Making Sense of Soft Information: Interpretation Bias and Loan Quality

Dennis Campbell
Harvard Business School

Maria Loumioti
The University of Texas at Dallas

Regina Wittenberg-Moerman[*]
University of Southern California

August 2018

ABSTRACT

We explore whether behavioral biases impede the effective processing and interpretation of soft information in private lending. Taking advantage of the internal reporting system of a large federal credit union, we delineate three important biases likely to affect the lending process: (1) limited attention (or distraction), (2) task-specific human capital, and (3) common identity. Specifically, we find that using soft information in lending decisions leads to worse loan quality when loan officers are busy or before weekends and around national holidays, when loan officers have earlier sales experience, and when both the officers and borrowers are men. Overall, we provide novel evidence of non-agency-related costs in the use of soft information in lending decisions.

[*] We are grateful to Allen Berger, Ethan Bernstein, Robert Bushman (discussant), Sarah Bonner, Christine Cuny (discussant), Doug Diamond, John Gallemore, Jacquelyn Gillette, Kathryn Kadous, Jung Koo Kang, Kristoph Kleiner (discussant), Robert Libby, Tracie Majors, Greg Matvos (discussant), Thomas Mosk (discussant), Mike Minnis (discussant), Venky Nagar, Alban Pruthi, George Serafeim, Eric So, Andrew Sutherland, and the conference participants at the Asian Bureau of Finance and Economic Research Conference, the Chicago Financial Institutions Conference, the FARS midyear meeting, the LBS Accounting Symposium, the Lisbon Accounting Conference, the Miami Behavioral Finance Conference, the MOFIR conference, the Penn State Accounting Research Conference, and workshop participants at the Bank of France, the Chinese University of Hong Kong, Harvard Business School, HEC Paris, the Hong Kong University of Science and Technology, IESE Business School, Emory University, NYU, The University of California, Berkeley, The University of Chicago, The University of Connecticut, The University of North Carolina, UT Dallas, and Tel-Aviv University for their helpful comments. We thank Michael Allen, Matthew Bouchard, Ryan Davis, Matias Ferandel, Steven Johnson, Brennan Novak, Zilu Pan and Lily Tan for their excellent research assistance. Dennis Campbell, Maria Loumioti, and Regina Wittenberg-Moerman acknowledge research support from Harvard Business School, MIT Sloan School of Management, the University of Texas at Dallas and the University of Southern California. All remaining errors are our own. This paper was previously circulated under the title "Making Sense of Soft Information: Interpretation Bias and Ex-post Lending Outcomes". Corresponding authors: dcampbell@hbs.edu; Maria.Loumioti@utdallas.edu; reginaw@marshall.usc.edu.

1. Introduction

Substantial research in accounting and finance has shown that private, qualitative, and hard-to-verify (i.e., "soft") information allows loan officers to better screen borrowers and thus enhances the quality of their loan decisions (e.g., Petersen and Rajan 1994; 1995; Berger and Udell 2002; Petersen 2004; Cassar et al. 2015). In contrast, another strand of research suggests that agents' behavioral biases can impede the effective processing and interpretation of less salient, non-quantitative information, undermining their decision making (e.g., Cyert and March 1963; Libby et al. 2002; Kahneman 2011). In this study, we explore whether behavioral biases can impede loan officers' effective interpretation and judgment of soft information, leading to lower quality loans.

To address our research question, we employ detailed loan, borrower, and loan officer data from a large federal credit union that follows a relationship, soft-information-based lending model.[1] While the poor processing of soft information can increase Type I errors (where a loan officer rejects high quality loans), due to data availability, we explore its effect on Type II errors only (where a loan officer approves low quality loans). Loan officers in the credit union have considerable authority over lending decisions, which largely rely on qualitative private information collected through their relationships with borrowers. To further facilitate soft-information-based lending, loan officers and other credit union employees use an internal reporting system to document and share their routine communications with clients. We use the employees' notes in this reporting system to develop a direct measure of soft information about borrowers.

Motivated by prior research (e.g., Petersen 2004), we identify soft-information-related keywords (soft keywords hereafter) as words associated with a borrower's social, professional, educational, and personal background (e.g., "friends," "job," "degree," "family") as well as words

[1] As of 2013, credit unions in the United States had $1 trillion assets under management, $600 billion loans outstanding and served about 94 million members (National Credit Union Administration Data Summary 2012Q4).

and phrases that capture feelings and employees' assessments (e.g., "overwhelmed," "frustrated," "I assess," "I think"). Our soft information measure, *Soft information*, is the ratio of soft keywords in employees' notes on a borrower to the total number of words in these notes, estimated based on notes written over the 45-day period prior to a loan origination. In line with prior banking literature (e.g., Petersen and Rajan 1994; Uzzi and Lancaster 2003), we validate our proxy by investigating whether it is associated with higher loan quality, measured by a loan's post-issuance performance (e.g., Agarwal and Hauswald 2010; Puri et al. 2011; Cole et al. 2015). Using four measures of loan quality – whether a loan has been charged off (*Charge off*), whether the borrower defaulted on a loan issued by the credit union (*Delinquency*), whether the borrower defaulted on any outstanding loan or filed for bankruptcy (*Bad customer*), and whether a borrower's credit score declined substantially following a loan's origination (*Credit score decline*) – we find that higher values of our soft information measure decrease the probability of bad credit outcomes. These findings are consistent with loan officers being able to better screen borrowers and understand the nuances of their creditworthiness when the amount of soft information about these borrowers is greater.

We examine the effect of soft information on the quality of loan decisions when loan officers are subject to three behavioral biases: (1) limited attention (or distraction), (2) task-specific human capital, and (3) common identity. Consistent with prior research on agents using heuristics to alleviate behavioral biases (e.g., Tversky and Kahneman 1974; Hastie and Dawes 2001; Kahneman and Frederick 2002; Bonner 2008), we argue that loan officers facing these biases will employ heuristics in processing the context, relevance, and implications of soft information, which may impede its effective interpretation and lead to a higher probability of issuing low quality loans.

We first predict that lending based on soft information leads to worse quality loans when loan officers are inattentive (or distracted), since they will fail to accurately interpret and reflect on soft information, which is more costly and time-consuming to process than hard information (e.g., Hirshleifer and Teoh 2003; Lim and Teoh 2010; Huang et al. 2017). Guided by prior research, we expect that loan officers likely misinterpret soft information on busy days (e.g., Hirshleifer et al. 2009; DeHaan et al. 2015) or before weekends and around holidays (e.g., DellaVigna and Pollett 2009; Pantzalis and Ucar 2014). We find strong support for the inattention hypothesis: lending based on soft information at these times leads to significantly worse loan quality. To exemplify, when a loan is approved on a busy day, a one standard deviation increase in *Soft information* increases the probability of *Charge off*, *Delinquency*, and *Bad customer* by about 13.45%, 12.10%, and 7.25% of the respective sample mean values of these lending outcomes.

Second, prior studies show that agents' early career experience imprints a specific professional mindset and attitude, which affects their judgment and decision-making in the long-term, despite significant environmental changes and subsequent professional developments (e.g., Gibbons and Waldman 2004; Marquis and Tilcsik 2013; Schoar and Zuo 2016; He et al. 2018). We focus on loan officers with an early career in sales. Salespeople learn to be optimistic about their tasks and typically develop a mindset of reaching or maximizing sales goals (e.g., Seligman and Schulman 1986; Seligman 1990). We predict that this imprinted sale-goal-oriented mindset will adversely affect loan officers' processing of soft information. Optimism directs people's attention to more positive information cues (e.g., Hecht 2013; Kress et al. 2018), and a goal implementation mindset directs their attention to information that supports the chosen goal (e.g., Heckhausen and Gollwitzer 1987; Gollwitzer and Bayer 1999; Griffith et al. 2015). Loan officers with sales backgrounds are thus more likely to direct their attention to positive information cues about borrowers or information cues related to their sales goal without carefully considering all the information available. Consequently, lending based on soft information by these loan officers is likely to lead to lower quality loans. The results support our prediction. Compared to loan officers with no prior sales experience, when officers have sales experience, a one standard deviation increase in *Soft information* increases *Charge off*, *Delinquency*, *Bad customer*, and *Credit score decline* by about 49.27%, 14.33%, 14.71%, and 17.01% of their respective mean values.

Third, we predict that a common identity between loan officers and borrowers will influence their interpretation of soft information. Similar characteristics likely reduce the processing costs of soft information and thus allow for its more accurate interpretation (e.g., Uzzi 1999; Uzzi and Lancaster 2003; Dewatripont and Tirole 2005). However, similarity has been shown to lead to more positive attitudes and greater trust (e.g., Byrne 1971; Clore and Byrne 1974; Glaeser et al. 2000). Loan officers may have more affirmative judgment of and perceive as more trustworthy borrowers who resemble them, thus viewing the soft information about these borrowers as more credible and processing it less diligently. Consequently, lending based on soft information when loan officers and borrowers share similar characteristics may lead to worse loan quality.

Focusing on the gender of loan officers and borrowers, we document that lending based on soft information by male loan officers to male borrowers leads to worse quality loans relative to when both parties are women or of different genders. To illustrate, when a loan officer and a borrower are both men, a one standard deviation increase in *Soft information* increases *Charge off*, *Delinquency*, and *Bad customer* by about 53.09%, 12.32%, and 8.73% of the respective mean values of these outcomes. These findings are consistent with prior evidence that male loan officers are more likely to query the commitment of female loan applicants and to develop a bond with male borrowers (Carter et al. 2007) and that men are more supportive of other men than they are of women (e.g., Brass 1985; Grunspan et al. 2016).

For all our behavioral biases, we also assess soft information’s effect on loan quality relative to situations when no soft information is used in lending. We find that when loan officers are subject to behavioral biases, lending based on soft information leads to *worse* loan quality. For example, relative to when no soft information is used, a one standard deviation increase in *Soft information* when loan officers originate a loan just before the weekend increases *Charge off*, *Delinquency*, and *Bad customer* by 36.00%, 11.07%, and 8.98% of their respective mean values.

We next examine several factors that likely mitigate the adverse effect of behavioral biases on soft information processing. First, we show that this effect is smaller when soft information is collected by the approving loan officer, rather than by other employees, consistent with soft information processing costs being lower under these circumstances. Second, we find that loan officers' experience at the credit union alleviates limited attention bias (e.g., loan officers learn over time how to deal with time pressure and/or distractions), but it is not helpful for imprinted biases driven by early career experience or common identity. Third, we find weak evidence that borrowers' prior relationships with the credit union or lower credit riskiness can alleviate the influence of behavioral biases on judging soft information. Last, focusing on the tone of the soft information, we show that the adverse effect of behavioral biases is somewhat smaller when the soft information about the borrower contains consistently positive or consistently negative cues, facilitating a loan officer's interpretation of it.

In supplemental analyses, we recognize that our findings may be affected by the endogenous matching between borrowers and loan officers. To alleviate this concern, we restrict our sample to loans issued by call-center loan officers, who randomly receive loan applications over the phone when branch loan officers are unavailable. Although our sample declines drastically, our findings generally continue to hold. Further, we show that behavioral biases have no effect on the use of hard information in lending (e.g., a borrower's credit score and debt-to-income ratio), consistent with the interpretation of quantitative information not being influenced by these biases (e.g., Hirshleifer and Teoh 2003). Another concern is that when making a loan decision, loan officers subject to behavioral biases may underweight soft and overweight hard information. We address this concern by showing that loan officers' reliance on soft and hard information in loan pricing and exception decisions is largely unaffected by the presence of behavioral biases, consistent with loan officers being unaware of the biases' adverse effects. In addition, loan interest rate analyses further support our inferences that behavioral biases induce poor loan decisions. If the worse loan quality that we document was driven by loan officers approving riskier loans, we would expect them to compensate for the higher risk by charging higher interest rates, which is not the case. Finally, we find that our results are robust to an alternative measure of soft information.

Our paper contributes to the literature in several ways. First, although substantial literature argues that banks specialize in producing private information about their borrowers (e.g., Diamond 1991; Dang et al. 2017), we have little evidence on how this information is created and processed. We show that lenders do not always efficiently process and assimilate soft information in their decision-making, which leads to low quality loan issuance and can distort credit allocation, adversely impacting the funding of valuable projects and economic activity. Relatedly, we complement studies that examine organizational and incentive structures that constrain lenders' ability to process soft information. Banks' organizational hierarchies are shown to decrease the use of soft information in loan decisions (e.g., Cole et al. 2004; Berger et al. 2005; Liberti and Mian 2009; Qian et al. 2015; Chen and Vashishtha 2017).[2] Further, loan officers' incentives to

[2] Cole et al. (2004) and Berger et al. (2005) find that large banks are ineffective at processing soft information and thus largely rely on borrowers' hard characteristics. Liberti and Mian (2009) and Qian et al. (2015) show that the greater organizational distance between loan officers and their managers limits the use of soft information in loan decisions. Chen and Vashishtha (2017) further demonstrate that mergers create more complex and hierarchical bank structures, which are less effective for collecting and processing soft information.

manipulate the content of soft information and hide unfavorable borrower performance reduce the information's effective use (e.g., Banerjee et al. 2009; Hertzberg et al. 2010; Paravisini and Schoar 2016).[3] These studies abstract away from loan officers' inherent ability to process this information. Our contribution lies in introducing previously unexplored *non-agency-based* limitations in the use of soft information that arise from loan officers' behavioral biases.

Second, we expand the literature on the role of soft information in private lending. Although prior studies document that soft information is associated with higher loan quality, they rely on indirect soft information proxies, such as the distance between a lender and a borrower and a lender's prior relationship with a borrower (e.g., Petersen and Rajan 1994; 2002; Berger and Udell 1995; Degryse and van Cayseele 2000; Agarwal and Hauswald 2010; Bharath et al. 2011; Cassar et al. 2015). To the best of our knowledge, our study is the first to develop a direct measure of soft information. We can thus not only provide a stronger support for the importance of soft information in generally improving loan quality, but also shed light on soft information's collection, processing and content, which prior studies leave unexplored.

Third, we add to the growing literature on the role of behavioral factors in lending decisions. Recent studies link the quality of lending decisions to changes in loan officers' sentiment as a consequence of the weather and the outcomes of sports events and TV shows (e.g., Agarwal et al. 2013; Cortes et al. 2016), negative shocks such as robberies (e.g., Morales-Acevedo and Ongena 2018), and religious practices (e.g., Demiroglu et al. 2017). These studies argue that loan officers' misjudgments, induced by emotions and moods, lead to a higher probability that bad quality loans

[3] Banerjee et al. (2009) show that since soft information is costly to verify and interpret, loan officers can hide bad firm performance and evergreen loans until they are too late to save. Consistent with loan officers suppressing unfavorable soft information about their borrowers, Hertzberg et al. (2010) show that when loan officers anticipate rotation, their reports are more accurate and contain more bad news about borrowers' quality. Paravisini and Schoar (2016) find that the introduction of an internal credit scoring system, which reduced loan officers' involvement in lending decisions, increased bank profitability, suggesting that lending based on soft information is potentially affected by loan officers' agency problems.

will be approved. Our contribution lies in exploring a direct link between behavioral biases and loan quality via loan officers' ineffective processing of soft information.

Last, we contribute to the well-established literature that examines how behavioral biases harm decision-making (e.g., Libby et al. 2002; Bloomfield 2002; Gibbons 2003; Kahneman 2011). Although limited attention bias has been shown to influence investment decisions in the equity market (e.g., Hirshleifer and Teoh 2003; Hirshleifer, Lim and Teoh 2009; Huang et al. 2017), our study is the first to explore the role of this bias in private lending. Further, we extend studies that document how early career stages shape professional mindsets (e.g., McEvily et al. 2012; Schoar and Zuo 2016; He et al. 2018). We empirically show that these "imprinted" mindsets persist not only over time, but also across very different occupations and tasks. In addition, we extend studies that show that a common identity between people breeds affirmative judgments and trust (e.g., Golightly et al. 1972; Baskett 1973; Glaeser et al. 2000; Guiso et al. 2009) by documenting that a shared gender between a borrower and a loan officer affects the officer's interpretation of soft information and consequently the loan quality. This finding further adds to the literature on the role of gender in private lending (e.g., Buttner and Rosen 1988; Bellucci et al. 2010; Ongena and Popov 2016). With a few exceptions (e.g., Ravina 2008; Carter et al. 2007), these studies do not examine whether the loan officer and the borrower share the same gender. We suggest that prior evidence of banks favoring male borrowers can be explained by male officers perceiving male borrowers' soft information as more credible.

2. The Role of Soft Information in Private Lending

Loan officers generally seek to originate good loans, which rests on them minimizing two types of errors: Type I errors, where a loan officer rejects a high quality loan (i.e., a loan with good ex-post performance) and Type II errors, where a loan officer approves a low quality loan (i.e., a loan with poor ex-post performance).[4] Screening borrowers on quantitative easy-to-obtain and -analyze characteristics (hard information) such as credit score and debt-to-income ratio is not sufficient to minimize these errors, as these standardized ratios are based on a limited set of backward looking and typically stale information. Iyer at al. (2016) show that a borrower's default on a loan is not just a result of her financial characteristics but is driven largely by the complexities and idiosyncrasies of human behavior. In a survey of loan officers, Lipshitz and Shulimovitz (2007) document that officers view specific cues from borrowers' behavior as better indicators of their creditworthiness than financial data.

Therefore, through their relationships with borrowers, loan officers collect soft information, which refers to private, qualitative, and costly-to-obtain and -verify information (e.g., Petersen 2004; Drexler and Schoar 2014; Liberti and Petersen 2017). Soft information reflects aspects of a borrower's creditworthiness and prospects that hard information cannot fully capture and thus plays a crucial role in lending decisions (e.g., Petersen and Rajan 1994; 1995; Berger et al. 2001; Agarwal and Hauswald 2010; Michels 2012; Cassar et al. 2015; Qian et al. 2015; Demiroglu et al. 2017). This relationship, soft-information-based lending model is common in informationally opaque credit markets, such as personal and small business lending. Agarwal and Hauswald (2010) emphasize that credit to small businesses relies crucially on loan officers' firm-specific subjective intelligence. Demiroglu et al. (2017) also highlight that small-business-loan decisions are primarily based on soft information about the borrower, not hard characteristics.

3. Research Setting

We study the role of soft information in loan decisions by using loan, borrower, and loan officer

[4] Prior studies suggest that loan officers focus more on avoiding Type II errors (approving bad loans) than on avoiding Type I errors (rejecting good loans), as the latter are more difficult to discover (e.g., Deakins and Hussain 1994).

data from a large federal credit union, which operates in a single state and offers traditional investment, depository, and lending products. With about $1.6 billion in assets and 140,000 customers, the credit union has consistently ranked in the top 15% in productivity (revenue per employee) and accounting performance when compared to other same-size financial institutions.

Credit unions are member-owned depository institutions, where members share a common bond (e.g., location, profession, or religion). They are an economically significant sector in the U.S. consumer lending market. As of 2013, there were 6,819 credit unions with total assets under management of $1 trillion and $600 billion loans outstanding, serving about 94 million members (National Credit Union Administration Data Summary 2012). Credit unions' primary objective is to maximize the surplus from deposits and loan accounts to better serve their members. Although credit unions have this unique mission, they function largely like commercial banks. Just as banks screen borrowers to decrease the probability of future defaults and sustain their capital adequacy, credit unions aim to avoid issuing low quality loans that can threaten their ability to serve their mandate. We therefore expect our findings to be relevant to commercial bank lending.

3.1. The lending process

The credit union operates under a highly decentralized structure, where loan officers have authority over decisions involving borrowers. Thus, although certain credit guidelines are in place, the officers can discretionarily override them and alter loan issuance decisions and terms. These credit guidelines recommend that the officers avoid lending to borrowers with credit score below 620 or a debt-to-income ratio above 45% and make suggestions about the loan terms (e.g., interest rate, maturity, and collateral) that should be used given a borrower's credit profile. To explain their decisions, loan officers are expected to rely on the soft information they collect by building strong relationships with the borrowers.[5] As one executive summarized, "the norm in our industry is quick decision making based on hard factors that we think are reliable but miss the human element. There are plenty of people with 800 credit score that make thousands of dollars a month but could default in the blink of an eye. There are also plenty of people with scores lower than 600 that are safe bets and are seeking to legitimately rebuild their credit." Moreover, as a loan officer stated, "I really try to get at the 'how and the why?' What happened that caused the credit score decline or bankruptcy? What if it is a temporary job loss, a healthcare issue, or some other issue beyond the control of the [customer]? I would consider all of these factors in making a lending decision." Loan officers also assess a borrower's behavior: "…I really look for accountability. Does the [customer] admit they did not handle a credit situation properly? I am really looking for a signal that the individual matured or learned. For example, I would view it very differently if the explanation was that [the customer] was young, got in over his head, and learned from those mistakes versus a customer that blames all of their problems on their previous bank."

