Assessing Human Information Processing in Lending Decisions: A Machine Learning Approach

Miao Liu[1]

Carroll School of Management, Boston College

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Abstract

Effective financial reporting requires efficient information processing. This paper studies factors that determine efficient information processing. I exploit a unique small business lending setting where I am able to observe the entire codified demographic and accounting information set that loan officers use to make decisions. I decompose the loan officers' decisions into a part driven by codified hard information and a part driven by uncodified soft information. I show that a machine learning model substantially outperforms loan officers in processing hard information. Using the machine learning model as a benchmark, I find that limited attention and overreaction to salient accounting information largely explain the loan officers' weakness in processing hard information. However, the loan officers acquire more soft information after seeing salient accounting information, suggesting salience has a dual role: It creates bias in hard information processing, but facilitates attention allocation in new information acquisition.

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1. Introduction

Research has shown that financial reporting facilitates decision-making and affects a wide range of financial and real outcomes (Beyer et al. 2010; Dechow et al. 2010; Leuz and Wysocki 2016; Roychowdhury et al. 2019). The extent to which the objective of financial reporting is met, however, depends on how decision-makers process the information. One strand of research in economics and psychology highlights human weaknesses in processing information, due to cognitive constraints (Blankespoor et al. 2019b) and behavioral biases (Kahneman 2011). Another strand in accounting and finance, however, emphasizes humans' strong ability to discover new information (Goldstein and Yang 2017), especially soft information (Liberti and Petersen 2018). In this paper, I investigate what factors determine these seemingly contradictory strengths and weaknesses in information processing by loan officers in their lending decisions, using a machine learning model-based decision rule as a benchmark.

To examine the efficacy of this decision-making, I rely on more than 30,000 detailed loan contracts from a large Chinese small business lender during the period of 2011 to 2015. Loan officers in this setting observe hard information on borrowers' demographics and accounting reports and exercise discretion to acquire additional soft information by making phone calls before make lending decisions. While the loan officers might not process hard information efficiently, as predicted by theories of cognitive constraints and behavioral biases, their efforts to collect soft information by interacting directly with borrowers should improve their lending decisions, as demonstrated in other similar settings (e.g., Petersen and Rajan 1994, 1995). In addition, the officers determine when and how to acquire soft information after observing hard information, suggesting the two types of information may interact. I use this setting to study which factors impede efficient hard information processing and how these factors further affect soft information acquisition.

Three challenges emerge when assessing information processing efficiency. First, it is difficult to study how information users process information if the underlying information is unobservable, as is usually the case. Second, which information to collect is often a choice. Consequently, different people

might appear to process information differently not because they have varying abilities but because they have different information sets. Third, evaluating errors requires a benchmark. In other words, what is the "correct" way to process a given piece of information? While a benchmark can often be established in a laboratory (such as the correct answer to a test), one is usually missing in the real world.

I combine my unique setting with a novel research design to overcome these challenges. Two key features of the setting help address the first two challenges. First, the data allow observation of the loan officers' entire hard information set about a borrower, sidestepping the unobservability problem. Second, borrowers are randomly assigned to loan officers, meaning each officer has the same pool of borrowers on average. As a result, any systematic difference in lending decisions across officers stems from their differing abilities in processing information and not because they are endogenously matched with different types of borrowers, helping overcome the second challenge that the information set is usually an endogenous choice.

To address the third challenge, I use a machine learning model as a benchmark to assess human decisions. I split my data randomly into a training sample and a hold-out sample. I train a machine learning model on the training sample to predict a borrower's repayment and design a feasible lending decision rule by reallocating larger loans to borrowers who are more likely to repay, as predicted by the model. Next, using the hold-out sample, I show my first result that this model-based decision rule can boost the lender's profit by at least 38%, making it a valid benchmark for examining loan officers' limitations in processing hard information.

To make the machine learning model a benchmark, I must address the fact that, while it only uses codified hard information as an input, loan officers can acquire additional soft information, mainly by making phone calls to the borrower. I decompose officers' decisions into a part driven by codified hard information and a part driven by uncodified soft information. Specifically, I fit a separate machine learning model for each loan officer, this time to predict the officer's lending decisions based on hard information. Unlike the first model, which predicts borrower repayment, the purpose of this model is to

mimic how each loan officer processes hard information. Soft information is then captured by the residual, as it represents variation in officers' decisions that cannot be explained by hard information. To validate the residual as a measure of soft information, I show that it strongly predicts loan outcomes.

These results suggest that while loan officers struggle to analyze hard information compared to a machine learning algorithm, they have strengths in acquiring soft information. I next test which characteristics of borrower information explain loan officers' underperformance in processing hard information and whether these characteristics also affect their ability to acquire soft information. I rely on two streams of theory to guide my search.

The first emphasizes bounded rationality (Simon 1955) recently surveyed by Blankespoor et al. 2019b in the context of accounting and finance. Agents in these models confront costs in processing information and allocate attention within their cognitive constraints. This theory predicts that loan officers can process only a subset of all useful variables. Regressing the fitted values of the two machine learning models on borrower characteristics using OLS, I find that, while the first model, which predicts borrower risk, identifies 147 variables with strong predictive power about repayment, the second one, which mimics how each loan officer processes hard information, suggests that officers only use between 25 to 56 variables in their decisions. Moreover, these 25 to 56 variables explain close to 90% of the variation in officers' decisions in these linear regressions, suggesting officers process hard information in a linear fashion. In contrast, the 147 variables explain only 66% of the variation in the first model's prediction about borrower repayment, indicating machine learning's ability to incorporate nonlinear signals in the data that are systematically ignored by loan officers. These results are consistent with information processing being costly.

The second stream of theory emphasizes that, even within the set of variables used for decision-making, people make systematic probabilistic errors, often because they employ representativeness heuristics (Kahneman 2011). Bordalo et al. (2016) formalizes this concept in economics as probability judgments based on the most distinctive differences between groups, and shows

that representativeness can exaggerate perceived differences. This theory predicts that loan officers will approve loan sizes too small for borrowers with distinct characteristics representative of high risk as such characteristics catch officers' attention and exaggerate their perception of the risk. One such distinct characteristic of risky borrowers is negative salient information. Indeed, among borrowers who default, 28.1% have (negative) salient characteristics, defined as large negative realizations in accounting variables. The proportion is only 15.8% among borrowers who do not default. Using the machine learning model as a benchmark, I find that loan officers overreact to salient information and approve loan sizes too small to borrowers with salient information, in line with such information being representative of a risky borrower.

Having established that both bounded rationality and representativeness help explain loan officers' underperformance in processing hard information, I next test how they affect soft information acquisition. Although theories of representativeness do not directly model information acquisition, it is plausible that overreaction to salient hard information might impede soft information acquisition. Intuitively, interacting with borrowers with a biased perception can undermine officers' ability to extract unbiased soft information signals. Perhaps surprisingly, however, I find that officers acquire more soft information after seeing salient hard information. Why would salience impede hard information processing but facilitate soft-information acquisition? Theories of representativeness are silent on this question, but I next examine how combining bounded rationality with representativeness helps explain this puzzling result.

Theories of bounded rationality predict that acquiring new information is costly and thus that loan officers must allocate effort to such activity. I build a simple model to show that, faced with information acquisition costs, salience can guide this allocation. In this model, a loan officer tries to infer a borrower's type from a hard accounting signal but faces uncertainty about the precision of the signal (for example, does a jump in cash flow reflect business fundamentals or noise?).[2] The officer can incur a cost to acquire additional soft information on the precision of the accounting signal (for example, asking the borrower to

[2] This setup is built on a stream of accounting theory considering the impact of earnings disclosures when investors face uncertainty over the variance of cash flows (Beyer 2009; Heinle and Smith 2017) or the precision of the earnings disclosure (Hughes and Pae 2004; Kirschenheiter and Melumad 2002; Subramanyam 1996).

explain the jump in cash flow). I show that it is more efficient to incur the cost to acquire soft information when the accounting signal has a larger realization (i.e., is more salient). To see this, assume the signal is cash flow. The officer would have more incentive to call a borrower with a large jump in cash flow. This is because learning whether the jump is a precise or noisy signal tells the officer a lot about a borrower's type, while learning whether a report of no jump in cash flow is precise reveals much less about a second borrower. Therefore salience serves a dual role: it distorts loan officers' belief when processing hard information but facilitates their attention allocation in their acquisition of soft information.

This paper contributes to three strands of literature. First, it provides new insights into the literature on investors' information processing. I differentiate between bounded rationality theory and representativeness bias theory. Due to the difficulty in observing the decision-maker's information set, empirical studies under the bounded rationality framework have relied on various market outcomes as indirect evidence of information processing constraints (Blankespoor et al. 2019b).[3] In contrast, by observing loan officers' entire set of hard information, I provide direct evidence of bounded rationality that loan officers choose to process a small subset of all useful information. Relatedly, empirical studies under the representativeness bias framework provide sparse evidence outside of laboratories due to the challenge of lack of a rational benchmark in real world settings (Floyd and List 2016). Using machine learning model as such a benchmark, I add to this literature and provide evidence of representativeness in human information processing in a non-experimental setting.

Finally and more importantly, bounded rationality theory and behavioral bias theory are often studied and tested separately and considered as competing theories to explain the same market phenomenon (Blankespoor et al. 2019b; Banerjee et al. 2020). My finding on the dual role of salience bridges these two lines of research. While salience impedes hard information processing, as predicted by representativeness bias, it facilitates the allocation of attention, a costly resource as emphasized by bounded rationality. This

[3] These outcomes include investors' trading (Blankespoor et al. 2019a), consumer and manager's use of tax rates (Chetty et al. 2009; Graham et al. 2017), stock price responsiveness to disclosure (Hirshleifer et al. 2009, 2011; Dellavigna et al. 2009; Lawrence et al. 2018), and firms' disclosure choices in response to shocks to investors' information processing costs (Dehaan et al. 2015; Blankespoor 2019; Abramova et al. 2019).

new result indicates a unique interaction between behavioral bias and bounded rational reasoning and highlights a setting where combining both kinds of models can further advance our understanding of human information processing.

Second, my paper contributes to the literature on soft and hard information and their differing roles in loan contracts (Liberti and Petersen 2018). Since soft information is hard to quantify, researchers have relied on indirect measures at bank-branch or loan-officer levels.[4] This literature highlights the value of soft information as a substitute for hard information in mitigating information frictions in the credit market. Contrary to these studies, I design an approach to identify soft information embedded in officers' individual lending decisions at the loan level. This approach allows me to investigate within loan officers how they use certain features of hard information as cues to acquire additional soft information, making hard and soft information complements. A closely related study is the work of Campbell et al. (2019), which uses keywords in loan officers' internal reports to construct soft information at loan level and document that human limitations and biases impede soft information production. My paper complements Campbell et al. (2019) by focusing on how human limitations hamper hard information processing and how bias induced by salience can facilitate soft information production.

Lastly, my paper contributes to the nascent literature studying how advances in AI technology are transforming financial markets (e.g., Berg et al. 2020; Bartlett et al. 2019; Erel et al. 2019).[5] I add to this literature in two ways. First, while most researchers focus on demonstrating human underperformance, I go a step further by searching for factors explaining underperformance.[6] The power of the machine in my study does not lie in its ability to process alternative sources of data, such as digital footprints in Berg et

[4] These measures include geographical distance between lenders and borrowers (e.g., Petersen and Rajan, 1994, 2002; Granja et al. 2019), cultural distance between loan officers and borrowers (Fisman et al. 2017), or loan officer fixed effects (Bushman et al. 2019).

[5] Applications of AI to improve decision-making in other settings and industries include Hoffman et al. 2018, Kleinberg et al. 2018, Einav et al. 2018, and Mullainathan and Obermeyer 2019.

[6] This line of research has roots in older, foundational efforts within psychology to compare human predictions to statistical rules (e.g., Meehl 1954; Dawes 1971, 1979; Dawes et al. 1989; Libby 1975). There is a parallel research in accounting and finance that compares the performance of analyst forecasts on earnings to that from random walk time-series forecasts (e.g., Brown et al. 1987). This literature largely concluded that analysts' forecasts of annual earnings are superior to those from time-series models (Kothari, 2001), although more recent research shows that this conclusion does not generalize to small, young firms and long forecast horizons (Bradshaw et al. 2012).

al. (2020). Rather, loan officers and the machine have access to the same set of hard information. As such, my approach allows the machine to serve as a decision aid to inform humans of their potential limitations and biases. Second, I document that humans have strengths, relative to machines, in acquiring soft information and show that these strengths are facilitated by human bias. Costello et al. (2019), a related paper, finds in a randomized experiment that allowing humans to incorporate private information into a machine-based credit score improves loan outcomes. Using a different approach to recover private soft information, my paper also shows that soft information has value, consistent with Costello et al. (2019). My paper differs in that I focus on examining how cognitive constraints and behavioral factors affect hard information processing and soft information acquisition.

