Making Sense of Soft Information: Interpretation Bias and Ex-post Lending Outcomes

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ABSTRACT

We explore how cognitive constraints can impede the effective processing and interpretation of less salient, non-quantitative (soft) information in private lending. Taking advantage of the internal reporting system of a large federal credit union, we delineate four important constraints likely to affect the lending process: (1) limited attention (or distraction), (2) task-specific human capital, (3) peer perception and (4) learning over the credit cycle. Specifically, we find that utilizing soft information in lending decisions leads to worse credit outcomes when loan officers are busy or before weekends and national holidays; when loan officers had earlier non-banking and, in particular, sales-related experience; when both officers and borrowers are men and when loan officers are members of informal organizational networks; and during periods of credit expansion. Overall, we provide novel evidence of non-agency-related costs in the use of soft information in credit decisions.

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1. Introduction

Substantial research in accounting and finance has established that collecting and using private, qualitative and hard-to-verify (i.e., "soft") information allows lenders to better screen and monitor their borrowers, reducing the likelihood of future defaults (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' cognitive constraints can impede the effective processing and interpretation of less salient, non-quantitative information, thus undermining their decision making process (e.g., Shiller 1999, Shleifer 2000). The influence of these non-agency-based limitations on the use of soft information has yet to be explored in the private lending setting.

We suggest that lending based on soft information (i.e., utilizing soft information in lending decisions) is likely affected by how loan officers interpret and process this information (e.g., Libby et al. 2002, Gibbons 2003, Kahneman 2011). In particular, we focus on four cognitive constraints that can impede loan officers' accurate judgment in interpreting soft information and thus adversely affect ex-post lending outcomes: (1) limited attention (or distraction), (2) task-specific human capital, (3) peer perception and (4) learning over the credit cycle.

We attempt to assess the effect of cognitive constraints on the value of soft information in private lending by utilizing the internal reporting system of a large federal credit union.[1] Loan officers and other union employees use this system to document their routine communications with clients, which allows us to construct two proxies for soft information. First, we identify in employees' notes keywords that relate to soft information. Motivated by prior research (e.g., Petersen 2004), we define *soft keywords* as words associated with a borrower's social (e.g., "friends", "hobby"), professional (e.g., "job", "manager"), educational (e.g., "education",

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

“degree”) and personal background (e.g., “family”, “child(ren)”). We also define as *soft keywords* words and phrases that capture feelings, such as “overwhelmed”, “frustrated”, and “stress” (Plutchik 1980, Parrot 2001), and employees’ judgments and assessments (e.g., “I assess”, “I think”). Our first proxy for soft information is the ratio of soft keywords in employees’ notes on a borrower to the total number of words in these notes (*Soft information 1* hereafter). To alleviate concerns associated with our choices of the specific keywords to capture soft information, our second soft information measure is defined as the absolute value of the residual from the regression of the total number of words in the borrower-related notes on the borrower’s hard (quantitative) and transaction-related information available to loan officers, such as credit score, debt-to-income ratio and the number and balance of different products the borrower has with the credit union (*Soft information 2* hereafter). Both measures are estimated based on notes written over the 45-day period prior to a loan origination.[2]

Using four measures of adverse ex-post credit outcomes – 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 measures decrease the probability of these outcomes. These results are consistent with prior banking studies and help us validate these measures (e.g., Petersen and Rajan 1994, Uzzi and Lancaster 2003, Agarwal and Hauswald 2010).

[2] We acknowledge that a textual description of employees’ communication with borrowers can be considered hardened soft information because it can be passed to colleagues. However, the precise meaning of the information, the exact event to which it refers, the context under which it was collected, as well as the employee’s feelings and subjective judgments need to be processed and interpreted by loan officers and therefore represent relatively softer and less salient information about a borrower (e.g., Cremer et al. 2007).

We first predict that lending based on soft information leads to worse ex-post credit outcomes when loan officers have limited attention (are distracted), since they will fail to accurately interpret and reflect on less salient information cues (e.g., Abarbanell and Bushee 1997, Dessein 2002, Hirshleifer and Teoh 2003, Lim and Teoh 2010). Guided by prior research, we hypothesize that loan officers are likely to inaccurately interpret soft information when they are busy (e.g., Hirshleifer, Lim and Teoh 2009, DeHaan et al. 2015) or before weekends and holidays (DellaVigna and Pollett 2009, Murfin and Petersen 2016).

We find strong support for the inattention hypothesis. Relative to when a loan officer is not subject to limited attention bias, lending based on soft information when the loan officer is inattentive leads to significantly worse ex-post credit outcomes. To exemplify, when loan officers are busy, a one standard deviation increase in *Soft information 1* increases *Charge off, Delinquency, Bad customer* and *Credit score decline* by 0.29%, 1.40%, 2.46% and 0.84%, which represent about 13.27%, 9.25%, 10.68% and 4.44% of the respective sample mean values of these lending outcomes.

Second, recent studies have documented the role of early professional experience in imprinting specific skills on employees, which carry over through their subsequent career, despite significant professional changes in future periods (e.g., Gibbons and Waldman 2004, McEvily et al. 2012, Marquis and Tilcsik 2013). We therefore predict that employees with previous non-banking experience will fail to attend to soft information, because their judgment is influenced by skills and habits acquired through their previous professional experience unrelated to the loan underwriting process.

Identifying loan officers' earlier professional experience on LinkedIn, we show that lending based on soft information by officers with previous non-banking experience, and sales-related experience in particular, is associated with worse credit outcomes, potentially because these loan officers pursue new loan issuances without carefully processing the soft information's implications for a borrower's future credit performance. For example, compared to loan officers with no prior sales-related skills, when officers have sales-related professional experience, a one standard deviation increase in *Soft information 1* increases *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 mean values.

Third, we focus on peer perception and predict that a common identity between loan officers and their borrowers will likely influence their interpretation of soft information. Similar characteristics reduce the processing costs of less salient information and thus allow for its more accurate interpretation (e.g., Uzzi 1999, Uzzi and Lancaster 2003, Dewatripont and Tirole 2005). However, a common identity between loan officers and their borrowers may bias the former's interpretation of soft information, since they may favorably perceive the shared characteristics as a signal of trust and lower risk and fail to carefully process the soft information in their loan decisions (e.g., Tajfel and Turner 1979, Tajfel 1982).

Focusing on the gender identity of loan officers and borrowers, we document that lending based on soft information by male loan officers to male borrowers leads to worse credit outcomes relative to when both parties are women or of different genders, consistent with prior evidence that men are more likely to trust, and are more biased in favor of, other men (e.g., Dion and Stein 1978, Rhoades 1979, Ridgeway 1981, Grunspan et al. 2016). To illustrate, when a loan officer and a borrower are both men, a one standard deviation increase in *Soft information 1* increases *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 the respective mean values of these outcomes.

Related, we examine the influence of small organizational networks of peer loan officers (informal cliques) on how soft information is processed. While strong network ties allow for the more efficient flow of new information across network members (e.g., Granovetter 1973, Burt 2004, Kearns et al. 2006, McCubbins et al. 2009), these ties may adversely affect members' decision making process because members are influenced by their peers' interpretations and past experience and thus do not independently process and explore new information (e.g., Centola and Macy 2007, Shore et al. 2015). We take advantage of loan officers' referral information to identify officers who were referred to their jobs at the credit union by other union employees. We consider a clique to be comprised of loan officers who provided references to their peers.[3]

We find some supporting evidence that when the borrower has interacted with one of the loan officer's clique peers prior to a loan's origination, lending based on soft information is associated with worse ex-post lending outcomes, potentially because loan officers' judgment and interpretation of soft information are biased due to a collective mindset in their clique. Economically, relative to when loan officers independently interpret soft information, a one standard deviation increase in *Soft information 1* when loan officers are influenced by their peers increases *Charge off* and *Credit score decline* by 0.90% and 1.52%, which represent about 40.91% and 8.00% of their respective mean values.

Last, we expect loan officers' interpretation of soft information to be influenced by the credit cycle. Motivated by Berger and Udell's (2004) institutional memory theory, we predict that lending based on soft information leads to worse ex-post credit outcomes during credit expansions. During credit downturns, loan officers learn significant insights about how best to process and judge soft information to differentiate between low- and high-quality borrowers. However, these

[3] For example, if Loan Officer A refers Loan Officer B, Loan Officer B refers Loan Officers C and D and Loan Officer D refers Loan Officer E, we consider employees A to E to be part of the same organizational clique.

skills atrophy during credit expansions, leading to a more biased interpretation of soft information and consequently worse credit outcomes. We find that, relative to other periods, when loan officers lend based on soft information during quarters of lax credit standards, ex-post credit outcomes are less favorable. To exemplify, when credit standards are lax, a one standard deviation increase in *Soft information 1* increases *Delinquency* and *Bad customer* by 1.32% and 2.52%, which represent about 8.77% and 10.96% of their respective mean values.

For all cognitive constraint analyses, we also assess the influence of soft information on lending outcomes relative to situations when no soft information is utilized in the lending process. Our findings suggest that while lending based on soft information generally improves ex-post lending outcomes, when loan officers' processing and interpretation of this information is influenced by cognitive limitations, its benefits substantially decline. Importantly, under these conditions, in most specifications, lending based on soft information actually leads to *worse* future loan and borrower quality. For example, relative to when no soft information is used, a one standard deviation increase in *Soft information 1* 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. Similarly, relative to when no soft information is used, a one standard deviation increase in *Soft information 1* when loan officers have prior sales-related experience increases *Charge off, Bad customer* and *Credit score decline* by 30.36%, 11.27% and 12.56% of their respective mean values.

We perform a number of supplementary tests. We recognize the possibility 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, the majority of our findings continues to hold. Further, we address the concern that cognitive constraints can also affect loan officers' information collection efforts. We differentiate between notes written by the loan officer approving the loan (who is subject to cognitive constraints) and those written by other employees and estimate soft information measures separately for these notes. We find that when loan officers are influenced by cognitive constraints, soft information leads to worse credit outcomes independent of its collection source, suggesting that our findings are driven primarily by loan officers' processing of this information, rather than by their information collection efforts. In addition, we find that cognitive constraints have no effect on the use of hard information in lending decisions, consistent with prior research that shows that the processing of this information is not influenced by cognitive limitations (e.g., Kothari 2001, Hirshleifer and Teoh 2003).

Our paper contributes to the literature in several ways. First, a common assumption embedded in the private lending literature is that loan officers efficiently process private information and thus bad credit decisions are primarily explained by low information quality and loan officers' incentives (e.g., Diamond 1991). Motivated by behavioral studies that explore cognitive-based limitations in interpreting and processing information (e.g., Tajfel and Turner 1979, Libby et al. 2002, Gibbons and Waldman 2004, Berger and Udell 2004, Hirshleifer et al. 2009, DeHaan et al. 2015), we show that bad credit decisions may be also explained by loan officers being inherently subject to cognitive constraints. Although agents' behavioral traits have been shown to influence their investment decisions and information processing in the equity market, our paper is one of the first to explore the role of cognitive constraints in private lending.

Second, we expand the extensive literature on the role of soft information in the lending process (e.g., Petersen and Rajan 1994, 1995, Berger et al. 2001, Berger and Udell 2002, Agarwal and

Hauswald 2010, Michels 2012, Qian et al. 2015). We provide novel evidence on the costs associated with lending based on soft information when the loan officers' cognitive capacity of information processing is constrained. By introducing new non-agency-based mechanisms that link soft information to worse ex-post credit outcomes, we also complement recent studies that highlight that soft information may adversely affect loan quality due to agency-based problems, such as loan officers' incentives to hide unfavorable borrower performance (e.g., Banerjee et al. 2009, Hertzberg et al. 2010, Paravisini and Schoar 2016).

Third, we contribute to the growing literature that examines the information demand of financial institutions (e.g., Minnis 2011, Berger et al. 2016, Minnis and Sutherland 2016, Sutherland 2016). While prior studies primarily focus on these institutions' collection and use of verifiable and quantitative borrower information, such as financial statements and tax returns, we demonstrate how the processing of less silent, qualitative information influences the lending process. In particular, we highlight that in contrast to processing hard information, which is not affected by cognitive constraints, these constraints impede the accurate interpretation of soft information and may have important implications for loan and borrower quality. Related, we add to recent studies investigating the cyclical properties of lenders' information demand, which show a substantial reduction in hard information collection during good times (e.g., Heider and Inderst 2012, Dilly and Mahlmann 2015, Lisowsky et al. 2016). By directly observing loan officers' documentation of their interactions with borrowers, we show that during credit expansion lenders also do not efficiently utilize their soft information.