3.2. Loan officer incentives

To motivate loan officers to apply the relationship, soft-information-based lending model, the credit union uses a set of monetary and non-monetary incentives. In terms of the former, loan officers receive a flat salary and an annual bonus. To determine the bonus, the credit union relies extensively on the subjective performance evaluation of employees (Baker et. al. 1994; Ittner et. al. 2003; Gibbs et. al. 2004). These evaluations are based on factors such as how successful the loan officer is in connecting to and establishing relationships with borrowers, how well she

[5] In 2005, the credit union moved from a highly hierarchical organizational structure, where lending decisions were made by the central administration based primarily on two hard information characteristics (i.e., a borrower's credit score and debt-to-income ratio), toward a flatter structure, where employees have decision authority (Campbell 2012). The move to the new structure was driven largely by the credit union's dissatisfaction with the prior lending model. To alleviate the concern that our findings are affected by loan officers' unfamiliarity with processing soft information, we exclude loans issued during the first year of this organizational change. Our results continue to hold (untabulated).

incorporates soft information in her lending decisions rather than merely focusing on hard credit guidelines, and how well she can articulate the rationale for her decisions in the notes.[6] Similarly, in terms of non-monetary incentives, loan officers who adhere to the relationship model are more likely to be promoted. In untabulated analyses, we find that a loan officer is more likely to be promoted to branch manager or assistant branch manager when she collects more soft information about her borrowers. This evidence is consistent with experimental findings showing career concerns to be a key non-monetary determinant of loan officer behavior (Cole et al. 2015).

Further, a strong corporate culture (i.e., shared norms, beliefs, and values on how lending activities should be performed) is another important mechanism that encourages loan officers to collect soft information. The credit union's management guides loan officers on how to build long-term relationships with clients, emphasizing the importance of the soft information these relationships generate. Every loan officer is trained on how she should apply the relationship lending model. Management also periodically issues white papers to clarify common questions loan officers have about interactions with borrowers and soft information collection.

3.3. Internal reporting system

When loan officers deviate from the credit guidelines, they must document their rationale in an internal reporting system. An important feature of this process is that the content of the information collected is not further quantified and remains highly discretionary. Thus they may briefly describe the transaction and refer to a borrower's quantitative characteristics, report both quantitative and qualitative characteristics, or only lay out softer information about the borrower.

Importantly, while the internal reporting system was developed to document loan exceptions,

[6] Loan officers are not penalized for bad loan outcomes. This is a common practice for financial institutions. Linking compensation to loan outcomes imposes substantial risk on loan officers, potentially undercutting their willingness to use decision-making authority at loan origination (e.g., Agarwal and Wang 2008).

it has become widely used by all the credit union's employees, including those on the deposit and investment sides, to document their routine interactions with customers. Employees typically enter notes into the system for any interaction they have with a customer, enabling their information to be communicated across all employees. As one employee explained, "the notes constitute a kind of storybook about the [customer's] life. We can use that information to start a conversation and have a more personal connection and interaction with the [customer]." Moreover, "[the reporting system] … ensures that the relationship is not just with one employee. I've been here for ten years and interacted with thousands of [customers]. Without this system, if I leave, their information goes with me." Examples of loan officers' notes are in Appendix A.

4. Hypotheses Development

Although soft information is an integral part of relationship lending and has been shown to enhance loan decisions, loan officers' interpretative adjustments and inferences are instrumental to the value of soft information in the lending process, and thus to loan quality. Motivated by the accounting, finance, and economics literatures that examine the role of behavioral biases in decision-making (e.g., Cyert and March 1963; Libby et al. 2002; Bloomfield 2002; Gibbons 2003; Bonner 2008; Kahneman 2011), we explore whether these biases impede loan officers' interpretation of soft information, leading to a higher probability of approving a bad quality loan.

We focus on three behavioral biases: 1) limited attention (or distraction), 2) task-specific human capital, and 3) common identity. Behavioral studies show that agents use heuristics to alleviate behavioral biases, which often adversely affect their decision-making (e.g., Tversky and Kahneman 1974; Hastie and Dawes 2001; Kahneman and Frederick 2002; Kahneman 2003; Bonner 2008). Therefore, across all hypotheses, we argue that loan officers will employ heuristics when processing and judging the context, relevance, and implications of soft information about a borrower, which can impede its effective interpretation.[7] Also, across all hypotheses, behavioral biases are expected to be more critical to processing soft information that is by nature qualitative and hard to verify relative to hard information that is more objectively defined and standardized.[8]

4.1. Soft information, limited attention, and loan quality

Limited attention theories argue that agents tend to incorrectly evaluate important qualitative information, due to constraints in their processing power. The limited attention (or distraction) bias has been well-documented in the equity market. Several studies show that investors and analysts do not adequately adjust their interpretations related to qualitative information in a company's earnings announcements, as this information is costly and time-consuming to process (e.g., Hirshleifer and Teoh 2003; Lim and Teoh 2010; Huang et al. 2017). Market participants' inattention or distraction is documented as being stronger on busy days, that is, when they need to attend to multiple events or tasks (e.g., Hirshleifer et al. 2009; DeHaan et al. 2015) or on Fridays, that is, just before the weekend (DellaVigna and Pollett 2009) and around holidays (e.g., Pantzalis and Ucar 2014). Motivated by this literature, we predict that inattentive or distracted loan officers will fail to accurately interpret soft information cues. As a result, lending based on soft information will adversely affect loan quality. Thus we hypothesize:

H1. Lending based on soft information by inattentive loan officers leads to worse loan quality, relative to when loan officers are not subject to inattention bias.

4.2. Soft information, task-specific human capital, and loan quality

Early career experiences have been shown to imprint a mindset that is carried through one's

[7] Heuristics involve the methods and strategies that people employ to reduce the cognitive effort associated with a task (and which people are often not consciously aware of having adopted). For example, people may not thoroughly process available information cues and may fail to comprehend the interpretation and validity (the predictive accuracy) of different cues (Shah and Oppenheimer 2008).
[8] Consistent with this argument, in supplemental analyses, we show that behavioral biases do not affect the use and interpretation of hard information in lending.

career and that affects future decisions, despite subsequent environmental changes and professional developments (e.g., Gibbons and Waldman 2004; Marquis and Tilcsik 2013).[9] McEvily et al. (2012) show how lawyers' early career experiences imprint on them, even if they move to different law firms. Schoar and Zuo (2016) and He et al. (2018) examine the professional attitudes of managers and auditors who started their careers during economic downturns and find that the formative early career stage shapes their judgment and decisions in the long term.

Building on this literature, we expect loan officers' early career experience to be instrumental in processing and interpreting soft information. We focus on loan officers with an early career in sales. Salespeople are trained to quickly close deals and thus develop a mindset of reaching or maximizing sales goals. Also, salespeople learn to be optimistic about their tasks, so that they can persevere and deal with frequent rejections from customers (e.g., Seligman and Schulman 1986; Seligman 1990; Rich 1999; Dixon and Schertzer 2005; Loveland et al. 2015). In contrast, while loan officers often seek new loan opportunities (e.g., Heider and Inderst 2012), they are trained to process all relevant information to evaluate a borrower's repayment ability. Thus they develop a mindset of balancing new loan opportunities with the risk of issuing bad quality loans.

These different professional mindsets (a loan-sale-goal-oriented approach versus a loan-quality-oriented approach) will affect how soft information about a borrower is processed and interpreted. Prior studies show that optimism directs people's attention to more positive information cues (e.g., Hecht 2013; Kress et al. 2018) and that having a goal-implementation mindset directs people's attention to information that supports the chosen goal (e.g., Heckhausen and Gollwitzer 1987; Gollwitzer and Bayer 1999; Henderson et al. 2008; Griffith et al. 2015). We thus expect loan officers with a sales background to direct their attention towards positive

[9] A mindset causes individuals to acquire and process information in a way that facilitates completion of the decision phase with which the mindset is associated (Gollwitzer, Heckhausen, and Steller 1990).

information cues about a borrower or information cues related to their sales goal, without carefully judging the full information set available. Thus we hypothesize:

H2. Lending based on soft information by loan officers with early professional experience in sales leads to worse loan quality relative to when loan officers do not have such experience.

4.3. Soft information, common identity, and loan quality

Similar characteristics shared by a loan officer and a borrower may have a significant effect on the loan officer's judgment. On the one hand, common traits can decrease information processing costs and facilitate the more accurate interpretation of borrower-specific information (e.g., Uzzi 1999; Uzzi and Lancaster 2003; Dewatripont and Tirole 2005; Fisman et al. 2012). Thus lending based on soft information when loan officers and borrowers share similar characteristics will lead to better loan quality.

On the other hand, people develop more positive perceptions and affirmative judgments towards those that resemble them in terms of demographic (age, gender, origin, religion, or race) or personality traits (e.g., Byrne 1971; Clore and Byrne 1974). The common identity bias has been documented in the organizational psychology literature examining recruitment and promotion evaluations (e.g., Baskett 1973; Rand and Wexley 1975; Pulakos and Waxley 1983; Orpen 1984; Brass 1985; Sackett et al. 1991; Harrison et al. 2002; Sears and Rowe 2003). There is also evidence that lenders are likely to lend to borrowers with greater demographic, biographical, or attitudinal similarities (e.g., Golightly et al. 1972; Ravina 2008; Bruns et al. 2008). Relatedly, studies in economics and psychology also show a positive relation between similarity and trust, that is, a person views those similar to her as more honest and truthful (e.g., Glaeser et al. 2000; Alesina and La Ferrara 2002; DeBruine 2002; Guiso et al. 2009; Ben-Ner et al. 2009; Farmer et al. 2014). The trust heuristic has been also documented in auditing research, where managers review trusted employees' work less intensively (Gibbins and Trotman 2002), and auditors fail to objectively assess the quality of trusted advisors' advice (Kadous et al. 2013).

As a result, we expect loan officers to develop more affirmative judgment of borrowers who resemble them and to perceive them as more trustworthy, thus viewing their soft information as more credible and consequently processing it less diligently. In contrast, loan officers will likely question and more thoroughly investigate soft information about dissimilar borrowers. Thus, lending based on soft information when loan officers and borrowers share similar characteristics will lead to worse loan quality relative to when they are dissimilar. Because prior literature suggests conflicting predictions, we hypothesize:

H3. Lending based on soft information when loan officers and borrowers share a common identity leads to better or worse loan quality, relative to when they do not.

5. Data Methodology and Descriptive Statistics

5.1. Data

We obtain data on the credit union's loan, employee, and borrower characteristics over the period from January 2005 through May 2010. We further use the content of employees' notes in the internal reporting system to capture soft information collected about borrowers. Our population of loans includes 119,625 loans with a size greater than $500 issued by 506 employees to 59,453 borrowers in 47 branches. We exclude 35,124 loans originated in 2009–2010, for which we cannot fully capture their future performance. We further eliminate 34,821 loans for which employees did not provide any notes, because we cannot disentangle cases in which no additional information was collected prior to loan origination from those where information was collected but not reported, nor can we assess whether both hard and soft information was collected or the extent of the latter. Our final sample of loans includes 49,680 unique loans originated in 2005–2008 by 415 unique employees in 41 branches to 31,601 unique borrowers. This sample consists of auto loans (23,456 loans), personal loans (17,805 loans), and mortgages or home equity loans (8,419 loans).

5.2. The soft information measure

Our soft information measure is based on the soft-information-related keywords in employees' notes. We identify these keywords following Li's (2010) suggestion about performing textual analyses based on dictionaries developed specifically to analyze the construct under consideration. We therefore read about 15,000 notes to determine repeating patterns in the words and phrases that employees commonly use. Motivated by prior research on the content of soft information (e.g., Petersen 2004) and based on commonly used words and phrases by employees, we define soft keywords as words that relate to a borrower's social (e.g., "friends," "holidays," "hobby," etc.), professional (e.g., "job," "manager," "business"), educational (e.g., "graduate," "education," "degree") and personal background (e.g., "family," "child(ren)," "parent(s)"). We supplement this list of keywords with words related to the borrower's or the employee's feelings, such as "overwhelmed," "frustrated," and "stress" (Plutchik 1980; Parrot 2001). We also attempt to capture employees' judgments and assessments expressed in notes using keyword phrases such as "I think," "I assess," and "I believe." The full list of soft keywords is reported in Appendix B.

We define *Soft information* as the ratio of soft keywords in employees' notes on a borrower to the total number of words in these notes (excluding stop-words, such as "and," "a," and "by"), estimated based on notes written during the 45-day period prior to loan origination.[10] Estimating

[10] Our soft information measure is likely subject to two caveats. First, while we try to develop a comprehensive list of keywords that capture soft information, our dictionary potentially misses important soft information cues included in the notes. Second, employees' notes represent hardened soft information about a borrower (Petersen 2004). However, the exact meaning of this information, the exact event to which it refers, the context under which it was collected, as well as the employee's feelings and judgments need to be processed and interpreted by the loan officer approving the loan (e.g., Cremer et al. 2007). Importantly, the content of employees' notes is not transformed into a numerical score, further reinforcing its qualitative nature. We therefore believe that our measure captures soft information.

soft keywords over this period allows us to measure relatively recent information about the borrower, while deflating by the total number of words in employees' notes allows us to capture the intensity of the soft information collected prior to loan origination.[11] All variables are described in Appendix C. There are 117,738 notes for our sample borrowers written within the 45-day period prior to loan origination (or three notes per borrower). The mean value of *Soft information* is 0.055 (Table 1, Panel A). Our empirical findings are unchanged when we estimate the soft information measure over the 30- or 60-day period prior to loan origination (untabulated).[12]

Note that the *Soft information* measure aims to capture the total amount of soft information that loan officers collect, in line with soft information proxies used in prior studies, which do not differentiate between positive and negative soft information about the borrower. For instance, prior literature uses the distance between a lender and a borrower or a borrower's tenure with the lender to proxy for access to a borrower's soft information (e.g., Petersen and Rajan 1994; 1995; Petersen and Rajan 2002; Hauswald and Marquez 2006; Mian 2006; Agarwal and Hauswald 2010). A shorter distance or longer tenure increases the total amount of soft information available to the lender, which can be positive or negative. Similarly, we expect that loans for which loan officers have more soft information are of better quality relative to loans with less soft information or only hard information available, as soft information allows the officers to better screen borrowers and understand the nuances of their financial performance. In Section 6.3.3, we examine how the tone of loan officers' notes affects the processing of soft information.

[11] Moreover, deflating the number of soft keywords by the total number of words written by employees allows us to control for routine information about a borrower related to her other accounts, such as investments and deposits.

[12] Two alternative measures for *Soft information* yield similar results (untabulated)—the ratio of the total number of words in sentences with at least one soft keyword to the total number of words in employee notes excluding stop-words (*Soft information words*) and the ratio of the number of sentences with at least one soft keyword to the total number of sentences in employee notes (*Soft information sentences*). The mean value of *Soft information sentences* is 26%, and the mean value of *Soft information words* is 44%, suggesting that a reasonable fraction of the words in employee notes relate to soft information. *Soft Information* is 76% (82%) correlated with *Soft information sentences* (*Soft information words*), consistent with all three measures capturing the same underlying construct (untabulated).

5.3. Measures of loan quality and borrower and loan characteristics

We follow prior studies that measure loan quality by a loan's poor post-issuance performance, such as loan default or delinquency (e.g., Agarwal and Hauswald 2010; Puri et al. 2011; Cole et al. 2015; Cortés et al. 2016; Demiroglu et al. 2017; Morales-Acevedo and Ongena 2018). We employ four proxies for ex-post loan performance. *Charge off* is an indicator variable equal to one if a loan is charged off and zero otherwise (the credit union's policy is to charge off a loan within 18 months after the borrower becomes delinquent on the loan). *Delinquency* is an indicator variable equal to one if the borrower defaulted on any loan with the credit union within the 18-month period following the loan's origination and zero otherwise. Because the credit union did not provide delinquency data, we proxy for a borrower's delinquencies by retrieving the following keywords from employees' notes: "loan or mortgage or balance (is) past due," "delinquent," "delinquency (-ies)," "default(ed)," "miss(ed) payment," and "delay(ed) payments."

To better capture a borrower's post-loan issuance creditworthiness, we further use information from a national credit bureau to measure the borrower's performance on credit obligations outside the credit union. *Bad customer* is an indicator variable equal to one if the borrower defaulted on any outstanding loan or filed for bankruptcy within 18 months after a loan's origination and zero otherwise. *Credit score decline* is an indicator variable equal to one if the borrower's credit score fell by 50 points or more within 18 months after a loan's origination and zero otherwise. This cutoff represents the bottom quintile of the distribution of changes in borrowers' credit scores over this post-loan issuance period and aims to capture severe credit performance deterioration. The mean probability of *Charge off* (*Delinquency*) is 2.21% (15.10%), while the mean probability of *Bad customer* (*Credit score decline*) is 23.70% (19.30%) (Table 1, Panel A).[13] *Soft information* is

[13] Sample size varies in the empirical tests depending on data availability. For example, in our tests on the relation between *Credit Score decline* (*Bad customer*), soft information, and behavioral biases, our sample decreases to 27,807

negatively correlated to all measures of loan quality, consistent with this information helping loan officers better screen loans (Table 1, Panel B). To alleviate the concern that measuring ex-post loan performance during the financial crisis (for loans issued in 2007 and 2008) may affect our results, we rerun our analyses for the 2005-2006 period. Although we lose 51% of our sample observations, our findings are mostly unchanged (untabulated).

We also employ a battery of borrower and loan characteristics that studies identify as being associated with loan quality. We proxy for hard measures of a borrower's credit quality, using the natural logarithm of her credit score (*Credit score*) and debt-to-income ratio (*Debt-to-income ratio*), which have mean values of 6.59 (i.e., a credit score of 708 points) and 37.20%, respectively (Table 1, Panel A). Moreover, we proxy for loan characteristics by the interest rate (*Loan interest rate*) and indicator variables reflecting whether the loan terms deviate from the credit union's guidelines (*Loan exception*) and whether the loan is collateralized (*Secured loan*).[14] We show that the mean value of the loan interest rate is 8.97%, while about 80.00% of the sample loans include an exception and 36.80% of the loans are collateralized.[15] We further control for the natural logarithm of the loan amount (*Loan amount*) and the natural logarithm of the loan maturity in months (*Loan maturity*). The mean natural logarithm of the loan amount is 8.90 (about $14,000) and the mean natural logarithm of the loan maturity is 4.09 (about five years). Last, we measure borrowers' prior relationship with the credit union using the natural logarithm of a borrower's

---

(15,972) observations because the data on changes in borrowers' credit scores over time (credit profiles outside the credit union) are not available for all sample borrowers. Further, the relatively high mean probability of *Bad customer* is attributed to loans issued in 2008, for which ex-post performance is measured solely within the credit crisis years; after excluding these loans, the probability of *Bad customer* drops to about 10%. The poor performance of loans issued in 2008 is consistent with the average delinquency and charge off rates reported by banks during the crisis years (https://www.federalreserve.gov/releases/chargeoff/).

[14] When we split our sample into secured and unsecured loans, our findings continue to hold for both subsamples (untabulated).

[15] About 47% of the exceptions are related to the loan terms (i.e., exceptions to interest rate, maturity and collateral) and 33% of the sample loans with exceptions include a credit score and/or debt-to-income ratio exception.

tenure (*Borrower tenure*) and the natural logarithm of the total number of accounts that the borrower maintains, such as deposits, loans, investment, and retirement accounts (*Total number of accounts*). The average borrower has been a customer of the credit union for about three years and has about seven accounts (with their logarithmic transformations equal to 0.85 and 1.60, respectively). Correlations between *Soft information* and borrower and loan characteristics are reported in Panel B of Table 1.[16]

5.4. Behavioral bias measures

We use three measures of limited attention bias. First, we measure how busy a loan officer is on a loan's origination day by the total number of notes she writes on that day (*Busy day*). *Busy day* equals one if the number of notes a loan officer writes on a loan's approval day falls in the top quartile of the distribution of the number of notes per day the officer writes during the current quarter and zero otherwise. We define *Busy day* in comparison to the officer's workload on other days during the same quarter because her ability to process information may change over time. For example, earlier in her career, a loan officer may be more time constrained by processing three notes, but as she gains experience, processing the same amount of information becomes easier.[17]

Second, loan officers may rush to approve loans or be distracted just before the weekend, consistent with inattention bias being stronger at that time (e.g., DellaVigna and Pollett 2009). We employ an indicator variable, *Before weekends*, equal to one if the loan is issued after 4 pm on Friday or on Saturday and zero otherwise. Third, we also expect loan officers to experience greater work overload and/or to be distracted around holidays (e.g., Pantzalis and Ucar 2014; Murfin and

[16] We exclude *Sales background* and *Bad customer* from the correlation matrix to avoid a substantial sample drop. The reported correlations are similar to those for the restricted sample when we include these variables (untabulated).
[17] Our results are unchanged when we define *Busy Day* based on the number of words a loan officer writes on a loan's approval day, i.e., *Busy Day* takes the value of one if this number falls in the top quartile of the distribution of the number of words per day the loan officer writes during the current quarter and zero otherwise (untabulated).

Petersen 2016). We define *Around holidays* as equal to one if the loan is issued within a [-4, +4] day window around major national holidays – Fourth of July, Thanksgiving, Christmas, and the New Year's Day. The mean value of *Busy day* is 0.25. The mean values of *Before weekends* and *Around holidays* are 0.06 and 0.07 respectively, suggesting that about 6.00% and 7.00% of the sample loans are issued just before the weekend or around holidays.