2. Setting

The data used to conduct the analyses in this paper come from a large Chinese lender with sales offices in 23 major cities spread across the country. The lender offers unsecured short-term cash loans to small businesses as well as personal loans. My sample contains all small business loans and runs through the lender's entire operating history from 2011 to 2015. As I will describe in detail in this section, the setting offers a unique opportunity to investigate human information processing because 1) I observe the entire set of codified information that loan officers observe, and 2) random assignment ensures that all loan officers with a sufficient number of observations face the same pool of borrowers. I restrict the sample to 28 officers who have approved at least 500 loan applicants. This restriction eliminates 8% of the sample. Due to random assignment, any loan officer level variation in contract terms and loan outcomes come from differences in loan officers' information processing, rather than differences in borrower characteristics.

2.1. The Lender

The lender receives an average of 32,000 loan applications and approves 14,000 loans per year, with an average loan size of around 55,000 Chinese yuan ($8,000). Most loans have a maturity term between

12 and 24 months. The lender diversifies risk by making small loans across regions and industries. None of the originated loans is sold or securitized. All borrowers face the same 24% to 25% effective annual interest rate.[7] Fixed interest rates are common in China's unsecured short-term small business credit market, and a common feature of this and other high-risk short-term lending markets is that credit demand is more responsive to the quantity margin than the price margin.[8] As the price of loans is fixed, loan officers' decisions are based solely on the quantity margin, namely loan size and maturity. Since maturity is typically determined by the management team based on the lender's funding liquidity condition — leaving little discretion to loan officers — I focus on loan size as the main decision variable.

The whole lending process, from the borrower's application to the final credit decision, typically takes one to two weeks. During the sample period, the lender has no algorithm to assign internal ratings to borrowers. As a result, lending decisions depend on how loan officers assess hard information and acquire soft information.[9] I describe loan officers' duties and incentives in the following section.

2.2. Loan Officers

There are on average 40 loan officers throughout the sample period. All loan officers work independently in the firm's headquarter and do not have any regional or industry specialization. Loan officers do not solicit loans. Borrowers' demographic information enters the lender's system once an application is completed. Field employees then visit borrowers' business sites to collect additional accounting information, such as account receivables/payables and bank statements. These employees are required to take a few pictures of the borrower, the business site, and inventories (if available). After information collection is completed, the system randomly assigns the borrower to a loan officer.[10]

[7] A 25% annualized interest rate is higher than the rate commercial banks charge for corporate loans backed by collaterals, but much lower than those in some other high-risk markets, such as the US payday loan market, which typically charges annualized rate of over 400% (Morse 2011).

[8] Loan contracts being sensitive on the quantity margin (loan size) but much less on the price margin (interest rate) is consistent with the credit rationing theory a la Stiglitz and Weiss (1981) and is confirmed by empirical findings in the US small business credit market (e.g. Petersen and Rajan 1994) and other high risk credit markets (e.g. Karlan and Zinman 2008).

[9] There are, however, certain rules that officers are required to follow. For example, the lender has a maximum lending amount of 500,000 yuan ($80,000). The lender only lends to borrowers whose age is between 20 and 60. Starting December 2012, the lender cannot lend to borrowers who cannot provide verified bank statement.

[10] In rare occasions, approximately 2% of the sample, a loan officer returns a randomly assigned borrower back to the pool. This happens when loan officers take days off before a decision is made or when they feel it is extremely difficult to make a decision.

Loan officers first make an accept/reject decision and, conditional on accepting, approve a loan size. The decisions are then randomly assigned to 12 credit managers for review. Credit managers can reject loans approved by loan officers, as happened in 20% of the sample. Credit managers also sometimes revise the approved loan size. These rejections and adjustments made by credit managers are generally based on the lender's funding constraint, not on concerns about an individual loan officer's ability. The correlation between loan officer approved loan size and the final loan size is higher than 0.9. Loan officers have no further interaction with the borrower once a decision is made. In particular, loan officers do not monitor loans or participate in collecting overdue debts.

In addition to a fixed salary, loan officers' bonuses and promotion prospects are linked to the overall revenues generated from their approved loans. Based on this compensation scheme, I assume that the objective of loan officers is to maximize the repayment of each loan. Due to random assignment, each loan officer receives a diversified pool of borrowers across regions and industries. As a result, officers do not need to manage their own portfolios to avoid large exposure to a certain region or industry. In addition, since less than 5% of borrowers return for a second loan, loan officers do not have the incentive to lend to low-quality borrowers to form relationships as in Rajan (1992). I drop all repeated borrowers.[11] Other than a loan size cap, the lender does not impose other constraints on loan officers that might conflict with profit maximization.[12]

Finally, since loan officers' compensation hinges on loan revenue, one may be concerned that loan officers might also aim at maximizing loan size subject to the size cap. To mitigate this concern, first note that loan officers take the borrower pool as given and do not prospect for loans as in Agarwal and Ben-David (2018). Second, as shown in section 4, I find that loan officers not only give loans too large to bad borrowers as identified by the machine learning model, they also give loans too small to good borrowers. The latter result further rules out that maximizing loan size explains loan officers'

All my results remain after dropping these cases.

[11] Since my sample period covers the entire operating history, it is clear that all borrowers in sample are first-time borrowers.

[12] For example, since all the borrowers are privately owned small enterprises without government connections, there is no political concern for doing business in this market.

underperformance. That said, I caution that I cannot conclude with certainty that maximizing individual loan repayment is a precise description of loan officers' objective.

2.3. Hard Information

Loan officers observe codified demographic and accounting information through the internal system. The former is mostly self-reported by borrowers. While some information, such as age and gender, is easy to verify, other information, such as months living at the current address, is not. The lender obtains borrowers' credit records from the central bank's credit system. These reports contain information on borrowers' credit history, such as number and types of loans, number of credit cards, and delinquencies. Accounting information is collected during field officers' visits to the borrowers' business sites. Overall, there are 70 hard information variables, all either submitted by borrowers or collected by field employees and made available to loan officers.[13] Table 1 reports a complete list of the collected variables.

2.4. Soft Information

In addition to codified hard information, loan officers can acquire uncodified soft information from two sources. First, they have access to pictures of the borrower, borrower's business site, and borrower's inventory. These pictures are taken by field employees and made available to loan officers through the lender's internal system. Since interpretations of pictures are ambiguous and vary across officers, I define them as soft information. Second, officers can call the borrower and the borrower's family members or coworkers.[14] Stein (2002) and Liberti and Petersen (2018) describe soft information as context-dependent information that cannot be verified and communicated to different parties without losing meaning. This definition corresponds well to the two sources of uncodified information in my setting.

Figure 1 summarizes the information structure and decision process. First, borrower i fills out a loan application with demographic information. The lender then sends field employees to collect accounting information and take pictures. Next, the system randomly assigns borrower i to one of the J officers. Finally, the officer being assigned (call her officer j) processes codified information X_i, determines how

[13] Many variables are categorical. There are overall 205 variables if all categorical variables are converted to dummies.
[14] Personal conversations with loan officers suggest that this happens in half of the sample on average, but varies significantly across loan officers.

much soft information s_i she would like to produce and makes a lending decision based on X_i and s_i.

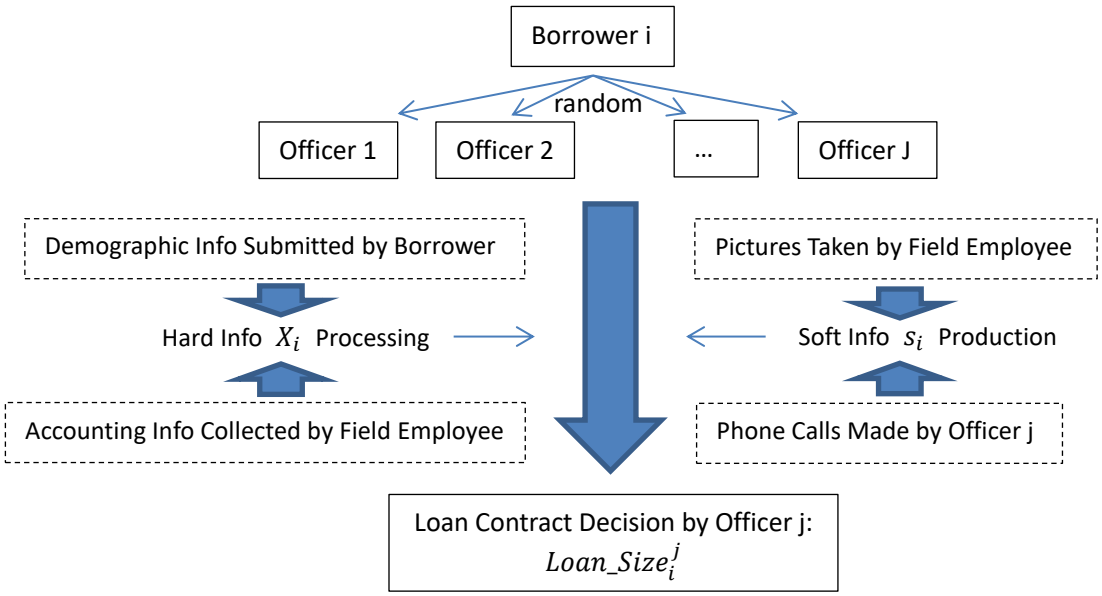

Figure 1: Information Structure and Decision Process

3. Conceptual Underpinnings and Research Design

The small business lending setting provides a suitable laboratory to study information processing by loan officers. In this section, I first connect this setting to the conceptual underpinnings in my research question. I then lay out a research design.

3.1. Conceptual Underpinning

3.1.1. Hard Information Processing

I differentiate between two categories of theories that explain the inefficiencies in loan officers' hard information processing. The first emphasizes bounded rationality, going back at least to the work of Herbert Simon (Simon 1955). These models focus on the limits of cognitive resources, such as attention, memory, or computation (Mullainathan 2002; Sims 2003; Gabaix 2014; Bordalo et al. 2019). Blankespoor et al. (2019b) surveys applications of this class of models in accounting and finance. Bounded rationality is apparent in my setting: Loan officers may not be able to attend to, process, or mentally represent the rich set of data available on borrowers and may instead resort to a simpler model of risk. I test two predictions from this class of models. First, if attention is costly and cognitive constraints bind, officers

can process only a subset of useful signals. Second, research has shown that humans have particular difficulty perceiving nonlinear relationships between variables. These relationships are usually simplified and represented mentally in a linear fashion (Stango and Zinman 2009).[15] For example, officers might recognize a borrower's education background and industry as individually important but have difficulty seeing how they might interact in determining risk if education is more relevant in certain industries than others. I thus test whether officers systematically fail to incorporate nonlinear signals in their decisions.

The second category of theory emphasizes that, even in the set of variables used for decision making, people make systematic probabilistic errors (Kahneman 2011; Benjamin 2019). An important class of model in this category studies representativeness heuristics and was first proposed in psychology by Kahneman and Tversky (1972) and Tversky and Kahneman (1974). Fischer and Verrecchia (1999; 2004) make early theoretical applications of representativeness heuristics in the accounting literature, focusing on trading and disclosure. Libby et al. (2002) and Bloomfield (2002) survey early experimental tests on such biases in accounting. Recently, Bordalo et al. (2016) formalizes this concept in economics as probability judgments based on the most distinctive differences between groups, and shows that representativeness heuristics can exaggerate perceived differences between groups.[16]

In my setting, the theory of representativeness predicts that loan officers approve loan sizes too small for borrower groups with characteristics representative of high risk, because such characteristics catch officers' attention and exaggerate their perception of the risks. One such distinctive characteristic that is both relevant and common in my setting is salient information, defined as large negative realizations in accounting variables (e.g., a large drop in cash flows). If loan officers consider such information as being representative of a "bad type" of borrower, they might overreact. Indeed, among borrowers who default, 28.1% have salient information, defined as having at least one accounting variable whose value falls into

[15] Wagenaar and Sagaria (1975) and Wagenaar and Timmers (1978, 1979) provide initial experimental evidence of this phenomenon.

[16] Bordalo et al. (2016) use this formalization to generate gender stereotypes. In recent years, this theoretical framework has been shown to explain a wide range of financial and economic outcomes, including consumer behavior (Bordalo et al. 2013b), corporate investment (Gennaioli et al. 2015), aggregate stock returns (Greenwood and Shleifer, 2014), cross-sectional stock returns (Bordalo et al. 2019), bank lending standards (Baron and Xiong 2017, Fahlenbrach et al. 2017), corporate bond returns (Greenwood and Hansen 2013), and credit cycles (Lopez-Salido et al. 2017; Bordalo et al. 2018). It also has been a leading framework to explain the various episodes of the global financial crisis and its aftermath (Gennaioli and Shleifer 2018).

5% in the left tail of the distribution of that variable across all borrowers. This proportion is only 15.8% among borrowers who do not default, making negative salient information a distinctive difference between good and bad borrowers. Based on this prediction, I test whether loan officers on average approve loan sizes that are too small to borrowers with negative salient information.[17]

A remark is in order for my definition of salience. The literature does not provide a uniform definition. Empirical papers often adopt a functional definition by assuming that something is more salient if it is more visible (e.g., Chetty et al. 2009). Theoretical research has established more rigorous definitions by stating that what is salient depends on what the decision-maker compares it to (e.g., Bordalo et al. 2012, 2013).[18] My definition that a borrower characteristic is more salient if it has a large realization fits well with both the functional definition in empirical research, because large realizations are rare and thus more noticeable, and the more rigorous theoretical definition, because large realizations of a characteristic have a greater distance from the average of that characteristic across all borrowers.