2. Literature Review and Hypotheses Development

2.1. The role of soft information in private lending

Soft information refers to the private, qualitative and costly to obtain and verify information that loan officers collect through their repeated interactions with borrowers (e.g., Petersen 2004, Drexler and Schoar 2014). Importantly, soft information has been shown to capture a borrower's characteristics and future prospects, which quantitative (hard) information, such as a borrower's credit score and financial ratios, does not reflect (e.g., Cassar et al. 2015). Strong social relationships and greater cultural or geographical proximity between loan officers and borrowers contribute to the greater collection and use of soft information (e.g., Uzzi 1999, Uzzi and Lancaster 2003, Agarwal and Hauswald 2010, Mian 2006, Fisman et al. 2012, Madsen and McMullin 2015). Prior studies have also documented the benefits of lending based on soft information. In particular, soft information reduces information asymmetry between borrowers and lenders and improves ex-post credit outcomes, allowing for greater credit supply and lower interest rates (e.g., Diamond 1991, Rajan 1992, Petersen and Rajan 1995, Cole 1998, Berger and Udell 2002, Agarwal et al. 2011, Michels 2012).

However, several recent studies have raised important concerns about whether soft information actually improves lending outcomes, arguing that loan officers are likely to collect low-quality soft information or to manipulate its context to hide unfavorable borrower performance. Banerjee et al. (2009) point out that because 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. Further, consistent with loan officers discretionarily 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. Related, 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 at least partially affected by loan officers' agency problems.

We extend these studies by exploring the mechanisms through which soft information can adversely affect ex-post lending outcomes. In particular, we introduce previously unexplored non-agency-based limitations in the use of soft information that arise from loan officers' cognitive constraints in interpreting and processing this information type. Motivated by the accounting and organizational economics literatures (e.g., Cyert and March 1963, Libby et al. 2002, Bloomfield 2002, Bonner 2008, Gibbons 2003, Kahneman 2011), we argue that loan officers' interpretative adjustments and inferences are instrumental to the value of soft information in the lending process, thus significantly affecting the quality of credit outcomes. Specifically, we examine four cognitive constraints that can impede loan officers' accurate judgment when they interpret soft information: 1) limited attention (or distraction), 2) task-specific human capital, 3) peer perception and 4) learning over the credit cycle.

2.2. Soft information, limited attention bias and ex-post lending outcomes

Limited attention theories imply that agents tend to neglect less salient important information signals due to their limited attention and processing power. The limited attention (or distraction) bias hypothesis has been well-examined in the equity market setting. Several studies show that investors and analysts tend to underweight financial disclosures (Abarbanell and Bushee 1997, Teoh and Wong 2002, Lim and Teoh 2010), because qualitative information is more costly and time-consuming to process (e.g., Dessein 2002, Hirshleifer and Teoh 2003). Market participants' inattention or distraction is also documented as being stronger on busy days, i.e., when they need to attend to multiple events or tasks (e.g., Hirshleifer, Lim and Teoh 2009, DeHaan et al. 2015) and on Fridays, i.e., just before the weekend (DellaVigna and Pollett 2009). Motivated by this literature, we examine how limited attention and distraction can affect loan officers' interpretation and processing of soft information. We predict that when loan officers have limited cognitive capacity, they will fail to accurately interpret and adequately reflect on less salient, abstract information cues. As a result, lending based on soft information will adversely affect ex-post credit outcomes. Thus, we formulate the following hypothesis:

H1. Lending based on soft information by inattentive loan officers leads to worse ex-post credit outcomes relative to when loan officers are not subject to inattention constraints.

2.3. Soft information, task-specific skills and ex-post lending outcomes

A recent strand of literature suggests that agents' early professional experiences "imprint" specific skills that are carried over through their subsequent careers and thus affect their future decisions (e.g., McEvily, Jaffee and Tortoriello 2012, Marquis and Tilcsik 2013). Gibbons and Waldman (2004) show that employees build task-specific skills through on-the-job learning, with early job assignments having a long term career impact because an agent's first job affects the type of human capital the agent acquires. These task-specific skills persist in subsequent periods despite significant environmental or professional changes (Schoar and Zuo 2016).

We extend this literature by examining how these task-specific traits relate to the quality of loan officers' credit decisions based on soft information. We predict that loan officers whose earlier professional experience was in non-banking industries are more likely to misinterpret and inaccurately process qualitative information, leading to worse ex-post lending outcomes. Although these loan officers may learn to process relevant salient and easy-to-interpret quantitative information, judging and inferring soft signals on borrower quality should be more difficult given that their judgment is influenced by the skills and habits acquired through their previous non-banking tasks. In particular, we further predict that loan officers who have a background in sales (i.e., with early professional experience in selling goods or services) will fail to attend to soft information appropriately. These loan officers are likely to be influenced by their early-career sales-related skills and thus focus on prospecting for new loans, without effectively interpreting less salient information cues to better assess the borrower's credit performance post-loan origination. We thus hypothesize the following:

H2. Lending based on soft information by loan officers with earlier non-banking or sales-related professional experience leads to worse ex-post credit outcomes relative to when loan officers do not have such experience.

2.4. Soft information, peer perception and ex-post lending outcomes

Commonalities between two parties' backgrounds and attributes can have a significant effect on the processing and interpretation of soft information. On the one hand, similar characteristics between the sender and receiver of a signal decrease processing costs and thus allow for a more accurate interpretation of less salient information (e.g., Dewatripont and Tirole 2005). Thus, common traits between loan officers and their borrowers allow loan officers to better process, understand and judge less verifiable qualitative borrower-specific information, leading to better ex-post lending outcomes (e.g., Uzzi 1999, Uzzi and Lancaster 2003, Fisman et al. 2012).

On the other hand, a common identity between two parties has been shown to increase familiarity and liking, leading people to act more favorably towards peers with whom they share important attributes (e.g., Tajfel and Turner 1979, Tajfel 1982, Turner et al. 1994).[4] This favoritism is at least partially driven by the fact that commonalities reduce feelings of risk in decision making as people view common traits as a foundation for trust (e.g., Weber et al. 2005). The in-group bias proposition suggests that a common identity between loan officers and their borrowers will adversely affect how loan officers process and judge soft information because they will perceive

[4] The bias associated with common identity has been documented in settings of social or cultural proximity (e.g., Ben-Ner and Kramer 2006, Glaeser et al. 2000, Guiso et al. 2009), and in the context of racial or gender differences (e.g., Munnell et al. 1996, Akerlof and Kranton 2000, Towry 2003, Ravina 2008).

borrowers with whom they share common characteristics as more trustworthy and less risky. Because prior literature offers conflicting predictions, we formulate the following non-directional hypothesis:

H3A. Lending based on soft information when loan officers and borrowers share a common identity leads to better or worse credit outcomes relative to when loan officers do not share a common identity.

A related strand of literature examines how the processing and interpretation of information cues is affected by an agent's membership in a small organizational network (i.e., clique). Thus, apart from familiarity between the sender and receiver of a signal, the same signal is shown to be interpreted differently to the extent that the receiver is influenced by strong network ties with his colleagues or peers. Strong network ties allow for mutual information to be shared among peers, leading to a more efficient search for new information and a greater information set (e.g., Granovetter 1973, Burt 2004, Kearns et al. 2006, McCubbins et al. 2009). However, strong network ties can adversely impact the organizational decision making process (e.g., Mason et al. 2008, Mason and Watts 2012). Specifically, clique members "copy" or are heavily influenced by their peers' judgements and past experience, while non-clique members independently interpret and explore the content of new information (e.g., Centola and Macy 2007, Shore et al. 2015). Overall, while loan officers who are members of a clique may possess a richer soft information set, they are likely to overweight their peers' collective view, causing a less efficient exploration of new soft information. Building on these arguments, we state our next hypothesis:

H3B. Lending based on soft information by loan officers who are members of an organizational clique leads to better or worse ex-post credit outcomes relative to when loan officers are not part of a clique.

2.5. Soft information, learning over the credit cycle and ex-post lending outcomes

Recent studies in accounting and finance have explored the cyclical properties of banks' information use in lending decisions. Loan officers are less likely to collect and verify borrower-specific information during credit upturns (e.g., Heider and Inderst 2012, Dilly and Mahlmann 2015, Lisowsky et al. 2016). Moreover, during these periods, loan officers are less effective at predicting loan losses (Brown, Kirschenmann and Spycher 2016) and construct less precise internal loan ratings (Becker et al. 2016).

Berger and Udell (2004) argue that fluctuations in loan quality over the credit cycle are explained, to a large extent, by how loan officers process and attend to borrower-specific soft information. Under their institutional memory proposition, during credit downturns, loan officers are more exposed to loan defaults and delinquencies, which allow them to develop greater expertise in interpreting soft information to differentiate between high- and low-quality borrowers. In contrast, during credit expansions, when loan officers have more distant experience with negative outcomes, their skills in assessing borrowers' soft information deteriorate ("atrophy"). Thus, while the interpretation of hard information embedded in credit scores is retained during credit expansions (Mullainathan 2002), soft information interpretation becomes more biased and loan officers tend to interpret the optimistic economic outlook as a signal of a borrower's quality (Furth 2001, Ruckes 2004). Therefore, there is considerable fluctuation in loan officers' efficiency in interpreting and processing soft information over credit cycles. Accordingly, our last hypothesis is as follows:

H4. Lending based on soft information in periods of credit expansion leads to worse ex-post credit outcomes relative to periods of tighter credit standards.

3. Research Setting and Data

The research setting for this study is a large U.S. federal credit union that operates in a single state and offers traditional investment, depository and lending products. With approximately $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.[5]

Credit unions are member-owned depository institutions, where all members share a common bond (e.g., location, profession, religion). Credit unions are an economically significant sector in the U.S. consumer lending market. As of the beginning of 2013, there were 6,819 credit unions in the U.S. with total assets under management of $1 trillion and $600 billion loans outstanding, serving about 94 million members (National Credit Union Administration Data Summary 2012Q4). 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. Similar to banks that screen and monitor borrowers to decrease the probability of future defaults and sustain their capital adequacy, credit unions are interested in avoiding adverse ex-post loan and borrower performance that can threaten their ability to serve their mandate. We therefore expect our analyses of how the union loan officers' cognitive constraints affect credit outcomes to also offer valuable insights into commercial banks' 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, while certain credit guidelines based on automated risk scoring methodologies are in place (e.g., loan applications from customers with a

[5] As of 2013, the mean (median) size of a U.S. credit union in terms of total assets is about $150 million ($21 million), while the mean (median) commercial bank size in terms of total assets is $2.04 billion ($168 million).

credit score below 620 and/or a debt-to-income ratio above 45% are recommended for rejection), loan officers can discretionarily override them and alter loan issuance/rejection decisions as well as loan terms.[6] 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."

When loan officers make loan exceptions by deviating from the formal guidelines, they are required to document the rationale behind the credit decision in an internal reporting system.[7] An important feature of this process is that the content of the information collected is not further quantified and remains highly discretionary, i.e., there are no guidelines on the type of information that employees are expected to acquire and report. Thus, employees may only provide a brief description of the transaction and refer to a borrower's quantitative characteristics, report both quantitative and qualitative characteristics, or only lay out softer characteristics and their subjective impressions and judgment about the borrower. With respect to soft information on their borrowers, as employees noted, "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,

[6] In 2005, the credit union moved from a highly hierarchical 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) towards a more flat organizational structure where employees have decision authority (Campbell 2012). 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).

[7] Loan officers can make loan exceptions related to a borrower's minimum credit score (620), maximum debt-to-income ratio (45%), as well as loan terms, including the interest rate, maturity and the collateral requirements. The vast majority of loans include an exception. To alleviate the concern that our findings are attributed primarily to high risk borrowers where loan officers may extensively comment on their rationale behind the loan exception, we perform our analyses separately for the subsamples of loans issued to high risk borrowers (those with credit scores lower than 620 or a debt-to-income ratio higher than 45.00%) and loans issued to higher credit quality borrowers (untabulated). We find similar results across both loan subsamples.

or some other issue beyond the control of the [customer]? I would consider all of these factors in making a lending decision." Moreover, employees also seek to delineate customers' rationales for a poor credit score: "…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." See examples of loan officers' notes in Appendix A.

Importantly, while the internal reporting system was initially developed to document exceptions in lending decisions, it has become widely used by all the credit union's employees to document their routine interactions with customers. Employees typically enter notes into the system for any communication they have with a customer, enabling the horizontal communication of information 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."

With respect to loan officer compensation, they receive a flat salary, not tied to loan volume or performance. Employees are annually ranked based on the revenues they generate, with consistently highly ranked employees being more likely to be promoted to branch managers in the long term. However, the timing of these promotions and salary increases are uncertain and not explicitly linked to loan performance.

3.2. Data

This data-rich internal reporting platform allows us to capture employees' collection of soft information prior to loan originations. We further obtain data on the credit union's loan, employee and borrower characteristics over the period from January 2005 through May 2010. Our population of loans includes 119,625 loans with a size greater than $500 issued by 506 unique employees to 59,453 unique borrowers in 47 unique credit union branches. We exclude 35,124 loans originated in 2009-2010 for which we cannot fully capture borrowers' ex-post credit performance. We further eliminate 34,821 loans for which employees did not report a note over the 45-day period prior to their origination (the period over which we estimate our soft information measures), because we cannot disentangle between cases where no additional information was collected prior to loan origination or those where it was collected but not reported, nor can we assess whether only hard or also 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 car (auto) loans (23,456 loans), personal loans (17,805 loans) and mortgages or home equity loans (8,419 loans).