We validate our limited attention measures by examining whether the number of grammar/syntax errors in loan officers' notes is greater during inattentive periods. If loan officers are busy or inattentive, we expect a higher likelihood of them making such errors. We calculate the number of grammar/syntax errors following the methodology of Gillette, Jayaraman, and Zimmerman (2017). Specifically, we assess a loan officer's mistakes by the following three proxies: 1) the number of errors per note; 2) the total number of errors to the total number of words; and 3) the total number of errors to the total number of sentences.[18] We report the results of these univariate tests in Appendix D. Our findings indicate that grammar/syntax errors are greater on busy days, before weekends, and around holidays for all the error proxies we employ, consistent with loans officers making more errors when inattentive or distracted.

Further, we measure loan officers' task-specific human capital by retrieving their biographies from LinkedIn. Loans from officers with no LinkedIn accounts are eliminated from the sample (23,208 observations). We further exclude loans by loan officers with incomplete LinkedIn profiles (17,108 observations), for which we cannot differentiate between loan officers who have no prior experience (i.e., the credit union is their first job) and those that chose to omit earlier career experience and list only their most recent employment, which is at the credit union. We

[18] To alleviate the concern that the lexicological skills of the officers who approve loans during inattentive periods are different from the skills of other loan officers, we adjust all grammar/syntax error proxies by subtracting the mean number of errors the loan officer made over the previous quarter. The results continue to hold (untabulated).

define *Sales background* as equal to one if the loan officer has professional experience in sales and zero if the loan officer has banking or other non-banking experience.[19] Twenty-two percent of our sample loans are issued by loan officers with earlier sales-related experience (Table 1).

We next construct our measures of common identity bias. Since we do not have information about borrowers' social, cultural, and racial backgrounds, we focus on loan officers' and borrowers' gender identity. Using GenderChecker.com, we identify loan officers' gender based on their first name (for 83 out of 415 loan officers in our sample the first name is unavailable or could apply to a man or a woman). Since borrowers' names are unobservable, we use employees' notes to retrieve their gender. We categorize a borrower as a man (woman) if employees mostly refer to a borrower as "he," "his," or "him" ("she," "her," and "hers") in the notes (the gender cannot be identified for 7,661 sample borrowers). *Male to male* (*Female to female*) is an indicator variable equal to one if the loan officer and the borrower are both men (women) and zero otherwise. As we report in Panel A of Table 1, 12.60% (30.90%) of our sample loans are issued by male (female) loan officers to male (female) borrowers.[20]

6. Research Design and Empirical Results

6.1. Validation tests

We first validate our soft information measure. Consistent with prior research showing that a greater amount of soft information improves loan quality, (e.g., Petersen and Rajan 1994; 1995; Berger and Udell 2002; Uzzi and Lancaster 2003; Agarwal and Hauswald 2010), we expect *Soft*

[19] Our results are robust to 1) restricting the control group of loan officers to those with either banking or other, non-banking professional experience and 2) including in the control group loans by loan officers with incomplete LinkedIn profiles (untabulated).
[20] Women make up about 67% and 56% of the credit union's loan officers and borrowers, respectively. This evidence is consistent with industry statistics that women represent about 70% of workforce employed in credit unions (Current population survey, Bureau of Labor Statistics, 2017; https://www.bls.gov/cps/cpsaat18.htm) and with prior research suggesting that relative to men, women rely more on financing from credit unions (Lee and Kelly 2004).

information to be negatively associated with our measures of loan quality. To examine this relation, we use a linear probability (ordinary least squares [OLS]) model, where the dependent variable is loan quality, measured by one of the following adverse ex-post lending outcome measures: *Charge off*, *Delinquency*, *Bad customer*, or *Credit score decline*.[21]

$$\begin{aligned} \textit{Loan quality} = \quad & \alpha + \beta_1 \textit{Soft information} + \beta_2 \textit{Credit score} + \beta_3 \textit{Debt-to-income ratio} \\ & + \beta_4 \textit{Loan interest rate} + \beta_5 \textit{Loan exception} + \beta_6 \textit{Secured loan} \\ & + \beta_7 \textit{Loan amount} + \beta_8 \textit{Loan maturity} + \beta_9 \textit{Borrower tenure} \\ & + \beta_{10} \textit{Total number of accounts} + \textit{Loan officer FE} + \textit{Branch FE} \\ & + \textit{Year of loan origination FE} + \textit{Loan type FE}. \end{aligned} \quad \text{(Model 1)}$$

We expect the coefficient on the soft information measure (β_1) to be negative. We control for hard measures of a borrower's credit quality (*Credit score* and *Debt-to-income ratio*), loan characteristics (*Loan interest rate*, *Loan exception*, *Secured loan*, *Loan amount*, and *Loan maturity*), and a borrower's prior relationship with the credit union (*Borrower tenure* and *Total number of accounts*). We include branch, loan year of origination, and loan type (mortgage, auto, and personal loan) fixed effects to control for differences in loan and borrower performance across branches, loan types, and years. Moreover, we employ loan officer fixed effects to control for differences in loan officers' skills. Standard errors are clustered at the borrower level.[22]

Table 2 reports the results of the validation tests. Consistent with our expectations, across most specifications, we find that our soft information measure is negatively and significantly associated with loan quality. Economically, a one standard deviation increase in *Soft information* reduces the probability of a loan's future charge off (*Charge off*), a borrower's delinquency on a loan with the

[21] We use an OLS, rather than a probit, model to estimate our specifications for two reasons. First, coefficient estimates from probabilistic models are biased if the models include a large number of indicator variables to estimate fixed effects (Madalla 1987; Greene 2004). Second, the estimation of the statistical and economic significance of the coefficients on the interaction terms between the soft information measures and the measures of behavioral biases, which are our main variables of interest, is more reliable with an OLS model (Angrist and Pischke 2008). However, using a probit model yields very similar results (untabulated).
[22] Throughout our analyses, our results are robust to excluding control variables for loan characteristics or clustering standard errors by loan officer (untabulated).

credit union (*Delinquency*), and the probability of a borrower defaulting on any outstanding loan or filing for bankruptcy (*Bad customer*) by 0.26%, 0.50%, and 0.64%, which represent about 12.00%, 3.31%, and 2.70% of the respective sample mean values of these loan quality measures.

To better assess these economic effects, we compare them to those of the hard information characteristics. A one standard deviation increase in a borrower's credit score reduces *Charge off*, *Delinquency*, *Bad customer*, and *Credit score decline* by 17.18%, 19.33%, 25.16%, and 5.55% of the respective mean values of these variables, while a one standard deviation increase in the debt-to-income ratio increases *Charge off*, *Delinquency*, *Bad customer*, and *Credit score decline* by 10.45%, 17.52%, 14.27%, and 18.71% of their respective mean values. Overall, these findings validate our soft information measure and are consistent with soft information providing an important incremental signal of loan quality over and above a borrower's hard information.[23]

6.2. Soft information, behavioral biases, and loan quality

We next perform our primary analyses, which examine whether loan officers' behavioral biases affect the processing and interpretation of soft information. We thus investigate how the effect of soft information on loan quality varies when loan officers are influenced by these biases. We augment Model 1 with our measures of behavioral biases and the interaction term between these measures and *Soft information*.

$$\begin{aligned} \textit{Loan quality} = \quad & \alpha + \beta_1 \textit{Soft information} + \beta_2 \textit{Behavioral bias} \\ & + \beta_3 \textit{Soft information} \times \textit{Behavioral bias} + \beta_4 \textit{Credit score} \\ & + \beta_5 \textit{Debt-to-income ratio} + \beta_6 \textit{Loan interest rate} + \beta_7 \textit{Loan exception} \\ & + \beta_8 \textit{Secured loan} + \beta_9 \textit{Loan amount} + \beta_{10} \textit{Loan maturity} \\ & + \beta_{11} \textit{Borrower tenure} + \beta_{12} \textit{Total number of accounts} + \textit{Loan officer FE} \\ & + \textit{Branch FE} + \textit{Year of loan origination FE} + \textit{Loan type FE}. \end{aligned} \qquad \text{(Model 2)}$$

[23] In untabulated multivariate analyses, we find that the amount of soft information about a borrower increases with her tenure, consistent with loan officers being able to collect more soft information by establishing long-term relationships with customers. Moreover, we find that the relation between a borrower's credit riskiness and soft information is positive but economically weak.

The variable of interest is the interaction term between *Soft information* and *Behavioral bias*. We predict a positive coefficient on this variable (β_3), suggesting that relative to when loan officers are not subject to behavioral biases, lending based on soft information by loan officers who are affected by them leads to worse loan quality. Loan quality measures, control variables, and model specifications are the same as in Model 1.

6.2.1. Soft information, limited attention, and loan quality

Table 3 reports the results of the analyses of the effect of soft information on loan quality when loan officers are inattentive (distracted). In line with our predictions, we find a positive and significant coefficient on the interaction terms between *Soft Information* and limited attention proxies in the majority of our specifications, where we measure limited attention by *Busy day* (Panel A), *Before weekends* (Panel B), and *Around holidays* (Panel C). Economically, our findings in Panel A suggest that relative to when a loan is not approved on a busy day, a one standard deviation increase in *Soft information* when it is approved on a busy day increases the probability of *Charge off*, *Delinquency*, and *Bad customer* by 0.30%, 1.82%, and 1.72%, respectively, representing about 13.45%, 12.10%, and 7.25% of their respective sample mean values. When loans are issued just before weekends, a one standard deviation increase in *Soft information* increases the probability of *Charge off*, *Delinquency*, and *Bad customer* by 1.05%, 2.15%, and 2.76%, relative to loans issued earlier in the week, representing about 47.82%, 14.23%, and 12.02% of their respective mean values. [24] When loans are issued around holidays, a one standard

[24] Riskier or more complicated loan applications may be processed at the end of the day or week, suggesting that our findings with respect to the adverse effect of inattention just before the weekend may be attributed to loan riskiness. To alleviate this concern, we employ two modifications of the *Before weekends* variable. *Before weekends* is thus defined as an indicator variable equal to one if the loan is originated after 4 pm on Friday or on Saturday and zero 1) if the loan is originated after 4 pm on a weekday or 2) if the loan is originated before 4 pm on Friday. We continue to find a significant and positive coefficient on the interaction term between soft information measures and *Before weekends* across both variable definitions. Further supporting the importance of inattention immediately before the weekend, we fail to find limited attention bias after 4 pm on days other than Friday and on Friday prior to 4 pm (untabulated).

deviation increase in *Soft information* increases the probability of *Charge off, Delinquency,* and *Credit score decline* by 0.77%, 2.32%, and 2.48%, relative to when loans are not issued around holidays, that is, about 34.91%, 15.41%, and 12.85% of their respective mean values.[25]

Importantly, across all three limited attention measures, we find that when loan officers are inattentive, soft information can even lead to worse loan quality (as reflected by the sum of coefficients β_1 and β_3). To exemplify, relative to when no soft information is used in the lending process, a one standard deviation increase in *Soft information* when a loan is approved on a busy day *increases* the probability of *Delinquency* and *Bad customer* by 6.85% and 3.82% of the respective sample mean values (Panel A). The economic significance of soft information is even stronger when we use *Before weekends* or *Around holidays* as proxies for limited attention bias (Panels B and C). This adverse effect of soft information on loan quality when loan officers are inattentive contrasts with its favorable influence at other times (as reflected by the negative and significant β_1 coefficients in most specifications across all three panels). Overall, our findings suggest that while soft information about a borrower typically benefits lenders, lending based on soft information when loan officers are inattentive (distracted) leads to lower quality loans.

6.2.2. Soft information, task-specific human capital, and loan quality

We next investigate the role of soft information in the quality of lending decisions when loan officers' judgment is influenced by a sales-related mindset developed in their early careers.[26] As

[25] In untabulated univariate tests, we find no systematic differences in borrower characteristics (credit score, debt-to-income ratio, the number of accounts and borrower tenure) across periods of limited attention and other periods. There are also no significant differences in the issuance of loans that are soft information intensive across limited attention and other periods or across limited attention periods and those immediately following limited attention periods (we define a loan to be soft information intensive when its *Soft Information* measure is in the upper quintile of the sample distribution). Thus our results are not driven by a different pool of borrowers receiving loans during limited attention periods or by loan officers postponing or rejecting soft-information-intensive loans during these periods.

[26] Because these analyses explore a loan officer's time-invariant characteristic, the estimations do not include loan officer fixed effects.

we report in Table 4, in most specifications, we find a positive and significant coefficient on *Soft information* × *Sales background*. When loans are issued by loan officers with sales experience, a one standard deviation increase in *Soft information* increases the probability of *Charge off*, *Delinquency*, *Bad customer*, and *Credit score decline* by 1.08%, 2.16%, 3.38%, and 3.23%, which represent about 49.27%, 14.33%, 14.71%, and 17.01% of their respective sample mean values. Pertaining to the economic effect of soft information relative to when no soft information is utilized in lending decisions, we find that when loan officers have prior experience in sales, soft information leads primarily to worse loan quality (as reflected by the sum of coefficients β_1 and β_3). A one standard deviation increase in *Soft information* increases the probability of *Charge off*, *Bad customer*, and *Credit score decline* by about 30.36%, 11.27%, and 12.56% of their respective mean values. Overall, our findings suggest that lending based on soft information by loan officers with prior sales experience impedes the effective processing of soft information, potentially because their sales-maximizing goal implementation or optimistic mindset directs their attention to (positive) information that supports the chosen goal of successfully closing a loan deal.[27]

6.2.3. Soft information, common identity, and loan quality

Last, we examine the effect of a shared gender between a loan officer and a borrower on the effective processing and interpretation of soft information. In Panel A of Table 5, we document a positive and significant coefficient on the *Soft information* × *Male to male* variable in most of our specifications, suggesting that lending on soft information when both the loan officer and the

[27] Indeed, in untabulated univariate tests, we find that loan officers with earlier experience in sales issue more loans and bring in more customers per quarter than loan officers with other non-banking or banking experience. At the same time, there are no economically significant differences in borrower credit score and debt-to-income ratio across loans issued by loan officers with sales backgrounds and other loan officers, suggesting that the lower loan quality of loans issued by these officers cannot be attributed to borrowers' credit risk. Further, to alleviate the concern that our results may be driven by the fact that loan officers with sales backgrounds are busier and thus inattentive, in untabulated tests we restrict our analyses to loans issued by these loan officers during non-limited attention periods (i.e., on non-busy days, weekdays, and not around holidays). Our results continue to hold.

borrower are men distorts the effective interpretation of soft information. When loans are issued by male loan officers to male borrowers, a one standard deviation increase in *Soft information* increases the probability of *Charge off*, *Delinquency*, and *Bad customer* by 1.17%, 1.86%, and 2.01%, which represent about 53.09%, 12.32%, and 8.73% of their respective mean values. In contrast, we find no significant effect for the common identity bias when the loan officer and the borrower are both women (Table 5, Panel B). Assessing the effect of soft information on loan quality relative to when no soft information is used, we find that when male loan officers lend to male borrowers, soft information increases the probability of adverse credit outcomes (as reflected by the sum of coefficients β_1 and β_3, reported in Panel A). A one standard deviation increase in *Soft information* increases the probability of *Charge off* and *Delinquency* by about 38.00% and 8.66% of their respective mean values.[28]

These findings suggest that male loan officers are more likely to trust soft information about male borrowers, while they more diligently investigate and try to understand the validity and relevance of the soft information about female borrowers. In contrast, female loan officers seem to carefully process soft information, regardless of whether the borrower is a man or woman. These differential effects of the common identity bias on the processing of soft information by male and female loan officers can be explained by several prior studies. Carter et al. (2007) show that male loan officers are more likely to follow their "gut instinct", to query the commitment of the loan applicant, especially when the loan applicant is a woman, and to value developing a rapport with a borrower, but only when the borrower is a man. Male loan officers are thus more likely to develop

[28] Our results are not driven by men being more likely to make risky decisions (e.g., Byrnes et al. 1999). We augment Model 1 by an indicator variable equal to one if the loan officer is a man and zero otherwise, and the interaction term between this variable and our soft information measure (excluding loan officer fixed effects). We find that the coefficients on the interaction term are insignificant in all specifications, suggesting that lending based on soft information by male loan officers does not lead to worse loan quality (untabulated).

a bond with male borrowers and trust the information shared by them to a greater extent.[29] Relatedly, gender seems to be a more important identification factor for men than women, based on studies that show that men are more supportive of other men than they are of women (e.g., Spangler et al. 1978; O'Farrell and Harlan 1982; Brass 1985; Grunspan et al. 2016).

6.3. Factors mitigating the adverse effect of behavioral biases on soft information processing

6.3.1. Soft information collection by loan officers and other employees

Our soft information measure covers soft information collected over the 45-day period prior to a loan origination by the loan officer who approves the loan and by other loan officers or employees, whose interactions with the borrower may relate to previously issued loans or non-lending-based activities, such as deposits or investments. Out of the three notes available, on average, for a borrower in our sample, two are written by employees other than the loan officer approving the loan. We expect that the adverse effect of behavioral biases on soft information processing will be smaller when the soft information about the borrower is based primarily on notes written by the approving loan officer, which are likely to be easier for her to interpret and process than those written by other employees.

To test this prediction, we construct the measure *Loan officer's notes*, which reflects the volume of notes written by the loan officer approving the loan. We start by estimating the ratio of the number of borrower-specific notes written by the approving loan officer over the 45-day period prior to a loan's origination, scaled by the total number of notes available about the borrower over this period. We then define *Loan officer's notes* as equal to one if this ratio for a loan under consideration falls in the upper quartile of the ratio distribution and zero otherwise. We augment

[29] We view the following note written by a male loan officer as a good example of such a bond: "I met J. today...what a guy! He slapped me on the back about eight times through the course of our conversation. He's looking to buy a motorcycle and/or a crotch rocket. He just found one he fell in love with, so we looked over some financing options."

Model 2 with the *Loan officer's notes,* the double interaction terms *Soft information x Loan officer's notes* and *Behavioral bias* x *Loan officer's notes*, and the triple interaction term *Soft information* x *Behavioral bias* x *Loan officer's notes*. All other control variables and model specifications are the same as in Model 2. As we report in Table 6, consistent with our predictions, the coefficient on the triple interaction term is negative and significant in the majority of specifications across the three behavioral biases we explore, suggesting that the adverse effect of behavioral biases is attenuated when the soft information processing costs are lower.

6.3.2. The role of loan officer and borrower characteristics

Next, we examine several loan officer and borrower characteristics that are likely to decrease the processing costs of soft information and thus may alleviate the effects of behavioral biases. First, we expect that the influence of the biases will attenuate as loan officers gain more experience with soft information processing, which should come as their tenure at the credit union lengthens. We construct an indicator variable equal to one if a loan officer's years of employment at the credit union ranks in the upper quartile of loan officers' tenure and zero otherwise (*Experienced loan officer*). We augment Model 2 with *Experienced loan officer*, the double interaction terms *Soft information* x *Experienced loan officer* and *Behavioral bias* x *Experienced loan officer*, and the triple interaction term *Soft information* x *Behavioral bias* x *Experienced loan officer*.

Consistent with our expectation, as we report in Panel A of Table 7, we find that loan officers' tenure significantly alleviates the adverse effect of limited attention bias on interpreting soft information. The coefficients on the triple interaction term are significant across most specifications for the *Busy day*, *Before weekends*, and *Around holidays* measures. We do not find that experience is helpful for task-specific human capital and common identity biases. The coefficient on the triple interaction term is insignificant for the *Sales background* and *Male to male* measures. These results suggest that experience seems to alleviate the detrimental effect of temporary behavioral biases (e.g., loan officers learn how to deal with time pressure or distractions). However, experience is not helpful with imprinted biases driven by early career experience or common identity.[30]

Second, we focus on the breadth of a borrower's relationship with the credit union. We expect that when the credit union provides more services to a borrower, the additional information loan officers obtain through these services, that is, the officers' greater familiarity with the borrower, will help them to more accurately process soft information even when subject to behavioral biases. We rank in quartiles the total number of accounts a borrower has with the credit union (based on the *Total number of accounts* variable). *Relationship intensity* is an indicator variable equal to one if a borrower's total number of accounts falls in the upper quartile of this variable's sample distribution and zero otherwise. We augment Model 2 with *Relationship intensity*, the double interaction terms *Soft information* x *Relationship intensity* and *Behavioral bias* x *Relationship intensity*, and the triple interaction *Soft information* x *Behavioral bias* x *Relationship intensity*. We report the results of this test in Panel B of Table 7. We find a negative and significant coefficient on the triple interaction term in a few specifications, providing somewhat weak support for the role of the intensity of a borrower-credit union relationship in mitigating the adverse effect of behavioral biases. The results are similar when we use a borrower's tenure as a proxy for the relationship intensity with the credit union (untabulated analyses).

Third, the detrimental effect of behavioral biases may be mitigated for borrowers with a high credit score who are generally less likely to default and whose creditworthiness is potentially easier to evaluate. We construct an indicator variable that equals one if a borrower's credit score is ranked

[30] Using a setting of judges working on parole decisions, Danziger et al. (2011) show that behavioral biases negatively affect the decision processes of even highly experienced agents.

in the upper quartile of the distribution of sample borrowers' credit scores and zero otherwise (*High credit score*). The mean credit score value for *High credit score* borrowers is 793, which is typically associated with high creditworthiness. We augment Model 2 with *High credit score*, the double interaction terms *Soft information* x *High credit score* and *Behavioral bias* x *High credit score*, and the triple interaction term *Soft information* x *Behavioral bias* x *High credit score*.