3.1.2. Soft Information Acquisition

Despite any inefficiency in hard information processing, loan officers should play a crucial role in collecting and processing qualitative and costly-to-verify soft information, as documented in other similar settings (e.g., Petersen and Rajan 1994, 1995; Agarwal and Hauswald 2010; Michels 2012; Cassar et al. 2015; Iyer et al. 2016; Campbell et al. 2019). For example, loan officers in my setting extract valuable signals by initiating and sustaining conversations with borrowers and it is difficult to train a computer to mimic humans' adaptability in conversations.[19] In addition, loan officers observe hard information before determining whether and how to acquire soft information, and certain features of hard information can

[17] Another borrower group potentially subject to representativeness bias consists of female borrowers as in the model of Bordalo et al. (2016). In appendix B, I test whether gender stereotypes explain loan officers' underperformance. It is important to note that, as discussed in Dobbie et al. (2019), my setting is not powerful enough to distinguish between gender bias due to representativeness and that is taste-based.

[18] Bordalo et al. (2013) define the salience of an attribute of a particular good to a consumer (e.g., the price of a particular bottle of wine) as the distance between its value and the average value of that attribute across all goods available to the consumer (e.g., the average price of all wine on the menu). Similarly, Bordalo et al. (2012) define the salience of a particular payoff of a lottery as the difference between its value and the average payoff yielded by all other available lotteries in that state.

[19] Hardening soft information plays a key role in the history of the credit scoring (Kraft 2015; Liberti and Petersen 2018). Although it is possible to ask loan officers to assign scores to borrowers based on conversations, and then feed scores to a model, we still need officers to acquire soft information before scores can be assigned. Moreover, such a process inevitably lose information as different people might interpret the same conversation differently, making scores hard to compare across officers.

trigger soft information acquisition. For example, when observing unusual patterns in cash flows, loan officers typically make calls and ask the borrower for an explanation. Consequently, factors that impede hard information processing might also affect soft information acquisition.

In settings with no friction, information acquisition is usually modeled under the rational expectation equilibrium framework in which investors learn about a fundamental (e.g., a borrower's type) by acquiring a signal of it (e.g., Verrecchia 1982; Diamond 1985). This framework imposes that investors' beliefs about the fundamental coincide with its true underlying distribution. If representativeness distorts loan officers' beliefs in my setting, such that their perception of a borrower's type differs from the borrower's true type, the acquired soft information might be polluted.[20] Intuitively, talking to a borrower but starting with an incorrect belief might make the conversation less effective. I thus test whether soft information acquisition is less efficient when the borrower has salient information.

3.2. Research Design

My research design has three components. First, assessing information processing by loan officers requires a benchmark. In section 3.2.1, I discuss the rationale for using machine learning as such a benchmark. Second, machine learning creates a useful benchmark for hard information processing, but not soft information acquisition. In section 3.2.2, I describe an approach to decompose officers' decisions into a part driven by hard information and a part driven by soft information. Third, an ideal comparison between humans and machines requires randomly assigning borrowers to each. Since all my data are generated by human decisions, I do not have a counterfactual about what a loan outcome would be if a different loan size were to be assigned by a machine. In section 3.2.3, I address this challenge by estimating a causal parameter between loan outcome and size and using this parameter to recover the counterfactual outcome.

3.2.1. Machine Learning as a Benchmark

[20] In mathematical terms, denote the true borrower type as $\theta \sim N(\bar{\theta}, \sigma)$. Under a rational expectation equilibrium, acquired soft information x is modeled as a signal that equals θ plus a noise term ε, $x = \theta + \varepsilon$, where ε has mean 0. Consequently, the signal x is an unbiased measure of θ. In contrast, if loan officers have a distorted belief about the borrower's type $\theta' \sim N(\bar{\theta}', \sigma)$ such that $\bar{\theta}' \neq \bar{\theta}$, the acquired soft information x' might become $x' = \theta' + \varepsilon$, which is a biased measure of the true type θ.

Suppose we observe the outcome of a decision made in the previous period:

$$Human\ Decision\ \ (Info_t) \rightarrow Outcome_{t+1}$$

How should we assess strengths and weaknesses of $\text{Human Decision}(\text{Info}_t)$? Defining decision error requires a benchmark. Such a benchmark is generally absent in the real world because the ideal, error-free decision is unobservable. One potential solution is to use the outcome ($Outcome_{t+1}$) as the benchmark. This approach has two limitations. First, it is usually impossible to know what Outcome_{t+1} would be if no error were to exist in $Human\ Decision\ \ (Info_t)$. As a result, we can only cross-sectionally estimate errors of worse decision-makers versus better ones. Second, any unpredictable shock between t and t+1 that changes $Outcome_{t+1}$ should not be used in assessing a decision at t. In my setting, this means that any unpredictable shock to a borrower's willingness and ability to repay should not be used to evaluate loan officers' decisions. But since shocks are often not observable and cannot be separated from $Outcome_{t+1}$, they would inevitably induce bias if I were to follow this approach.[21]

To avoid these difficulties, I instead use a machine learning model to predict a borrower's risk (e.g., expected repayment), using only information available at t, and treat this machine prediction as the benchmark. If the model makes considerably fewer decision errors than loan officers, this helps me avoid the challenge that the human error-free decision is unobservable. Since machine predictions are based only on information available when human decisions are made, it also avoids the look-ahead problem. Denote X_t as the set of machine-readable information. I train a machine learning model $M()$ that maps X_t into a machine predicted borrower riskiness and then further map this machine predicted riskiness into a loan contract. Call this loan contract $Machine\ Decision_t$:

$$Machine\ Decision_t = M(X_t) \tag{1}$$

It is important to ensure that the machine-based contract is feasible. In particular, does the lender have sufficient funding to implement this contract? Moreover, would the borrower accept this contract if it differed from the original one? To achieve feasibility, I follow a conservative approach with four steps.

[21] This point has been raised by Einav et al. (2018).

Step 1: For each month, sort borrowers by their machine predicted riskiness.[22]

Step 2: For the same month, sort the original human assigned contracts by loan size.

Step 3: Reallocate human-assigned loan sizes to borrowers according to the machine-predicted riskiness, where bigger loans are reallocated to borrowers with lower machine-predicted riskiness.

Step 4: If machine-based loan size exceeds the borrower's requested loan amount, I reset the machine-based loan size equal to the borrower's requested loan amount.

Figure 2 illustrates a hypothetical example with 3 borrowers (i=1, 2, 3). Suppose the model predicts that borrowers 1, 2, and 3 have small, medium, and large risk, respectively. And suppose loan officers give medium, small, and large loans to borrowers 1, 2, and 3, respectively. My machine-based decision rule would first reallocate the large loan to borrower 1, the medium loan to borrower 2, and the small loan to borrower 3, and then reset the reallocated loan size to the requested loan size if the latter is smaller.

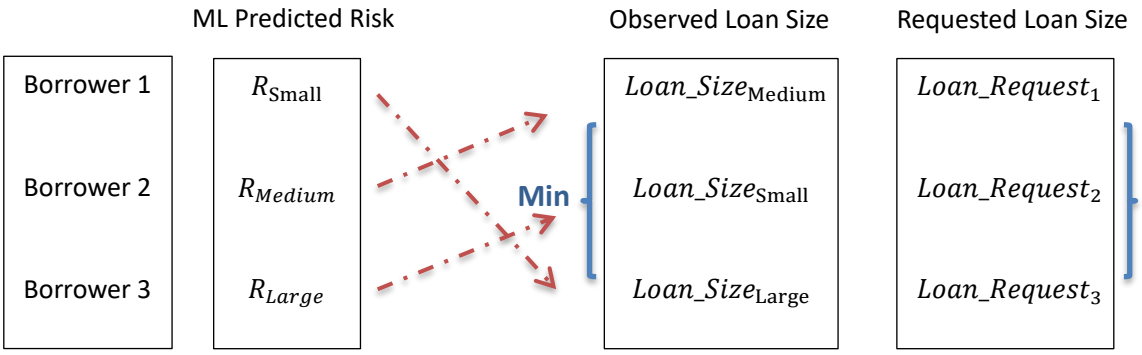

Figure 2: Generating machine-based Contracts

With Steps 1–3, I do not allow the machine to transfer funds across months as the lender might face time-varying funding liquidity shocks. Neither do I allow the model to optimize loan size distribution within a month. This step ensures that the strategy is feasible under the lender's credit supply constraint.

With respect to credit demand, there are two scenarios to consider. First, would a borrower accept the machine-based loan size $M(X_{i,t})$ if it were bigger than the original loan size? Second, would a borrower accept the machine-based loan size if it were smaller than the original loan size? Step 4 deals directly with

[22] I defer the details of how I train the machine learning model to Section 4.

the first scenario by not allowing the machine-based contract to surpass borrowers' credit requests. This is not an important constraint. Most borrowers request an amount far larger than the approved loan size, and only 0.17% request loans smaller than the approved size. Figure A1 in the appendix reports a histogram of excess demand, defined as the difference between requested and approved loan size, together with a histogram of actual approved loan size. The median excess demand is greater than the 93rd percentile of the approved loan size. This universal under-funding is consistent with credit rationing theory, such as by Stiglitz and Weiss (1981), and is a common feature in other highly risky credit markets (Adams et al. 2009).[23] Indeed, I only need to take Step 4 for less than 3% of the sample to implement $M(X_i)$.

Next, I consider the second scenario. 14% of approved loans are turned down by borrowers. I therefore test whether underfunding is a primary reason that some borrowers turn down an approved offer. The results are reported in Table A1. Controlling for credit demand (i.e., requested loan size), column (3) suggests that reducing approved loan size from the 75th percentile (60,000 yuan or $9,000) to the 25th percentile (27,000 yuan or $4,000) raises the probability of turning down an offered loan by 11.7%.[24] Since this effect is modest, I do not adjust for the likelihood of borrowers turning down a loan if the machine-based loan is smaller than the original loan. I revisit this assumption in the robustness checks.

Having established the rationale for using the machine learning model as the benchmark and a feasible implementation strategy, I must next take into account that loan officers have access to private, soft information not available to the machine in order to make an apples-to-apples comparison between human decisions and this benchmark. In the next section, I discuss a method that decomposes human decisions into variation driven by hard information X_i and variation driven by soft information s_i:

$$Human\ Decision_i = H(X_i) + s_i \tag{2}$$

3.2.2. Hard and Soft Information: a Decomposition

To perform decomposition (2), I must observe the entire hard information set X_i and know what

[23] While such gaps could be the result of a strategic game where borrowers request larger loans and anticipate underfunding, it is unlikely to explain all of the variation. Early repayment fees and immediate first month payment make the costs of excessive borrowing non-trivial. In addition, the average borrower may not be able to predict the loan officer's own lending preference.
[24] 11.7% = (60,000-27,000)*0.355/100,000

$H()$ looks like. My data satisfy the first requirement. To obtain $H()$, I search for the combination of X_t that best explains each loan officer's usage of hard information. This is not an inference problem, but rather a prediction problem suitable for machine learning (Mullainathan and Spiess 2017). Specifically, I allow different officers to have different $H()$ and train a machine learning model for each officer j to predict her decision, call it $H^j(X_{i,t})$. Unlike $M(X)$, whose purpose is to predict borrower risk, the purpose of $H^j(X_{i,t})$ is to mimic officer j's behavior in processing hard information $X_{i,t}$. Importantly, $H^j(X_{i,t})$ captures any limitation or bias that officer j might have in processing $X_{i,t}$. Finally, I recover soft information $s_{i,j,t}$ as the difference between officer j's actual decision and $H^j(X_{i,t})$:

$$s_{i,j,t} = Loan\_Size_{it}^{j} - H^j(X_{i,t}) \quad (3)$$

Note that (3) identifies variations in $s_{i,j,t}$ across loans but not its average effect in (2) as it is absorbed in the intercept of $H(X_i)$. One concern is that some variation in $Loan\_Size_{it}^{j}$ might be driven by human noise, such as mood and sentiment.[25] Such noise is pooled with soft information in $s_{i,j,t}$. To test whether there is a valid signal about borrower's risk in $s_{i,j,t}$, I show that soft information identified by (3) predicts loan performance.

In Figure 7, I compute the standard deviation of $s_{i,j,t}$ for each officer and plot it against two measures of officer performance—the average default rate and average profit rate, defined as (total repayment – loan size)/loan size. If $s_{i,j,t}$ captures a valid signal, officers better at acquiring soft information should have larger dispersion in $s_{i,j,t}$. Indeed, Figure 7 shows that officers with larger dispersion in $s_{i,j,t}$ have lower default rates and generate higher profits. Switching from officer-level to loan-level evidence, Table 2 shows that $s_{i,j,t}$ strongly predicts loan profit. For example, column (3) indicates that moving $s_{i,j,t}$ from 25% percentile (-0.67) to 75% percentile (0.56) is associated with 1.5% higher profit rate. These tests confirm that soft information identified by (3) captures a valid signal about

[25] Research suggests that mood generates noise in human information processing (Hirshleifer and Shumway 2003; Bushee and Friedman 2016; Dehaan et al. 2016; Cortes et al. 2016).

borrower risk.[26]

Figure 3 provides an overview of my methodological framework. I observe hard information set X_t and actual human-determined loan contracts $Loan\_Size_{it}^{j}$ (second box in the left column) directly from data. In section 3.2.1, I train a machine learning model $M(X_t)$ (first box in the right column) and obtain machine-based loan contracts (second box in the right column). In section 3.2.2, I decompose $Loan\_Size_{i,t}^{H}$ into $H(X_{i,t})$ and $s_{i,t}$ (first box in the left column). The final step is to compare the performance of $M(X_{i,t})$ and $H(X_{i,t})$. If $M(X_{i,t})$ considerably outperforms $H(X_{i,t})$, it can be used as a valid benchmark to study errors in $H(X_{i,t})$. Here, I face the lack of a counterfactual problem. While the performance of $H(X_{i,t}) + s_{i,t}$ is readily observable (third box in the left column), neither the performance of $H(X_{i,t})$ nor the performance of $M(X_{i,t})$ is observable.

