics, 31*, 732–750.

Gilligan, C. (1982). *In a Different Voice: Psychological Theory and Women's Development*. Harvard University Press.

Girardone, C., Kokas, S., & Wood, G. (2021). Diversity and women in finance: Challenges and future perspectives. *Journal of Corporate Finance, 71*, 101906.

Gropp, R., & Guettler, A. (2018). Hidden gems and borrowers with dirty little secrets: Investment in soft information. Borrower Self-Selection and Competition. *Journal of Banking and Finance, 87*, 26–39.

Gupta, V., Turban, D., Wasti, S., & Sikdar, A. (2009). The role of gender stereotypes in perceptions of entrepreneurs and intentions to become an entrepreneur. *Entrepreneurship Theory and Practice, 33*, 397–417.

Hafeez, B., Li, X., Kabir, M. H., & Tripe, D. (2022). Measuring bank risk: Forward-looking z-score. *International Review of Financial Analysis, 80*, 102039.

Hannan, T. H., & Hanweck, G. A. (1988). Bank insolvency and the market for large certificates of deposit. *Journal of Money, Credit and Banking, 20*, 203–211.

He, X., Kothari, S. P., Xiao, T., & Zuo, L. (2018). Long-term impact of economic conditions on auditors' judgment. *Accounting Review, 93*(6), 203–229.

Heilman, M. E., & Alcott, V. B. (2001). What I think you think of me: Women's reactions to being viewed as beneficiaries of preferential selection. *Journal of Applied Psychology, 86*, 574–582.

Henebry, K. L. (1997). A test of the temporal stability of proportional hazards models for predicting bank failure. *Journal of Financial and Strategic Decisions, 10*(3), 1–11.

Henry, E. (2006). Market reaction to verbal components of earnings press releases: Event study using a predictive algorithm. *Journal of Emerging Technologies in Accounting, 3*(1), 1–19.

Henry, E., & Leone, A. J. (2015). Measuring qualitative information in capital markets research: Comparison of alternative methodologies to measure disclosure tone. *The Accounting Review, 91*(1), 153–178.

Hertzberg, A., Liberti, J. M., & Paravisini, D. (2010). Information and incentives inside the firm: Evidence from loan officer rotation. *Journal of Finance, 65*, 795–828.

Houston, J. F., Lin, C., Lin, P., & Ma, Y. (2010). Creditor rights, information sharing, and bank risk taking. *Journal of Financial Economics, 96*(3), 485–512.

Huang, S.-C., Chen, W.-D., & Chen, Y. (2018). Bank liquidity creation and CEO optimism. *Journal of Financial Intermediation, 36*, 101–117.

Jappelli, T., & Pagano, M. (2002). Information sharing, lending and defaults: Cross country evidence. *Journal of Banking & Finance, 26*(10), 2017–2045.

Kräft, C. (2022). Equal pay behind the "Glass Door"? The gender gap in upper management in a male-dominated industry. *Gender Work & Organisation, 29*, 1910–1926.

Krishnan, G. V., & Parsons, L. M. (2008). Getting to the bottom line: An exploration of gender and earnings quality. *Journal of Business Ethics, 78*(1), 65–76.

Laeven, L., & Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics, 93*(2), 259–275.

Lane, W. R., Looney, S. W., & Wansley, J. W. (1986). An application of the cox proportional hazards model to bank failure. *Journal of Banking and Finance, 10*(4), 511–531.

Lau, V. W., Scott, V. L., Warren, M. A., & Bligh, M. C. (2023). Moving from problems to solutions: A review of gender equality interventions at work using an ecological systems approach. *Journal of Organizational Behavior, 44*(2), 399–419.

Li, F. (2010). Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature, 29*, 143–165.

Liberti, J. M. (2018). Initiative, incentives, and soft information. *Management Science, 64*(8), 3714–3734.

Liberti, J. M., & Mian, A. R. (2009). Estimating the effect of hierarchies on information use. *Review Financial Studies, 22*, 4057–4090.

Lins, K., Volpin, P., & Wagner, H. (2013). Does family control matter? International evidence from the 2008–2009 financial crisis. *Review of Financial Studies, 26*, 2583–2619.

Loughran, T., & Mcdonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance, 66*(1), 35–65.