We report the results of this test in Panel C. We find a negative and significant coefficient on the triple interaction term in only few specifications, providing relatively weak support for the prediction that the adverse effect of soft information processing due to behavioral biases is mitigated for borrowers with high credit scores. These findings are consistent with loan officers relying largely on soft information in loan decisions, even for borrowers whose hard information characteristics reflect high credit quality (see our discussion in Section 2).

6.3.3. The investigation of soft information tone

Although, consistent with prior research, our soft information measure captures the total amount of a borrower's soft information, we next explore whether its tone can provide further insight into loan officers' judgment in the presence of behavioral biases. We classify notes with respect to a borrower's creditworthiness into one of four categories: 1) overall more negative information, 2) overall more positive information, 3) neutral information (which typically indicates that a note includes both positive and negative information cues, resulting in a tone that is neutral overall), and 4) no information.[31] Out of a sample of 24,927 notes associated with 17,395 loans, 1,260 are classified as having no information about a borrower's creditworthiness; 12,127 as having neutral

[31] Generally, it is difficult to assess empirically whether the tone of soft information is positive or negative. For instance, consider the note we report in Appendix A about a customer whose husband has a drinking problem. On the one hand, this discussion may indicate that this customer will experience financial difficulties. On the other hand, a loan officer may interpret the customer's determination to get a divorce as a positive indicator of her creditworthiness, as the customer's finances will no longer be affected by an alcoholic husband.

information; 9,354 as having positive information; and 2,186 as having negative information.[32]

Since multiple notes may relate to the same loan, we categorize a loan as a positive (negative) soft information loan if at least 50% of the notes related to it are classified as overall more positive (negative). The rest of the loans are classified as neutral soft information loans. This process results in 6,708 loans classified as positive soft information loans, 1,092 as negative soft information loans and 9,595 as neutral. These classifications indicate that 1) the majority of loans in our sample are associated with neutral soft information, suggesting that both positive and negative soft information is collected about a borrower and 2) loans in our sample are significantly more likely to be associated with positive, as opposed to negative, soft information, consistent with us exploring a sample of approved loans.

Based on this evidence, we conduct the following two sets of analyses. First, we examine whether the adverse effect of behavioral biases is mitigated when soft information is less ambiguous. We construct *Non-ambiguous notes*, an indicator variable that is equal to one if a loan is a positive or negative soft information loan (i.e., if at least 50% of the notes related to the loan are classified as overall more positive or overall more negative) and zero otherwise. We augment Model 2 with *Non-ambiguous notes*, the double interaction terms *Soft information* x *Non-ambiguous notes* and *Behavioral bias* x *Non-ambiguous notes*, and the triple interaction term *Soft information* x *Behavioral bias* x *Non-ambiguous notes*. As we report in Panel A of Table 8, we find negative and significant coefficients on the triple interaction term in 8 out of 20 specifications. Thus the adverse effect of behavioral biases is somewhat smaller when soft information about the

[32] We assigned research assistants 33,000 notes, which represent almost 50% of those we identified as having at least one soft information keyword. Each note was assigned to two research assistants. To minimize noise in the classification process, we conditioned that both research assistants had to agree on the classification for each note. They had different classifications for 8,073 notes; we excluded these from subsequent analyses. Although the research assistants assessed the entire note, which may contain both hard and soft information, we believe that this assessment provides a reliable evaluation of the tone of a note's soft information.

borrower contains consistently positive or consistently negative cues, making it easier for a loan officer to process it.

Second, we examine whether our primary results differ when the soft information about the borrower is generally negative. Even when subject to behavioral biases, loan officers may process negative soft information more diligently than positive information, as they are concerned about approving a bad quality loan. We construct a *Negative notes* indicator variable, which is equal to one if a loan is a negative soft information loan (i.e., if at least 50% of the notes related to the loan are classified as overall more negative) and zero otherwise. We augment Model 2 with *Negative notes*, the double interaction terms *Soft information* x *Negative notes* and *Behavioral bias* x *Negative notes*, and the triple interaction term *Soft information* x *Behavioral bias* x *Negative notes*. As we report in Panel B, we find negative and significant coefficients on the triple interaction term in 6 out of 20 specifications, providing weak support for the conjecture that having consistently more negative notes alleviates the influence of behavioral biases.

6.4. Supplementary analyses

6.4.1. Endogeneity

An important concern is whether our findings are driven by non-random, endogenous matching between loan officers and borrowers. To address this concern, we restrict our sample to loans originated by call-center loan officers, who randomly receive calls from customers when branch-based loan officers are busy or absent. For specifications for which we could obtain at least 500 observations with available data, we replicate our primary analyses and report the coefficients on the interaction terms *Soft information* x *Behavioral bias* in Table 9. Although our sample size declines drastically (the number of loan observations ranges from 1,655 to 4,777), we continue to find significant coefficients on the interaction term in a number of specifications, suggesting that it is unlikely our results are driven by endogeneity.[33]

6.4.2. Hard information, behavioral biases, and loan quality

We next investigate whether behavioral biases affect the interpretation of hard information. We augment Model 1 with our measures of behavioral biases and the interaction term between these measures and the two most commonly used hard information characteristics: a borrower's credit score and debt-to-income ratio. As we report in Table 10, in most specifications, we find no evidence suggesting that behavioral biases affect the way hard information is impounded into loan decisions. These results are consistent with behavioral biases primarily affecting the processing of soft rather than hard information (e.g., Hirshleifer and Teoh 2003).

6.4.3. Do loan officers subject to behavioral biases ignore soft information?

An additional concern related to our tests is that when making a loan decision, loan officers subject to behavioral biases may ignore or underweight soft information. For example, because processing soft information is time-consuming, when a loan officer is busy, she may ignore it and instead overweight hard information (credit score and debt-to-income ratio). In this case, our results may be driven by loan officers omitting soft information rather than misinterpreting it.

We note that such behavior is unlikely given the credit union's emphasis on relationship, soft-information-based lending and loan officers' monetary and non-monetary incentives (as we discuss in Section 2). Relatedly, prior literature suggests that the heuristics agents use to mitigate behavioral biases are typically applied without awareness (e.g., Hastie and Dawes 2001; Bonner 2008). Therefore, loan officers fail to realize that biases lead to the incorrect interpretation of soft information and are thus unlikely to ignore it.

[33] We do not perform analyses of the effect of task-specific human capital bias due to the limited number of observations.

We also address this issue empirically by exploring whether loan officers subject to behavioral biases underweight (overweight) borrower's soft (hard) information when making a loan pricing or exception decision. We estimate Model 2 with *Loan interest rate* and *Loan exceptions* as the dependent variables. We augment Model 2 with interaction terms of the hard information measures and behavioral biases. If loan officers rationally respond to behavioral biases, we expect to find a positive and significant coefficient on the *Soft information* x *Behavioral bias* interaction term, a negative and significant coefficient on *Credit Score* x *Behavioral bias*, and a positive and significant coefficient on *Debt-to-income ratio* x *Behavioral bias*, reflecting lower (higher) weights on soft (hard) information in loan pricing and exception decisions.

As we report in Table 11, in most specifications, the coefficients on the interaction terms are insignificant. These findings suggest that loan officers' reliance on soft and hard information in loan pricing and exception decisions is largely unaffected by the presence of behavioral biases, consistent with loan officers being unaware of their biases' adverse effects.[34] In addition, interest rate analyses further support our inferences that worse loan quality is attributed to the loan officers' misinterpretation of soft information due to behavioral biases. If, instead, poor loan quality is explained by loan officers approving riskier loans and rationally compensating for the higher risk with higher interest rates, the coefficient on the interaction term between the *Soft Information* and behavioral bias proxies would be positive. We do not find evidence supporting this argument.

6.4.4. An alternative measure of soft information

To alleviate the concern that our findings may be affected by our choice of the specific

[34] In untabulated multivariate tests, we examine whether loan officers modify their soft information collection when subject to behavioral bias. If loan officers are aware that they misinterpret soft information when they are subject to behavioral biases, they may be less incentivized to collect such information, resulting in less soft information about the borrower being available. We find that the amount of soft information is unaffected by the approving loan officer's behavioral biases.

keywords we employ in constructing *Soft information,* we develop an additional soft information measure. Our second measure, *Soft information residual*, is the absolute value of the residual from the regression of the total number of words in borrower-specific notes during the 45 days prior to loan origination on the hard and transaction-related information about a borrower that is available to loan officers.[35] The independent variables include a borrower's credit score and debt-to-income ratio, the logarithmic transformation of the number of quantitative (numerical) words in the notes, a borrower's tenure with the credit union and the logarithmic transformation of the number and the balance of the different products the borrower has with the union.[36] We also control for systematic differences in reporting characteristics across loan officers, branches, loan types, and over time by including the relevant fixed effects. We estimate the following model:

$$\begin{aligned}
\textit{Log of word-count} = \alpha &+ \beta_1 \textit{Credit score} + \beta_2 \textit{Debt-to-income ratio} + \beta_3 \textit{Borrower tenure} \\
&+ \beta_4 \textit{Log of quantitative word-count} + \beta_5 \textit{Number of deposit accounts} \\
&+ \beta_6 \textit{Deposit account balance} + \beta_7 \textit{Number of credit cards} + \beta_8 \textit{Credit card} \\
&\textit{balance} + \beta_9 \textit{Number of personal loans} + \beta_{10} \textit{Personal loan balance} \\
&+ \beta_{11} \textit{Number of mortgages} + \beta_{12} \textit{Mortgage balance} + \beta_{13} \textit{Number of home} \\
&\textit{equity accounts} + \beta_{14} \textit{Home equity balance} + \beta_{15} \textit{Number of IRA accounts} \\
&+ \beta_{16} \textit{IRA balance} + \beta_{17} \textit{Number of auto loans} + \beta_{18} \textit{Auto loan balance} \\
&+ \beta_{19} \textit{Number of ATM accounts} + \beta_{20} \textit{ATM account balance} + \beta_{21} \textit{Number of} \\
&\textit{lines of credit} + \beta_{22} \textit{Line of credit balance} + \beta_{23} \textit{Number of other loans} \\
&+ \beta_{24} \textit{Other loan balance} + \textit{Loan officer FE} + \textit{Branch FE} \\
&+ \textit{Loan year of origination FE} + \textit{Loan type FE}.
\end{aligned} \qquad \text{(Model 3)}$$

The R^2 of Model 3 is 28%. The mean value of *Soft Information residual* is 0.27. The Spearman correlation between *Soft information* and *Soft information residual* is 25%, suggesting that both

[35] Agarwal and Hauswald (2010) use a similar approach for measuring soft information by regressing loan officers' internal credit score on publicly available estimates of a borrower's credit quality.

[36] We use the absolute value of the residual to measure information reported in the notes that departs from hard information about the borrower. If the information reported includes only hard information, we expect the residual to be close to zero, as such information should be almost fully explained by the borrower's quantitative characteristics, included in Model 3. If employees report both hard and soft information, we expect the residual to be positive. However, if employees lay out mostly soft information, without discussing hard information, we expect the residual to be negative.

variables likely capture the same underlying concept. We employ Model 2 by using *Soft information residual* as the proxy for soft information and replicate the specifications reported in Tables 3–5. All other specifications and control variables are the same as in Model 2. We report the results of these robustness tests in Table 12. Across all behavioral biases (limited attention, task-specific human capital, and common identity), we show that our results are robust to using this measure of soft information. We further use *Soft information residual* as the measure of soft information to replicate the analyses related to the factors mitigating the adverse effect of behavioral biases on soft information processing as well as our supplementary analyses. We find that our results hold in all these tests (untabulated).

7. Conclusion

We examine three behavioral biases that may affect the use of soft information in lending decisions: 1) limited attention, 2) task-specific human capital, and 3) common identity. Although the majority of prior studies have shown that soft information improves loan quality, we predict that these biases impede loan officers' ability to effectively process and interpret soft information and thus can lead to lower quality loans.

Using the internal reporting system of a large credit union, we develop a direct measure of soft information based on the notes employees use to document their communications with the borrowers. We find that lending based on soft information leads to worse quality loans when loan officers are busy or when they approve loans before the weekend or around national holidays. We also document that loan officers who have a sales-related background fail to accurately interpret soft information in their loan decisions. In addition, we find that lending based on soft information is associated with worse loan quality when male loan officers lend to male borrowers. With respect to factors mitigating the adverse effect of behavioral biases on loan quality, we show that when the loan officer approving the loan collects most of the borrower-specific soft information or when she is more experienced, this effect is significantly mitigated. Relatedly, the adverse effect is somewhat attenuated when soft information about the borrower contains consistently positive or negative cues. We find weak evidence that the intensity of a borrower's prior relationship with the credit union or her low credit riskiness can mitigate the influence of behavioral biases. Overall, our analyses provide novel evidence on non-agency-related limitations in the use of soft information by showing that bad credit decisions may be explained by loan officers' behavioral biases. We, however, highlight that our findings do not imply that an automated lending process can efficiently substitute for the role of loan officers, because, in the absence of behavioral biases, soft information leads to significantly better loan quality.

Our study offers opportunities for future research. First, extensive literature on the use of soft information in private lending argues that soft information cannot be easily stored and diffused within the bank (e.g., Berger and Udell 2002; Stein 2002; Liberti and Petersen 2017). Our research setting suggests that an internal reporting system can be a repository of soft information without it being codified or standardized, consistent with prior accounting studies suggesting that internal reporting systems can successfully facilitate the sharing and use of tacit knowledge across employees (e.g., DeFond et al. 2013; Li and Sandino 2018). Future research can explore the usefulness of internal reporting systems in storing and diffusing soft information within financial institutions. Moreover, prior research has not sufficiently explored how private information about borrowers is created or processed. While our paper speaks to the role of loan officers' behavioral biases in affecting soft information processing, understanding the organizational and incentive structures that are instrumental to banks' private information processing can provide a fruitful avenue for future research.

REFERENCES

Agarwal, S., and F.H. Wang, 2008. Motivating loan officers: An analysis of salaries and piece rates compensation. *Working paper, Federal Reserve Bank of Chicago.*

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

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

Alesina, A., and E. La Ferrara, 2002. Who trusts others? *Journal of Public Economics* 85: 207–234.

Angrist, J. D., and J.S. Pischke, 2008. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Baker, G. P., R. Gibbons, and K. J. Murphy, 1994. Subjective performance measures in optimal incentive contracts. *Quarterly Journal of Economics* 109 (4): 1125–1156.

Banerjee, A., S. Cole, and E. Duflo, 2009. Default and punishment: Incentives and lending behavior in Indian banks. *Working paper*, *Massachusetts Institute of Technology, Cambridge.*

Baskett, G. D., 1973. Interview decisions as determined by competency and attitude similarity. *Journal of Applied Psychology* 57: 343–345.

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

Ben-Ner, A., B. P. McCall, M. Stephane, and H. Wang, 2009. Identity and in-group/out-group differentiation in work and giving behaviors: Experimental evidence. *Journal of Economic Behavior and Organization* 72 (1): 153–170.

Berger, A. N., and G. F. Udell, 2002. Small business credit availability and relationship lending: The importance of bank organizational structure. *Economic Journal* 112 (477): F32–F53.

Berger, A. N., L. Klapper, and G. F. Udell, 2001. The ability of banks to lend to informationally opaque small businesses. *Journal of Banking and Finance* 25 (12): 2127–2167.

Berger, A., N. Miller, M. Petersen, R. Rajan, and J. Stein, 2005. Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics* 76: 237–269.

Bloomfield, R. J., 2002. The "Incomplete Revelation Hypothesis" and financial reporting. *Accounting Horizons* 16 (3): 233–243.

Bonner, S., 2008. *Judgment and Decision Making in Accounting*. Pearson Prentice Hall, New Jersey.

Brass, D. J., 1985. Men's and Women's Networks: A Study of Interaction Patterns and Influence in an Organization. *Academy of Management Journal* 28 (2): 327–343.

Bruns, V., D. V. Holland, D. A. Shepherd, and J. Wiklund, 2008. The role of human capital in loan officers' decision policies. *Entrepreneurship Theory and Practice*: 485–506.

Buttner, H. E., and B. Rosen, 1988. Bank loan officers' perceptions of the characteristics of men, women, and successful entrepreneurs. *Journal of Business Venturing* 3: 249–258.

Byrne, D., 1971. The Attraction Paradigm. Academic Press, New York.

Byrnes, J. P., D. C. Miller, and W. D. Schafer, 1999. Gender differences in risk taking: A meta-analysis. *Psychological Bulletin* 125 (3): 367–383.

Campbell, D., 2012. Employee selection as a control system. *Journal of Accounting Research* 50 (4): 931–966.

Carter, S., S. Eleanor, W. Lam, and F. Wilson, 2007. Gender, entrepreneurship, and bank lending: The criteria and processes used by bank loan officers in assessing applications. *Entrepreneurship Theory and Practice* 31: 427–444.

Cassar, G., C. D. Ittner, and K. S. Cavalluzzo, 2015. Alternative information sources and information asymmetry reduction: Evidence from small business debt. *Journal of Accounting and Economics* 59: 242–263.

Chen, Q., and Vashishtha R., 2017. The effects of bank mergers on corporate information disclosure. *Journal of Accounting and Economics* 64: 56-77.

Clore, G.L., and D. Byrne, 1974. A Reinforcement-Affect Model of Attraction. In T.L. Huston (ed.) Foundations of Interpersonal Attraction, 143–170. New York: Academic Press.

Cole, S., M. Kanz, and L. Klapper, 2015. Incentivizing calculated risk-taking: Evidence from an experiment with commercial bank loan officers. *The Journal of Finance* 70 (2): 537-575.

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

Cremer, J., L. Garicano, and A. Prat, 2007. Language and the theory of the firm. *The Quarterly Journal of Economics* 122 (1): 373–407.

Cyert, R., and J. March, 1963. A Behavioral theory of the firm. Englewood Cliffs, NJ: Prentice-Hall.

Dang, T., G. Gorton, B. Holmstrom, and G. Ordonez, 2017. Banks as secret keepers. *American Economic Review* 107 (4):1005–1029.

Danziger, S., J. Levav, and L. Avnaim-Pesso, 2011. Extraneous factors in judicial decisions. *Proceedings of the National Academy of Science of the United States of America*, 108 (17): 6889–6892.

Deakins, D., and G. Hussain, 1994. Risk assessment with asymmetric information. *International Journal of Bank Marketing* 12 (1): 24–31.

DeBruine, L. M., 2002. Facial resemblance enhances trust. *Proc Biol Sci.* 269: 1307–1312.

DeFond, M. L, Y. Konchitchki, J. L. McMullin, and D. E. O'Leary, 2013. Capital markets valuation and accounting performance of Most Admired Knowledge Enterprise (MAKE) award winners. *Decision Support Systems* 56: 348–360.

DeHaan, E., T. Shevlin, and J. Thornock, 2015. Market (in)attention and the strategic scheduling and timing of earnings announcements. *Journal of Accounting and Economics* 60 (1): 36–55.

DellaVigna, S., and J. M. Pollet, 2009. Investor inattention and Friday earnings announcements. *The Journal of Finance* 64 (2): 709–749.

Demiroglu, C., O. Ozbas, R. Silva, and M. F. Ulu, 2017. Does religion affect economic decisions? Evidence from Ramadan Loans. *Working paper.*

Dewatripont, M., and J. Tirole, 2005. Modes of communication. *Journal of Political Economy* 113 (6): 1217–1238.

Diamond, D. W., 1991. Monitoring and Reputation: The Choice between Bank Loans and Directly Placed Debt. *The Journal of Political Economy* 99 (4): 689–721.

Dixon, A. L., and S. M. Schertzer, 2005. Bouncing back: How salesperson optimism and self-efficacy influence attributions and behaviors following failure. *Journal of Personal Selling & Sales Management* 25 (4): 361–369.

Drexler, A., and A. Schoar, 2014. Do relationships matter? Evidence from loan officer turnover. *Management Science* 60 (11): 2722–2736.

Farmer, H., R. McKay, and M. Tsakiris, 2014. Trust in me: Trustworthy others are seen as more physically similar to the self. *Psychological Science* 25 (1): 290–292.

Fisman, R.J., D. Paravisini, and V. Vig, 2012. Cultural proximity and loan outcomes. *NBER Working Paper.*

Gibbins, M., and K. Trotman, 2002. Audit review: Managers' interpersonal expectations and conduct of the review. *Contemporary Accounting Research* 19 (3): 411-444.

Gibbons, R., 2003. Team theory, garbage cans and real organizations: Some history and prospects of economic research on decision-making in organizations. *Industrial and Corporate Change* 12 (4): 753–787.

Gibbons, R., and M. Waldman, 2004. Task-specific human capital. *American Economic Review* 94: 203–207.

Gibbs M., K. Merchant, W. Van der Stede, and M. Vargus, 2004. Determinants and effects of subjectivity in incentives. *The Accounting Review* 79 (2): 409–436.

Gillette, J., S. Jayaraman, and J. Zimmerman. Malfeasance versus optimal incompetence: Determinants of earnings quality. *Working paper.*

Glaeser, E. L., D. I. Laibson, J. A. Scheinkman, and C. L. Soutter, 2000. Measuring trust. *Quarterly Journal of Economics* 115: 811–846.

Golightly, C., D. M. Huffman, and D. Byrne, 1972. Liking and loaning. *Journal of Applied*

Psychology 56 (6): 521–523.