That is, to the extent that a borrower's repayment behavior is a function of loan size, this behavior would differ if no soft information is used (i.e., $H^j(X_{i,t}) \neq H^j(X_{i,t}) + s_{i,j,t}$) or a different loan contract is assigned by the machine (i.e., $M(X_{it}) \neq H^j(X_{i,t}) + s_{i,j,t}$). In the next section, I describe a method to generate these unobservable counterfactuals.

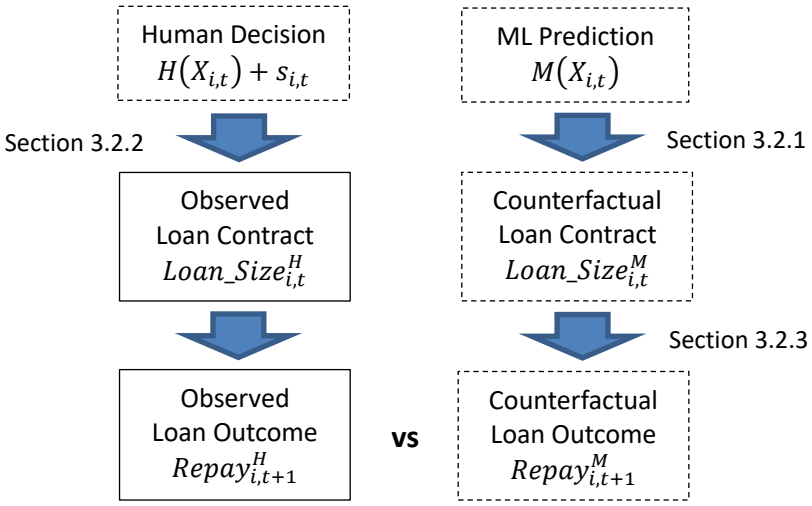

Figure 3: Overview of Methodological Framework

[26] This result does not suggest that loan officers have no constraints in producing soft information. Cognitive constraints and behavioral biases can affect soft information production as well, as shown by Campbell et al. (2019). This result indicates that on net the soft information is useful.

3.2.3. Generating Counterfactual

The goal of this section is to generate the following two unobserved counterfactuals.

1. The loan outcome if no soft information were used in loan officers' decisions: The counterfactual decision rule here is $H^j(X_{i,t})$. Call this counterfactual $Repay_{i,t+1}^{Hard}$.
2. The loan outcome if the loan size were determined by the machine: The counterfactual decision rule here is $M(X_{i,t})$. Call this counterfactual $Repay_{i,t+1}^{M}$.

Both counterfactuals require estimating changes in loan outcomes induced by changes in loan size while keeping everything else fixed. The first counterfactual requires estimating changes in loan outcome when loan size changes by $s_{i,j,t}$. The second counterfactual requires estimating changes in loan outcome when loan size changes by $M(X_{i,t}) - Loan\_Size_{it}^{H}$ Denote the parameter governing the (causal) relation between changes in loan size and changes in loan outcome by β:

$$\Delta Repay = \beta \Delta Loan\_Size \tag{4}$$

Once β is estimated, the two counterfactuals can be generated by

$$Repay_{i,t+1}^{Hard} = Repay_{i,j,t+1}^{H} + \beta s_{i,j,t} \tag{5}$$

$$Repay_{i,t+1}^{M} = Repay_{i,j,t+1}^{H} + \beta(M(X_{i,t}) - Loan\_Size_{i,j,t}^{H}) \tag{6}$$

I examine two measures of loan outcomes. The first is $Repay\_Ratio$, defined as the total repayment amount over the loan amount. Total repayment includes interest payments, management fees, early repayment fees, and principal repayment. My second measure of loan outcome $Repay\_Dollar$ is simply total dollar repayment (i.e., nominator of $Repay\_Ratio$). I estimate (4) for both measures and obtain β_{ratio} for $Repay\_Ratio$ and β_{dollar} for $Repay\_Dollar$.

Both measures are useful because their strengths lie in different aspects. Since $Repay\_Ratio$ is unit free, it better captures a borrower's type in that a higher quality borrower repays a higher proportion of obligations, irrespective of loan size. On the contrary, $Repay\_Dollar$ has a dollar unit. β_{dollar} thus confounds the effect of β_{ratio} with a mechanical effect that larger loans on average have more money paid back. Therefore the economic meaning of β_{dollar} is hard to interpret. β_{dollar}, however, has

practical value in that it maps dollar changes in loan size directly to dollar changes in profit, facilitating model performance comparison. For this reason, I focus on β_{ratio} when discussing the underlying economics and use β_{dollar} when computing profits for each counterfactual.

One point is worth discussing before diving into details about estimating βs. The four-step rule to implement $M(X_{i,t})$ specified in section 3.2.1 does not depend on how precisely β is estimated. This is because I merely reallocate credit across borrowers and any change in loan outcome induced by some borrower receiving a larger loan should be offset by some other borrower receiving a loan smaller by the same amount.[27] In equation (6), it implies that the term $\beta(M(X_{i,t}) - Loan\_Size_{i,j,t}^{H})$ disappears after aggregating across borrowers.[28] Consequently, the entire profit gain by implementing $M(X_{i,t})$ comes from reallocating larger (smaller) loans to borrowers who are more (less) likely to repay, as predicted by $M(X_{i,t})$. Nonetheless, it is useful to estimate β for other strategies to implement $M(X_{i,t})$.

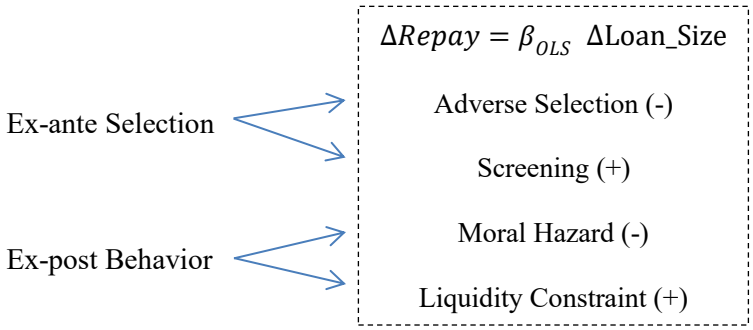

Figure 4: Economic Channels Captured by $\boldsymbol{\beta_{OLS}}$

It is helpful to first consider an OLS estimator for (4). In principle, there are four economic channels that connect loan size and repayment, summarized in Figure 4. First, adverse selection predicts a negative relation as the low-quality type has the incentive to self-select larger loans (Jaffee and Russell 1976). Second, screening serves as a counterforce where loan officers try to assign larger loans to the

[27] This is not true for cases that require Step 4. But since such cases represent less than 3% of the sample, and the adjustments made in Step 4 for these cases are typically small, these cases only have a marginal effect.
[28] The only assumption required for this logic is that the relation between loan size and profit is linear as specified in (4). Figure A2 in the appendix provides reduced-form supporting evidence that this relation is linear throughout the range of loan size.

high-quality type. Third, moral hazard predicts a negative relation since borrowers who receive larger loans have an incentive to take too much risk *ex post* (Stiglitz and Weiss, 1981) because they have less skin in the game. Finally, the theory of liquidity constrained entrepreneurs suggests a positive relation because more funding allows more positive NPV projects to be undertaken and improves repayment ability (Evans and Jovanovic, 1989; Holtz-Eakin et al. 1994).[29]

The OLS estimator pools all four effects. But for the purpose of generating the counterfactuals, my goal is to capture the two *ex post* effects of changing loan size and eliminate the two *ex ante* selection effects. This is because the counterfactuals should capture what happens to a borrower's repayment behavior if a different loan size is assigned to the same borrower. If loan officers' screening effort cannot eliminate adverse selection (i.e., the *ex ante* selection effect is negative), then β_{OLS} underestimates β.

I exploit random assignment and use officers' average loan size as an instrument for actual loan size to estimate the causal relation between loan size and repayment. Since all officers face the same pool of borrowers due to random assignment, their average loan size (i.e., "leniency") should be orthogonal to borrower characteristics and affect repayment only through officer-specific characteristics, such as their style or level of risk aversion. Instrumenting actual loan size with officer leniency, the IV estimator is not polluted by borrowers with different characteristics, observable or unobservable, systematically self-selecting into different loan contracts. Specifically, I run the following 2SLS regression.

$$\text{First Stage: } Loan\_Size^{H}_{i,j,t} = \gamma Leniency_j + controls_{i,j,t} \tag{7}$$

$$Second\ \ Stage\text{: } Repay^{H}_{i,j,t+1} = \beta_{IV}\widehat{Loan\_Size}^{H}_{i,j,t} + controls_{i,j,t}$$

$Leniency_j$ is defined as the average loan size by officer j. $Repay^{H}_{i,j,t+1}$ is the observed repayment ratio or dollar repayment. Before reporting the results of the 2SLS model, I first show evidence of random assignment in Table A2 in the appendix. If borrowers are randomly assigned, their characteristics should not systematically vary with officer characteristics. In Table A2, I regress each borrower characteristic on

[29] It is well understood in the empirical contract literature that β_{OLS} pools adverse selection and moral hazard effects in the consumer credit market and insurance market (Adam et al. 2009; Chiappori and Salanie 2000). I add a liquidity constraint effect since the borrowers are entrepreneurs and the amount of credit should affect repayment by changing future cash flows.

a full set of loan officer fixed effects and test if these officer fixed effects are jointly indifferent form zero. Indeed, p-values of the Likelihood Ratio tests confirm the officer fixed effects are jointly zero, suggesting borrower characteristics are evenly distributed across officers.

Table 3 reports the results of testing Equation (7). In both Panel A ($Repay\_Ratio$) and Panel B ($Repay\_Dollar$), the IV estimates are larger than the OLS estimates, consistent with the previous conjecture that the OLS estimator is biased downward due to adverse selection. Note that this result is unlikely to be driven by a weak IV, as the first stage coefficient is strong.[30]

One might worry that $Leniency_j$ captures an officer's ability to acquire soft information because officers good at this might have the confidence to approve larger loans. This is unlikely to violate the exclusion restriction condition if officers only use soft information to make decisions at the intensive margin (i.e., loan size) but not at the extensive margin (i.e., whether to grant the loan). The identification assumption is that leniency can only affect repayment through its impact on loan size. Since officers do not interact with borrowers after the contract is signed, they can only affect repayment through loan size. There is no other channel at the intensive margin through which officers with different soft information acquisition abilities can affect repayment differently other than loan size. However, if officers use soft information to make grant/reject decisions as well, β_{IV} might overestimate β. This is because if more lenient officers are better at using soft information to reject bad borrowers, they will face a better pool of borrowers at the intensive margin, leading to inflated β_{IV}. I therefore interpret β_{IV} as the upper bound and β_{OLS} as the lower bound of β. My results are robust to any value of β within this range.

All the pieces in Figure 3 are now complete and ready to take to data. Since I use machine learning tools extensively, I introduce the procedure to train these models in the next section.

[30] In Table 3, standard errors are clustered at loan officer level. Since I only include 28 officers with at least 500 observations in these regressions, I have a relatively small number of clusters with large number of observations in each cluster. Consequently, standard asymptotic results for consistent standard error estimators might not apply. Therefore, I also report block Bootstrapped standard errors in Table A3 in the appendix. Conley et al. (2018) show that another alternative, standard errors calculated using the Fama-MacBeth procedure, is preferable especially when the homogeneity condition across clusters might not hold. Although random assignment renders support that the homogeneity condition is plausible in my setting, I nonetheless reports results based on Fama-MacBeth procedure in Table A4. All three approaches to compute standard errors yield similar results and a strong first-stage of the 2SLS model.

4. Machine Learning Models

Machine learning is a powerful tool for prediction problems.[31] In my setting, it involves fitting a model $M(X)$ on borrower characteristics X to predict an outcome, such as loan repayment. In principle, one can fit $M(X)$ with OLS. OLS usually does not perform well in prediction problems, however, because it imposes a linear functional form on $M(X)$. For example, if the effect of borrower's education on repayment depends on the borrower's industry, OLS does not capture this interactive feature, unless one puts in an interaction between education and industry. Without strong theoretical reasons to guide which interactions to include in $M(X)$, it is computationally infeasible to put in all pairwise interactions in OLS because the number of variables would far exceed the number of observations.