4. Variable Definitions and Summary Statistics

4.1. Soft information measures

We develop our soft information measures by taking advantage of the credit union's internal reporting system in which employees document their routine communications with clients. Our measures aim to capture the total amount of soft information that loan officers process in the lending process, in line with soft information proxies used in prior studies that do not differentiate between positive and negative information content (e.g., Uzzi and Lancaster 2003, Mian 2006, Agarwal and Hauswald 2010, Madsen and McMullin 2006).

Our first soft information measure is based on the soft-information-related keywords in employees' notes. We focus on 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 identify repeating patterns in the words and phrases that employees commonly use. Motivated by prior research on the context of soft information in lending transactions (e.g., Petersen 2004) and based on the common words and phrases employees use, we define as *soft keywords* 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, by utilizing keyword phrases such as "I think", "I assess", and "I believe." The full list of *soft keywords* and *phrases* is reported in Appendix B.

We define *Soft information 1* 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. Estimating soft keywords over this pre-origination 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.[8] All variables are also described in Appendix C. There are 117,738 notes for our sample borrowers written within the 45-day period prior to loan origination (or 4 notes per borrower).

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

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[8] Moreover, deflating the number of soft keywords by the total number of words written by employees allows us to control for routine information reported in the course of employees' and borrowers' interactions, which might be confounded by the extent of borrowers' operations with the credit union, such as borrowers' transaction volumes and number of products.

keywords we employ to capture soft information, we develop an additional soft information measure. Our second measure – *Soft information 2* – is the absolute value of the residual from the regression of the total number of words in borrower-related notes during the 45-day window prior to loan origination on a borrower's hard and transaction-related information available to loan officers.[9,10] We measure hard information using a borrower's credit score, debt-to-income ratio and the number of quantitative (numerical) words written in the notes, as well as transaction-related information using the borrower's tenure with the credit union and the number and the balance of different products the borrower maintains with the union.[11] We also control for systematic differences in reporting characteristics across employees, branches, loan types, and over time. More specifically, we estimate the following model:

$$
\begin{aligned}
\textit{Log of word-count} = {} & \alpha + \beta_1 \textit{Credit score} + \beta_2 \textit{Debt-to-income ratio} + \beta_3 \textit{Borrower tenure} \\
& + \beta_4 \textit{Log of quantitative word-count} \\
& + \beta_5 \textit{Number of deposit accounts} + \beta_6 \textit{Deposit account balance} \\
& + \beta_7 \textit{Number of credit cards} + \beta_8 \textit{Credit card balance} \\
& + \beta_9 \textit{Number of personal loans} + \beta_{10} \textit{Personal loan balance} \\
& + \beta_{11} \textit{Number of mortgages} + \beta_{12} \textit{Mortgage balance} \\
& + \beta_{13} \textit{Number of home equity accounts} + \beta_{14} \textit{Home equity balance} \\
& + \beta_{15} \textit{Number of IRA accounts} + \beta_{16} \textit{IRA balance} + \beta_{17} \textit{Number of auto loans} \\
& + \beta_{18} \textit{Auto loan balance} + \beta_{19} \textit{Number of ATM accounts} \\
& + \beta_{20} \textit{ATM account balance} + \beta_{21} \textit{Number of lines of credit} \\
& + \beta_{22} \textit{Line of credit balance} + \beta_{23} \textit{Number of other loans} \\
& + \beta_{24} \textit{Other loan balance} + \text{Employee FE} + \text{Branch FE} \\
& + \text{Loan year of origination FE} + \text{Loan type FE}.
\end{aligned}
\qquad \textit{(Model 1)}
$$

[9] Agarwal and Hauswald (2010) use a similar approach to measuring soft information by regressing the lender's internal credit score on publicly available estimates of a borrower's credit quality.

[10] We use the absolute value of the residual to measure the information reported in the notes that departs from hard information about the borrower. If the information reported includes hard information only, we expect the residual to be close to zero, as this information should be almost fully explained by borrower quantitative characteristics included in Model 1. 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. Consistent with our assessments, *Soft information 2* is positively and significantly correlated with *Soft information 1* (0.15) and the absolute values of the negative residual values are significantly and positively correlated with *Soft information 1* (0.09).

[11] Account and credit balances are log-transformed.

Table 1 reports the summary statistics for our variables. The mean value of *Soft information 1* is 0.055. The mean value of *Soft Information 2* is 0.270. Note that our empirical findings are unchanged when we estimate both soft information measures over the 30- or 60-day period prior to loan origination (untabulated). Two alternative measures for *Soft information 1* – 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 and the ratio of the number of sentences with at least one soft keyword to the total number of sentences in employee notes – yield similar results (untabulated).

We acknowledge that our soft information measures are subject to two caveats. First, with respect to *Soft information 1*, while we try to develop a comprehensive list of keywords that capture soft information, we recognize that 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 subjective 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' textual notes cannot be easily transformed into a numerical score, further reinforcing their qualitative nature (Petersen 2004). Consistently, the credit union does not quantify the content of the notes and does not impose any guidance on what information the employees are expected to collect. We therefore believe that our soft information measures successfully capture the softer and less salient information employed in the lending process.

4.2. Measures of ex-post credit outcomes and loan characteristics

To capture loan performance and borrower quality following loan origination, we use four proxies for ex-post credit outcomes. *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). *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 does not report delinquency information at the loan level, 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", "delay(ed) payments."

To better capture a borrower's post-loan issuance creditworthiness, we further utilize 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 that takes the value of one if the borrower defaulted on any outstanding loan or filed for bankruptcy within the 18-month period after a loan's origination and zero otherwise. Our second credit-bureau-based measure – *Credit score decline* – is an indicator variable that takes the value of 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 captures the bottom quintile of the distribution of changes in the creditworthiness of the credit union's borrowers over this post-loan issuance period. Table 1 reports the summary statistics for these measures of ex-post credit outcomes. The mean probability of *Charge off* (*Delinquency*) is 2.21% (15.1%), while the mean probability of *Bad customer* (*Credit score decline*) is 23.70% (19.30%).

We also employ a battery of borrower and loan characteristics that prior studies have shown to be associated with ex-post lending outcomes. We proxy for observable hard measures of a borrower's credit quality, using the natural logarithm of her credit score (*Credit score*) and the debt-to-income ratio (*Debt-to-income ratio*), which have mean values of 6.59 (i.e., a credit score of 708 points) and 37.00%, respectively (Table 1). 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 (*Exception*) and whether the loan is collateralized (*Secured*).[12] We show that the mean value of the loan interest rate is 8.97%, while about 80.00% of the sample loans include a credit exception and 36.80% of the loans are collateralized. 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 9.60 (about $15,000) and the mean natural logarithm of the loan maturity is 4.09 (about 5 years). Last, we control for borrowers' prior relationship with the credit union, measured by the natural logarithm of a borrower's tenure there (*Borrower tenure*) and the natural logarithm of the total number of products that the borrower maintains with it, such as deposits, credit cards, loans, investment and retirement products (*Total number of accounts*). The average borrower has been a customer of the credit union for about three years and has about seven products with it (with their logarithmic transformations equal to 0.85 and 1.60, respectively).

4.3. Cognitive constraint 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 number of notes that the officer writes on that day, ranked in quintiles (*Busy loan officer*). The number of notes a loan officer writes captures the workload volume on a given day, such as the number of new loan applications, the number of calls received from existing borrowers, in-office meetings with customers, new loans issued or rejected and calls made to monitor existing loans or to prospect for new loans. Because loan officers may not always record a note after their communications with a borrower, we presume that the number of a loan

[12] When we split our sample into secured (auto loans and mortgages) and non-secured loans (personal loans), we find that our findings hold for both subsamples.

officer's tasks (his workload) on a given day cannot be smaller than the number of loans she originates on that day. Thus, if the number of loans approved by the loan officer exceeds the number of notes she writes on a loan's origination day, we replace the number of notes with the number of loans.[13]

Second, loan officers may be rushed 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 equal to one if the loan is issued after 4pm on Friday or on Saturday (*Before weekends*) and zero otherwise. Third, we also expect loan officers to experience greater work overload (e.g., Murfin and Petersen 2016) and/or to be distracted before holidays. Therefore, our third limited attention measure takes the value of one if the loan is issued within a [-4, +4] day window around major national holidays, such as July 4th, Thanksgiving, Christmas and the New Year (*Holidays*).[14] The mean value of *Busy loan officer* is 2.89, which represents about 14 notes daily. The mean values of *Before weekends* and *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 major holidays.

Further, we construct measures of a loan officer's task-specific human capital by retrieving loan officers' biographies from LinkedIn and measuring their earlier professional experience. To ensure that our measures capture earlier task-specific human capital rather than the lack of prior experience, we exclude from the analyses loan officers with no LinkedIn profiles, those that list the credit union as their only professional affiliation (i.e., employees who potentially chose to share

[13] We find similar results when we measure *Busy loan officer* by the number of loans a loan officer approves on a loan's origination day, ranked in quintiles.

[14] *Holidays* may also capture loan officers' optimism and positive attitude around national holidays (e.g., DeHaan et al. 2016). Thus, loan officers' positive mood may bias their credit risk assessments by leading them to more favorably reflect on soft information. Unfortunately, we cannot distinguish among these two alternative mechanisms (i.e., limited attention and mood).

only their current job on LinkedIn) and those that list the credit union as their first job. We define *Non-banking background* as an indicator variable that equals one if a loan officer has had non-banking experience prior to joining the credit union and zero otherwise. *Sales background* equals one if the loan officer has had prior professional experience in sales, and zero if the loan officer has had prior banking or other non-banking experience. Sixty-one percent of our sample loans are issued by loan officers with non-banking experience prior to joining the credit union and 22.20% of the loans are issued by officers with earlier sales-related experience (Table 1).

We next construct our measures of peer perception bias. Since we do not have information about borrowers' social, cultural and racial backgrounds, we focus on loan officers' and their 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 borrowers' genders. We categorize a borrower as male (female) if employees mostly refer to the borrower as "he", "his" or "him" ("she", "her" and "hers") in the notes (the gender cannot be identified for 7,661 of 31,601 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), zero otherwise. As we report in Table 1, 12.60% (30.90%) of our sample loans are issued by male (female) loan officers to male (female) borrowers.

Our next proxy for the peer perception bias focuses on whether a loan officer is a member of a small informal network of loan officers within the credit union. We utilize loan officers' referral information, which allows us to identify which loan officers were referred to work at the credit union by other union employees. We then construct informal cliques that comprise loan officers who provided references to their peers. To exemplify, consider the following hypothetical example: a loan officer A provides a reference to loan officer B, loan officer B provides a reference to loan officers C and D and loan officer D refers loan officer E. We will consider employees A to E to be part of the same informal clique. Further, to assess whether a loan officer's processing and interpretation of soft information can be influenced by clique peers, we identify whether the peers have transacted with the borrower in the past. Consequently, we define *Peer group* as an indicator variable equal to one if the borrower has interacted with one of the loan officers' clique peers prior to a loan's origination and zero otherwise. In Table 1, we show that there is a possible peer-group bias among employees in 3.10% of our sample loans.

Last, we build a measure of lax credit standards to proxy for credit expansion in the quarter of loan origination. We employ the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices to identify the percentage of domestic banks reporting a tightening in their standards. We collect this measure for each loan category in our sample – mortgage, personal and auto loans – for each quarter over the 2005-2010 period. We define *Lax credit standards* as an indicator variable that takes the value of one if the quarter of a loan's origination falls into the bottom quintile of the distribution of the percentage of domestic banks reporting a tightening in their standards (the least stringent (lax) standards) and zero otherwise. In Table 1, we show that about 26.00% of our sample loans are issued under lax credit standards.[15]

5. Research Design and Empirical Results

5.1. Validation tests

We begin our analyses by validating our soft information measures – *Soft information 1* and

[15] We rank quarterly credit standards over the 2005-2010 period (rather than the 2005-2008 sample period) to obtain a more balanced distribution of the tightening in credit standards across the quintile ranks. Because we measure quintiles over a longer period of time than our sample period, the bottom quintile comprises the higher percentage of sample loans (about 26%). Note that the distribution of the mortgage, auto and personal loan categories in the bottom quintile of credit standards is similar to what it is for our entire sample.

Soft information 2 – constructed using content analysis on borrower-specific employees' notes. Prior research has demonstrated that a greater amount of soft information allows lenders to better screen and monitor a borrower and thus leads to stronger ex-post loan and borrower performance (e.g., Petersen and Rajan 1994, 1995, Berger and Udell 2002, Uzzi and Lancaster 2003, Agarwal and Hauswald 2010). We therefore predict that if our soft information measures successfully capture the amount of soft information employed in the lending process, we should observe a negative and significant relation between these measures and ex-post credit outcomes.