Gollwitzer, P. M., and U. Bayer, 1999. Deliberative versus implemental mindsets in the control of action. In *Dual-Process Theories in Social Psychology,* edited by S. Chaiken and Y. Trope. New York: Guilford Press, 1999: 403–422.

Gollwitzer, P. M., H. Heckhausen, and B. Steller, 1990. Deliberative and implemental mindsets: Cognitive tuning toward congruous thoughts and information. *Journal of Personality and Social Psychology* 59: 1119–1127.

Greene, W., 2004. The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *The Econometrics Journal* 7 (1): 98–119.

Griffith, E. E., J. S. Hammersley, K. Kadous, and D. Young, 2015. Auditor Mindsets and Audits of Complex Estimates. *Journal of Accounting Research* 53 (1): 49–77.

Grunspan, D.Z., S.L. Eddy, S.E. Brownell, B.L. Wiggins, A.J. Crowe, and S.M. Goodreau, 2016. Males underestimate academic performance of their female peers in undergraduate biology classrooms. *PLoS ONE* 11 (2): e0148405. doi:10.1371/journal.pone.0148405.

Guiso, L., P. Sapienza, and L. Zingales, 2009. Cultural biases in economic exchange? *Quarterly Journal of Economics* 124: 1095–1131.

Harrison, D.A., K.H. Price, H.G. Joanne, and A.T. Florey, 2002. Time, teams, and task performance: Changing effects of surface- and deep-level diversity on group functioning. *Academy of Management Journal* 45(5): 1029–1045.

Hastie, R., and R. Dawes, 2001. Rational choice in an uncertain word: The psychology of judgment and decision making. Thousand Oaks, CA: Sage Publications.

Hauswald, R., and R. Marquez, 2006. Competition and strategic information acquisition in credit markets. *The Review of Financial Studies* 19 (3): 967–1000.

He, X., S.P. Kothari, T. Xiao, and L. Zuo, 2018. Long-term impact of economic conditions on auditors' judgment. *The Accounting Review*, forthcoming.

Heckhausen, H., and P. M. Gollwitzer, 1987. Thought contents and cognitive functioning in motivational versus volitional states of mind. *Motivation and Emotion* 11: 101–120.

Hect, D., 2013. The neural basis of optimism and pessimism. *Experimental Neurobiology* 22 (3): 173–199.

Heider, F., and R. Inderst, 2012. Loan prospecting. *Review of Financial Studies* 25 (8): 2381–2415.

Henderson, M. D., Y. De Liver, and P. M. Gollwitzer, 2008. The effects of an implemental mindset on attitude strength. *Journal of Personality and Social Psychology* 94: 396–411.

Hertzberg, A., J.M. Liberti, and D. Paravisini, 2010. Information and incentives inside the firm: Evidence from loan officer rotation. *Journal of Finance* 65 (3): 795–828.

Hirshleifer, D., and S. H. Teoh, 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting & Economics* 36: 337–386.

Hirshleifer, D., S. S. Lim and S. H. Teoh, 2009. Driven to distraction: Extraneous events and underreaction to earnings news. *The Journal of Finance* 64 (5): 2289–2325.

Huang, X., A. Nekrasov, and S.H. Teoh, 2017. Headline salience, managerial opportunism, and over- and underreactions to Earnings. *Working paper.*

Ittner, C., D. Larcker, and M. Meyer, 2003. Subjectivity and the Weighting of Performance Measures: Evidence from a Balanced Scorecard. *The Accounting Review* 78 (3): 725–758.

Iyer, R., A. I. Khwaja, E. F. P. Luttmer, and K. Shue, 2016. Screening peers softly: Inferring the quality of small borrowers. *Management Science* 62 (6): 1554–1577.

Kadous, K., J. Leiby, and M. E. Peecher, 2013. How do auditors weight informal contrary advice? The joint influence of advisor social bond and advice justifiability. *The Accounting Review* 88 (6): 2061–2087.

Kahneman D., 2003. Maps of bounded rationality: A perspective on intuitive judgment and choice. In Les Prix Nobel: The Nobel Prizes 2002, edited by T. Frangsmyr, 449–489. Stockholm, Sweden: The Nobel Foundation.

Kahneman, D., 2011. *Thinking, Fast and Slow*. New York: Farrar, Straus and Giroux.

Kahneman, D., and S. Frederick, 2002. Representativeness revisited: Attribute substitution in intuitive judgment. In Heuristics and Biases: The Psychology of Intuitive Judgment, edited by Gilovich, T., D. Griffin, and D. Kahneman, 49–81. New York, NY:Kress, L., M. Bristle, and T. Aue, 2018. Seeing through rose-colored glasses: How optimistic expectancies guide visual attention. *PLoS ONE* 13 (2): e0193311.

Lee, J., and W.A. Kelly, 2004. Who Uses Credit Unions? Filene Research Institute, Third Edition.

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

Li, S.X., and T. Sandino, 2018. Effects of an Information Sharing System on Employee Creativity, Engagement, and Performance. *Journal of Accounting Research* 56 (2): 713–747.

Libby, R., R. Bloomfield, and M. W. Nelson, 2002. Experimental research in financial accounting. *Accounting, Organizations and Society* 27: 775–810.

Liberti, J., and A. Mian, 2009. Estimating the effect of hierarchies on information use. Review of Financial Studies 22: 4057–4090.

Liberti, J. M., and M. A. Petersen, 2017. Information: Hard and Soft. *Working paper.*

Lim, S. S., and S. H. Teoh, 2010. Limited attention. In: H. Kent Baker & John R. Nofsinger (eds.), *Behavioral Finance: Investors, Corporations, and Markets*. Hoboken: NY, John Wiley, pp. 295–312.

Lipshitz, R., and N. Shulimovitz, 2007. Intuition and emotion in bank loan officers' credit decisions. *Journal of Cognitive Engineering and Decision Making* 1 (2):212–233.

Loveland, J. M., J. W. Lounsbury, S. Park, D. W. Jackson, 2015. Are salespeople born or made?

Biology, personality, and the career satisfaction of salespeople. *Journal of Business & Industrial Marketing* 30 (2): 233–240.

Maddala, G. S., 1987. Limited dependent variable models using panel data. *The Journal of Human Resources* 22 (3): 307–338.

Marquis, C., and A. Tilcsik, 2013. Imprinting: Toward a multilevel theory. *Academy of Management Annals* 7: 193–243.

McEvily. B., J. Jaffee, and M. Tortoriello, 2012. Not all bridging ties are equal: Network imprinting and firm growth in the Nashville legal industry, 1933–1978. *Organization Science* 23: 547–563.

Mian, A., 2006. Distance constraints: The limits of foreign lending in poor economies. *Journal of Finance* 61 (3): 1465–1505.

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

Morales-Acevedo, P., and S. Ongena, 2018. Fear, anger, and credit. On Bank robberies and loan conditions. *Working paper.*

Murfin, J., and M. Petersen, 2016. Loans on sale: Credit market seasonality, borrower need, and lender rents. *Journal of Financial Economics, forthcoming.*

O'Farrell, B., and S. L. Harlan, 1982. Craftworkers and clerks: The effect of male co-worker hostility on women's satisfaction in non-traditional jobs. *Social Problems* 29: 252–265.

Ongena, S., and A. Popov, 2016. Gender bias and credit access. *Journal of Money, Credit and Banking* 48 (8): 1691–1724.

Orpen, C., 1984. Attitude Similarity, Attraction, and Decision-Making in the Employment Interview. *The Journal of Psychology* 117 (1): 111–120.

Pantzalis, C., and E. Ucar. 2014. Religious holidays, investor distraction, and earnings announcement effects. *Journal of Banking & Finance* 47: 102–117.

Paravisini, D., and A. Schoar, 2016. The incentive effect of scores: Randomized evidence from credit committees. *Working paper, Massachusetts Institute of Technology, Cambridge.*

Parrott, W.G., 2001. *Emotions in social psychology: Essential readings*. New York: Psychology Press.

Petersen, M., 2004. Information: Hard and soft. *Working paper.*

Petersen, M., and R. Rajan, 1994. The benefits of firm-creditor relationships: Evidence from small business data. *Journal of Finance* 49 (1): 3–37.

Petersen, M., and R. Rajan, 1995. The effect of credit market competition on lending relationships. *Quarterly Journal Economics* 110 (2): 407–443.

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

Plutchik, R., 1980. *Emotion: A Psychoevolutionary Synthesis*. New York: Harper & Row.

Pulakos, E.D., and K.N. Wexley, 1983. The relationship among perceptual similarity, sex, and performance ratings in manager-subordinate dyad. *Academy of Management Journal* 26 (1): 129–139.

Puri, M., J. Rocholl, and S. Steffen, 2011. Rules versus discretion in bank lending decisions. *Working paper*.

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

Rand, T. M., and K. N. Wexley, 1975. Demonstration of the effect, "Similar to Me," in simulated employment interviews. *Psychological Reports* 36 (2): 535–544.

Ravina, E., 2008. Love & loans: The effect of beauty and personal characteristics in credit markets. *Working paper*.

Rich, G.A., 1999. Salesperson optimism: Can sales managers enhance it and so what if they do? *Journal of Marketing Theory and Practice* 7 (1): 53–63.

Sackett, P. R., C. L. Z. DuBois, and A. W. Noe, 1991. Tokenism in performance evaluation: The effects of work group representation on male-female and white-black differences in performance ratings. *Journal of Applied Psychology* 76 (2): 263–267.

Schoar, A., and L. Zuo, 2016. Shaped by booms and busts: How the economy impacts CEO careers and management styles. *NBER Working Paper*.

Sears, G. J., and P. M. Rowe, 2003. A personality-based similar-to-me effect in the employment interview: Conscientiousness, affect- versus competence-mediated interpretations, and the role of job relevance. *Canadian Journal of Behavioral Science* 35 (1): 13–24.

Seligman, M. E.., and P. Schulman, 1986. Explanatory style as a predictor of productivity and quitting among life insurance sales agents. *Journal of Personality and Social Psychology* 50 (4): 832–838.

Seligman, M. E., 1990. Learned optimism. New York: Knopf.

Shah, A., and D. Oppenheimer, 2008. Heuristics made easy: An Effort-reduction framework, Psychological Bulletin 134: 207-222.

Spangler, E., M. A. Gordon, and R. M. Pipkin, 1978. Token women: An empirical test of kanter's hypothesis. *American Journal of Sociology* 84 (1): 160–170.

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

Tversky, A., and D. Kahneman, 1974. Judgment under uncertainty: heuristics and biases. *Science* 185 (4157): 1124–1131.

Uzzi, B., 1999. Embeddedness and the making of financial capital: How social relations and networks benefit firms seeking financing. *American Sociological Review* 64: 481–505.

Uzzi, B., and R. Lancaster, 2003. Relational embeddedness and learning: The case of bank loan managers and their clients. *Management Science* 49 (4): 383–399.

APPENDIX A

Examples of employees' notes

"Member was in yesterday… very upset and distraught as to what is going to happen here in the future due to action that her husband has taken. Her husband has a drinking problem is he is a recovering alcoholic and he has been clean now for about 4 years. Her husband has been to recovery a number of times as this will be his fourth relapse. He ended up taking the new truck that he had purchased in the ditch while he was drinking and member and the kids were on a short summer vacation. So when member was getting calls from the neighbors and she had not heard from him she knew something was not right. She then returned home to find this out. He is in jail right now with a 12K bail over his head which member is not going to satisfy for him… she will be pursuing a divorce. Member can't put the kids through this anymore or herself. Member and I discussed a number of items that she can list for sale as she has to move back towards family in Iowa and rent an apartment."

"Followed up with K. regarding opportunities on the loan approval. Discussed importance of looking back at previous loan applications. Also making sure we have vehicle value in the system. We had already paid off negative equity in the truck 2 years ago and now we moved them out to a 5 year loan again. Also follow up on credit cards and if we can help them pay those off, or come up with a plan for them."

"B. called to finish up his car loan today. He called Friday to see if he can get approved for a car loan. Whoever he spoke with told him he is approved and all he needs to do is let us know how much he needs, and he will be set to go. I looked, but no application was ever loaded. I ran the application, and thankfully they have excellent credit and have more than sufficient income. I have $15,000 sent out to his checking account at [] Bank."

"T. and A. recently purchased a new vehicle and financed through a dealership. Although they received a fairly good rate (5.79), our rate is better and they also have member loyalty points that will bring the rate down to 4.99% for a 72 month term. They also have an account with [] bank and they would like to bring that here. It is for about $16k. They owe $117k on the first and tax assessed value is around $190k. They are looking to fix this."

"Worked with N. and C. today and yesterday (extensively) as to help them with their finances. N. has struggled with her finances and the stress is evident in their relationship. They want to take a trip to Mexico in Mar. 2006, as to achieve that goal, we're setting $445 into [deposit account] to cover it. The $475 is going to C. to cover housing expenses as they have separate accounts to cover individual expenses with their individual children (from previous marriages) and the related expenses. We are going to operate on a cash-basis ($200 this pay period) and see where it goes from there. After the 3/9/06 paycheck we can allocate the $445 differently into additional (new?) accounts for i.e., hockey, vacations, etc."

"How do I even begin...P. in today to determine how to deal with 120K - her mother's funeral was just yesterday and she just drove in from M.. P.'s divorce just finalized last month and today she received the settlement check of 120K. Wow! P. seems like a strong woman- her divorce took 4 years to complete - she has three children, one is studying at L. to be an Opera Singer, one is at the University studying to be a dentist and one is a sophomore at R. High School and enjoys Drama. P. works with the State of [] working with foster care situations where abuse is happening - she travels throughout northern [] and primarily stays in G.R. when up north. She stays at the S. Inn and has a specific room that she stays in every time - they know her there and she is a regular at a number of places. She has been doing this for 20 years. I said that she probably cherishes her kids in a way many do not know how due to her experiences with work. P's father J. moved into assisted living when her mother was hospitalized this past fall and he remains there now in M. P.'s three brothers live in M. and are able to help her father. The reason P. originally wanted to sit down with someone today was to express her immense gratitude to [the credit union] for taking a chance back in 2007 when we issued a 20K loan at 7.5% to her. Her husband had drained her accounts and they had just begun divorce - she needed money to pay her attorney & support herself and daughter at the time. [The credit union] took a chance and P. is soooooooo thankful - she paid off that loan, her [loans] today and is now going to buy a 2008-09 Subaru Outback or Legacy, paying 10K and doing a loan for the rest. and here's the best part.....for 10 years, before having kids, P. was a NUN! How about that. It was a joy to meet her today and hear her story – P. will be partnering with Investment center on additional investing with other funds she will be receiving as [] in the coming months."

"The church that D. works at just gave her and the other music director a bonus! They had a big celebration and the church even invited their parents! She said it was a lot of fun and she is really happy, everything is good!"

"I met J. today...what a guy! He slapped me on the back about eight times through the course of our conversation. He's looking to buy a motorcycle and/or a crotch rocket. He just found one he fell in love with, so we looked over some financing options."

"Stability, credibility, and relationship are great. Ability is borderline but taking into effect that her husband has considerable income I feel comfortable going forward with this."

"S. is a wonderful 17-year old. She is a junior at S. High and will be going to [] and then transfer to the U to study Marine Biology! She also works at "[]". She is an only child and very mature for her age. LOVE HER! She made some suggestions on which kind of fish I should get if my daughter asks for one that very low maintenance and had to overfeed."

"A. and I met and I am committed to helping her pull her home out of foreclosure and to stay on track. She has a better budget plan in place and has a solid tenant lined up for her rental. She is moving in with her daughter to share expenses while awaiting the sale of her home/rental property. Today we consolidated the money she needs for the home with her signed loan against her car and she had her social security direct deposit switched over; it will start in September. I approved the loan as I believe in A. and that her commitment to [the credit union] is sincere. She was trying to sell her home/rental property alone and has now listed it with [real estate company] so this will help her. She will still own the other rental property in [town name] for now but wants to sell that soon also. I know A. has had many struggles but I like her and I know she is a fighter. She is so caring as she took care of her terminally ill husband until he passed and her passion for people is evident in that she has worked in day care for 40 years! I will keep in close contact with A. and see how she is doing under her new budget and efforts on selling one of her properties."

"M. called - he is in a bind - his daughter had some medical problems, and he switched insurance companies, but because she had a pre-existing condition, they didn't cover it, so he has a large medical bill to pay. His checking is overdrawn this morning but he will be getting a [check] tomorrow that will cover that, and gets another regular payroll check next Friday. I told M. that I trust him, but I want to make sure that I am not burying him in debt that he can't get out of. He told me that he is starting a 2nd job next month where he will earn an extra $1500 per month, that he plans to use to knock down some of this unsecured debt faster than is required. M. has always been faithful to [the credit union], and does everything with us, and has been a member for over 5 years. I am not super excited about adding unsecured debt, but I am going to help him out with this today."

"P. has hit hard times. She is really struggling and came to [the credit union] because W.F. basically told her she didn't matter. She has filed bankruptcy, but it has been discharged. She has also had her car re-possessed and her rental car has to be turned in by 4:00 today. Her son is graduating from the military tomorrow in CA, she needs to get there to see him. She has great income, work history and she can afford the auto loan we are doing. I am working with her on getting her finances secured and also working on establishing future success at [the credit union]. I believe that P. wants to succeed financially and will do so. I went out on a limb on this one but I feel that I trust her and want to help her."

"I worked with B. and K. and they did express their frustration with their phone calls being answered in other parts of the state. They are very proud members but still wish they could have their phone calls here. Their daughter A. is getting married in Aug to J. They are both 18 but are much in love and looking forward to beginning their lives together. K. has been stressed with getting things ready for the wedding but they are excited. Helped them with some wedding expenses and purchase 2 cars by refinancing their [home equity] loan and taking cash out. Members have 6 kids and home schooled them all but their youngest is doing post-secondary at [academic institution name] this year so she will only be teaching math to her."

APPENDIX B

Soft keywords and phrases

Borrower's educational background	academi, arts, college, conference, degree, educated, education, graduate, grant, phd, master, scholar, school, science, seminar, stud, tuition, university, mba, undergrad
Borrower's professional background	army, boss, business, compensation, deployed, employ, hir, income, job, laid off, fraud, military, profession, promot, retir, salary, supervisor, unemploy, work, company, career, venture, vocation, manager, fired, director, executive, chief, entrepreneur, merchant, apprentice, corporation, firm, management, administrator, chief, commander, ceo, cfo, coo, wealth, occupation, colleague
Borrower's personal background	babies, baby, boy, boyfriend, break up, broke up, brother, cousin, child, nephew, dad, daughter, daycare, divorce, engaged, family, father, girl, girlfriend, home, hubby, husband, kid, mam, married, marry, mom, mother, nannies, nanny, parent, pregnancy, pregnant, sister, son, spouse, twins, wedding, wife, move to, moved to, moves to, moving to, fiancé, religion, significant other, mom, antecedent, predecessor, accident, cancer, clinic, disability, disabled, heart attack, hospital, medical, stroke, surgery, casualt, health, illness, disease, sickness, therapeutic, pathological
Borrower's social background	carnival, christmas, concert, easter, festival, folk, friend, halloween, hobbies, hobby, buddy, thanksgiving, holidays, feast, celebration, entertainment, vacation, volunteer, cat, dog, trip
Feelings	afraid, anger, angry, annoyed, anxious, bothered, cheat, concerned, confus, cried, cry, disappointed, discouraged, discriminat, displeased, dissatisfy, distressed, disturbed, doleful, embarrass, envious, envy, fear, fool, frustrated, gloomy, hard, horrified, hostil, intimidated, jealous, opportunistic, overwhelmed, panic, resent, rude, sad, shame, sorry, stress, struggle, stumble, stunned, suspicious, terrified, terror, tight, troubled, uneas, unfriendly, unhappy, unhelpful, unreliable, unresponsive, unsettled, untrust, indifferent, astonish, sentimental, hate, impolite, reserved, bold, unresponsibl, careless, unconfident, dishonest, unsuccessful, unfaithful, intolerant, worried, inconvenient, affectionate, agreeable, amicable, blissful, caring, cheer, compassionat, confident, conservative, decent, delight, eager, easy going, encouraged, energetic, enjoy, enthusiastic, excited, favor, friendly, fun, good faith, gracious, happy, honest, hopeful, humorous, integrity, joy, kind, lighthearted, lively, love, moral, nice, optimistic, passion, pleased, pride, promising, proud, relaxed, relief, relieved, responsibl, satisfy, smart, successful, trust, undisturbed, untroubled, unworried, zeal, calm, devoted, considerate, responsive, respectful, polite, candid, outgoing, faithful, dedicated, sociable, courteous, cautious, careful, tolerant, humble, brave, appeal, contented, convenient
Employees' assessments	my assessment, my assumption, I am sure, I anticipate, I assess, I assume, I believe, I conclude, I consider, I evaluate, I expect, I feel, I get the impression, I guess, I have the impression, I imagine, I perceive, I presume, I realize, I recognize, I sense, I suspect, I take in, I think, my anticipation, my belief, my conclusion, my conviction, my expectation, my guess, my impression, my judgment, my opinion, my perception, my perspective, my position, my sense, my suspicion, my thinking, my thought, my view, point of view, viewpoint, I had the impression

APPENDIX C

Variable definitions

Variable	Definition
Loan quality	
Charge off	An indicator variable equal to one if a loan was charged off by the credit union and zero otherwise. The credit union's policy is to charge off a loan within the 18-month period after a borrower is delinquent on the loan.
Delinquency	An indicator variable equal to one if the borrower defaulted on any loan with the credit union within the 18-month period following a loan's origination and zero otherwise. We use textual data from loan officers' notes to identify past-due loans.
Bad customer	An indicator variable equal to one if the borrower has defaulted on an outstanding loan or filed for bankruptcy during the 18-month period following a loan's origination and zero otherwise. We use data from a national credit bureau to identify borrowers' delinquencies and bankruptcies.
Credit score decline	An indicator variable equal to one if the borrower's credit score fell by 50 points or more within the 18-month period following a loan's origination and zero otherwise. This cutoff represents the bottom quintile of the distribution of changes in borrowers' credit score over this post-loan issuance period and aims to capture severe credit performance deterioration. Credit scores are provided by a national credit bureau.
Soft information	
Soft information	The ratio of soft keywords in employees' notes on a borrower to the total number of words in these notes (excl. stop-words), estimated based on notes written during the 45-day period prior to a loan's origination.
Behavioral biases	
<u>Limited attention</u>	
Busy day	An indicator variable equal to one if the number of notes a loan officer writes on a loan's approval day falls in the top quartile of the distribution of the number of notes per day this loan officer writes during the current quarter, and zero otherwise.
Before weekends	An indicator variable equal to one if the loan is originated after 4pm on Friday or on Saturday, and zero otherwise.
Around holidays	An indicator variable equal to one if the loan origination date falls within a [-4, +4] day-window around the national holidays: Fourth of July, Thanksgiving, Christmas and the New Year's Day, and zero otherwise.
<u>Task-specific human capital</u>	
Sales background	An indicator variable equal to one if the loan officer has professional experience in sales prior to joining the credit union, and zero if the loan officer has prior banking or other non-banking experience. We retrieve loan officers' bios from LinkedIn.