As alternatives, many machine learning models do not impose *a priori* what to include but let the data "speak" to identify variables and interactions that have out-of-sample predictive power. This approach is problematic for inference but suitable for prediction problems (Mullainathan and Spiess 2017). Following prior research (Bertomeu et al. 2018; Kleinberg et al. 2018), I use gradient boosted decision trees (GBM) as my main model (Friedman 2001). I test whether my results are robust to other models in the robustness checks. To emphasize the importance of the ability of machine learning models to capture nonlinear and interactive signals in the data, I also report results that use OLS to fit $M(X)$.

The basic building block of GBM is a decision tree, in which the data are divided through a sequence of binary splits. Figure 5 illustrates an example. To predict loan repayment, the first split might be a borrower's education (whether the borrower has a college degree). In the next step, we can split each of the two nodes created by that first split by different variables, such as industry (whether the borrower is in retail). Based on these two characteristics, the sample of borrowers is divided into three categories. The predicted repayment of a new borrower in the hold-out sample who falls into category i is set to equal to

[31] Hastie et al. (2009) provide comprehensive treatment of machine learning models. Varian (2014), Mullainathan and Spiess (2017), and Athey and Imbens (2019) provide introductions to machine learning for economic research. Though my focus is on prediction, an emerging strand of literature studies how machine learning can aid causal inference (e.g. Belloni, et al. 2014; Athey and Imbens 2017). In the accounting literature, machine learning models have been used to predict misstatements and fraud (Bertomeu et al. 2018; Bao et al. 2020) and in textual analysis (Li 2010; Loughran and Mcdonald 2016; Brown et al. 2020).

the average repayment of borrowers in the training sample in category i. This sequential procedure allows for a high degree of interactivity in the data, a key advantage of machine learning models over OLS.

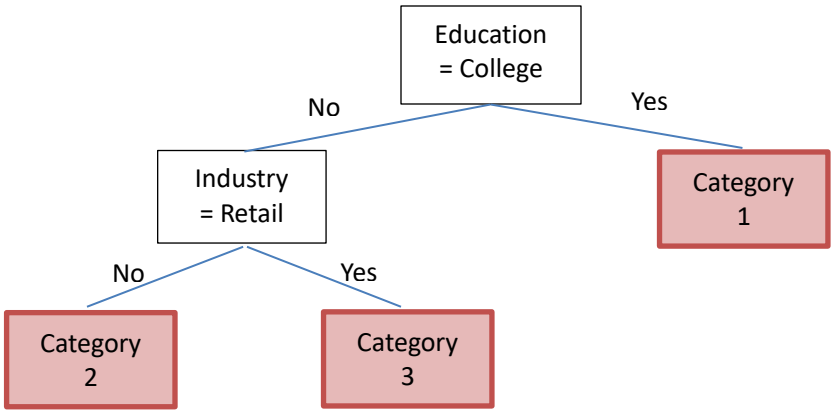

Figure 5: Regression Tree Example

I use machine learning for two purposes. Figure 6 demonstrates the analysis strategy for both purposes. First, I train a model $M(X)$ to predict a borrower's repayment. An accurate evaluation of $M(X)$ requires an out-of-sample test. I therefore divide the whole sample randomly into a training sample that $M(X)$ is fitted on and then use the remaining data, a hold-out sample, to evaluate $M(X)$ against $H(X)$. This is a standard procedure to prevent $M(X)$ from appearing to do well simply because it is being evaluated on data it has already seen. A concern with this strategy is that, at each period t, it allows $M(X)$ to see future data not available to loan officers. To rule out this as the main reason for $M(X)$'s outperformance, I use a second strategy that trains $M(X)$ month-by-month by feeding it with data up to month t and compare its performance with loan officers out-of-sample in month t+1. This alternative strategy still allows $M(X)$ to see historical data generated by all loan officers. Loan officers, despite having access, might not actively study their peers' data due to limited cognitive constraint. Therefore, I employ a third strategy that trains a separate $M(X)$ on each loan officer's data month-by-month and compare the average performance of these $M(X)$s with loan officers out-of-sample in month t+1.

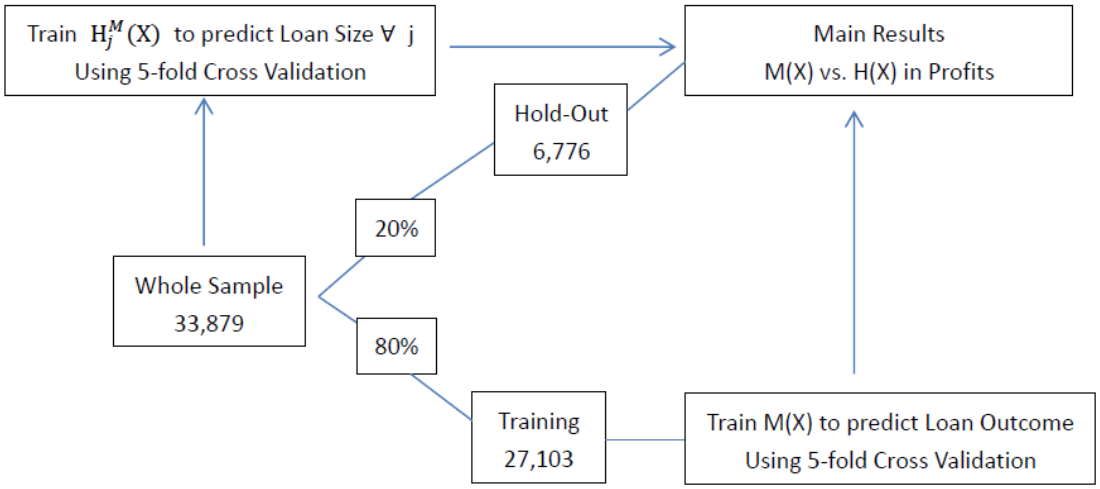

Figure 6: Data Partition, Model Training, and Model Evaluation

The second purpose of using machine learning is to predict loan officers' decisions. I train a separate model $H_j^M(X)$ for each officer j's decision, allowing different officers to have different models to process X. After obtaining $H_j^M(X)$, I compare the performance of $H_j^M(X)$ with that of $M(X)$ on the hold-out sample by evaluating their ability to generate profits (or equivalently, to rank borrowers correctly).

The performance of a GBM model depends on a few parameters.[32] Following standard practice (e.g., Kleinberg et al. 2018), I search for the optimal values of these parameters using fivefold cross-validation. I then estimate the final model using the full training sample. In robustness checks, I test whether my main results are robust to other machine learning models, including Random Forest, LASSO, and Neural Nets. I describe the details of the GBM and other models in the online appendix.

5. Results

In this section, I first test whether $M(X)$ outperforms loan officers. If so, $M(X)$ can be used as a valid benchmark to assess loan officers' weaknesses in processing hard information. Then I explore which

[32] These parameters include the depth of each tree, the total number of trees averaged together, and the weighting scheme for each subsequent tree.

factors best explain the different decisions and performance between $M(X)$ and loan officers' hard information processing. I next examine how these factors affect loan officers' soft information acquisition. Finally, I interpret these findings using a unifying theoretical framework.

5.1. Human Performance and Machine Performance

Table 4 compares human and machine performance using the loan profit aggregated over the entire hold-out sample as a performance measure.[33] I compare the performance of three types of decisions: A) the observed loan officer decision based on both hard and soft information $\mathrm{H}(\mathrm{X_t}) + \mathrm{S_t}$, B) the officer decision based on hard information only $\mathrm{H}(\mathrm{X_t})$, and C) the machine decision $\mathrm{M}(\mathrm{X_t})$.

The actually observed profit is 15.6%, as shown in column 2. The difference between columns 1 and 2 is due to the effect of soft information. This should be interpreted as a lower bound for the contribution of soft information for two reasons. First, some soft signal is captured by $H(X)$ if hard and soft information are correlated. This happens if, for example, officers ask specific questions when they observe certain patterns in hard information. Second, as discussed in Section 3.2.2, since soft information is identified as the residual term, its average effect is absorbed in the intercept and not identified. Moving to column 4, the GBM model generates a profit rate of 21.5%, a 38% increase from observed profit. To demonstrate the importance of the machine learning model's ability to capture nonlinear and interactive features of the data, I report in column 3 the performance of $M(X)$ trained with OLS. The 13.5% profit generated is worse than human performance and far worse than $M(X)$ trained with GBM. Table A5 in the appendix shows similar results with other machine learning models.

Another way to see the different performances between loan officers and the machine is to compare how they differ in ranking borrowers. While machine learning models (OLS and GBM) produce predicted profit as output, which can be used to infer their rankings of borrowers, it is not immediately clear how loan officers rank borrowers. Since officers have an incentive to assign larger loans to higher-quality borrowers, conditional on credit demand, I regress observed loan size on requested loan size and treat the

[33] Profit is defined as the repayment ratio (Total Repayment – Total Lending/Total Lending).

residual as a basis for officers' ranking through revealed preference. Indeed, this residual is small for a borrower who receives a small loan, despite having requested a large loan, indicating officers perceive this borrower as less profitable. I obtain the officers' ranking of borrowers by sorting this residual.

For each of the three models (human, OLS, and GBM), I first sort borrowers into deciles by their rankings. I then compute the average observed profit for each decile of borrowers. A model performs better if loans it predicts to be more profitable (and thus ranks higher) are indeed more profitable. Figure 8 plots average observed profits across predicted profit deciles as predicted by each model. A better performing model should have a more positive slope in the graph. Two messages emerge. First, while GBM has a clear positive slope in all deciles, OLS and human models are rather flat, suggesting their predicted profit does not match well with observed profit.[34] Second, compared to GBM, officers show similar ability to differentiate borrowers in middle deciles but have severe trouble toward the two tails. Table 5 reports the performance of the three models in the tails. It is clear that borrowers whom GBM identifies as bad (good) indeed have bad (good) observed profits. On the contrary, borrowers whom officers and OLS identify as bad generate the same level of profit as borrowers they identify as good. Figure A3 and Table A6 in the appendix show similar results with other machine learning models.[35]

The machine learning model might outperform because it does not have human limitations or because it has access to more data. To rule out the latter as the main explanation, I train a model month-by-month by feeding it with data up to month t and compare its performance with loan officers in month t+1. This procedure does not allow the machine to see future data. Figure 9A reports the results. The model starts to show its superiority in the sixth month, and its advantage increases over time. Since most loan officers work more than six months, this result suggests that the amount of data is not the most important factor

[34] Flat curve does not mean loan officers (or OLS) give out loans randomly (or have zero predication ability). If loan officers (or OLS) have zero screening ability and give out loans randomly, their curves should be downward sloping, due to adverse selection. An easy way to see this is through the standard asset substitution argument of Jensen and Meckling (1976). Suppose there are two borrowers with the same expected future cash flows but different levels of risk. The first borrower's future cash flow is 0.5 for sure. The second borrower has a future cash flow of 0 or 1, each with a probability of 0.5. Borrower 2 is riskier and thus a worse type from a lender's perspective. Borrower 1 will not accept any loan obligation larger than 0.5. In contrast, borrower 2 will accept loan obligation up to 1 when there is limited liability to protect the downside. Therefore adverse selection suggests that worse type borrowers select bigger loans, leading to a downward sloping curve if loans are handed out randomly.

[35] The result that loan officers rank good borrowers (as identified by the machine learning model) too low and approve loans too small to these borrowers suggests that maximizing loan sizes does not explain their underperformance.

explaining the performance gap.[36] In Figure 9B (green curve), I impose a further restriction on the machine by training it on each officer's data separately up to month t and compare the average performance of these models with loan officers in month t+1. This procedure not only forbids the machine to see future data, but it also disallows the machine to see data from other officers.[37] Figure 9B shows that the machine still outperforms with this further restriction. As yet another piece of supporting evidence, I will show in the next section that officers' bias does not disappear with experience.

To sum up, I have shown strong evidence that the machine learning model substantially outperforms loan officers, making it a valid benchmark to assess weaknesses in human decisions. The substantial gap in performance suggests that loan officers mis-rank a considerable number of borrowers when compared to the machine. Figure 10 plots the distribution of the mis-ranking. Bar X represents the percentage of borrowers that officers rank X deciles away from the machine's ranking. Officers rank 74% of borrowers more than one decile away and 22% of borrowers more than five deciles away from machine's ranking.

5.2. Assessing Hard Information Processing

In this section, I first examine whether cognitive constraint helps explain the human underperformance, as predicted by bounded rationality theories. I examine whether loan officers can only process a subset of useful variables. To show this, I regress $M(X)$ and each $\mathrm{H}_j^M(\mathrm{X})$ on the entire set of X using an OLS forward stepwise selection procedure. This procedure begins with an empty model and adds in variables in X one by one. In each step, a variable that has the lowest p-value is added. The procedure stops if no variable left has a p-value smaller than 5% if added. Figure 11 reports the results. Among a total of 205 codified variables, $M(X)$ (performer 0 on the vertical axis) finds 147 variables useful to predict loan outcomes. In contrast, officers use only 25 to 56 of these variables in their decisions. I next test whether officers systematically fail to incorporate nonlinear signals in their lending decisions. I compare the R-squared of the stepwise OLS regressions in Figure 11 and report the results in Figure 12.