To examine this relation, we use a linear probability (ordinary least square [OLS]) model, where the dependent variable is one of the following ex-post credit outcomes measures: *Charge off*, *Delinquency*, *Bad customer* or *Credit score decline*.[16]

$$\begin{aligned}\textit{Ex-post lending outcomes} = {}& \alpha + \beta_1 \textit{Soft information} + \beta_2 \textit{Credit score} + \beta_3 \textit{Debt-to-income ratio} \\ & + \beta_4 \textit{Loan interest rate} + \beta_5 \textit{Exception} + \beta_6 \textit{Secured} + \beta_7 \textit{Loan amount} \\ & + \beta_8 \textit{Loan maturity} + \beta_9 \textit{Borrower tenure} \\ & + \beta_{10} \textit{Total number of accounts} + \text{Loan officer FE} + \text{Branch FE} \\ & + \text{Loan year of origination FE} + \text{Loan type FE.}\end{aligned} \qquad \textit{(Model 2)}$$

In line with prior studies, we expect the coefficient on the soft information measures (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, Exception, Secured, Loan amount* and *Loan maturity*) and a borrower's prior relationship with the credit union (*Borrower tenure* and *Total number of accounts*). In the analyses, we also include branch, loan year of origination and loan type (mortgage, auto and personal loan) fixed effects to control for differences in loan and

[16] 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 coefficients on the interaction terms between the soft information measures and the measures of cognitive constraints, which are our main variables of interest, is more reliable with an OLS model (Angrist and Pischke 2008). However, we note that using a probit model yields very similar results (untabulated).

borrower performance across branches, loan types and years. Moreover, we control for loan officer fixed effects to capture variation in the lending behavior and personality traits across different loan officers in the credit union.

Table 2 reports the results of the validation tests. Consistent with our expectations, we find that both soft information measures are negatively and significantly associated with ex-post adverse lending outcomes across most of the specifications. Economically, a one standard deviation increase in *Soft information 1* reduces the probability of a loan's future charge off (*Charge off*), a borrower's delinquency on a loan with the 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 ex-post credit outcomes. Similarly, a one standard deviation increase in *Soft information 2* decreases *Charge off*, *Delinquency* and the probability of a future material decline in a borrower's credit score (*Credit score decline*) by 0.20%, 0.59% and 0.84%, which represent about 8.91%, 3.89% and 4.35% of their respective sample mean values.

To better assess the economic effect of the soft information measures, we estimate the economic significance of the hard information characteristics that we control for in our specifications. 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%, 24.85% and 5.55% of the respective mean values of these variables, while a one standard deviation increase in a borrower's debt-to-income ratio increases *Charge off*, *Delinquency, Bad customer* and *Credit score decline* by 10.45%, 16.75%, 13.42% and 19.01% of their respective mean values. These findings suggest that soft information provides an important incremental signal of a loan and a borrower's future performance over and above the borrower's hard information. Overall, the validation test provides evidence consistent with our soft information measures successfully capturing less salient, qualitative information that loan officers use in the lending process.

The coefficients on other control variables are also consistent with expectations. Loans with a higher interest rate and those that deviate from the credit guidelines experience a worse future performance. In a number of specifications, we also find that *Borrower tenure* and *Total number of accounts* reduce the probability of adverse future outcomes.

5.2. Soft information, cognitive constraints and ex-post lending outcomes

We next perform our primary analyses that examine whether loan officers' cognitive constraints (limited attention, task-specific human capital, peer perception and learning over the credit cycle) affect the use of soft information in the lending process. We thus investigate how the effect of soft information on ex-post lending outcomes varies when loan officers are influenced by these constraints. We augment Model 2 with our measures of cognitive constraints and the interaction term between these measures and *Soft information 1* (or *Soft information 2*):

$$\begin{aligned} \textit{Ex-post lending outcomes} = \ & \alpha + \beta_1 \textit{Soft information} + \beta_2 \textit{Cognitive constraint} \\ & + \beta_3 \textit{Soft information} \times \textit{Cognitive constraint} + \beta_4 \textit{Credit score} \\ & + \beta_5 \textit{Debt-to-income ratio} + \beta_6 \textit{Loan interest rate} + \beta_7 \textit{Exception} \\ & + \beta_8 \textit{Secured} + \beta_9 \textit{Loan amount} + \beta_{10} \textit{Loan maturity} \\ & + \beta_{11} \textit{Borrower tenure} + \beta_{12} \textit{Total number of accounts} \\ & + \text{Loan officer FE} + \text{Branch FE} + \text{Loan year of origination FE} \\ & + \text{Loan type FE.} \end{aligned}$$

(Model 3)

The variable of interest is the interaction term between *Soft information* and *Cognitive constraint*. We predict a positive coefficient on this variable (β_3), suggesting that relative to when loan officers are not subject to cognitive constraints, lending based on soft information by loan officers who are affected by them leads to worse credit outcomes. The ex-post outcome measures, control variables and model specifications are the same as in Model 2.

5.2.1. Soft information, limited attention bias and ex-post lending outcomes

Table 3 reports the results of the analyses of the effect of soft information on ex-post lending outcomes when loan officers are inattentive (distracted). In line with our predictions, we find a positive and significant coefficient on the interaction terms between the soft information measures and limited attention proxies in the majority of our specifications, where we measure limited attention by *Busy loan officer* (Panel A), *Before weekends* (Panel B) and *Holidays* (Panel C). Economically, our findings in Panel A suggest that relative to when a loan officer is not busy, a one standard deviation increase in *Soft information 1* when the officer is busy increases the probability of *Charge off*, *Delinquency*, *Bad customer* and *Credit score decline* by 0.29%, 1.40%, 2.46% and 0.84%, respectively. These figures represent about 13.27%, 9.25%, 10.68% and 4.44% of the respective sample mean values of these lending outcomes. Similarly, a one standard deviation increase in *Soft information 2* increases the probability of *Charge off*, *Delinquency and Credit score decline* by 0.17%, 1.23% and 2.13%, which represent about 7.64%, 8.16% and 11.20% of their respective mean values. The economic significance of the interaction terms is mostly stronger when we measure limited attention by *Before weekends* and *Holidays*.[17, 18]

[17] Economically, when loans are issued before weekends, a one standard deviation increase in *Soft information 1* 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. Similarly, a one standard deviation increase in *Soft information 2* increases the probability of *Charge off, Delinquency* and *Bad customer* by 0.31%, 4.51% and 1.62%, which represent about 14.00%, 29.85% and 7.06% of their respective mean values. Moreover, when loans are issued around national holidays, a one standard deviation increase in *Soft information 1* 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 during holidays, representing about 34.91%, 15.36% and 13.05% of their respective mean values. Similarly, a one standard deviation increase in *Soft information 2* increases the probability of *Charge off, Delinquency, Bad customer* and *Credit score decline* by 0.48%, 3.33%, 4.14% and 3.30%, which represent about 21.64%, 22.07%, 18.02% and 17.39% of their respective mean values.

[18] In untabulated robustness tests, we verify that our findings with respect to the adverse effect of inattention just before the weekend cannot be attributed to riskier or more complicated loans being approved by the end of the day or the week. First, we restrict the sample to loans issued after 4 pm on any weekday and continue to find a significant and positive coefficient on the interaction term between soft information measures and *Before weekends*. Our findings are also unchanged when we restrict the sample to loans issued on Friday and Saturday only. Further supporting the importance if inattention immediately before the weekend, we fail to find limited attention bias after 4 pm on days other than on Friday and, on Friday, prior to 4 pm.

Importantly, across all three limited attention measures, we find that when loan officers are inattentive, soft information is mostly ineffective in improving ex-post lending outcomes or even increases the probability of adverse outcomes (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 1* when loan officers are busy (Panel A) *increases* the probability of *Delinquency*, *Bad customer* and *Credit score decline* by 5.43%, 9.09% and 3.01% of the respective sample mean values. The economic significance of soft information is even stronger when we use *Before weekends* or *Holidays* as proxies for limited attention bias (Panels B and C). This adverse effect of soft information on ex-post lending outcomes when loan officers are inattentive contrasts with its favorable influence when loan officers are not subject to limited attention bias (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 is typically highly beneficial to lenders, lending based on soft information when loan officers are inattentive (distracted) may lead to worse ex-post lending outcomes.

5.2.2. Soft information, task-specific human capital and ex-post lending outcomes

We next investigate the role of soft information in the quality of lending decisions when loan officers are likely to be influenced by skills acquired earlier in their career. Panel A of Table 4 reports the results of the analyses using *Non-banking background* as our measure of task-specific human capital, which reflects whether loan officers had been trained to perform non-banking-related tasks prior to joining the credit union. We find a positive and significant coefficient on the *Soft information* × *Non-banking background* interaction variable, but only in three specifications using the *Soft information 2* measure. Economically, relative to when loan officers are not subject to task-specific skill bias, when loans are issued by loan officers who have a non-banking background, a one standard deviation increase in *Soft information 2* increases the probability of *Charge off*, *Delinquency* and *Credit score decline* by 0.53%, 5.12% and 7.20%, which represent about 24.18%, 33.93% and 37.87% of the respective mean sample values of these ex-post credit outcomes.[19]

Our findings are significantly stronger when we utilize the *Sales background* variable to proxy for task-specific human capital, which captures loan officers' sales-related skills developed prior to joining the credit union. In most specifications, we find a positive and significant coefficient on *Soft information* × *Sales background*. Economically, when loans are issued by loan officers with prior sales professional experience, a one standard deviation increase in *Soft information 1* 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. In addition, a one standard deviation increase in *Soft information 2* increases the probability of *Delinquency and Credit score decline* by 5.88% and 7.14%, which represent about 38.94% and 37.58% 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 are influenced by previously developed sales-related skills, soft information leads primarily to worse ex-post credit outcomes (as reflected by the sum of coefficients β_1 and β_3). A one standard deviation increase in *Soft information 1* 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. Our findings are similar when we use the *Soft information 2* measure.

In untabulated robustness tests, we verify that our findings are unaffected by loan officers'

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

experience within the credit union. Loan officers who have worked at the credit union for a longer time could develop stronger underwriting skills and be less affected by their non-banking related human capital. However, when we split our sample into loans issued by loan officers with a shorter tenure with the credit union (less than four years) and those issued by loan officers with a longer tenure (greater than 4 years) our findings are similar across both subsamples. This evidence is consistent with early-career skills carrying over to employees' new professional environments, despite significant professional changes (Schoar and Zuo 2016). Overall, our findings suggest that lending based on soft information by loan officers with prior sales-related professional experience impedes the effective processing of soft information, potentially because these loan officers focus on prospecting for new loans without carefully processing the implications of the soft information on the borrower's future credit performance.

5.2.3. Soft information, peer perception bias and ex-post lending outcomes

An additional cognitive constraint through which lending based on soft information can lead to worse ex-post credit outcomes is peer perception. We first examine whether the effective interpretation of soft information is distorted when loan officers and borrowers share the same gender identity, measured by *Male to male* and *Female to female* (Table 5, Panels A and B). Although we find no evidence on the adverse influence of female perception bias (Panel B), we show that such bias exists when the loan officer and the borrower are both men. In Panel A of Table 5, we document a positive and significant coefficient on the *Soft information* × *Male to male* interaction variable in most of our specifications. Economically, relative to when loan officers are not subject to peer perception bias, when loans are issued by male loan officers to male borrowers, a one standard deviation increase in *Soft information 1* 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. Similarly, a one standard deviation increase in *Soft information 2* increases the probability of *Charge off, Delinquency* and *Credit score decline* by 0.20%, 4.03% and 6.33%, which represent about 8.91%, 26.70% and 33.31% of their respective mean values.

Assessing the effect of soft information on lending outcomes relative to when no soft information is utilized, we find that when male loan officers lend to male borrowers, soft information mostly 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 1* increases the probability of *Charge off*, *Delinquency* and *Bad customer* by about 38.00%, 8.66% and 5.22% of their respective mean values. Our findings and inferences are unchanged when we use the *Soft information 2* measure. These results support our peer perception bias hypothesis and are consistent with prior studies showing that men are more likely to trust and are more biased in favor of other men (e.g., Dion and Stein 1978, Rhoades 1979, Ridgeway 1981, Grunspan et al. 2016).[20]

In addition, loan officers' interpretation of soft information can be influenced by their strong informal network ties with peer employees. As we report in Panel C of Table 5, we find a positive and significant coefficient on *Soft information* × *Peer group* in four out of eight specifications, suggesting that if the borrower has interacted with one of the loan officer's clique peers prior to a loan's origination, soft information can lead to worse credit outcomes. This evidence is consistent with our prediction that when loan officers are influenced by their peers' judgments and past

[20] Note that our results are not driven by men being more likely to make risky decisions (e.g., Byrnes et al. 1999). We augment Model 2 by an indicator variable equal to one when a loan officer is a man and the interaction term between this variable and our soft information measures. We find that coefficients on the interaction term are insignificant in all specifications, suggesting that lending by male loan officers based on soft information does not lead to worse future credit outcomes (untabulated).

experience, their exploration of soft information is less efficient. Relative to loan officers not subject to peer perception bias, when loans officers are affected by their peers, a one standard deviation increase in *Soft information 1* increases the probability of *Charge off* and *Credit score decline* by 0.90% and 1.52%, which represent about 40.91% and 8.00% of their respective mean values. Further, a one standard deviation increase in *Soft information 2* increases the probability of *Charge off* and *Bad customer* by 0.34% and 5.60%, which represent about 15.27% and 24.35% of their respective mean values.[21]

Similar to previously discussed cognitive constraints, we find that when loan officers are affected by their peers, soft information is largely ineffective in improving ex-post lending outcomes or that it even increases the probability of adverse outcomes, as reflected by the sum of coefficients β_1 and β_3. Overall, the results presented in Table 5 support our hypothesis that the interpretation and processing of soft information is affected by the perception bias arising from lender-borrower common identity and loan officers' informal organizational networks, leading to worse ex-post lending outcomes.