APPENDIX C (Continued)

<u>Common identity</u>	
Male to male	An indicator variable equal to one if the loan officer and the borrower are both men and zero otherwise.
Female to female	An indicator variable equal to one if the loan officer and the borrower are both women and zero otherwise.
Borrower and loan characteristics	
Credit score	The natural logarithm of a borrower's credit score. Credit scores are provided by a national credit bureau.
Debt-to-income ratio	A borrower's debt-to-income ratio.
Loan interest rate	The loan interest rate in %.
Loan exception	An indicator variable equal to one if the loan includes an exception relative to the union's credit guidelines and zero otherwise.
Secured loan	An indicator variable equal to one if the loan is collateralized and zero otherwise.
Loan amount	The natural logarithm of the loan amount.
Loan maturity	The natural logarithm of the loan maturity (in months).
Borrower tenure	The natural logarithm of the number of years a borrower has been a customer of the credit union.
Total number of accounts	The natural logarithm of the total number of products the borrower has with the credit union.

APPENDIX D

The validation of limited attention measures

	(I) *Number of errors per note*	(II) *Number of errors/ Number of words*	(III) *Number of errors/ Number of sentences*
Non-busy day	8.370	0.158	1.671
	(0.028)	(0.000)	(0.005)
Busy day	11.722	0.184	2.192
	(0.446)	(0.001)	(0.008)
t-test	-51.050***	-24.362***	-47.082***
Weekdays	8.828	0.161	1.743
	(0.027)	(0.000)	(0.005)
Before weekends	10.718	0.205	2.092
	(0.086)	(0.001)	(0.011)
t-test	-20.710***	-29.539***	-23.069***
Non-holidays	8.801	0.159	1.713
	(0.025)	(0.000)	(0.004)
Around holidays	10.486	0.195	2.318
	(0.112)	(0.002)	(0.023)
t-test	-17.489***	-22.782***	-37.794***

This table reports descriptive statistics for the number of grammar/syntax errors per note across periods of limited attention and other periods. For *Busy day*, we assess a loan officer's mistakes by the following three measures: 1) the number of errors per note, averaged daily; 2) the total number of errors to the total number of words in all notes recorded during the day; and 3) the total number of errors to the total number of sentences in all notes recorded during the day. For *Before weekends*, consistent with the inattention period under consideration, we estimate these proxies based on notes written on Friday after 4 pm and on Saturday. For *Around holidays*, consistent with the inattention period under consideration, we estimate these proxies based on the days around national holidays. The variables *Busy day*, *Before weekend* and *Around holidays* are defined in Appendix C, with *Non-busy day*, *Weekdays* and *Non-holidays* being the reverse of these variables, respectively. Standard errors are in parentheses. T-statistics for the difference in the mean values of the variables across limited attention and other periods are reported. $***$, $**$ and $*$ denote significance at the 1%, 5% and 10% levels, respectively.

TABLE 1

Descriptive statistics

Panel A: Summary statistics for the variables used in our primary analyses	Obs.	Mean	STD	Median
Loan quality				
Charge off	49,680	0.022	0.135	0.000
Delinquency	49,680	0.151	0.364	0.000
Bad customer	15,972	0.237	0.412	0.000
Credit score decline	27,807	0.193	0.394	0.000
Soft information				
Soft information	49,680	0.055	0.040	0.034
Behavioral biases				
Limited attention				
Busy day	49,680	0.250	0.431	0.000
Before weekends	49,680	0.063	0.215	0.000
Around holidays	49,680	0.069	0.238	0.000
Task-specific human capital				
Sales background	9,364	0.222	0.420	0.000
Common identity				
Male to male	40,747	0.126	0.332	0.000
Female to female	40,747	0.309	0.462	0.000
Borrower and loan characteristics				
Credit score	49,680	6.592	0.210	6.589
Debt-to-income ratio	49,680	0.372	0.230	0.352
Loan interest rate	49,680	8.967	3.841	8.050
Loan exception	49,680	0.795	0.349	1.000
Secured loan	49,680	0.368	0.448	0.000
Loan amount	49,680	8.899	1.243	9.137
Loan maturity	49,680	4.090	1.274	4.108
Borrower tenure	49,680	0.845	0.951	0.688
Total number of accounts	49,680	1.602	0.905	1.791

TABLE 1 (Continued)

Panel B: Spearman correlations among the variables used in our primary analyses

	Obs.= 22,140	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)	*Charge off*	1.000																
(2)	*Delinquency*	0.227																
(3)	*Credit score decline*	0.119	0.287															
(4)	*Soft information*	-0.010	-0.032	-0.014														
(5)	*Busy day*	-0.001	-0.007	-0.001	0.029													
(6)	*Before weekends*	-0.008	-0.010	-0.015	0.012	-0.036												
(7)	*Around holidays*	0.010	0.002	-0.002	0.010	-0.001	-0.003											
(8)	*Male to male*	-0.012	0.032	0.010	-0.016	0.011	0.006	-0.004										
(9)	*Female to female*	0.000	-0.016	0.004	0.026	-0.008	-0.010	0.009	-0.614									
(10)	*Credit score*	-0.107	-0.424	-0.224	-0.053	0.003	0.011	-0.017	-0.012	-0.009								
(11)	*Debt-to-income*	0.031	0.055	0.092	0.022	-0.008	0.011	0.022	-0.014	-0.006	-0.105							
(12)	*Loan interest rate*	0.078	0.321	0.179	-0.088	-0.006	-0.030	0.007	-0.008	0.029	-0.562	0.107						
(13)	*Loan exception*	0.007	0.111	0.007	0.020	-0.039	-0.033	-0.044	-0.022	0.048	0.055	-0.142	0.154					
(14)	*Secured loan*	-0.026	-0.044	-0.070	-0.041	-0.004	-0.014	-0.045	0.027	-0.036	0.136	-0.144	-0.262	0.234				
(15)	*Loan amount*	-0.047	-0.173	-0.134	0.046	-0.017	0.023	-0.018	0.007	-0.005	0.334	0.065	-0.570	0.017	0.285			
(16)	*Loan maturity*	-0.024	-0.071	-0.045	0.011	-0.034	0.011	0.006	0.015	-0.003	0.134	0.067	-0.203	0.009	0.129	0.546		
(17)	*Borrower tenure*	-0.013	-0.064	-0.042	0.059	0.001	0.011	0.001	-0.001	0.008	0.143	0.121	-0.202	0.083	-0.113	0.196	0.104	
(18)	*Total number of accounts*	-0.065	-0.049	-0.076	-0.057	-0.050	-0.004	-0.011	-0.013	-0.003	0.072	0.047	-0.040	0.028	-0.028	0.001	0.070	0.152

This table presents descriptive statistics and correlations for the variables used in our primary tests. Panel A presents summary statistics; the values of the continuous variables are winsorized at 1% and 99%. Panel B presents the spearman correlations. Variables are defined in Appendix C.

TABLE 2

Validation tests

	(I) *Charge off*	(II) *Delinquency*	(III) *Bad customer*	(IV) *Credit score decline*
Soft information	-0.066***	-0.125***	-0.160**	-0.056
	(-4.585)	(-3.033)	(-2.188)	(-0.920)
Credit score	-0.018***	-0.139***	-0.284***	-0.051***
	(-5.278)	(-12.402)	(-11.907)	(-3.076)
Debt-to-income ratio	0.010**	0.115***	0.147***	0.157***
	(2.358)	(11.871)	(8.361)	(11.147)
Loan interest rate	0.004***	0.037***	0.033***	0.017***
	(9.353)	(38.027)	(19.096)	(12.619)
Loan exception	0.001	0.019***	0.039***	-0.005
	(0.492)	(3.074)	(3.424)	(-0.465)
Secured loan	0.004	0.005	-0.054***	0.015*
	(1.451)	(0.781)	(-4.450)	(1.674)
Loan amount	0.000	-0.009***	-0.011**	-0.018***
	(0.011)	(-3.766)	(-2.499)	(-5.610)
Loan maturity	-0.001	-0.001	0.003	0.014***
	(-0.971)	(-0.804)	(0.943)	(4.182)
Borrower tenure	-0.000	-0.004*	-0.007*	-0.005
	(-0.289)	(-1.664)	(-1.817)	(-1.428)
Total number of accounts	-0.004***	0.004	0.007	-0.006
	(-3.408)	(1.232)	(1.339)	(-1.147)
Fixed effects: Loan officer, branch, year, loan type				
Economic significance of *Soft information*	-12.000%	-3.311%	-2.700%	
Obs.	49,680	49,680	15,972	27,807
R^2	4.20%	18.19%	27.34%	6.56%

This table reports the analyses of the relation between soft information and loan quality. *Soft information* is the ratio of soft keywords in employees' notes on a borrower to the total number of words in these notes (excl. stop-words), estimated based on notes written during the 45-day period prior to a loan's origination. In specification (I), the dependent variable is equal to one if a loan was charged off by the credit union and zero otherwise (*Charge off*). In specification (II), the dependent variable is equal to one if a borrower defaulted on any loan issued by the credit union during the 18-month period following a loan's origination and zero otherwise (*Delinquency*). In specification (III), the dependent variable is equal to one if a national credit bureau reports that the borrower has defaulted on an outstanding loan or filed for bankruptcy during the 18-month period following a loan's origination and zero otherwise (*Bad customer*). In specification (IV), the dependent variable is equal to one if a borrower's credit score fell by 50 points or more during the 18-month period following a loan's origination and zero otherwise (*Credit score decline*). All other variables are defined in Appendix C. The values of the continuous variables are winsorized at 1% and 99%. Loan officer, branch, loan type and year fixed effects are included but not tabulated. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. We also report the economic significance of the *Soft information* variable. We measure the economic significance by the effect of a one standard deviation increase in the soft information measure on ex-post lending outcomes, as a percentage of the mean value of ex-post lending outcomes. ***, ** and * denote significance at the 1%, 5% and 10% (two-sided) levels, respectively.

TABLE 3

Soft information, limited attention bias and loan quality

Panel A: Loan quality and lending based on soft information on busy days

	(I) *Charge off*	(II) *Delinquency*	(III) *Bad customer*	(IV) *Credit score decline*
Soft information	-0.089***	-0.198***	-0.200***	-0.069
	(-5.870)	(-5.518)	(-3.945)	(-1.011)
Busy day	-0.002	-0.003	-0.003	-0.003
	(-1.072)	(-1.008)	(-1.091)	(-0.471)
Soft information* × *Busy day	**0.074*** **	**0.455*** **	**0.429*** **	**0.023**
	(2.845)	**(6.724)**	**(3.345)**	**(0.233)**
Controls	YES	YES	YES	YES
Fixed effects:				
Loan officer, branch, year, loan type				
$\beta_1 + \beta_3$	-0.02	0.23	0.23	-0.04
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.73	0.00	0.08	0.64
Economic effect of *Soft information* when loan officers are subject to biases		6.85%	3.82%	
Obs.	49,680	49,680	15,972	27,807
R^2	4.31%	18.86%	28.20%	6.71%

Panel B: Loan quality and lending based on soft information before weekends

	(I) *Charge off*	(II) *Delinquency*	(III) *Bad customer*	(IV) *Credit score decline*
Soft information	-0.065***	-0.119***	-0.160**	-0.055
	(-4.539)	(-2.881)	(-2.182)	(-0.897)
Before weekends	-0.004	0.004	0.015	-0.018*
	(-1.495)	(0.497)	(1.078)	(-1.748)
Soft information* × *Before weekends	**0.263** **	**0.537*** **	**0.692* **	**-0.030**
	(2.420)	**(7.709)**	**(1.747)**	**(-0.108)**
Controls	YES	YES	YES	YES
Fixed effects:				
Loan officer, branch, year, loan type				

TABLE 3 (Continued)

$\beta_1 + \beta_3$	0.20	0.42	0.53	-0.09
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.00	0.00	0.09	0.76
Economic effect of *Soft information* when loan officers are subject to biases	36.00%	11.07%	8.98%	
Obs.	49,680	49,680	15,972	27,807
R^2	4.23%	18.32%	27.37%	6.60%

Panel C: Loan quality and lending based on soft information around national holidays

	(I) *Charge off*	(II) *Delinquency*	(III) *Bad customer*	(IV) *Credit score decline*
Soft information	-0.068***	-0.130***	-0.164**	-0.062
	(-4.745)	(-3.154)	(-2.237)	(-1.009)
Around holidays	0.001	-0.002	-0.007	-0.010
	(0.237)	(-0.335)	(-0.603)	(-1.095)
Soft information × Around holidays	**0.192*** **	**0.582*** **	**0.302**	**0.620*** *
	(3.861)	**(2.725)**	**(0.797)**	**(2.071)**
Controls	YES	YES	YES	YES
Fixed effects:				
Loan officer, branch, year, loan type				
$\beta_1 + \beta_3$	0.12	0.45	0.14	0.56
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.02	0.04	0.72	0.04
Economic effect of *Soft information* when loan officers are subject to biases	22.55%	11.97%		11.57%
Obs.	49,680	49,680	15,972	27,807
R^2	4.25%	18.21%	27.36%	6.62%

This table reports the analyses of whether using soft information in lending decisions by inattentive loan officers leads to worse loan quality. We proxy for loan officer's limited attention (distraction) as follows: in Panel A, *Busy day* is equal to one if the number of notes a loan officer writes on a loan's approval day falls in the top quartile of the distribution of the number of notes per day this loan officer writes during the current quarter, and zero otherwise; in Panel B, *Before weekends* is equal to one if the loan is originated after 4 pm on Friday or on Saturday and zero otherwise; in Panel C, *Around holidays* is equal to one if the loan origination date falls within a [-4, +4] day-window around Fourth of July, Thanksgiving, Christmas and the New Year's Day and zero otherwise. *Soft information* is the ratio of soft keywords in employees' notes on a borrower to the total number of words in these notes (excl. stop-words), estimated based on notes written during the 45-day period prior to a loan's origination. In specification (I), the dependent variable is equal to one if a loan was charged off by the credit union and zero otherwise (*Charge off*). In specification (II), the dependent variable is equal to one if a borrower defaulted on any loan issued by the credit union during the 18-month period following a loan's origination and zero otherwise (*Delinquency*). In specification (III), the dependent variable is equal to one if a national credit bureau reports that the borrower has defaulted on an outstanding loan or filed for bankruptcy during the 18-month period following a loan's origination and zero otherwise (*Bad customer*). In specification (IV), the dependent variable is equal to one if a borrower's credit score fell by 50 points or more during the 18-month period following a loan's origination and zero otherwise (*Credit score decline*). All other variables are defined in Appendix C. The values of the continuous variables are winsorized at 1% and 99%. Model specifications and control variables (untabulated) are the same as in Model 2. Loan officer, branch, loan type and year fixed effects are included but not tabulated. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. We also report the sum of the coefficients on our soft information measure (β_1) and the interaction term between this measure and our proxies for limited attention bias (β_3), as well as the p-values that indicate whether this sum is statistically different from zero. For specifications where the sum of the coefficients on the soft information measure and the interaction term is significantly different from zero, we also report the economic significance of the effect of soft information when loan officers are subject to a behavioral bias. We measure the economic significance by the effect of a one standard deviation increase in soft information when loan officers are subject to behavioral biases on ex-post lending outcomes, as a percentage of the mean value of ex-post lending outcomes. $***$, $**$ and $*$ denote significance at the 1%, 5% and 10% (two-sided) levels, respectively. Coefficients of interest are in boldface.

TABLE 4

Soft information, task-specific human capital bias and loan quality

	(I) *Charge off*	(II) *Delinquency*	(III) *Bad customer*	(IV) *Credit score decline*
Soft information	-0.104***	-0.265***	-0.198	-0.202***
	(-3.207)	(-3.065)	(-1.127)	(-3.361)
Sales background	-0.002	-0.009	-0.004	-0.010
	(-0.489)	(-0.845)	(-0.209)	(-0.607)
Soft information × Sales background	**0.271*** **	**0.541*** **	**0.846** **	**0.808** **
	(3.707)	**(2.877)**	**(2.038)**	**(2.478)**
Controls	YES	YES	YES	YES
Fixed effects:				
Branch, year, loan type				
$\beta_1 + \beta_3$	0.17	0.28	0.65	0.61
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.02	0.17	0.10	0.06
Economic effect of *Soft information* when loan officers are subject to biases	30.36%		11.27%	12.56%
Obs.	9,364	9,364	2,926	5,472
R^2	4.14%	17.54%	29.07%	5.41%

This table reports the analyses of whether using soft information in lending decisions by loan officers with prior experience in sales leads to worse loan quality. *Sales background* is an indicator variable equal to one if a loan officer has had professional experience in sales prior to joining the credit union and zero otherwise. *Soft information* is the ratio of soft keywords in employees' notes on a borrower to the total number of words in these notes (excl. stop-words), estimated based on notes written during the 45-day period prior to a loan's origination. In specification (I), the dependent variable is equal to one if a loan was charged off by the credit union and zero otherwise (*Charge off*). In specification (II), the dependent variable is equal to one if a borrower defaulted on any loan issued by the credit union during the 18-month period following a loan's origination and zero otherwise (*Delinquency*). In specification (III), the dependent variable is equal to one if a national credit bureau reports that the borrower has defaulted on an outstanding loan or filed for bankruptcy during the 18-month period following a loan's origination and zero otherwise (*Bad customer*). In specification (IV), the dependent variable is equal to one if a borrower's credit score fell by 50 points or more during the 18-month period following a loan's origination and zero otherwise (*Credit score decline*). All other variables are defined in Appendix C. The values of the continuous variables are winsorized at 1% and 99%. Model specifications and control variables (untabulated) are the same as in Model 2. Branch, loan type and year fixed effects are included but not tabulated. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. We also report the sum of the coefficients on our soft information measure (β_1) and the interaction term between this measure and our proxy for task-specific human capital bias (β_3), as well as the p-values that indicate whether this sum is statistically different from zero. For specifications where the sum of the coefficients on the soft information measure and the interaction term is significantly different from zero, we also report the economic significance of the effect of soft information when loan officers are subject to a behavioral bias. We measure the economic significance by the effect of a one standard deviation increase in soft information when loan officers are subject to behavioral biases on ex-post lending outcomes, as a percentage of the mean value of ex-post lending outcomes. ∗∗∗, ∗∗ and ∗ denote significance at the 1%, 5% and 10% (two-sided) levels, respectively. Coefficients of interest are in boldface.