[36] Figure A4 in the appendix shows that this result generalizes to other machine learning models.

[37] Conversations with loan officers suggest that a portion of them look at their peers' data. In addition, all loan officers have gained working experience in the small business and consumer lending market before they take the loan officer position. Therefore, this procedure ensures that the machine has a strictly smaller set of data than the loan officers.

The 147 variables that $M(X)$ uses explain 66% of the variation in its predictions, the much smaller sets of variables that loan officers use explain a much larger portion of the variation in their decisions, ranging from 83% to 92%. This finding suggests that, while loan officers process information in a linear fashion, the machine learning model captures a remarkable nonlinear and interactive feature of the data that contains useful signals of borrowers' risk.

Having established that cognitive constraint impedes hard information processing, I move on to test whether loan officers systematically make probabilistic errors, as predicted by theories of representativeness heuristics. In particular, I test whether salient information explain loan officers' mis-ranking of borrowers in the following regression.

$$Mistranking_{ijt}^{K} = \beta Salience_{ijt} + \varepsilon_{it}$$

$Mistranking_{ijt}^{K}$ is a 0-1 indicator variable equal to 1 if officer j ranks borrower i more than K deciles away from machine's ranking. I consider K=1 and K=5. $Salience$ is an indicator equal to 1 if the borrower has at least one accounting variable whose value falls into 5% in the left tail of the distribution of that variable across all borrowers. Table 6 (for K=1) and Table 7 (for K=5) summarize the results.

Column (2) in Table 6 suggests that loan officers are 28% more likely to mis-rank when they observe salient information in borrowers' hard information. Table 7 changes the outcome variable from K=1 to K=5 (i.e., a borrower is ranked by loan officers at least five deciles away from her machine ranking). All results are similar but more pronounced.[38] Consistent with theories of representativeness, loan offices tend to rank borrowers with salient information too low comparing to the machine.[39]

Finally, I examine whether these biases disappear with experience. Loan officers in my sample have a large dispersion of working experience at the lender, ranging from having processed 1,089 to 7,531 loan applications, with a median of 3,793 applications.[40] In Table 8, I split the sample into loans that are

[38] Table A7 and A8 in the appendix provide further supporting evidence by changing the dependent variable from absolute mis-ranking to directional mis-ranking.
[39] Table A9-A11 in the appendix report that the findings in Table 6 are robust to using other machine learning models as benchmarks, including Random Forest (Table A9), LASSO (Table A10), and Neural Nets (Table A11). Results in Table 7 also generalize to these other machine learning models (untabulated).
[40] These numbers include rejected loan applications.

processed by officers with above and below median experience (i.e., 3,793 applications) and test whether experience affects biases. If anything, the results suggest that experience worsens biases. Why this is the case is outside the scope of this paper and is left for future research. But at the minimum, it provides strong evidence that having access to less data does not explain loan officers' underperformance.

5.3. Assessing Soft Information Acquisition

The results in the previous section suggest that salience impedes hard information processing, as predicted by the theory of representativeness heuristics. Next, I study how salience affects officers' ability to acquire new soft information, a task where human strength may lie.

In Table 9, I split the sample into a subsample with borrowers who have salient information and a subsample without. A different pattern emerges. In Panel A, soft information produced on the salient subsample has stronger predictive power on loan repayment, as shown by both the magnitude of the coefficient and the R-squared. To provide further evidence, Panel B shows that the standard deviation of soft information, $s_{i,j,t}$, is 40% larger for the salient subsample. Therefore, while Panel A indicates that each unit of $s_{i,j,t}$ contains a greater signal of a borrower's risk for the salient subsample, loan officers also produce greater amount of soft information for the salient subsample as measured by the dispersion of $s_{i,j,t}$. In addition, officers spend 13% more time processing borrowers with salient information.[41]

Why would salience impede hard information processing but facilitate soft information acquisition? Existing theories are silent on this issue. In the next section, I present a simple model to explain this result.

5.4. Interpretation

In this model, a loan officer tries to infer a borrower's type $\theta \sim N(0,1)$ from a hard accounting signal X. X measures θ up to a random noise, $\varepsilon \sim N(0, \sigma_\varepsilon^2)$:

$$X = \theta + \varepsilon$$

[41] Table A12-A13 in the appendix report results when salience is defined as extreme positive accounting variable realizations. They show that 1) loan officers also overreact to salient positive news, but less so comparing to salient negative news, and 2) salient positive news do not trigger soft information acquisition.

The loan officer faces uncertainty in the accounting signal's precision σ_ε^2. For example, cash flow is an accounting signal for θ. But without knowing the borrower's payment policy with her customers, the officer does not know for sure how noisy cash flow is as a signal. Therefore σ_ε^2 is a random variable, rather than a known constant, to the officer. I model this in a simple way by assuming σ_ε^2 to be binomial:

$$\sigma_\varepsilon^2 = \begin{cases} \text{H} & \text{with probability } 1/2 \\ \text{L} & \text{with probability } 1/2 \end{cases}$$

This setup is similar to accounting theories considering the impact of earnings disclosures when investors face uncertainty over the variance of cash flows (Beyer 2009; Heinle and Smith 2017) or the precision of earnings disclosures (Hughes and Pae 2004; Kirschenheiter and Melumad 2002; Subramanyam 1996). I depart from this literature by studying how uncertainty in signal precision σ_ε^2 affects an information user's incentive to acquire another signal on σ_ε^2. In particular, I assume that the officer has an option to acquire additional soft information by incurring a cost C. I model this soft information as a signal on σ_ε^2. For example, the loan officer can call the borrower and ask directly about her customer payment policy. To make the model simple and similar to that of Grossman and Stiglitz (1980), I assume the officer can completely resolve the uncertainty if she acquires additional soft information. That is, by incurring a cost C, the loan officer learns whether σ_ε^2 is H or L.

I assume that the loan officer has a standard quadratic loss function and thus has the goal to learn the mean of θ, conditional on her information set. Denote the lowercase x as the realization of the accounting signal X. I provide a proof of the following proposition that the loan officer chooses to acquire additional soft information if and only if the magnitude of x is large enough.

Proposition 1: The loan officer chooses to incur cost C to acquire additional soft information if and only if

$$x^2 > C/Var(\tfrac{1}{1+\sigma_\varepsilon^2}). \tag{8}$$

Proof: In the appendix

$\frac{1}{1+\sigma_\varepsilon^2}$ is the precision of the accounting signal, relative to the variance of the fundamental (which equals 1). The right-hand side of condition (8) states that the officer has a greater incentive to acquire soft

information when the cost of doing so is low and when the variance of the precision of the accounting signal is high. The reason for the latter is that resolving uncertainty is more valuable when the uncertainty is high. The left-hand side of (8) highlights the key takeaway. It says that the officer has more incentive to acquire soft information if the accounting signal is more salient, as measured by the magnitude of realization x. The intuition, building on the previous example, is that learning a borrower's customer payment policy has more value when the borrower has bigger jumps in her cash flows. Therefore salience serves as an attention allocation device that helps the officer decide when and where to pay costly attention.

This simple model shows that salience has a dual role: It distorts belief but at the same time helps attention allocation. Two important implications follow. First, the dual role of salience bridges the theory of bounded rationality and the theory of representativeness heuristics. While salience impedes hard information processing, as predicted by representativeness, it facilitates attention allocation, a costly resource, as emphasized by bounded rationality. This result highlights the value of combining the two categories of theories to understand human decision-making. Second, hiding salient information might improve humans' ability to process hard information but with the cost of losing an attention allocation device. This trade-off echoes a fundamental principle in economics. When there are multiple frictions (e.g., cognitive constraint and behavioral bias), it cannot be presumed that removing one will necessarily improve overall efficiency because other frictions might become more severe.

6. Discussion and Conclusion

Accounting information facilitates decision-making to the extent that it is properly processed by investors. Which factors determine information processing efficiency is not well understood (Blankespoor et al. 2019b). In this paper, I investigate such factors by leveraging a unique lending setting where the entire hard information set used by loan officers is observable. I show that a machine learning model substantially outperforms loan officers in processing hard information. Using the machine learning model

as a benchmark, I find that limited attention and overreaction to salient information largely explain loan officers' weakness in processing hard information. However, officers acquire more soft information after seeing salient hard information, suggesting salience has a dual role: It creates bias in hard information processing, but facilitates attention allocation in soft information acquisition.

My finding on the attention allocation role of salience may generalize from soft information acquisition by loan officers in my setting to acquisition of any type of information by investors in other markets. Research highlights the key role of information acquisition to mitigate frictions in the capital market (Goldstein and Yang 2017; Blankespoor et al. 2019b) and the credit market (Minnis 2011; Berger et al. 2017; Breuer et al. 2017; Carrizosa and Ryan 2017; Ertan et al. 2017; Lisowsky et al. 2017; Minnis and Sutherland 2017; Sutherland 2018; Darmouni and Sutherland 2019). In such settings, although salience can induce overreaction and inefficiency in information processing, it might still be a desirable feature of disclosure as it facilitates attention allocation and increases new information discovery. I leave such a trade-off between the quality of information processing and the total amount of information discovered in other markets for future research.

My methods to 1) decompose human decisions into hard information processing and soft information discovery and 2) evaluate human ranking using machine ranking as a benchmark are applicable to settings without randomization. Generating unobservable counterfactuals (such as loan profit under a machine decision), however, requires random assignment. Randomization is not uncommon in other high-risk markets for small short-term loans (for example, the UK lender in Dobbie et al. 2019 and Liberman et al. 2019, and the call-center loans of the US credit union in Campbell et al. 2019). In addition, this approach can be applied to two other types of settings. The first is laboratory and field experiments, where humans (e.g., auditors) are randomly matched with objects (Duflo et al. 2013, 2018; Cole et al. 2015; see Floyd and List 2016 for a survey). The second is settings with an exogenously determined rotation policy, (for example, routinely reassigning loan officers to different borrowers as in Hertzberg et al. 2010 and Fisman et al. 2017). In these settings, my approach for generating counterfactual outcomes is readily applicable.

Another area warrants future research is how to combine the strengths of humans and the machine. As an initial step in this direction, in appendix D, I develop such a procedure. The key step is to train the machine learning algorithm on a subsample of data generated by the loan officers most skilled at acquiring soft information. The machine then puts more weight on hard variables that have higher correlations with useful soft signals and consequently captures a portion of the soft signals. I show that this procedure results in better decisions than humans or the machine working alone, suggesting a means of combining humans and machines in settings where both hard and soft information matter.

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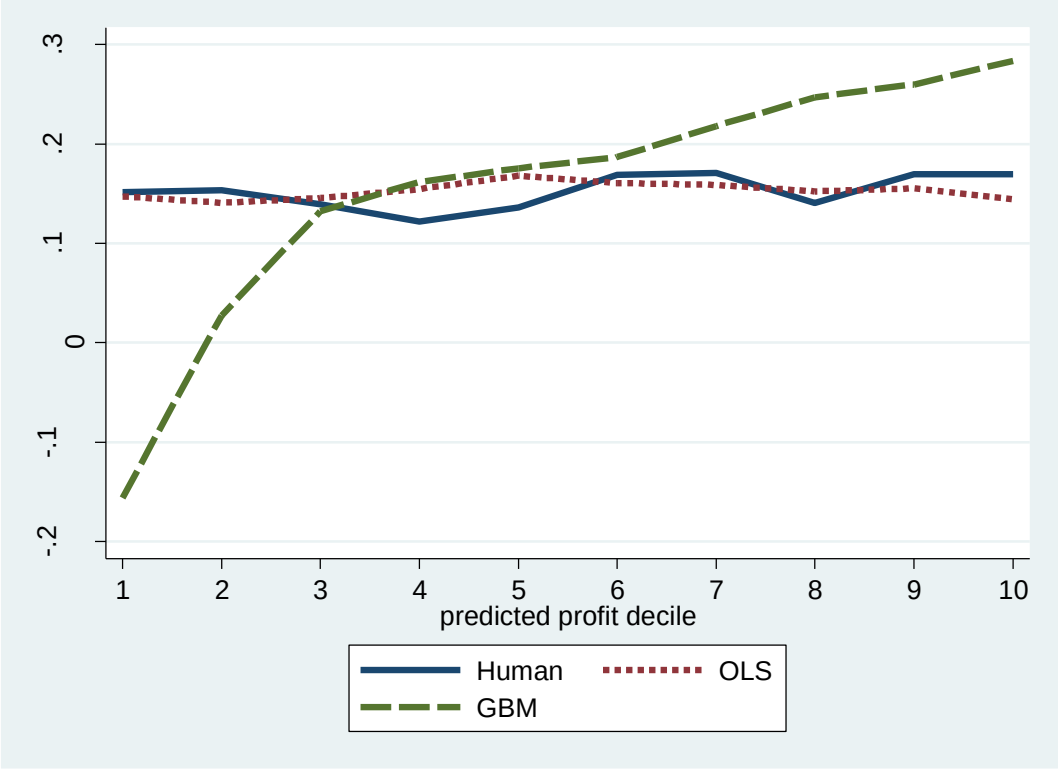
Figure 7

The Relation between Soft Information and Loan Performance (Officer Level)

Note: The figure presents the relation between an officer-level measure of soft information acquisition and loan outcome. The vertical axis measures average profit (red) or average default rate (yellow) for each loan officer. Profit is defined as (total repayment – loan size)/loan size. Default is an indicator variable that equals one if a borrower fails to fully repay all her loan obligation. The horizontal axis measures each loan officer's soft information acquisition ability, defined as the standard deviation of loan-level soft information, s_{ijt}, for each loan officer.