5.2.4. Soft information, learning over the credit cycle and ex-post lending outcomes

Last, we examine whether loan officers adequately process soft information across different stages of the credit cycle. Table 6 reports the results of this test. Consistent with our expectations, we document a positive and significant coefficient on the *Soft information* × *Lax credit standards* interaction variable in most specifications, suggesting that when loan officers lend based on soft information during quarters of lax credit standards, ex-post credit outcomes are less favorable. Economically, relative to loans issued in other periods, when loans are issued during quarters of

[21] While we argue that our results are attributed to clique peers' collective mindset, we cannot rule out that loan officers may also exhibit less care and effort in processing soft information if the notes were written by a peer.

lax credit standards a one standard deviation increase in *Soft information 1* increases the probability of *Delinquency* and *Bad customer* by 1.32% and 2.52%, which represent about 8.77% and 10.96% of their respective mean values. Similarly, a one standard deviation increase in *Soft information 2* increases the probability of *Charge off, Delinquency*, *Bad customer* and *Credit score decline* by 0.95%, 4.96%, 3.86% and 7.84%, which represent about 43.00%, 32.82%, 16.80% and 41.26% of their respective mean values.

Further, we find that when loans are issued under lax credit standards, utilizing soft information in the lending process relative to when no soft information is used primarily leads to an increase in the probability of a bad credit outcome (as reflected by the sum of coefficients β_1 and β_3). To exemplify, when a loan is issued under lax credit standards, a one standard deviation increase in *Soft information 1* increases the probability of *Delinquency* and *Bad customer* by about 5.88% and 8.91% of their respective mean values. Our results are economically stronger using the *Soft information 2* measure. Note that our findings are not attributed to loan officers' inattention during credit upturns, when loan officers are likely to be busier with a high volume of loan applications. In untabulated analyses, we continue to find the significant effect of credit expansion on the processing of soft information when we restrict our sample to loans issued by loan officers ranked in the two bottom quintiles of *Busy loan officer* (i.e., loan officers who are less busy on a loan origination day).

Collectively, our findings presented in Tables 3-6 suggest that while lending based on soft information generally improves ex-post lending outcomes, this effect becomes significantly weaker when loan officers' judgment is affected by cognitive constraints. Importantly, we document that under these circumstances, the inadequate processing of soft information can actually lead to worse future loan and borrower quality.

5.3. Supplementary analyses

We perform several supplementary tests to provide additional insights into our main findings. The results of our primary analyses are consistent with our hypothesis that when loan officers are subject to cognitive constraints, lending based on soft information leads to worse ex-post credit outcomes. However, an important potential 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 loan officers in the branch 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 variables of interest in Table 7.[22] Although our sample size declines drastically (the number of loan observations ranges from 1,655 to 4,777), the majority of our findings continue to hold, suggesting that our results are unlikely to be driven by endogeneity.

In our next set of analyses, we examine whether our results can be driven by differences in the information collection efforts of loan officers subject to cognitive constraints and those not influenced by them. To exemplify, loan officers who are inattentive or distracted may collect lower quality soft information, which will adversely affect ex-post credit outcomes. To alleviate this concern, we re-estimate our soft information measures separately based on the information collected by the officer who approves the loan (*Soft information by the loan officer*) and other employees (*Soft information by other employees*). To the extent that our results are attributed to soft information collection efforts rather than information's inaccurate interpretation, we expect the adverse effect of cognitive constraints to be prevalent for the soft information collected by the

[22] We do not perform the analyses of the effect of task-specific human capital bias and peer group perception bias due to the limited number of observations.

approving loan officer. Table 8 reports the results of these tests. Across all specifications, we show that our primary findings generally continue to hold, independent of the collection source of soft information.

We further investigate whether cognitive constraints affect the interpretation of hard information available to loan officers. We augment Model 2 with our measures of cognitive constraints and the interaction term between these measures and the two most commonly used hard information characteristics: the natural logarithm of a borrower's credit score and the debt-to-income ratio. As we report in Table 9, in most specifications we find no evidence suggesting that cognitive constraints affect the way hard information is impounded into loan decisions. These results are consistent with prior studies that indicate that cognitive constraints primarily affect the processing of less salient information, rather than numerical score interpretation (e.g., Kothari 2001, Bloomfield 2002, Hirshleifer and Teoh 2003).

Finally, we perform a number of untabulated analyses that focus on loan officers' incentives and learning. We start by examining whether our results are affected by officers' promotion incentives, as Cole at al. (2015) show that these incentives may significantly affect loan officers' behavior. First, we identify top-rated loan officers based on the union's internal valuation system and those close to being promoted to branch manager (i.e., assistant branch managers and member advisor specialists). We fail to find that these officers are differently affected by cognitive constraints relative to loan officers with a lower promotion likelihood. Second, we look at branches with high employee turnover, where employees are likely to work temporarily or the probability of getting fired is higher, i.e., where short term promotion incentives are significantly lower. We find a similar influence of cognitive constraints on soft information processing by loan officers in these branches.

In addition, we investigate whether loan officers can learn from their past experience and thus be less affected by cognitive constraints. To measure potential learning, we estimate the number of loans of the same type as the loan under consideration that the loan officer approved over the prior calendar year. We find weak evidence that learning can alleviate the adverse effects of limited attention bias, potentially suggesting that experienced loan officers may, to some extent, more accurately process and interpret soft information even when they are distracted. However, relative to the less experienced ones, such loan officers are similarly affected by other cognitive constraints. Overall, these additional tests suggest that loan officers' incentives and learning are unlikely to significantly mitigate the adverse effects of cognitive constraints on loan and borrower quality, in line with the prior behavioral literature (e.g., Simon 1957, Danziger et al. 2011).

6. Conclusion

We examine four cognitive constraints that may affect the use of soft information in the lending process: 1) limited attention, 2) task-specific human capital, 3) peer perception and 4) learning over the credit cycle. Although the vast majority of prior studies have shown that soft information improves credit decisions, we predict that these cognitive constraints impede the effective processing and interpretation of soft information and thus lead to adverse subsequent credit outcomes.

Taking advantage of the internal reporting system of a large federal credit union, we develop two novel measures of soft information based on the notes of union employees who document their communication with borrowers. Supporting the adverse effect of limited attention bias on loan officers' interpretation of soft information, we find that lending based on soft information leads to worse ex-post credit performance when loan officers are busy or when they approve loans before the weekend or around major national holidays. We also document that loan officers who have a non-banking professional background, and particularly those with prior sales-related experience, fail to accurately interpret soft information in their credit decisions. In addition, consistent with the adverse impact of peer perception bias on the efficient processing of soft information, we find that lending based on soft information is associated with worse credit performance when male loan officers lend to male borrowers or when loan officers are likely to be influenced by peers in their organizational cliques. Last, we show that loan officers inaccurately process soft information during quarters of lax credit standards, leading to worse ex-post loan and borrower quality. We further show that our results are unlikely to be affected by potential endogenous matching between loan officers and borrowers, as well as by loan officers' information collection efforts. We also find that cognitive constraints do not affect the interpretation and processing of hard information, further highlighting the importance of these constraints in assessing less salient, qualitative information about the borrower.

Our analyses provide novel evidence on non-agency-related limitations in the use of soft information in private lending. In contrast to other studies that attribute low loan quality to loan officers' moral hazard and risk taking (e.g., Banerjee et al. 2009, Hertzberg et al. 2010), we show that bad credit decisions may be also explained by the fact that humans are inherently subject to cognitive limitations (i.e., even if loan officers do their best to make accurate judgments, there are limits to how well they can actually do (Newell and Simon 1972)). However, it is important to highlight that our findings do not indicate that an automated lending process can efficiently substitute for the role of loan officers, as, in the absence of cognitive constraints, soft information leads to significantly better credit outcomes. Moreover, certain characteristics of organizational structure and task design, unexplored in the current paper, may alleviate cognitive constraints' adverse effects. We leave it to future research to explore these avenues.

REFERENCES

Abarbanell, J., and B. Bushee, 1997. Fundamental analysis, future earnings, and stock prices. *Journal of Accounting Research* 35 (1): 1–24.

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

Agarwal, S., B.W. Ambrose, and S. Chomsisengphet, 2011. The role of soft information in a dynamic contract setting: Evidence from the home equity credit market. *Journal of Money, Credit and Banking* 43 (4): 633–655.

Akerlof, G. A., and R. E. Kranton, 2000. Economics and identity. *The Quarterly Journal of Economics* 115: 715–753.

Angrist, J. D., and J.S. Pischke, 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

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.*

Becker, B., M. Bos, and K. Roszbach, 2016. Bad times, good credit. *Working paper.*

Ben-Ner, A., and A. Kramer, 2006. Do we prefer people who are similar to us? Experimental evidence on giving and work behaviors. *Working paper.*

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., and G. F. Udell, 2004. The institutional memory hypothesis and the procyclicality of bank lending behavior. *Journal of Financial Intermediation* 13 (4): 458–495.

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, P.G., M. Minnis, and A. G. Sutherland, 2016. Commercial lending concentration and bank expertise: Evidence from borrower financial statements. *Working paper.*

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.

Brown, M., K. Kirschenmann, and T. Spycher, 2016. Numeracy and on-the-job decision quality: Evidence from loan officers. *Working paper.*

Burt, R.S., 2004. Structural holes and good ideas. *American Journal of Sociology* 110 (2): 349–399.

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.

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.

Centola, D., and M. Macy, 2007. Complex contagions and the weakness of long ties. *American Journal of Sociology* 113 (3): 702–734.

Cole, R., 1998. The importance of relationships to the availability of credit. *Journal of Banking and Finance* 22 (1): 959–977.

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.

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.

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.

DeHaan, E., J. Madsen, and J. D. Piotroski, 2016. Do weather-induced moods affect the processing of earnings news? *Journal of Accounting Research, forthcoming.*

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.

Dessein, W., 2002. Authority and communication in organizations. *Review of Economic Studies* 69: 811–838.

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. *Journal of Political Economy* 99: 688–721.

Dilly, M., and T. Mählmann, 2015. Is there a 'boom bias' in agency ratings? *Review of Finance* 20 (3): 979–1011.

Dion, K.K., and S. Stein, 1978. Physical attractiveness and interpersonal influence. *Journal of Experimental Psychology* 12: 97–108.

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

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

Furth, D.L., 2001. Anticipating the next wave of bad loans: Function like a secondary market player. *The Secured Lender* (September/October), 31.

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.

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

Granovetter, M.S., 1973. The strength of weak ties. *American Journal of Sociology* 78 (6): 1360–1380.

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.

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.

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

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.

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

Kearns, M., S. Suri, and N. Montfort, 2006. An experimental study of the coloring problem on human subject networks. *Science* 313 (5788): 824–827.

Kothari, S.P., 2001. Capital markets research in accounting. *Journal of Accounting and Economics* 31 (1–3): 105–231.

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

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

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.

Lisowsky, P., M. Minnis, and A. G. Sutherland, 2016. Credit cycles and financial verification. *Journal of Accounting Research, forthcoming*.

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

Madsen, J., and J. McMullin, 2015. Unverifiable information and investment decisions: Evidence from crowdfunding. *Working paper*.

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

Mason W. A., A. Jones, and R. L. Goldstone, 2008. Propagation of innovations in networked groups. *Journal of Experimental Psychology: General* 137 (3): 422–433.

Mason, W. A., and D. J. Watts, 2012. Collaborative learning in networks. *Proceedings of the National Academy of Sciences* 109 (3): 764–769.

McCubbins, M.D., R. Paturi, and N. Weller, 2009. Connected coordination network structure and group coordination. *American Politics Research* 37 (5): 899–920.

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.

Minnis, M., 2011. The value of financial statement verification in debt financing: Evidence from private U.S. firms. *Journal of Accounting Research* 49 (2): 457-506.

Minnis, M., and A.G. Sutherland, 2016. Financial statements as monitoring mechanisms: Evidence from small commercial loans. *Journal of Accounting Research, forthcoming*.

Mullainathan, S., 2002. A memory-based model of bounded rationality. *Quarterly Journal of Economics* 117: 735–774.

Munnell, A., L. Browne, J. McEneaney, and G. Tootell, 1996. Mortgage lending in Boston: Interpreting the HMDA data. *American Economic Review* 86 (l): 25–53.