TABLE 5

Soft information, common identity bias and loan quality

Panel A: Loan quality and lending based on soft information when the loan officer and the borrower are both men				
	(I)	(II)	(III)	(IV)
	Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
Soft information	-0.083***	-0.138***	-0.202**	-0.100
	(-5.291)	(-2.959)	(-2.322)	(-1.420)
Male to male	-0.007*	0.024**	0.014	0.012
	(-1.650)	(2.288)	(0.769)	(0.809)
Soft information* × *Male to male	**0.292*** **	**0.465** **	**0.502** **	**0.332**
	(2.868)	**(2.090)**	**(2.413)**	**(0.988)**
Controls	YES	YES	YES	YES
Fixed effects:				
Loan officer, branch, year, loan type				
$\beta_1 + \beta_3$	0.21	0.33	0.30	0.23
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.01	0.05	0.11	0.47
Economic effect of *Soft information* when loan officers are subject to biases	38.00%	8.66%		
Obs.	40,747	40,747	13,251	22,140
R^2	4.29%	18.55%	26.20%	6.32%

Panel B: Loan quality and lending based on soft information when the loan officer and the borrower are both women				
	(I)	(II)	(III)	(IV)
	Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
Soft information	-0.069***	-0.115**	-0.148*	-0.087
	(-4.519)	(-2.529)	(-1.762)	(-1.289)
Female to female	-0.039	-0.214*	-0.146	-0.006**
	(-0.802)	(-1.908)	(-1.109)	(-1.984)
Soft information* × *Female to female	**-0.026**	**0.057**	**0.024**	**-0.277** **
	(-0.869)	**(0.713)**	**(0.160)**	**(-2.230)**
Controls	YES	YES	YES	YES
Fixed effects:				
Loan officer, branch, year, loan type				

TABLE 5 (Continued)

$\beta_1 + \beta_3$	-0.10	-0.06	-0.12	-0.36
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.02	0.52	0.47	0.00
Economic effect of *Soft information* when loan officers are subject to biases	-17.27%			-7.54%
Obs.	40,747	40,747	13,251	22,140
R^2	4.27%	18.28%	23.10%	6.34%

This table reports the analyses of whether using soft information in lending decisions by loan officers subject to common identity bias leads to worse loan quality. We proxy for common identity as follows: in Panel A, *Male to male* is equal to one if the loan officer and the borrower are both men and zero otherwise; in Panel B, *Female to female* is equal to one if the loan officer and the borrower are both women and zero otherwise. *Soft information* is the ratio of soft keywords in employees' notes on a borrower to the total number of words in these notes (excl. stop-words), estimated based on notes written during the 45-day period prior to a loan's origination. In specification (I), the dependent variable is equal to one if a loan was charged off by the credit union and zero otherwise (*Charge off*). In specification (II), the dependent variable is equal to one if a borrower defaulted on any loan issued by the credit union during the 18-month period following a loan's origination and zero otherwise (*Delinquency*). In specification (III), the dependent variable is equal to one if a national credit bureau reports that the borrower has defaulted on an outstanding loan or filed for bankruptcy during the 18-month period following a loan's origination and zero otherwise (*Bad customer*). In specification (IV), the dependent variable is equal to one if a borrower's credit score fell by 50 points or more during the 18-month period following a loan's origination and zero otherwise (*Credit score decline*). All other variables are defined in Appendix C. The values of the continuous variables are winsorized at 1% and 99%. Loan officer, branch, loan type and year fixed effects are included but not tabulated. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Model specifications and control variables (untabulated) are the same as in Model 2. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. We also report the sum of the coefficients on our soft information measure (β_1) and the interaction term between this measure and our proxies for common identity bias (β_3), as well as the p-values that indicate whether this sum is statistically different from zero. For specifications where the sum of the coefficients on the soft information measure and the interaction term is significantly different from zero, we also report the economic significance of the effect of soft information when loan officers are subject to a behavioral bias. We measure the economic significance by the effect of a one standard deviation increase in soft information when loan officers are subject to behavioral biases on ex-post lending outcomes, as a percentage of the mean value of ex-post lending outcomes. ∗∗∗, ∗∗ and ∗ denote significance at the 1%, 5% and 10% (two-sided) levels, respectively. Coefficients of interest are in boldface.

TABLE 6

Soft information collected by the approving loan officer, behavioral biases and loan quality

		(I)	(II)	(III)	(IV)
		Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
	Soft information	-0.113***	-0.224***	-0.307***	-0.054
		(-6.907)	(-4.035)	(-3.560)	(-0.633)
	Soft information × Busy day	0.090***	0.568***	0.536***	-0.024
		(3.110)	(7.470)	(3.627)	(-0.209)
	Soft information × Busy day × Loan officer's notes	**-0.071****	**-0.494*****	**-0.437***	**0.165**
		(-2.105)	**(-3.533)**	**(-1.695)**	**(0.763)**
	Obs./ R^2	49,680/4.32%	49,680/18.95%	15,972/28.50%	27,807/6.73%
Limited attention	*Soft information*	-0.108***	-0.153***	-0.238***	-0.084*
		(-6.838)	(-2.933)	(-2.894)	(-1.633)
	Soft information × Before weekends	0.158**	0.873***	0.789**	-0.168
		(2.373)	(8.306)	(1.963)	(-0.595)
	Soft information × Before weekends × Loan officer's notes	**0.072**	**-0.600*****	**-0.199**	**0.584***
		(0.603)	**(-2.768)**	**(-0.467)**	**(1.797)**
	Obs./ R^2	49,680/4.25%	49,680/18.52%	15,972/28.09%	27,807/6.80%
	Soft information	-0.027**	-0.164***	-0.123**	0.014
		(-2.575)	(-3.038)	(-2.251)	(0.144)
	Soft information × Around holidays	0.346**	0.556***	0.920**	0.789**
		(2.158)	(3.116)	(2.283)	(2.390)
	Soft information × Around holidays × Loan officer's notes	**-0.197***	**-0.399****	**-0.926****	**-0.501***
		(-1.853)	**(-2.548)**	**(-2.164)**	**(-1.934)**
	Obs./ R^2	49,680/4.48%	49,680/18.59%	15,972/29.45%	27,807/6.87%
Task specific human capital	*Soft information*	-0.132***	-0.443***	-0.331*	-0.313**
		(-3.553)	(-3.765)	(-1.724)	(-2.488)
	Soft information × Sales background	0.314***	0.865***	0.890***	0.760**
		(4.204)	(3.587)	(3.418)	(2.571)
	Soft information × Sales background × Loan officer's notes	**-0.166**	**-0.808****	**-0.881****	**-0.673**
		(-0.981)	**(-2.104)**	**(-2.234)**	**(-1.315)**
	Obs./ R^2	9,364/4.20%	9,364/18.58%	2,926/29.31%	5,472/5.87%

TABLE 6 (Continued)

Common identity	*Soft information*	-0.127***	-0.211***	-0.282***	-0.162*
		(-6.703)	(-3.490)	(-2.785)	(-1.676)
	Soft information × Male to male	0.160***	0.614***	0.678*	0.534*
		(2.814)	(3.623)	(1.913)	(1.726)
	Soft information × Male to male x Loan officer's notes	**-0.106***	**-0.508***	**-0.449**	**-0.378**
		(-2.655)	**(-3.028)**	**(-1.203)**	**(-2.499)**
	Obs./ R^2	40,747/4.31%	40,747/18.56%	13,251/29.20%	22,140/6.49%

This table reports the analyses of whether the adverse effect of behavioral biases on soft information lending is attenuated when soft information has been primarily collected by the approving loan officer. *Loan officer's notes* is equal to one if the ratio of the number of borrower-specific notes written by the approving loan officer over the 45-day period prior to a loan's origination, scaled by the total number of notes available about the borrower over this period, falls in the upper quartile of the ratio distribution, and zero otherwise. We augment Model 2 with the *Loan officer's notes* indicator variable, the double interaction terms *Soft information x Loan officer's notes* and *Behavioral bias x Loan officer's notes*, and the triple interaction term *Soft information x Behavioral bias x Loan officer's notes*. All other control variables (untabulated) and model specifications are the same as in Model 2. The coefficients on *Soft information*, *Soft information* x *Behavioral bias* and *Soft information x Behavioral bias x Loan officer's notes* are reported. All other variables are defined in Appendix C. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. ***, ** and * denote significance at the 1%, 5% and 10% (two-sided) levels, respectively. Coefficients of interest are in boldface.

TABLE 7

Loan officer's and borrower's characteristics and soft information processing costs

Panel A: The role of a loan officer's tenure at the credit union in mitigating the adverse effect of behavioral biases on soft information processing

		(I)	(II)	(III)	(IV)
		Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
	Soft information	-0.084***	-0.256***	-0.306***	-0.095
		(-4.653)	(-5.206)	(-3.571)	(-1.246)
	Soft information × Busy day	0.092***	0.512***	0.482***	0.010
		(3.415)	(7.377)	(3.541)	(0.095)
	Soft information × Busy day × Experienced loan officer	**-0.119****	**-0.517*****	**-0.510**	**-0.120**
		(-2.522)	**(-4.111)**	**(-1.430)**	**(-0.420)**
	Obs./ R^2	49,680/4.34%	49,680/18.87%	15,972/28.40%	27,807/6.71%
	Soft information	-0.063***	-0.144***	-0.226***	-0.138**
Limited attention		(-3.828)	(-3.252)	(-2.954)	(-2.015)
	Soft information × Before weekends	0.180*	0.233**	0.673*	0.392**
		(1.894)	(2.225)	(1.818)	(1.991)
	Soft information × Before weekends × Experienced loan officer	**-0.179****	**-0.290****	**-0.652****	**-0.508**
		(-2.428)	**(-2.195)**	**(-2.053)**	**(-1.056)**
	Obs./ R^2	49,680/4.23%	49,680/18.36%	15,972/27.67%	27,807/6.60%
	Soft information	-0.068***	-0.151***	-0.237***	-0.147**
		(-4.107)	(-3.409)	(-3.069)	(-2.146)
	Soft information × Around holidays	0.448***	0.662***	0.672*	0.769***
		(5.132)	(3.162)	(1.702)	(2.757)
	Soft information × Around holidays × Experienced loan officer	**-0.410*****	**-0.579***	**-0.715****	**-0.744***
		(-3.579)	**(-1.738)**	**(-2.072)**	**(-1.824)**
	Obs./ R^2	49,680/4.25%	49,680/18.21%	15,972/27.36%	27,807/6.62%
Task specific human capital	*Soft information*	-0.097***	-0.356***	-0.247**	-0.378**
		(-2.684)	(-3.812)	(-2.343)	(-2.178)
	Soft information × Sales background	0.166***	0.827***	0.866**	0.880**
		(3.373)	(3.978)	(2.264)	(2.356)

TABLE 7 (Continued)

	Soft information × Sales background × Experienced loan officer	**0.008**	**-0.492**	**-0.162**	**-0.277**
		(0.052)	**(-1.379)**	**(-1.013)**	**(-0.363)**
	Obs./ R^2	9,364/4.14%	9,364/18.11%	2,926/29.08%	5,472/5.41%
Common identity	*Soft information*	-0.072***	-0.153***	-0.227**	-0.188**
		(-3.421)	(-2.745)	(-2.157)	(-2.170)
	Soft information × Male to male	0.168**	0.555***	0.589**	0.267**
		(2.382)	(3.334)	(2.020)	(2.121)
	Soft information × Male to male × Experienced loan officer	**-0.052**	**0.155**	**-0.020**	**-0.332**
		(-0.627)	**(1.061)**	**(-0.024)**	**(-0.926)**
	Obs./ R^2	40,747/4.29%	40,747/18.55%	13,251/26.20%	22,140/6.32%

Panel B: The role of a borrower's relationship with the credit union in mitigating the adverse effect of behavioral biases on soft information processing

		(I)	(II)	(III)	(IV)
		Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
	Soft information	-0.095***	-0.277***	-0.326***	-0.093
		(-6.177)	(-6.131)	(-4.172)	(-1.372)
	Soft information × Busy day	0.073***	0.469***	0.456***	-0.036
		(2.691)	(6.727)	(3.452)	(-0.341)
	Soft information × Busy day × Relationship intensity	**-0.033**	**-0.359***	**-0.504**	**0.420**
		(-0.829)	**(-1.727)**	**(-1.164)**	**(1.398)**
	Obs./ R^2	49,680/4.33%	49,680/18.91%	15,972/28.20%	27,807/6.75%
	Soft information	-0.079***	-0.182***	-0.177**	-0.074
		(-5.677)	(-4.337)	(-2.544)	(-1.055)
Limited attention	*Soft information × Before weekends*	0.160**	0.765***	0.776**	0.065
		(2.547)	(7.847)	(1.968)	(0.239)
	Soft information × Before weekends × Relationship intensity	**-0.010**	**0.369**	**0.295**	**-0.057**
		(-0.261)	**(0.855)**	**(1.497)**	**(-0.128)**
	Obs./ R^2	49,680/4.35%	49,680/18.50%	15,972/27.98%	27,807/6.68%

TABLE 7 (Continued)

	Soft information	-0.084***	-0.200***	-0.188***	-0.085*
		(-6.019)	(-4.761)	(-2.729)	(-1.709)
	Soft information × Around holidays	0.377***	0.667***	0.477	0.911***
		(4.334)	(3.198)	(1.118)	(2.745)
	Soft information × Around holidays × Relationship intensity	**-0.283*** **	**-0.162**	**-0.049**	**-0.774***
		(-3.491)	**(-1.302)**	**(-1.408)**	**(-1.662)**
	Obs./ R^2	49,680/4.30%	49,680/18.29%	15,972/27.41%	27,807/6.69%
Task specific human capital	*Soft information*	-0.115**	-0.353***	-0.245	-0.294*
		(-2.595)	(-2.870)	(-1.269)	(-1.825)
	Soft information × Sales background	0.301***	0.683**	0.724**	0.902**
		(3.257)	(2.151)	(2.458)	(2.369)
	Soft information × Sales background × Relationship intensity	**-0.058*** *	**-0.133**	**-0.214**	**-0.212**
		(-2.288)	**(-1.322)**	**(-0.741)**	**(-0.320)**
	Obs./ R^2	9,364/4.21%	9,364/17.77%	2,926/29.09%	5,472/5.51%
Common identity	*Soft information*	-0.096***	-0.208***	-0.210**	-0.146*
		(-5.896)	(-4.128)	(-2.537)	(-1.754)
	Soft information × Male to male	0.263**	0.301	0.833*	0.583
		(2.215)	(1.170)	(1.663)	(1.468)
	Soft information × Male to male × Relationship intensity	**-0.078***	**0.397**	**0.277**	**-0.821***
		(-1.750)	**(1.027)**	**(0.332)**	**(-1.905)**
	Obs./ R^2	40,747/4.36%	40,747/18.55%	13,251/27.59%	22,140/6.46%

Panel C: The role of a borrower's high credit score in mitigating the adverse effect of behavioral biases on soft information processing

		(I)	(II)	(III)	(IV)
		Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
	Soft information	-0.107***	-0.290***	-0.500***	-0.062
		(-5.830)	(-5.226)	(-3.521)	(-0.762)
	Soft information × Busy day	0.075***	0.480***	0.370***	0.006
		(2.668)	(6.667)	(2.809)	(0.056)

TABLE 7 (Continued)

	Soft information × Busy day × High credit score	**-0.034**	**-0.411*****	**-0.198**	**-0.098**
		(-0.820)	**(-5.109)**	**(-1.298)**	**(-0.498)**
Limited attention	Obs./ R^2	49,680/4.31%	49,680/19.40%	15,972/33.84%	27,807/7.41%
	Soft information	-0.090***	-0.186***	-0.411***	-0.090
		(-5.244)	(-3.676)	(-2.991)	(-1.226)
	Soft information × Before weekends	0.139**	0.466**	0.854**	0.546*
		(2.515)	(2.322)	(2.405)	(1.800)
	Soft information × Before weekends × High credit score	**-0.167**	**-0.100**	**-0.018**	**-0.427**
		(-1.043)	**(-0.449)**	**(-0.621)**	**(-0.941)**
	Obs./ R^2	49,680/4.20%	49,680/18.52%	15,972/32.62%	27,807/6.76%
	Soft information	-0.094***	-0.193***	-0.424***	-0.103
		(-5.461)	(-3.808)	(-3.037)	(-1.401)
	Soft information × Around holidays	0.257***	0.715***	0.596	0.108***
		(4.143)	(2.721)	(0.928)	(2.928)
	Soft information × Around holidays × High credit score	**-0.174**	**-0.399****	**-0.489**	**-0.161*****
		(-1.339)	**(-2.017)**	**(-1.055)**	**(-3.526)**
	Obs./ R^2	49,680/4.22%	49,680/18.54%	15,972/32.57%	27,807/6.78%
Task specific human capital	*Soft information*	-0.136***	-0.405***	-0.561	-0.234
		(-3.336)	(-3.698)	(-1.378)	(-1.234)
	Soft information × Sales background	0.339***	0.778***	0.518*	0.891**
		(3.729)	(3.267)	(1.679)	(2.203)
	Soft information × Sales background × High credit score	**-0.328**	**-0.080**	**-0.748****	**-0.599**
		(-1.304)	**(-0.248)**	**(-1.911)**	**(-1.069)**
	Obs./ R^2	9,364/4.25%	9,364/18.58%	2,926/35.35%	5,472/6.96%
Common identity	*Soft information*	-0.103***	-0.195***	-0.358**	-0.124
		(-5.314)	(-3.367)	(-2.172)	(-1.460)
	Soft information × Male to male	0.193***	0.561**	0.739**	0.325
		(3.077)	(2.140)	(2.227)	(0.822)

TABLE 7 (Continued)

Soft information* × *Male to male* × *High credit score	**-0.249**	**-0.463*****	**-0.401**	**-0.191**
	(-1.218)	**(-2.732)**	**(-1.070)**	**(-0.508)**
Obs./ R^2	40,747/4.38%	40,747/18.77%	13,251/31.70%	22,140/5.90%

This table reports the analyses of whether a loan officer's experience at the credit union (Panel A), borrower's prior relationship with the credit union (Panel B) and borrower's high credit score (Panel C) mitigate the adverse effects of behavioral biases on soft lending. *Experienced loan officer* equals one if a loan officer's years of employment at the credit union ranks in the upper quartile of loan officers' tenure, and zero otherwise. *Relationship intensity* equals one if a borrower's total number of accounts falls in the upper quartile of this variable's sample distribution, and zero otherwise. *High credit score* equals one if a borrower's credit score is ranked in the upper quartile of the distribution of sample borrowers' credit scores, and zero otherwise. In Panel A, we augment Model 2 with *Experienced loan officer*, the double interaction terms *Soft information* x *Experienced loan officer*, *Behavioral bias* x *Experienced loan officer* and the triple interaction term *Soft information* x *Behavioral bias* x *Experienced loan officer*. Model specifications and control variables (untabulated) are the same as in Model 2. In Panel B, we augment Model 2 with *Relationship intensity*, the double interaction terms *Soft information* x *Relationship intensity*, *Behavioral bias* x *Relationship intensity* and the triple interaction *Soft information* x *Behavioral bias* x *Relationship intensity*. All specifications and control variables –other than *Total number of accounts* which is omitted– are the same as in Model 2. In Panel C, we augment Model 2 with *High credit score*, the double interaction terms *Soft information* x *High credit score*, *Behavioral Bias* x *High credit score* and the triple interaction term *Soft information* x *Behavioral bias* x *High credit score*. All specifications and control variables –other than *Credit score* which is omitted– are the same as in Model 2. The coefficients on *Soft information*, *Soft information* x *Behavioral bias* and the triple interaction terms are reported. All other variables are defined in Appendix C. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. ∗∗∗, ∗∗ and ∗ denote significance at the 1%, 5% and 10% (two-sided) levels, respectively. Coefficients of interest are in boldface.