Figure 8

Observed Profit across Predicted Profit Deciles

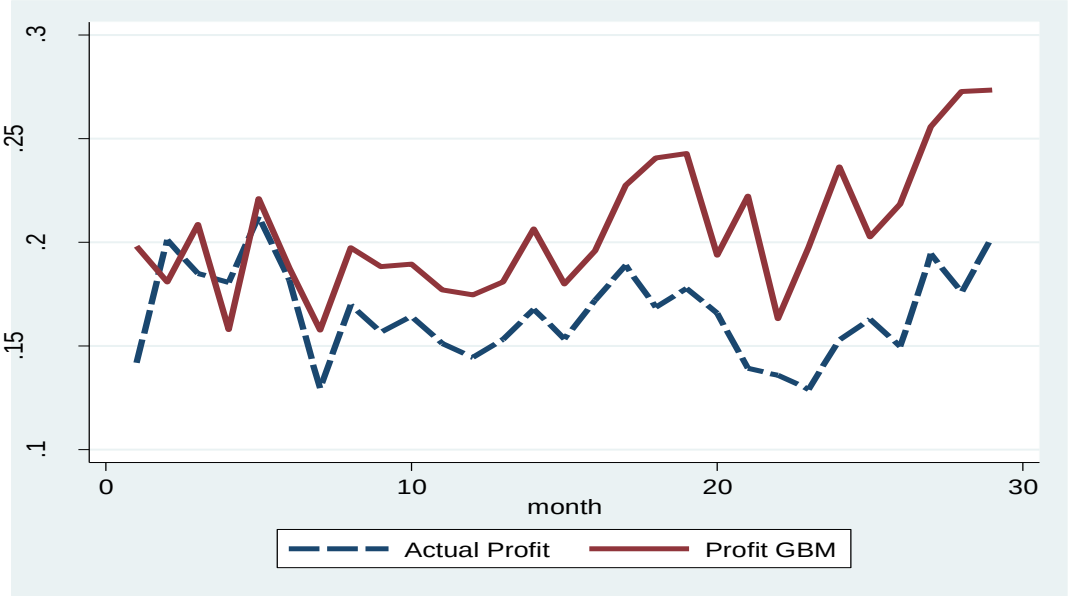


Note: The figure presents the relation between the average observed profit of loans in each predicted profit decile as predicted by each model (human, OLS, and GBM). A model performs better if loans it predicts to be more profitable (and thus ranks higher) are indeed more profitable, indicating the model ranks borrowers closer to borrowers' true ranking. Therefore, a better performing model should have a more positive slope in the graph. To obtain the GBM (OLS) curve, I first predict a borrower's loan repayment (i.e., profit) using the $M(X)$ trained by GBM (OLS). Next, for each month, I sort all borrowers in the hold-out sample into deciles by their GBM (OLS) predicted profit and then pool borrowers in the same decile across months together. Finally, for each decile, I compute its average observed profit. The GBM (OLS) curve tracks average observed profit for each predicted profit decile as predicted by GBM (OLS). To obtain the Human curve, I first regress observed loan size on the requested loan amount and keep the residual. Next, for each month, I sort all borrowers in the hold-out-sample into deciles by this residual and then pool borrowers in the same decile across months together. Finally, for each decile, I compute its average observed profit. The observed profit rate is defined as (total repayment – loan size)/loan size.

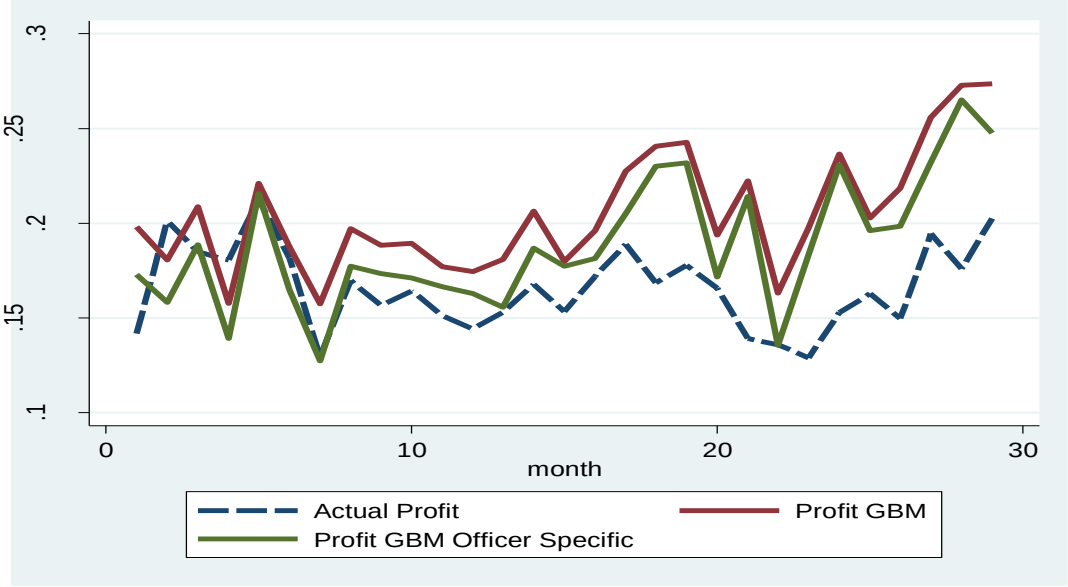
Figure 9

Monthly Performance Comparison between Machine Learning and Loan Officers

(A)



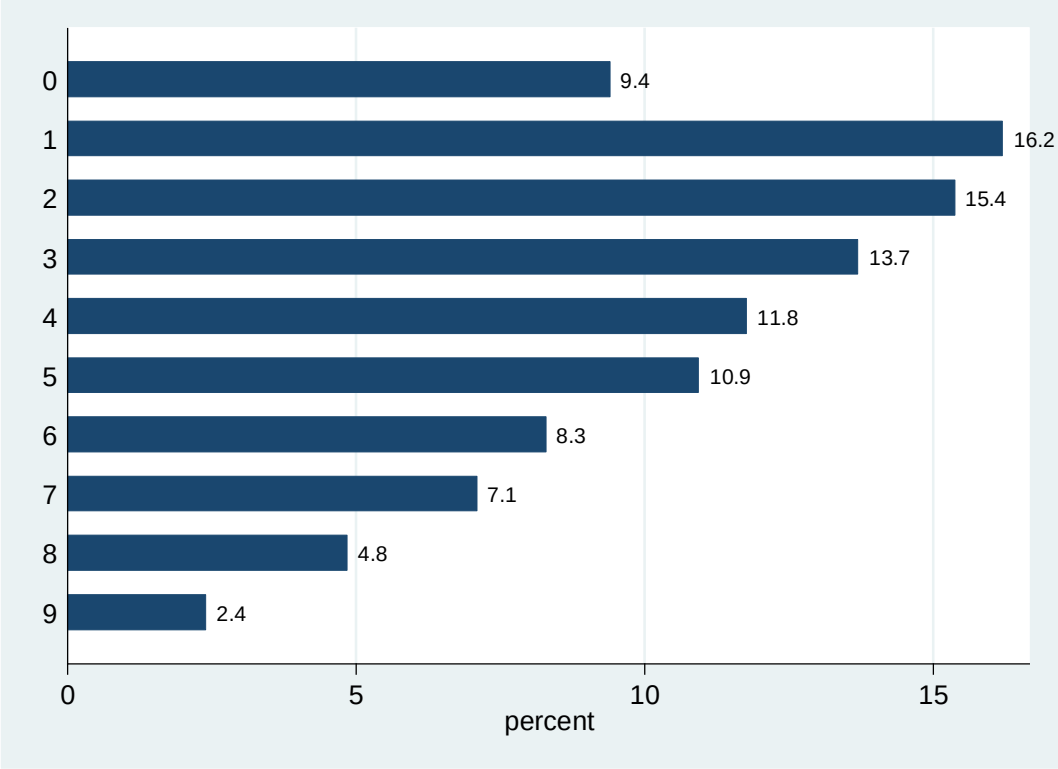
(B)



Note: These figures compare de-trended loan officers' performance with the machine learning model (GBM)'s performance month by month. The dashed curve is the observed monthly profit of loans, defined as (total repayment – loan size)/loan size. The solid red curve is the out-of-sample monthly profit of the machine learning model (GBM) in month t trained with data from all loan officers up to month t-1. The solid green curve is the average of out-of-sample monthly profit of the machine learning models in month t trained on each officer's data up to month t-1 separately.

Figure 10

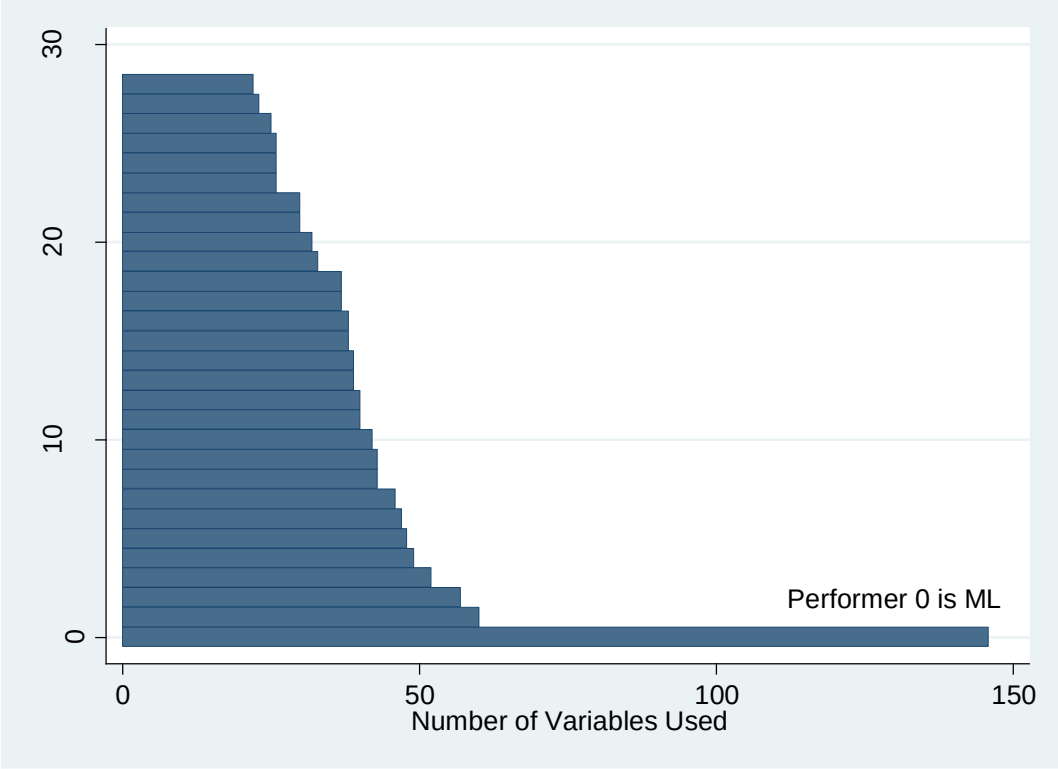
Distribution of Human and Machine Disagreement



Note: This figure presents the distribution of disagreement between loan officers and the machine learning model in their ranking of borrowers in the hold-out sample. Bar X represents the percentage of borrowers that loan officers rank X deciles away from the machine learning model's ranking. To obtain the decile ranking of borrowers by loan officers, I first regress observed loan size on the requested loan amount and keep the residual. Next, for each month, I sort all borrowers in the hold-out sample into deciles by this residual and then pool borrowers in the same decile across months together. To obtain the decile ranking of borrowers by the machine learning model, I first predict a borrower's loan repayment using the $M(X)$ trained by GBM. Next, for each month, I sort all borrowers in the hold-out sample into deciles by their GBM predicted repayment and then pool borrowers in the same decile across months together.