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

Newell, A., and H. Simon, 1972. *Human Problem Solving*. Englewood Cliffs, NJ: Prentice-Hall.

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.

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

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.

Rajan, R. G., 1992. Insiders and outsiders: The choice between informed and arm's-length debt. *Journal of Finance* 47 (4): 1367–1400.

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

Rhoades, M.J.R., 1979. A social psychology investigation of the differential influence of male and female advocates of non-traditional sex roles. *Dissertation Abstracts International* 41, 4747.

Ridgeway, C.L., 1981. Nonconformity, competence and influence in groups: A test of two theories. *American Sociological Review* 46: 333–347.

Ruckes, M., 2004. Bank competition and credit standards. *Review of Financial Studies* 17 (4): 1073–1102.

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

Shiller, R. J., 1999. Human behavior and the efficiency of the financial system. In: J. B. Taylor & M. Woodford (eds.), *Handbook of Macroeconomics*, Vol 1A, first ed. San Diego: Elsevier, pp. 1305–1340.

Shleifer, A., 2000. Inefficient markets: An introduction to behavioral finance. Oxford: Oxford University Press

Shore, J., E. Bernstein, and D. Lazer, 2015. Facts and figuring: An experimental investigation of network structure and performance in information and solution spaces. *Organization Science* 26 (5):1432–1446.

Simon, H.A., 1957. *Models of Man*. New York: Wiley & Sons.

Sutherland, A.G., 2016. The economic consequences of borrower information sharing: Relationship dynamics and investment. *MIT Sloan Working Paper*.

Tajfel, H., 1982. Social psychology of intergroup relations. *Annual Review of Psychology* 33: 1–39.

Tajfel, H., and J.C. Turner, 1979. An integrative theory of intergroup conflict. In: W. G. Austin & S. Worchel (eds.), *The Social Psychology of Inter-Group Relations*. Monterey, CA: Brooks/Cole: 33–47.

Teoh, S.H., and T.J. Wong, 2002. Why new issues and high-accrual firms underperform: The role of analysts' credulity. *Review of Financial Studies* 15 (3): 869–900.

Towry, K. L., 2003. Control in a teamwork environment: The impact of social ties on the effectiveness of mutual monitoring contracts. *The Accounting Review* 78 (4): 1069–1095.

Turner, J. C., P. J. Oakes, A. Haslam, and C. McGarty, 1994. Self and collective: Cognition and social context. *Personality and Social Psychology Bulletin* 20: 454–463.

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.

Weber, E.U., N. Siebenmorgen, and M. Weber, 2005. Communicating asset risk: How name recognition and the format of historic volatility information affect risk perception and investment decisions. *Risk Analysis* 25: 597–609.

APPENDIX A

Examples of employees' notes

"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."

"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."

"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
Ex-post lending outcomes	
Charge off	An indicator variable equal to one if a loan is 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. Credit scores are provided by a national credit bureau.
Soft information	
Soft information 1	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.
Soft information 2	The absolute value of the residual from the regression of the total number of words in borrower-related notes during the 45-day window prior to loan origination on the hard quantitative information loan officers have about a borrower. Specifically, we estimate the following regression: *Log of word-count* = α +β_1*Credit score* +β_2*Debt-to-income ratio* +β_3*Borrower tenure* +β_4*Log of quantitative word-count* +β_5*Number of deposit accounts* +β_6*Deposit account balance* +β_7*Number of credit cards* +β_8*Credit card balance* +β_9*Number of personal loans* +β_{10}*Personal loan balance* +β_{11}*Number of mortgages* +β_{12}*Mortgage balance* +β_{13}*Number of home equity accounts* +β_{14}*Home equity balance* +β_{15}*Number of IRA accounts* +β_{16}*IRA balance* +β_{17}*Number of auto loans* +β_{18}*Auto loan balance* +β_{19}*Number of ATM accounts* +β_{20}*ATM account balance* +β_{21}*Number of lines of credit* +β_{22}*Line of credit balance* +β_{23}*Number of other loans* +β_{24}*Other loan balance* +Employee FE +Branch FE +Loan year of origination FE +Loan type FE, where account and credit balances are log-transformed.
Cognitive constraints	
<u>Limited attention</u>	
Busy loan officer	The number of notes a loan officer writes on the loan's origination day, ranked in quintiles. If the number of loans issued by the loan officer exceeds the number of notes she writes on the loan's origination day, we replace the number of notes with the number of loans.

APPENDIX C (Continued)

Before weekends	An indicator variable equal to one if the loan is originated after 4pm on Friday or on Saturday and zero otherwise.
Holidays	An indicator variable equal to one if the loan origination date falls within a [-4, +4] day-window around the national holidays: July 4, Christmas, the New Year and Thanksgiving and zero otherwise.
<u>Task-specific human capital</u>	
Non-banking background	An indicator variable equal to one if a loan officer has had non-banking experience prior to joining the credit union and zero otherwise. We retrieve loan officers' bios from LinkedIn.
Sales background	An indicator variable equal to one if the loan officer has had 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.
<u>Peer perception</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.
Peer group	An indicator variable equal to one if the borrower has interacted with one of the loan officer's clique peers prior to a loan's origination and zero otherwise. A loan officer's peers are employees within the officer's clique of referred employees.
<u>Learning over the credit cycle</u>	
Lax credit standards	An indicator variable that takes the value of one if the quarter of a loan's origination falls into the bottom quintile of the distribution of bank credit standards (the least stringent (lax) standards) and zero otherwise. We measure credit standards based on the percentage of domestic banks reporting a tightening in their standards by loan category (mortgage, personal and auto loans) for each quarter over the period 2005-2010, according to the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS), which is available from the Federal Reserve Bank of St. Louis.

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 %.

APPENDIX C (Continued)

Exception	An indicator variable equal to one if the loan includes an exception relative to the union's credit guidelines and zero otherwise.
Secured	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.

TABLE 1

Summary statistics

	Obs.	Mean	STD	Median
Ex-post lending outcomes				
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 1	49,680	0.055	0.040	0.034
Soft information 2	49,680	0.270	0.282	0.162
Cognitive constraints				
Limited attention				
Busy loan officer	49,680	2.887	1.491	3.000
Before weekends	49,680	0.063	0.215	0.000
Holidays	49,680	0.069	0.238	0.000
Task-specific human capital				
Non-banking background	9,364	0.608	0.485	1.000
Sales background	9,364	0.222	0.420	0.000
Peer perception				
Male to male	40,747	0.126	0.332	0.000
Female to female	40,747	0.309	0.462	0.000
Peer group	49,680	0.031	0.151	0.000
Learning over the credit cycle				
Lax credit standards	49,680	0.255	0.435	0.000
Borrower and loan characteristics				
Credit score	49,680	6.590	0.210	6.580
Debt-to-income ratio	49,680	0.372	0.230	0.352
Loan interest rate	49,680	8.967	3.841	8.050
Exception	49,680	0.795	0.439	1.000
Secured	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

This table presents descriptive statistics for the variables used in our primary tests. The values of the continuous variables are winsorized at 1% and 99%. Variables are described in Appendix C.

TABLE 2

Validation tests

	(I)		(II)		(III)		(IV)	
	Charge off		*Delinquency*		*Bad customer*		*Credit score decline*	
Soft information 1	**-0.066*****		**-0.125*****		**-0.160****		**-0.056**	
	(-4.585)		**(-3.033)**		**(-2.188)**		**(-0.920)**	
Soft information 2		**-0.007*****		**-0.021*****		**-0.017**		**-0.030*****
		(-2.890)		**(-3.269)**		**(-1.423)**		**(-3.260)**
Credit score	-0.018***	-0.018***	-0.139***	-0.136***	-0.284***	-0.279***	-0.051***	-0.050***
	(-5.278)	(-5.212)	(-12.402)	(-12.541)	(-11.907)	(-12.054)	(-3.076)	(-2.995)
Debt-to-income ratio	0.010**	0.013***	0.115***	0.118***	0.147***	0.149***	0.157***	0.158***
	(2.358)	(2.990)	(11.871)	(12.018)	(8.361)	(8.338)	(11.147)	(11.175)
Loan interest rate	0.004***	0.004***	0.037***	0.036***	0.033***	0.033***	0.017***	0.017***
	(9.353)	(9.285)	(38.027)	(37.730)	(19.096)	(18.915)	(12.619)	(12.632)
Exception	0.001	0.002	0.019***	0.021***	0.039***	0.041***	-0.005	-0.004
	(0.492)	(0.637)	(3.074)	(3.361)	(3.424)	(3.510)	(-0.465)	(-0.415)
Secured	0.004	0.003	0.005	0.004	-0.054***	-0.057***	0.015*	0.014*
	(1.451)	(1.120)	(0.781)	(0.570)	(-4.450)	(-4.546)	(1.674)	(1.647)
Loan amount	0.000	-0.000	-0.009***	-0.009***	-0.011**	-0.012***	-0.018***	-0.018***
	(0.011)	(-0.065)	(-3.766)	(-4.152)	(-2.499)	(-2.780)	(-5.610)	(-5.658)
Loan maturity	-0.001	-0.001	-0.001	-0.001	0.003	0.003	0.014***	0.014***
	(-0.971)	(-1.153)	(-0.804)	(-0.871)	(0.943)	(1.030)	(4.182)	(4.144)
Borrower tenure	-0.000	0.000	-0.004*	-0.003	-0.007*	-0.007*	-0.005	-0.005
	(-0.289)	(0.048)	(-1.664)	(-1.443)	(-1.817)	(-1.698)	(-1.428)	(-1.426)
Total number of accounts	-0.004***	-0.004***	0.004	0.005	0.007	0.005	-0.006	-0.006
	(-3.408)	(-3.070)	(1.232)	(1.564)	(1.339)	(0.934)	(-1.147)	(-1.128)
Fixed effects:								
Loan officer, branch, year, loan type								
Economic significance of *Soft information*	-12.000%	-8.909%	-3.311%	-3.894%	-2.700%			-4.352%
Obs.	49,680	49,680	49,680	49,680	15,972	15,972	27,807	27,807
Adj-R^2	3.39%	3.34%	18.12%	17.53%	26.79%	26.65%	6.26%	6.33%

This table reports the analyses of the relation between soft information and ex-post lending outcomes (loan and borrower future performance). We employ two measures of soft information. *Soft information 1* 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. *Soft information 2* is the absolute value of the residual from the regression of the total number of words in borrower-related 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 Appendix C). 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. A constant is 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. For specifications where the coefficient on the soft information measure is statistically significant, we also report the economic significance of this 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. Coefficients of interest are in boldface.

TABLE 3

Soft information, limited attention bias and ex-post lending outcomes

Panel A: Future credit quality and lending based on soft information during busy days								
	(I)		(II)		(III)		(IV)	
	Charge off		*Delinquency*		*Bad customer*		*Credit score decline*	
Soft information 1	-0.070***		-0.144***		-0.183**		-0.066	
	(-4.864)		(-3.434)		(-2.444)		(-1.077)	
Busy loan officer	0.000		0.004***		0.004		0.002	
	(0.717)		(3.062)		(1.616)		(1.193)	
Soft information 1 × Busy loan officer	**0.073*** **		**0.349*** **		**0.614*** **		**0.211* **	
	(2.912)		**(4.677)**		**(4.369)**		**(1.894)**	
Soft information 2		-0.011***		-0.052***		0.009		-0.089***
		(-3.448)		(-6.319)		(0.616)		(-7.088)
Busy loan officer		0.000		0.024***		0.015*		0.019***
		(0.095)		(5.434)		(1.826)		(2.891)
Soft information 2 × Busy loan officer		**0.006** **		**0.044*** **		**0.010**		**0.076*** **
		(2.151)		**(6.453)**		**(0.785)**		**(7.515)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:								
Loan officer, branch, year, loan type								
$\beta_1 + \beta_3$	0.003	-0.005	0.205	-0.008	0.431	0.109	0.145	-0.013
Statistical significance of $\beta_1 + \beta_3$ (*p*-values)	0.901	0.044	0.008	0.237	0.000	0.210	0.109	0.179
Economic effect of *Soft information* when loan officers are subject to a cognitive constraint		-2.545%	5.430%		9.093%		3.005%	
Obs.	49,680	49,680	49,680	49,680	15,972	15,972	27,807	27,807
Adj. R^2	4.35%	4.35%	18.71%	17.99%	26.89%	26.60%	6.28%	6.56%

TABLE 3 (Continued)

Panel B: Future credit quality and lending based on soft information before the weekend

	(I)		(II)		(III)		(IV)	
	Charge off		*Delinquency*		*Bad customer*		*Credit score decline*	
Soft information 1	-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 1 × Before weekends	**0.263****		**0.537*****		**0.692***		**-0.030**	
	(2.420)		**(7.709)**		**(1.747)**		**(-0.108)**	
Soft information 2		-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 2 × Before weekends		**0.011*****		**0.161*****		**0.058*****		**0.048**
		(4.294)		**(3.784)**		**(3.665)**		**(0.122)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:								
Loan officer, branch, year, loan type								
$\beta_1 + \beta_3$	0.198	0.004	0.418	0.140	0.532	0.042	-0.025	0.018
Statistical significance of $\beta_1 + \beta_3$ (*p*-values)	0.000	0.736	0.000	0.008	0.015	0.040	0.761	0.960
Economic effect of *Soft information* when loan officers are subject to cognitive constraint	36.000%		11.073%	25.960%	8.979%	4.962%		
Obs.	49,680	49,680	49,680	49,680	15,972	15,972	27,807	27,807
Adj. R^2	3.35%	5.01%	18.24%	17.53%	26.81%	26.85%	6.27%	6.33%