TABLE 8

The tone of soft information, behavioral biases and loan quality

Panel A: Non-ambiguous soft information tone, behavioral biases and loan quality

		(I)	(II)	(III)	(IV)
		Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
	Soft information	-0.085***	-0.186***	-0.241***	0.012
		(-5.115)	(-3.831)	(-2.776)	(0.163)
	Soft information × Busy day	0.078***	0.473***	0.442***	0.001
		(2.899)	(6.773)	(3.282)	(0.009)
	Soft information × Busy day × Non-ambiguous notes	**-0.064**	**-0.409**	**-0.118**	**0.059**
		(-0.823)	**(-1.580)**	**(-0.292)**	**(0.185)**
	Obs./ R^2	31,894/4.31%	31,894/18.88%	10,774/28.24%	18,773/6.71%
	Soft information	-0.072***	-0.088**	-0.149**	-0.023
Limited attention		(-5.574)	(-2.076)	(-2.003)	(-0.355)
	Soft information × Before weekends	0.155**	0.809***	0.781**	-0.041
		(2.447)	(8.138)	(1.993)	(-0.150)
	Soft information × Before weekends × Non-ambiguous notes	**-0.034***	**-0.269***	**-0.119****	**-0.010**
		(-1.727)	**(-1.654)**	**(-2.549)**	**(-0.024)**
	Obs./ R^2	31,894/4.20%	31,894/18.57%	10,774/28.60%	18,773/6.30%
	Soft information	-0.077***	-0.108**	-0.160**	-0.029**
		(-6.002)	(-2.580)	(-2.179)	(-2.453)
	Soft information × Around holidays	0.410***	0.584***	0.462	0.638*
		(5.072)	(2.788)	(1.036)	(1.879)
	Soft information × Around holidays × Non-ambiguous notes	**-0.292*****	**-0.348**	**-0.314***	**-0.194**
		(-3.361)	**(-0.785)**	**(-1.847)**	**(-0.328)**
	Obs./ R^2	31,894/4.29%	31,894/18.66%	10,774/28.67%	18,773/6.27%
Task specific human capital	*Soft information*	-0.118***	-0.192**	-0.167*	-0.202*
		(-3.189)	(-1.996)	(-1.854)	(-1.655)
	Soft information × Sales background	0.264***	0.776**	0.976**	0.817***
		(3.276)	(2.178)	(2.334)	(2.743)

TABLE 8 (Continued)

	Soft information × Sales background × Non-ambiguous notes	**-0.040*****	**-0.244**	**-0.979****	**0.495**
		(-3.214)	**(-1.545)**	**(-1.969)**	**(0.559)**
	Obs./ R^2	5,796/4.15%	5,796/17.99%	1,777/29.12%	3,088/5.65%
Common identity	*Soft information*	-0.078***	-0.112**	-0.167*	-0.065
		(-5.061)	(-2.246)	(-1.848)	(-0.824)
	Soft information × Male to male	0.272**	0.296*	0.446**	0.262
		(2.407)	(1.913)	(2.345)	(1.001)
	Soft information × Male to male × Non-ambiguous notes	**-0.036**	**-0.095****	**-0.141**	**0.007**
		(-0.334)	**(-2.238)**	**(-0.196)**	**(0.015)**
	Obs./ R^2	23,958/4.29%	23,958/18.48%	7,712/28.27%	14,244/6.37%

Panel B: Negative soft information tone, behavioral biases and loan quality

		(I)	(II)	(III)	(IV)
		Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
Limited attention	*Soft information*	-0.090***	-0.253***	-0.305***	-0.066
		(-5.877)	(-5.606)	(-3.894)	(-0.978)
	Soft information × Busy day	0.076***	0.465***	0.432***	0.006
		(2.905)	(6.866)	(3.364)	(0.061)
	Soft information × Busy day × Negative notes	**-0.641**	**-0.704****	**-0.185**	**-0.226**
		(-1.184)	**(-2.548)**	**(-1.082)**	**(-0.697)**
	Obs./ R^2	31,894/4.31%	31,894/18.87%	10,774/28.21%	18,773/6.71%
	Soft information	-0.076***	-0.150***	-0.205***	-0.091
		(-6.275)	(-3.774)	(-2.948)	(-1.511)
	Soft information × Before weekends	0.160**	0.766***	0.760*	-0.091
		(2.575)	(8.197)	(1.951)	(-0.338)
	Soft information × Before weekends × Negative notes	**-0.086***	**0.429**	**0.520**	**0.359**
		(-1.750)	**(0.182)**	**(0.075)**	**(1.576)**
	Obs./ R^2	31,894/4.23%	31,894/18.35%	10,774/28.38%	18,773/6.70%

TABLE 8 (Continued)

	Soft information	-0.079***	-0.165***	-0.211***	-0.098
		(-5.661)	(-4.154)	(-3.025)	(-1.637)
	Soft information × Around holidays	0.314***	0.522**	0.257	0.669**
		(4.264)	(2.517)	(0.706)	(2.265)
	Soft information × Around holidays × Negative notes	**-0.291**	**0.063**	**-0.087**	**-0.201****
		(-0.600)	**(1.053)**	**(-1.627)**	**(-2.073)**
	Obs./ R^2	31,894/4.25%	31,894/18.24%	10,774/28.36%	18,773/6.27%
Task specific human capital	*Soft information*	-0.105***	-0.310***	-0.179	-0.257*
		(-3.198)	(-3.642)	(-1.024)	(-1.743)
	Soft information × Sales background	0.275***	0.606***	0.884**	0.752**
		(3.762)	(3.231)	(2.140)	(2.334)
	Soft information × Sales background × Negative notes	**-0.110**	**-0.221***	**-0.583**	**0.361**
		(-0.920)	**(-1.843)**	**(-0.708)**	**(0.640)**
	Obs./ R^2	5,796/4.16%	5,796/17.65%	1,777/29.32%	3,088/5.57%
Common identity	*Soft information*	-0.088***	-0.173***	-0.228***	-0.131*
		(-5.509)	(-3.739)	(-2.650)	(-1.878)
	Soft information × Male to male	0.208**	0.371*	0.895**	0.357
		(2.520)	(1.694)	(2.176)	(1.060)
	Soft information × Male to male × Negative notes	**0.075**	**-0.134***	**0.038**	**-0.254***
		(0.718)	**(-1.767)**	**(1.147)**	**(-1.765)**
	Obs./ R^2	23,958/4.31%	23,958/18.39%	7,712/28.22%	14,244/6.38%

This table reports the analyses of whether the tone of soft information can mitigate the adverse effects of behavioral biases on soft information lending. In Panel A, *Non-ambiguous notes* equals one if a loan is a positive or negative soft information loan (i.e., if at least 50% of the notes related to the loan are classified as overall more positive or overall more negative), and zero otherwise. We augment Model 2 with *Non-ambiguous notes*, the double interaction terms *Soft information* x *Non-ambiguous notes*, *Behavioral bias* x *Non-ambiguous notes* and the triple interaction term *Soft information* x *Behavioral bias* x *Non-ambiguous notes*. Model specifications and control variables (untabulated) are the same as in Model 2. In Panel B, *Negative notes* equals one if a loan is a negative soft information loan (i.e., if at least 50% of the notes related to the loan are classified as overall more negative), and zero otherwise. We augment Model 2 with *Negative notes*, the double interaction terms *Soft information* x *Negative notes*, *Behavioral bias* x *Negative notes* and the triple interaction term *Soft information* x *Behavioral bias* x *Negative notes*. Model specifications and control variables (untabulated) are the same as in Model 2. The coefficients on *Soft information*, *Soft information* x *Behavioral bias* and the triple interaction terms are reported. All other variables are defined in Appendix C. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. Sample size drops across specifications due to the exclusion of loans associated with notes for which soft information tone is not assessed. ∗∗∗, ∗∗ and ∗ denote significance at the 1%, 5% and 10% (two-sided) levels, respectively. Coefficients of interest are in boldface.

TABLE 9

Soft information, behavioral biases and loan quality: Call-center loan officers

		Limited attention			Common identity
		(I)	(II)	(III)	(IV)
Dependent variables:	Interaction variables:	*Busy day*	*Before weekends*	*Around holidays*	*Male to male*
	Soft information x				
Charge off	*Behavioral bias*	0.278**	0.244**	0.279*	-0.005
		(2.139)	(1.979)	(1.749)	(-0.018)
	Obs.	4,777	4,777	4,777	4,127
	R^2	3.74%	3.66%	3.41%	3.35%
	Soft information x				
Delinquency	*Behavioral bias*	0.099	0.184***	0.071	0.023
		(0.370)	(3.447)	(0.092)	(0.043)
	Obs.	4,777	4,777	4,777	4,127
	R^2	16.97%	17.97%	17.89%	18.67%
	Soft information x				
Bad customer	*Behavioral bias*	0.960*	-0.336	0.428*	0.980*
		(1.875)	(-0.245)	(1.911)	(1.922)
	Obs.	1,933	1,933	1,933	1,655
	R^2	24.39%	30.74%	27.01%	24.15%
	Soft information x				
Credit score decline	*Behavioral bias*	-0.255	-0.141	0.265	-0.343
		(-0.658)	(-0.182)	(1.010)	(-0.404)
	Obs.	3,007	3,007	3,007	2,641
	R^2	7.20%	6.22%	6.31%	6.60%

This table reports the analyses of whether our primary findings are driven by the endogenous matching between loan officers and borrowers. We restrict our sample to loans issued by call-center loan officers who randomly receive calls from borrowers when their loan officers in the branch are busy or absent. We limit these analyses to behavioral bias tests for which we have at least 500 observations of available data. We report the coefficients of the interaction terms of the soft information measure with the measures of loan officers' behavioral biases (limited attention bias and common identity), employing the same specifications as in Tables 3 and 5. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. ∗∗∗, ∗∗ and ∗ denote significance at the 1%, 5% and 10% (two-sided) levels, respectively.

TABLE 10

Hard information, behavioral biases and loan quality

		Limited attention			Task specific human capital	Common identity
		(I)	(II)	(III)	(IV)	(V)
Dependent variables:	Interaction variables:	*Busy day*	*Before weekends*	*Around holidays*	*Sales background*	*Male to male*
Charge off	*Credit score* x *Behavioral bias*	-0.008	0.018	0.018	-0.037**	-0.006
		(-1.012)	(0.912)	(1.098)	(-1.993)	(-0.602)
	Debt to income ratio x *Behavioral bias*	-0.020**	0.010	0.015	0.009	0.020
		(-2.092)	(0.843)	(1.057)	(0.558)	(1.314)
	Obs.	49,680	49,680	49,680	9,364	40,747
	R^2	4.26%	4.23%	4.23%	4.03%	4.28%
Delinquency	*Credit score* x *Behavioral bias*	-0.011	0.060	0.022	-0.101*	-0.036
		(-0.458)	(1.119)	(0.561)	(-1.774)	(-1.086)
	Debt to income ratio x *Behavioral bias*	0.012	0.006	0.001	-0.047	0.000
		(0.565)	(0.184)	(0.019)	(-1.106)	(0.006)
	Obs.	49,680	49,680	49,680	9,364	40,747
	R^2	18.73%	18.20%	18.20%	17.50%	18.35%
Bad customer	*Credit score* x *Behavioral bias*	0.022	0.110	0.050	-0.098	-0.114*
		(0.442)	(1.335)	(0.660)	(-1.003)	(-1.718)
	Debt to income ratio x *Behavioral bias*	0.002	0.146**	-0.002	-0.093	0.055
		(0.060)	(2.429)	(-0.046)	(-1.097)	(1.067)
	Obs.	15,972	15,972	15,972	2,926	13,251
	R^2	28.11%	27.41%	27.34%	29.02%	26.20%
Credit score decline	*Credit score* x *Behavioral bias*	-0.016	-0.050	0.049	-0.046	-0.044
		(-0.445)	(-0.771)	(0.900)	(-0.519)	(-0.847)
	Debt to income ratio x *Behavioral bias*	0.000	0.024	-0.013	0.054	0.018
		(0.072)	(0.507)	(-0.318)	(0.772)	(0.423)
	Obs.	27,807	27,807	27,807	5,472	22,140
	R^2	6.71%	6.58%	6.58%	5.29%	6.32%

This table reports the analyses of whether behavioral biases affect how loan officers interpret hard information in the lending process. We augment Model 1 with our measures of behavioral biases and the interaction terms *Credit score* x *Behavioral bias* and *Debt-to-income ratio* x *Behavioral bias*. We report the coefficients of these interaction terms. All other model specifications and control variables (untabulated) remain the same. All variables are defined in Appendix C. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. ∗∗∗, ∗∗ and ∗ denote significance at the 1%, 5% and 10% (two-sided) levels, respectively.

TABLE 11

Soft and hard information, behavioral biases and loan decisions

Panel A: The effect of a borrower's soft and hard information on loan pricing when loan officers are subject to behavioral biases

	Loan interest rate				
		Limited attention		Task-specific human capital	Common identity
	(I)	(II)	(III)	(IV)	(V)
	Busy day	*Before weekends*	*Around holidays*	*Sales background*	*Male to male*
Soft information	-0.889**	-0.758***	-0.759***	-0.345	-0.743**
	(-2.065)	(-2.880)	(-2.887)	(-0.568)	(-2.379)
Behavioral bias	0.062	-0.547	5.234**	0.034	1.569
	(0.044)	(-0.209)	(2.623)	(0.476)	(0.894)
Soft information x Behavioral bias	**-0.385**	**0.593**	**-0.957**	**0.579**	**1.126**
	(-0.606)	**(0.563)**	**(-0.682)**	**(0.428)**	**(1.183)**
Credit score	-4.225***	-4.218***	-4.211***	-4.332***	-4.321***
	(-48.557)	(-52.187)	(-52.239)	(-21.623)	(-45.820)
Credit score x Behavioral bias	**0.008**	**0.097**	**-0.757****	**-1.181****	**-0.202**
	(0.038)	**(0.246)**	**(-2.500)**	**(-2.463)**	**(-0.761)**
Debt to income ratio	0.157**	0.125*	0.134**	0.238	0.102
	(2.227)	(1.903)	(2.035)	(1.512)	(1.376)
Debt to income ratio x Behavioral bias	**-0.242**	**-0.352**	**-0.318**	**-0.107**	**-0.261**
	(-1.517)	**(-1.338)**	**(-1.574)**	**(-0.336)**	**(-1.270)**
Controls	YES	YES	YES	YES	YES
Obs.	49,680	49,680	49,680	9,364	40,747
R^2	60.79%	60.81%	60.83%	59.93%	61.15%

TABLE 11 (Continued)

Panel B: The effect of a borrower's soft and hard information on loan exceptions when loan officers are subject to behavioral biases

	Loan exceptions				
		Limited attention		Task-specific human capital	Common identity
	(I)	(II)	(III)	(IV)	(V)
	Busy day	*Before weekends*	*Around holidays*	*Sales background*	*Male to male*
Soft information	0.030***	0.016***	0.018***	0.037***	0.019***
	(5.386)	(3.181)	(3.582)	(3.126)	(3.125)
Behavioral bias	0.010	-0.001	-0.013***	-0.004***	0.001
	(0.651)	(-0.801)	(-9.996)	(-3.045)	(0.758)
Soft information x Behavioral bias	**-0.003**	**0.013**	**-0.143**	**0.028**	**-0.040**
	(-0.199)	**(0.606)**	**(-1.457)**	**(0.937)**	**(-1.559)**
Credit score	0.000	0.001	0.002	-0.003	-0.001
	(0.476)	(0.176)	(0.551)	(-1.317)	(-0.050)
Credit score x Behavioral bias	**-0.001**	**-0.001**	**0.005**	**-0.005**	**-0.001**
	(-0.552)	**(-0.578)**	**(1.610)**	**(-0.771)**	**(-0.429)**
Debt to income ratio	-0.004***	-0.003***	-0.003***	-0.003	-0.005**
	(-3.084)	(-2.650)	(-2.662)	(-0.143)	(-2.375)
Debt to income ratio x Behavioral bias	**-0.001**	**0.001**	**0.003**	**-0.012***	**-0.005**
	(-0.459)	**(0.629)**	**(1.113)**	**(-1.844)**	**(-1.437)**
Controls	YES	YES	YES	YES	YES
Obs.	49,680	49,680	49,680	9,364	40,747
R^2	80.73%	80.25%	80.30%	80.09%	80.71%

This table reports the analyses of whether loan officers underweight or ignore soft information while overweighting hard information in loan pricing and exception decisions when they are subject to behavioral biases. *Loan exceptions* is the number of loan exceptions granted for a loan relative to the formal guidelines. We estimate Model (2) with *Loan interest rate* (Panel A) and *Loan exceptions* (Panel B) as the dependent variables. We augment Model 2 with interaction terms of hard information measures and behavioral biases (*Credit Score* x *Behavioral bias* and the *Debt-to-income ratio* x *Behavioral bias*). In panel A (panel B), we exclude *Loan interest rate* (*Loan exception*) from the control variables. All other control variables (untabulated) and model specifications are the same as in Model 2. All other variables are defined in Appendix C. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. ∗∗∗, ∗∗ and ∗ denote significance at the 1%, 5% and 10% (two-sided) levels, respectively. Coefficients of interest are in boldface.

TABLE 12

An alternative soft information measure, behavioral biases and loan quality

Panel A: Loan quality and lending based on soft information on busy days				
	(I)	(II)	(III)	(IV)
	Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
Soft information residual	-0.009***	-0.026***	-0.020	-0.030***
	(-3.735)	(-3.923)	(-1.603)	(-3.450)
Busy day	-0.005	-0.003	-0.001	-0.004
	(-1.178)	(-1.046)	(-0.983)	(-0.151)
Soft information residual* × *Busy day	**0.022*** **	**0.068*** **	**0.020**	**0.037**
	(3.698)	**(4.535)**	**(0.674)**	**(0.177)**
Controls	YES	YES	YES	YES
Fixed effects:				
Loan officer, branch, year, loan type				
$\beta_1 + \beta_3$	0.01	0.04	0.00	0.01
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.03	0.01	0.99	0.96
Economic effect of *Soft information residual* when loan officers are subject to biases	16.55%	7.79%		
Obs.	49,680	49,680	15,972	27,807
R^2	4.37%	18.56%	28.09%	6.76%

Panel B: Loan quality and lending based on soft information before weekends				
	(I)	(II)	(III)	(IV)
	Charge off	*Delinquency*	*Bad customer*	*Credit score decline*
Soft information residual	-0.007***	-0.021***	-0.016	-0.030***
	(-3.150)	(-3.310)	(-1.313)	(-3.269)
Before weekends	-0.083*	-0.034	-0.004	-0.017
	(-1.787)	(-0.983)	(-0.191)	(-1.115)
Soft information residual* × *Before weekends	**0.011*** **	**0.161*** **	**0.058*** **	**0.048**
	(4.294)	**(3.784)**	**(3.665)**	**(0.122)**
Controls	YES	YES	YES	YES
Fixed effects:				
Loan officer, branch, year, loan type				

TABLE 12 (Continued)

$\beta_1 + \beta_3$	0.00	0.14	0.04	0.02
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.74	0.01	0.04	0.76
Economic effect of *Soft information residual* when loan officers are subject to biases		25.96%	4.96%	
Obs.	49,680	49,680	15,972	27,807
R^2	5.97%	18.52%	27.48%	6.77%

Panel C: Loan quality and lending based on soft information around national holidays

	(I) *Charge off*	(II) *Delinquency*	(III) *Bad customer*	(IV) *Credit score decline*
Soft information residual	-0.008***	-0.029***	0.006	-0.039***
	(-3.090)	(-4.217)	(0.475)	(-3.882)
Around holidays	0.002	-0.023	-0.035**	0.004
	(0.662)	(-0.577)	(-2.089)	(1.640)
Soft information residual × Around holidays	**0.017***	**0.119*****	**0.148****	**0.118*****
	(1.651)	**(3.549)**	**(2.341)**	**(2.704)**
Controls	YES	YES	YES	YES
Fixed effects:				
Loan officer, branch, year, loan type				
$\beta_1 + \beta_3$	0.01	0.09	0.15	0.08
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.35	0.00	0.00	0.05
Economic effect of *Soft information residual* when loan officers are subject to biases		16.68%	18.19%	11.46%
Obs.	49,680	49,680	15,972	27,807
R^2	4.25%	18.50%	27.31%	6.79%

TABLE 12 (Continued)

Panel D: Loan quality and lending based on soft information by loan officers with prior sales-related experience

	(I) *Charge off*	(II) *Delinquency*	(III) *Bad customer*	(IV) *Credit score decline*
Soft information residual	-0.007	-0.039**	0.018	-0.085***
	(-1.049)	(-2.354)	(0.547)	(-3.117)
Sales background	0.002	-0.034***	0.016	-0.005
	(0.493)	(-2.713)	(0.688)	(-0.770)
Soft information residual × Sales background	**0.004**	**0.210*** **	**0.197**	**0.255*** **
	(0.204)	**(3.344)**	**(1.626)**	**(2.729)**
Controls	YES	YES	YES	YES
Fixed effects:				
Branch, year, loan type				
$\beta_1 + \beta_3$	0.00	0.17	0.22	0.17
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.88	0.00	0.09	0.03
Economic effect of *Soft information residual* when loan officers are subject to biases		31.71%	26.17%	24.66%
Obs.	9,364	9,364	2,926	5,472
R^2	4.02%	17.52%	29.01%	5.54%

Panel E: Loan quality and lending based on soft information when the loan officer and the borrower are both men

	(I) *Charge off*	(II) *Delinquency*	(III) *Bad customer*	(IV) *Credit score decline*
Soft information residual	-0.010***	-0.042***	0.004	-0.061***
	(-3.982)	(-5.296)	(0.284)	(-5.132)
Male to male	-0.008	0.017*	0.029	-0.015
	(-0.170)	(1.777)	(1.635)	(-1.047)
Soft information residual × Male to male	**0.007*** *	**0.144*** **	**0.099**	**0.226*** **
	(2.494)	**(4.353)**	**(1.508)**	**(4.701)**
Controls	YES	YES	YES	YES
Fixed effects:				
Loan officer, branch, year, loan type				
$\beta_1 + \beta_3$	0.00	0.10	0.10	0.17
Statistical significance of $\beta_1 + \beta_3$ (p-values)	0.80	0.00	0.08	0.00

TABLE 12 (Continued)

Economic effect of *Soft information residual* when loan officers are subject to biases		18.91%	12.54%	24.32%
Obs.	40,747	40,747	13,251	22,140
R^2	4.24%	18.38%	26.13%	6.47%

This table reports the analyses that examine whether our results are robust to an alternative measure of soft information. *Soft information residual* is the absolute value of the residual from the regression of the total number of words in borrower-specific notes during the 45-day window prior to a loan's origination on the hard quantitative information loan officers have about the borrower (detailed variable definitions are provided in Section 6.4.4). We employ the same specifications as in Tables 3-5. All other variables are defined in Appendix C. The values of the continuous variables are winsorized at 1% and 99%. OLS regressions are used to estimate the models, with T-statistics reported in parentheses. Standard errors are corrected for heteroskedasticity and clustered at the borrower level. We also report the sum of the coefficients on our soft information measure (β_1) and the interaction term between this measure and our proxies for behavioral biases (β_3), as well as the p-values that indicate whether this sum is statistically different from zero. For specifications where the sum of the coefficients on the soft information measure and the interaction term is significantly different from zero, we also report the economic significance of the effect of soft information when loan officers are subject to a behavioral bias. We measure the economic significance by the effect of a one standard deviation increase in soft information when loan officers are subject to behavioral biases on ex-post lending outcomes, as a percentage of the mean value of ex-post lending outcomes. $***$, $**$ and $*$ denote significance at the 1%, 5% and 10% (two-sided) levels, respectively. Coefficients of interest are in boldface.