Malmström, M., Burkhard, B., Sirén, C., Shepherd, D., & Wincent, J. (2024). A meta-analysis of the impact of entrepreneurs' gender on their access to bank finance. *Journal of Business Ethics, 192*, 803–820.

Manove, M., Padilla, A. J., & Pagano, M. (2001). Collateral versus project screening: A model of lazy banks. *The RAND Journal of Economics, 32*(4), 726–744.

McCabe, A. C., Ingram, R., & Conway Dato-on, M. (2006). The business of ethics and gender. *Journal of Business Ethics, 64*, 101–116.

Michels, J. (2012). Do unverifiable disclosures matter? Evidence from peer-to-peer lending. *Accounting Review, 87*(4), 1385–1413.

Montalvo, J. G., & Reynal-Querol, M. (2020). Gender Differences in Compliance: Evidence from Loan Officers, SSRN Working Paper: https://ssrn.com/abstract=3560308.

Morales-Acevedo, P., & Ongena, S. (2020). Fear, anger, and credit. *On Bank Robberies and Loan Conditions, Economic Enquiry, 58*(2), 921–952.

Østergaard, C. R., Timmermans, B., & Kristinsson, K. (2011). Does a different view create something new? The effect of employee diversity on innovation. *Research Policy, 40*(3), 500–509.

Pagano, M., & Jappelli, T. (1993). Information sharing in credit markets. *Journal of Finance, 48*(5), 1693–1718.

Petersen, M. A., & Rajan, R. G. (2002). Does distance still matter? The information revolution in small business lending. *Journal of Finance, 57*(6), 2533–2570.

Powell, M., & Ansic, D. (1997). Gender differences in risk behaviour in financial decision-making: An experimental analysis. *Journal of Economic Psychology, 18*, 605–628.

Kalbfleisch, J. D., & Prentice, R. L. (2002). *The Statistical Analysis of Failure Time Data, Wiley Series in Probability and Statistics*. Wiley

Price, M. K., Doran, J. S., Peterson, D. R., & Bliss, B. A. (2012). Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking & Finance, 36*(4), 992–1011.

Ravina, E. (2008). Love & loans: The effect of beauty and personal characteristics in credit markets. Working Paper, Columbia University.

Ridgeway, C. J., & Diekema, D. (1992). Are gender differences status differences? In C. J. Ridgeway (Ed.), *Gender, interaction, and inequality* (pp. 157–180). Springer.

Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica, 20*(3), 431–449.

Ryan, M. K., Haslam, S. A., Morgenroth, T., Rink, F., Stoker, J., & Peters, K. (2016). Getting on top of the glass cliff: Reviewing a decade of evidence, explanations, and impact. *The Leadership Quarterly, 27*(3), 446–455.

Schoar, A., & Zuo, L. (2017). Shaped by booms and busts: How the economy impacts CEO careers and management styles. *Review Financial Studies, 30*(5), 1425–1456.

Stein, J. (2002). Information production and capital allocation: decentralized versus hierarchical firms. *Journal of Finance, 57*(5), 1891–1921.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review, 71*(3), 393–410.

Stiglitz, J.E. (1989). Financial markets and development, *Oxford Review of Economic Policy, 5* (4).

Stojmenovska, D. (2019). Management gender composition and the gender pay gap: Evidence from British panel data. *Gender Work & Organisation, 26*, 738–764.

Tanaka, T. (2014). Gender diversity in the boards and the pricing of publicly traded corporate debt: Evidence from japan. *Applied Financial Economics, 24*, 247–258.

Qian, J., & Strahan, P. E. (2007). How laws and institutions shape financial contracts: The case of bank loans. *Journal of Finance, 62*(6), 2803–2834.

Qian, J., Strahan, P. E., & Yang, Z. (2015). the impact of incentives and communication costs on information production and use: evidence from bank lending. *Journal of Finance, 70*(4), 1457–1493.

Villanueva-Moya, L., & Expósito, F. (2022). Are gender roles associated with well-being indicators? *The Role of Femininity, Fear of Negative Evaluation, and Regret in Decision-Making in a Spanish Sample, Current Psychology, Online First.* https://doi.org/10.1007/s12144-022-03142-7

Wang, J. (2020). Screening soft information: Evidence from loan officers. *The RAND Journal of Economics, 51*(4), 1287–1322.