TABLE 3 (Continued)

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

	(I)		(II)		(III)		(IV)	
	Charge off		*Delinquency*		*Bad customer*		*Credit score decline*	
Soft information 1	-0.068***		-0.130***		-0.164**		-0.062	
	(-4.745)		(-3.154)		(-2.237)		(-1.009)	
Holidays	0.001		-0.002		-0.007		-0.010	
	(0.237)		(-0.335)		(-0.603)		(-1.095)	
Soft information 1 × Holidays	**0.192*** **		**0.582*** **		**0.302**		**0.620** **	
	(3.861)		**(2.725)**		**(0.797)**		**(2.071)**	
Soft information 2		-0.008***		-0.029***		0.006		-0.039***
		(-3.090)		(-4.217)		(0.475)		(-3.882)
Holidays		0.002		-0.023		-0.035**		0.004
		(0.662)		(-0.577)		(-2.089)		(1.640)
Soft information 2 × Holidays		**0.017***		**0.119*** **		**0.148** **		**0.118*** **
		(1.651)		**(3.549)**		**(2.341)**		**(2.704)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:								
Loan officer, branch, year, loan type								
$\beta_1 + \beta_3$	0.124	0.009	0.452	0.090	0.138	0.154	0.558	0.079
Statistical significance of $\beta_1 + \beta_3$ (*p*-values)	0.000	0.351	0.043	0.000	0.724	0.010	0.033	0.049
Economic effect of *Soft information,* when loan officers are subject to cognitive constraint	22.545%		11.974%	16.689%		18.194%	11.565%	11.461%
Obs.	49,680	49,680	49,680	49,680	15,972	15,972	27,807	27,807
Adj. R^2	3.36%	3.34%	18.14%	17.92%	26.79%	26.68%	5.97%	6.36%

This table reports the analyses of whether utilizing soft information in lending decisions by inattentive loan officers leads to worse credit outcomes. We proxy for loan officer's limited attention (distraction) as follows: in Panel A, *Busy loan officer* is measured as the number of notes a loan officer writes on the loan's origination day, ranked in quintiles; in Panel B, *Before weekends* is equal to one if the loan is originated after 4pm on Friday or on Saturday and zero otherwise; in Panel C, *Holidays* is equal to one if the loan origination date falls within a [-4, +4] day-window around July 4, Christmas, the New Year and Thanksgiving and zero otherwise. We employ two measures of soft information. *Soft information 1* 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. *Soft information 2* is the absolute value of the residual from the regression of the total number of words in borrower-related 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 Appendix C). 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. A constant is 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 cognitive constraint. We measure the economic significance by the effect of a one standard deviation increase in soft information when loan officers are subject to cognitive constraints 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 and ex-post lending outcomes

Panel A: Future credit quality and lending based on soft information by loan officers with prior non-banking experience

	(I)		(II)		(III)		(IV)	
	Charge off		*Delinquency*		*Bad customer*		*Credit score decline*	
Soft information 1	-0.109***		-0.189**		-0.172		-0.148	
	(-2.972)		(-2.057)		(-0.919)		(-0.920)	
Non-banking background	0.004		0.003		0.008		-0.024	
	(1.317)		(0.337)		(0.476)		(-1.552)	
Soft information 1 × Non-banking background	**0.217**		**-0.560**		**-0.305**		**-0.070**	
	(1.029)		**(-1.224)**		**(-0.305)**		**(-0.085)**	
Soft information 2		-0.010		-0.048***		-0.023		-0.107***
		(-1.414)		(-2.602)		(-1.634)		(-3.307)
Non-banking background		0.005		0.015		0.012		-0.011
		(1.461)		(1.609)		(0.705)		(-0.664)
Soft information 2 × Non-banking background		**0.019***		**0.183*****		**0.040**		**0.257*****
		(1.922)		**(3.160)**		**(0.363)**		**(2.797)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:								
Branch, year, loan type								
$\beta_1 + \beta_3$	0.108	0.009	-0.749	0.135	-0.477	0.017	-0.218	0.150
Statistical significance of $\beta_1 + \beta_3$ (*p*-values)	0.578	0.431	0.025	0.000	0.328	0.841	0.570	0.034
Economic effect of *Soft information* when loan officers are subject to a cognitive constraint			-19.841%	25.033%				21.762%
Obs.	9,364	9,364	9,364	9,364	2,926	2,926	5,472	5,472
Adj. R^2	3.33%	3.20%	17.20%	16.91%	28.57%	28.49%	4.67%	4.96%

TABLE 4 (Continued)

Panel B: Future credit quality and lending based on soft information by loan officers with prior sales-related experience

	(I)		(II)		(III)		(IV)	
	Charge off		*Delinquency*		*Bad customer*		*Credit score decline*	
Soft information 1	-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 1 × Sales background	**0.271*** **		**0.541*** **		**0.846** **		**0.808** **	
	(3.707)		**(2.877)**		**(2.038)**		**(2.478)**	
Soft information 2		-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 2 × Sales background		**0.004**		**0.210*** **		**0.197**		**0.255*** **
		(0.204)		**(3.344)**		**(1.626)**		**(2.729)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:								
Branch, year, loan type								
$\beta_1 + \beta_3$	0.167	-0.003	0.276	0.171	0.648	0.215	0.606	0.170
Statistical significance of $\beta_1 + \beta_3$ (*p*-values)	0.023	0.875	0.168	0.001	0.015	0.088	0.055	0.030
Economic effect of *Soft information* when loan officers are subject to cognitive constraint	30.364%			31.709%	11.270%	26.174%	12.560%	24.663%
Obs.	9,364	9,364	9,364	9,364	2,926	2,926	5,472	5,472
Adj. R^2	3.48%	3.18%	17.24%	16.92%	28.69%	28.56%	4.77%	5.01%

This table reports the analyses of whether utilizing soft information in lending decisions by loan officers with prior non-banking or sales-related experience leads to worse credit outcomes. We proxy for task-specific human capital as follows: in Panel A, *Non-banking background* is an indicator variable equal to one if a loan officer has a non-banking experience prior to joining the credit union and zero otherwise; in Panel B, *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. We employ two measures of soft information. *Soft information 1* 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. *Soft information 2* is the absolute value of the residual from the regression of the total number of words in borrower-related 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 Appendix C). 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%. Branch, loan type and year fixed effects are included but not tabulated. A constant is 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 approving loan officer's task-specific human capital (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 cognitive constraint. We measure the economic significance by the effect of a one standard deviation increase in soft information when loan officers are subject to cognitive constraints 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, peer perception bias and ex-post lending outcomes

Panel A: Future credit 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 1	-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 1 × Male to male	**0.292*** **		**0.465** **		**0.502** **		**0.332**	
	(2.868)		**(2.090)**		**(2.413)**		**(0.988)**	
Soft information 2		-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 2 × Male to male		**0.007** **		**0.144*** **		**0.099**		**0.226*** **
		(2.494)		**(4.353)**		**(1.508)**		**(4.701)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:								
Loan officer, branch, year, loan type								
$\beta_1 + \beta_3$	0.209	-0.003	0.327	0.102	0.300	0.103	0.232	0.165
Statistical significance of $\beta_1 + \beta_3$ (*p*-values)	0.052	0.804	0.048	0.000	0.011	0.092	0.469	0.000
Economic effect of *Soft information* when loan officers are subject to a cognitive constraint	38.000%		8.662%	18.914%	5.217%	12.539%		24.316%
Obs.	40,747	40,747	40,747	40,747	13,251	13,251	22,140	22,140
Adj. R^2	3.35%	3.23%	18.49%	17.21%	25.89%	25.62%	5.81%	5.98%

TABLE 5 (Continued)

Panel B: Future credit 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 1	-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 1 × Female to female	**-0.026**		**0.057**		**0.024**		**-0.277****	
	(-0.869)		**(0.713)**		**(0.160)**		**(-2.230)**	
Soft information 2		-0.009***		-0.025***		0.016		-0.031***
		(-3.517)		(-3.687)		(1.201)		(-3.075)
Female to female		-0.030		-0.216**		-0.154		-0.009*
		(-0.828)		(-2.090)		(-1.172)		(-1.903)
Soft information 2 × Female to female		**0.000**		**0.007**		**-0.028**		**-0.039***
		(0.055)		**(0.517)**		**(-0.997)**		**(-1.937)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects: Loan officer, branch, year, loan type								
$\beta_1 + \beta_3$	-0.095	-0.009	-0.058	-0.018	-0.124	-0.012	-0.364	-0.070
Statistical significance of $\beta_1 + \beta_3$ (*p*-values)	0.000	0.180	0.523	0.248	0.474	0.708	0.000	0.000
Economic effect of *Soft information* when loan officers are subject to a cognitive constraint	-17.273%						-7.544%	-10.155%
Obs.	40,747	40,747	40,747	40,747	13,251	13,251	22,140	22,140
Adj. R^2	3.33%	3.23%	17.68%	17.49%	20.66%	21.66%	5.83%	5.87%

TABLE 5 (Continued)

Panel C: Future credit quality and lending based on soft information when the loan officer is influenced by her peer group

	(I)		(II)		(III)		(IV)	
	Charge off		*Delinquency*		*Bad customer*		*Credit score decline*	
Soft information 1	-0.066***		-0.125***		-0.160**		-0.055	
	(-4.592)		(-3.036)		(-2.178)		(-0.903)	
Peer group	-0.006		-0.017		0.037		0.015	
	(-1.368)		(-1.111)		(1.351)		(0.713)	
Soft information 1 × Peer group	**0.225****		**0.594**		**0.226**		**0.380****	
	(2.415)		**(1.023)**		**(0.924)**		**(2.151)**	
Soft information 2		-0.007***		-0.023***		-0.008*		-0.032***
		(-2.903)		(-7.657)		(-1.781)		(-3.371)
Peer group		-0.008		-0.001		-0.004		0.008
		(-1.686)		(-1.002)		(-0.126)		(0.30)
Soft information 2 × Peer group		**0.012****		**0.082**		**0.202****		**0.053**
		(1.985)		**(1.452)**		**(2.519)**		**(0.708)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects: Loan officer, branch, year, loan type								
$\beta_1 + \beta_3$	0.159	0.005	0.469	0.059	0.066	0.194	0.325	0.021
Statistical significance of $\beta_1 + \beta_3$ (*p*-values)	0.000	0.664	0.428	0.285	0.290	0.001	0.043	0.779
Economic effect of *Soft information* when loan officers are subject to a cognitive constraint	28.909%					23.617%	6.842%	
Obs.	49,680	49,680	49,680	49,680	15,972	15,972	27,807	27,807
Adj. R^2	3.34%	3.38%	18.13%	17.83%	24.35%	24.28%	5.05%	5.49%

This table reports the analyses of whether utilizing soft information in lending decisions by loan officers subject to peer perception bias leads to worse credit outcomes. We proxy for peer perception bias 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; in Panel C, *Peer group* is equal to one if the borrower has interacted with one of the loan officer's clique peers prior to a loan's origination and zero otherwise. A loan officer's peers are employees within the loan officer's network of referred employees. We employ two measures of soft information. *Soft information 1* 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. *Soft information 2* is the absolute value of the residual from the regression of the total number of words in borrower-related 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 Appendix C). 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. A constant is 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 peer perception 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 cognitive constraint. We measure the economic significance by the effect of a one standard deviation increase in soft information when loan officers are subject to cognitive constraints 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, learning over the credit cycle and ex-post lending outcomes

	(I) *Charge off*		(II) *Delinquency*		(III) *Bad customer*		(IV) *Credit score decline*	
Soft information 1	-0.062***		-0.109**		-0.103*		-0.064	
	(-4.194)		(-2.573)		(-1.926)		(-1.033)	
Lax credit standards	0.005**		0.021***		0.036***		-0.002	
	(2.390)		(4.191)		(4.438)		(-0.225)	
Soft information 1 × Lax credit standards	**0.070**		**0.331****		**0.631****		**-0.121**	
	(1.270)		**(2.357)**		**(2.576)**		**(-0.566)**	
Soft information 2		-0.012***		-0.050***		-0.003		-0.088***
		(-4.026)		(-6.439)		(-0.211)		(-7.492)
Lax credit standards		0.000**		0.005***		0.013		0.013***
		(2.042)		(3.862)		(1.301)		(4.779)
Soft information 2 × Lax credit standards		**0.034*****		**0.177*****		**0.138*****		**0.280*****
		(2.983)		**(6.366)**		**(2.765)**		**(8.193)**
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects:								
Loan officer, branch, year, loan type								
$\beta_1 + \beta_3$	0.008	0.022	0.222	0.127	0.528	0.135	-0.185	0.192
Statistical significance of $\beta_1 + \beta_3$ (*p*-values)	0.898	0.033	0.066	0.000	0.011	0.000	0.427	0.000
Economic effect of *Soft information* when loan officers are subject to a cognitive constraint		28.000%	5.881%	23.550%	8.911%	15.949%		27.855%
Obs.	49,680	49,680	49,680	49,680	15,972	15,972	27,807	27,807
Adj. R^2	3.41%	3.37%	18.15%	18.01%	26.84%	24.44%	6.27%	6.61%

This table reports the analyses of whether utilizing soft information in lending decisions during quarters of lax credit standards leads to worse credit outcomes. *Lax credit standards* is equal to one if the quarter of loan origination falls into the bottom quintile of the distribution of bank credit standards (reflecting the least stringent standards) and zero otherwise. We employ two measures of soft information. *Soft information 1* 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. *Soft information 2* is the absolute value of the residual from the regression of the total number of words in borrower-related 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 Appendix C). 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. A constant is 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 learning over the credit cycle (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 cognitive constraint. We measure the economic significance by the effect of a one standard deviation increase in soft information when loan officers are subject to cognitive constraints 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 7

Soft information, cognitive constraints and ex-post lending outcomes: Call-center loan officers

		Limited attention			**Peer perception**	**Credit cycle**
		(I)	(II)	(III)	(IV)	(V)
Dependent variables:	Interaction variables:	*Busy loan officer*	*Before weekends*	*Holidays*	*Male to male*	*Lax credit standards*
Charge off	*Soft information 1*	0.157	0.244**	0.279*	-0.005	-0.244
		(1.503)	(1.979)	(1.749)	(-0.018)	(-0.951)
	Soft information 2	-0.002	0.425***	0.044**	-0.007	0.057
		(-0.171)	(5.598)	(2.472)	(-0.264)	(1.314)
	Obs.	N= 4,777	N= 4,777	N= 4,777	N= 4,127	N= 4,777
Delinquency	*Soft information 1*	0.346**	0.184***	0.071	0.023	0.260
		(2.582)	(3.447)	(0.092)	(0.043)	(0.551)
	Soft information 2	0.015	0.154**	0.063*	0.125**	0.065*
		(0.818)	(2.479)	(1.776)	(2.478)	(1.721)
	Obs.	N= 4,777	N= 4,777	N= 4,777	N= 4,127	N= 4,777
Bad customer	*Soft information 1*	0.793*	-0.336	0.428*	0.980*	0.349**
		(1.901)	(-0.245)	(1.911)	(1.922)	(2.362)
	Soft information 2	0.026	0.551***	-0.018	-0.105	0.244
		(0.649)	(3.813)	(-0.107)	(-0.684)	(1.251)
	Obs.	N= 1,933	N= 1,933	N= 1,933	N= 1,655	N= 1,933
Credit score decline	*Soft information 1*	0.060*	-0.141	0.265	-0.343	0.578*
		(1.722)	(-0.182)	(1.010)	(-0.404)	(1.763)
	Soft information 2	0.065**	0.487***	0.194**	0.158*	0.144**
		(2.129)	(4.471)	(2.326)	(1.741)	(2.193)
	Obs.	N= 3,007	N= 3,007	N= 3,007	N= 2,641	N= 3,007

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 cognitive constraint tests for which we have at least 500 observations of available data. We report the interaction terms of the soft information measures with the measures of loan officers' cognitive constraints (limited attention bias, peer perception bias and learning over the credit cycle), employing the same specifications as in Tables 3-6. 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 8

Soft information collected by the loan officer approving the loan and other employees, cognitive constraints and ex-post lending outcomes

		Limited attention			**Task-specific human capital**		**Peer perception**		**Credit cycle**
		(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Dependent variables:	Interaction variables:	*Busy loan officer*	*Before weekends*	*Holidays*	*Non-bank background*	*Sales background*	*Male to male*	*Peer group*	*Lax credit standards*
Charge off	*Soft info 1 by the loan officer*	0.002	0.175*	0.141**	0.129	0.195**	0.135*	0.110	0.109*
		(0.054)	(1.690)	(2.259)	(1.357)	(2.330)	(1.797)	(0.501)	(1.765)
	Soft info 1 by other employees	0.060**	0.156***	0.114**	-0.071	0.056	0.008	0.203**	-0.013
		(2.093)	(2.794)	(1.967)	(-1.165)	(0.781)	(0.157)	(2.558)	(-0.356)
	Soft info 2 by the loan officer	0.004*	0.003*	0.004	0.017	0.046	0.180***	0.026**	0.016***
		(1.890)	(1.890)	(0.373)	(0.579)	(1.339)	(3.624)	(2.514)	(2.731)
	Soft info 2 by other employees	0.003***	0.010***	0.016	0.047***	0.072**	0.009**	0.036*	0.031***
		(4.184)	(4.042)	(1.548)	(2.616)	(2.410)	(2.082)	(1.906)	(3.778)
Delinquency	*Soft info 1 by the loan officer*	0.203***	0.147***	0.677***	-0.147	0.441***	0.668***	0.223	0.381***
		(2.871)	(4.765)	(3.193)	(-0.683)	(4.823)	(3.574)	(0.378)	(2.902)
	Soft info 1 by other employees	0.096	0.421***	0.412**	-0.194	0.299	0.453***	0.453	0.086
		(1.627)	(7.131)	(2.097)	(-0.896)	(1.305)	(2.705)	(1.167)	(0.755)
	Soft info 2 by the loan officer	0.020***	0.087***	0.049*	0.270***	0.093**	0.318***	0.112**	0.102***
		(3.159)	(2.906)	(1.717)	(3.590)	(1.990)	(4.620)	(2.346)	(4.515)
	Soft info 2 by other employees	0.013***	0.060*	0.046***	0.161***	0.301***	0.172***	0.053	0.086***
		(2.581)	(1.815)	(2.752)	(3.458)	(4.016)	(2.958)	(1.203)	(4.799)

TABLE 8 (Continued)

Dependent variables:	Interaction variables:	Limited attention			Task-specific human capital		Peer perception		Credit cycle
		(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
		Busy loan officer	*Before weekends*	*Holidays*	*Non-bank background*	*Sales background*	*Male to male*	*Peer group*	*Lax credit standards*
Bad customer	*Soft info 1 by the loan officer*	0.465***	0.219	0.288	-0.505	0.883*	0.478***	0.788	0.544**
		(3.443)	(1.333)	(0.874)	(-0.992)	(1.882)	(4.183)	(1.384)	(2.041)
	Soft info 1 by other employees	0.248**	0.340***	0.139	0.160	-0.235	-0.118	-0.087	0.172
		(2.390)	(2.840)	(0.369)	(0.404)	(-0.557)	(-0.351)	(-0.136)	(0.892)
	Soft info 2 by the loan officer	0.005	0.075	0.041	0.036	0.037	0.092*	0.289***	0.216*
		(0.443)	(1.351)	(0.823)	(0.173)	(0.295)	(1.754)	(3.577)	(1.798)
	Soft info 2 by other employees	0.010	0.026**	0.151***	0.025*	0.155**	0.001	0.454***	0.104***
		(1.049)	(2.280)	(3.506)	(1.686)	(2.205)	(1.083)	(4.516)	(3.165)
Credit score decline	*Soft info 1 by the loan officer*	0.205*	0.012***	-0.079	-0.595	0.394	0.073	0.286	0.120
		(1.871)	(2.735)	(-0.405)	(-1.592)	(0.448)	(0.263)	(0.386)	(0.668)
	Soft info 1 by other employees	0.032	-0.018	0.343	0.116	0.757*	0.342	0.399	-0.135
		(0.751)	(-1.406)	(1.143)	(0.303)	(1.818)	(1.269)	(0.773)	(-0.787)
	Soft info 2 by the loan officer	0.059***	0.026	0.026	0.307***	0.140*	0.433**	0.013	0.166*
		(3.551)	(0.755)	(0.755)	(2.770)	(1.689)	(2.459)	(0.255)	(1.798)
	Soft info 2 by other employees	0.006	0.011	-0.040	0.047	-0.058	-0.005	0.020	0.250**
		(0.685)	(0.076)	(-0.316)	(0.633)	(-0.483)	(-0.151)	(0.359)	(1.980)

This table reports the analyses of whether our findings can be attributed to loan officers' soft information collection efforts rather than to the inaccurate interpretation of this information. We report the interaction terms of the soft information measures with the measures for loan officers' cognitive constraints (limited attention bias, task-specific human capital, peer perception bias and learning over the credit cycle), employing the same specifications as in Tables 3-6. Soft information measures are re-estimated separately based on information collected by the approving loan officer (*Soft information 1 by the loan officer* and *Soft information 2 by the loan officer*) and other employees (*Soft information 1 by other employees* and *Soft information 2 by other employees*) during a 45-day window prior to a loan's origination. Variables are defined in detail in Appendix C. In specifications (I) through (III), (VII) and (VIII), when *Charge off* and *Delinquency* are the dependent variables, the sample size is 23,985 (33,190) observations using measures of soft information collected by the loan officer (other employees). When *Bad customer* and *Credit score decline* are our dependent variables, the sample size is 9,004 and 14,477 (9,588 and 17,901) observations respectively when we use measures of soft information collected by the loan officer (other employees). In specifications (IV) and (V), when *Charge off* and *Delinquency* are the dependent variables, the sample size is 4,044 (6,607) observations using measures of soft information collected by the loan officer (other employees). When *Bad customer* and *Credit score decline* are our dependent variables, the sample size is 1,460 and 2,282 (1,825 and 3,156) observations respectively using measures of soft information collected by the loan officer (other employees). Last, in specification (VI), when *Charge off* and *Delinquency* are the dependent variables, the sample size is 19,466 (27,220) observations using measures of soft information collected by the loan officer (other employees). When *Bad customer* and *Credit score decline* are our dependent variables, the sample size is 7,363 and 11,494 (7,829 and 14,143) observations respectively when we use measures of soft information collected by the loan officer (other employees). 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 9

Hard information, cognitive constraints and ex-post lending outcomes

		Limited attention			**Task-specific human capital**		**Peer perception**		**Credit cycle**
		(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Dependent variables:	Interaction variables:	*Busy loan officer*	*Before weekends*	*Holidays*	*Non-bank background*	*Sales background*	*Male to male*	*Peer group*	*Lax credit standards*
Charge off	*Credit score*	-0.003	0.018	0.018	-0.004	-0.037**	-0.006	-0.000	-0.013
		(-1.370)	(0.912)	(1.098)	(-0.266)	(-1.993)	(-0.602)	(-0.012)	(-1.625)
	Debt-to-income ratio	0.005**	0.010	0.015	0.023*	0.009	0.020	-0.075	0.007
		(1.982)	(0.843)	(1.057)	(1.685)	(0.558)	(1.314)	(-1.083)	(0.664)
Delinquency	*Credit score*	0.002	0.060	0.022	-0.023	-0.101*	-0.036	-0.262*	0.023
		(0.272)	(1.119)	(0.561)	(-0.590)	(-1.774)	(-1.086)	(-1.766)	(1.023)
	Debt-to-income ratio	0.002	0.006	0.001	0.030	-0.047	0.000	-0.048	0.040
		(0.391)	(0.184)	(0.019)	(0.883)	(-1.106)	(0.006)	(-0.347)	(1.591)
Bad customer	*Credit score*	0.006	0.110	0.050	-0.114	-0.098	-0.114*	0.170	-0.130**
		(0.494)	(1.335)	(0.660)	(-1.538)	(-1.003)	(-1.718)	(0.772)	(-2.469)
	Debt-to-income ratio	0.009	0.146**	-0.002	-0.065	-0.093	0.055	0.345*	0.092**
		(0.977)	(2.429)	(-0.046)	(-0.976)	(-1.097)	(1.067)	(1.786)	(2.010)
Credit score decline	*Credit score*	-0.001	-0.050	0.049	-0.008	-0.046	-0.044	-0.181	-0.074**
		(-0.093)	(-0.771)	(0.900)	(-0.118)	(-0.519)	(-0.847)	(-1.042)	(-2.094)
	Debt-to-income ratio	0.005	0.024	-0.013	-0.051	0.054	0.018	0.036	0.075**
		(0.701)	(0.507)	(-0.318)	(-0.978)	(0.772)	(0.423)	(0.190)	(2.038)

This table reports the analyses of whether cognitive constraints affect how loan officers interpret hard (quantitative) information in the lending process. We report the interaction terms of the hard information measures with the measures of loan officers' cognitive constraints (limited attention bias, task-specific human capital, peer perception bias and learning over the credit cycle), employing the same specifications as in Tables 3-6. We use two measures of hard information: the natural logarithm of a borrower's credit score (*Credit score*) and the debt-to-income ratio (*Debt-to-income ratio*). The number of observations across specifications is the same as the one reported in Tables 3-6. 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.