Figure 11

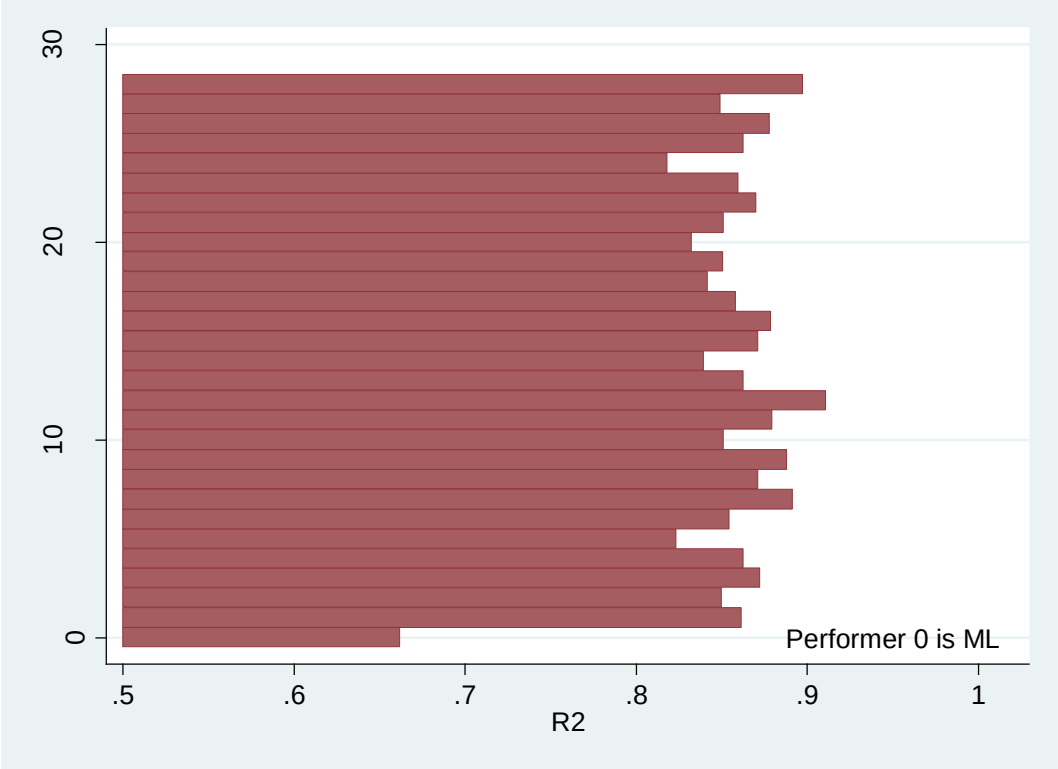
Number of Variables Used by the Machine Learning Model and Each Loan Officer



Note: This figure presents whether the machine learning model uses far more variables to predict loan outcomes than each loan officer uses in her decision. I regress the fitted values of $M(X)$ and each $H_j^M(X)$ on the entire set of borrower characteristics X using an OLS forward stepwise selection procedure. This procedure begins with an empty model and adds in variables in X one by one. In each step, a variable that has the lowest p-value is added. The procedure stops if no variable left has a p-value smaller than 5% if added. Among a total of 205 borrower characteristics, the machine learning model (performer 0 on the vertical axis) finds 147 useful to predict loan outcomes. In contrast, officers use 22 to 56 of these variables in their decisions, suggesting that cognitive constraint is an important factor explaining their underperformance.

Figure 12

The Proportion of Variation (R^2) Explained by Linear Projection



Note: This figure presents if loan officers systematically fail to incorporate nonlinear signals in their lending decisions. It reports the R-squared of the stepwise OLS regressions in Figure 11. The 147 variables that the machine learning model (Performer 0 on the vertical axis) uses explain 66% of the variation in its predictions. The much smaller sets of variables that loan officers use in their decisions explain a much larger portion of the variation in their decisions, ranging from 83% to 92%.

Table 1
List of Variables

Continuous Variables
Loan Contracts
loan size (yuan)
loan maturity (months)
Demographic Information
Age
number of children
number of months living in the current address
monthly earning (yuan)
number of months working in the current company
Accounting Information - Credit
history max loan amount
history loan overdue period
history loan overdue amount
history number of mortgage loans
history number of other types of loans
number of credit cards
number of credit card issuing banks
number of loan issuing banks
Number of outstanding loans
Accounting Information - Cash Flow
annual profit (self-reported)
monthly revenue from bank statement
monthly rent payment from bank statement
monthly short-term debt payment from bank statement
monthly long-term debt payment from bank statement
monthly total cash flows from bank statement

Note: This table reports a full list of codified variables available to the loan officers through the lender's internal system. To preserve the confidentiality of the lender that provided the data, I do not report the summary statistics for these variables.

Table 1 (cont'd)
List of Variables

Discrete Variables

Demographic Info	Accounting Info – Credit	Accounting Info - Current Assets/Liabilities
gender	**if have secured loan**	**Buyer**
male	Yes	have >= 2 Fortune Global 500 buyers
female	No	have>= 3 Fortune Chinese 500 buyers
education	**if have a business loan**	have >=5 buyers
college or above	Yes	have <5 buyers
3-year college	No	no buyer information provided
high school	**if have a mortgage loan**	**Supplier**
junior high or below	Yes	have >= 2 Fortune Global 500 suppliers
marriage status	No	have>= 3 Fortune Chinese 500 suppliers
married		have >=5 suppliers
unmarried	**Accounting Info – Industry**	have <5 suppliers
other	Restaurant	no supplier information provided
residential type	food processing	**account receivable**
self-owned	Retail	<50% of revenue, average age <30 days
family-owned	hotel and accommodation	<50% of revenue, average age <45 days
rental	finance and insurance	<50% of revenue, average age <60 days
dorm	ICT	<50% of revenue, average age <90 days
reside with	wholesale trade	>=50% of revenue
self	retail trade	no account receivable information provided
with parents	resident services	**account payable**
with spouse	textile and garment manufacturing	<50% of revenue, average age <30 days
with co-workers	Entertainment	<50% of revenue, average age <45 days
with relatives	scientific and polytechnic services	<50% of revenue, average age <60 days
with others	Leasing	<50% of revenue, average age <90 days
job status	Construction	>=50% of company revenue
self-employed	Manufacturing	no account payable information provided
employee		**Inventory**
other	**Accounting Info – Location**	>10% of company revenue
if house owner	23 cities	>20% of company revenue
yes		>30% of company revenue
no		>50% of company revenue
if have insurance		no inventory information provided
yes		
no		
if have automobile		
yes		
no		

Table 2

The Relation between Soft Information and Loan Outcome

Dependent = Profit				
	(1)	(2)	(3)	(4)
Soft Info	0.144***	0.148***	0.129***	0.128***
	(7.58)	(7.48)	(7.24)	(7.22)
Control	N	N	Y	Y
Time Fixed	N	Y	Y	Y
Officer Fixed	N	Y	N	Y
R2	0.003	0.016	0.055	0.056
N	33,879	33,879	33,879	33,879

Note: This table reports if loan-level measure of soft information, $s_{i,t}$, predicts loan outcome. The dependent variable is loan profit, defined as the repayment ratio = (total repayment – loan size)/loan size. Soft Info is $s_{i,t}$ estimated in equation (3) using the decomposition method in section 3.2.2. Control variables include all codified borrower characteristics. T-stats are in parentheses. Standard errors are clustered by loan officers.

*** significance at 1% level

** significance at 5% level

Table 3

Causal Relation between Loan Size and Loan Outcome

Panel A: Dependent = Repay Ratio				
	OLS		2SLS	
	(1)	(2)	(3)	(4)
			IV=Leniency	IV=Leniency
Loan Size	0.010	0.053***	0.522***	0.613**
	(1.66)	(7.34)	(7.54)	(1.97)
			First-Stage	
			0.561***	0.154***
			(5.17)	(4.60)
Controls	N	Y	N	Y
Time Fixed	N	Y	N	Y
N	33,879	33,879	33,879	33,879

Panel B: Dependent = Repay Dollar				
	OLS		2SLS	
	(1)	(2)	(3)	(4)
			IV=Leniency	IV=Leniency
Loan Size	0.167***	0.223***	0.544***	0.714**
	(11.78)	(15.30)	(13.42)	(2.55)
			First-Stage	
			0.561***	0.154***
			(5.17)	(4.60)
Controls	N	Y	N	Y
Time Fixed	N	Y	N	Y
N	33,879	33,879	33,879	33,879

Note: This table reports regression of repayment ratio (Panel A) or repayment dollar (Panel B) on loan size. Column (3) and (4) use officer leniency as an instrument for loan size. Officer leniency is the average loan size for each officer. Control variables include all codified borrower characteristics. T-stats are in parentheses. Standard errors are clustered by loan officers.

*** significance at 1% level

** significance at 5% level

Table 4

Model Performance: Human vs. Machine Learning

Model Performance (Profit Rate)	(1) Human H(X)	(2) Human H(X)+S	(3) ML(OLS) M(X)	(4) ML(GBM) M(X)
Hold-out Sample (n=6,776)	0.140	0.156	0.135	0.215

Note: This table reports profit generated by each model aggregated across all loans in the hold-out sample. Profit for each loan is defined as (total repayment – total loan size)/total loan size. In column (1), $H(X)$ represents the loan officers' decision rule based on hard information only. In column (2), $H(X)$+S represents loan officers' observed decisions based on both hard and soft information. So 15.6% in column (2) is the lender's actual profit. Column (3) and (4) are generated by machine decisions $M(X)$ trained with OLS and GBM, respectively.

Table 5

Model Performance: Human vs. Machine in the Tails

	Average Observed Loan Profit Rate		
Predicted Profit Percentile	Human	ML(OLS)	ML(GBM)
10%	0.15	0.15	-0.16
20%	0.15	0.14	0.03
30%	0.14	0.15	0.13
80%	0.14	0.15	0.25
90%	0.17	0.16	0.26
100%	0.17	0.14	0.28

Note: The table presents the average observed profits in each tail decile of predicted profit as predicted by each of the three models. To obtain the GBM (OLS) deciles of predicted profit, I first predict a borrower's loan repayment using the $M(X)$ trained by GBM (OLS). Next, for each month, I sort all borrowers in the hold-out sample into deciles by their GBM (OLS) predicted repayment and then pool borrowers in the same decile across months together. Finally, for each decile, I compute its average observed repayment rate (i.e. profit). To obtain the Human predicted profit, I first regress observed loan size on the requested loan amount. Next, for each month, I sort all borrowers in the hold-out-sample into deciles by this residual and then pool borrowers in the same decile across months together. Finally, for each decile, I compute its average observed repayment rate (i.e. profit). Observed repayment rate (i.e. profit) is defined as (total repayment – loan size)/loan size.

Table 6

Explaining Human Mis-ranking

Dependent = Misranking (H(X) vs. M(X))		
	Probit	
	(1)	(2)
Salience	0.275***	0.279***
	(6.71)	(6.72)
R2	0.006	0.011
Officer Fixed	N	Y
N	6,776	6,776

Note: This table reports results from Probit regressions of the loan officer's mis-ranking of borrowers on behavioral factors. The dependent variable is an indicator of mis-ranking that equals one if a borrower is ranked by loan officers more than 1 decile away from her ranking by the machine learning model $M(X)$. $Salience$ is an indicator equals 1 if at least one accounting variable whose value falls into 5% in the left tail of the distribution of that variable across all borrowers. T-stats are in parentheses. Standard errors are clustered by loan officers.

*** significance at 1% level

** significance at 5% level

Table 7

Explaining Human Mis-ranking (2)

Dependent = High Misranking (H(X) vs. M(X))		
	Probit	
	(1)	(2)
Salience	0.391***	0.392***
	(12.30)	(12.49)
R2	0.014	0.020
Officer Fixed	N	Y
N	6,776	6,776

Note: This table reports results from Probit regressions of the loan officer's mis-ranking of borrowers on behavioral factors. The dependent variable is an indicator of mis-ranking that equals one if a borrower is ranked by loan officers more than 5 deciles away from her ranking by the machine learning model $M(X)$. $Salience$ is an indicator equals 1 if at least one accounting variable whose value falls into 5% in the left tail of the distribution of that variable across all borrowers. T-stats are in parentheses. Standard errors are clustered by loan officers.

*** significance at 1% level

** significance at 5% level

Table 8

Human Mis-ranking by Experience

Panel A: Dependent = Misranking (H(X) vs. M(X))				
	Low Experience		High Experience	
	(1)	(2)	(3)	(4)
Salience	0.189***	0.192***	0.372***	0.377***
	(5.32)	(5.16)	(5.39)	(5.47)
R2	0.003	0.011	0.011	0.013
Officer Fixed	N	Y	N	Y
N	6,776	6,776	6,776	6,776

Panel B: Dependent = High Misranking (H(X) vs. M(X))				
	Low Experience		High Experience	
	(1)	(2)	(3)	(4)
Salience	0.328***	0.331***	0.456***	0.454***
	(6.41)	(6.44)	(16.64)	(16.61)
R2	0.010	0.019	0.019	0.022
Officer Fixed	N	Y	N	Y
N	6,776	6,776	6,776	6,776

Note: The dependent variable is an indicator of mis-ranking that equals one if a borrower is ranked by officers more than 1 decile away (Panel A) or 5 deciles away (Panel B) from her ranking by the machine learning model $M(X)$. Experience is measured by the total loan applications processed. A borrower falls into a High (Low) Experience sample if the application is processed by an officer with the above (below) median experience. $Salience$ is an indicator equals 1 if at least one accounting variable whose value falls into 5% in the left tail of the distribution of that variable across all borrowers. T-stats are in parentheses. Standard errors are clustered by loan officers.

*** significance at 1% level

** significance at 5% level

Table 9

Salience and Soft Information Acquisition

Panel A

Dependent = Profit						
	Whole Sample		Non-salient Sample		Salient Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
Soft Info	0.126***	0.127***	0.120***	0.121***	0.129***	0.131***
	(7.21)	(7.22)	(6.52)	(6.65)	(4.64)	(4.86)
					(5)-(3)	(6)-(4)
					0.009*	0.013**
p-value of Chi-square Test					(0.08)	(0.04)
Control	Y	Y	Y	Y	Y	Y
Time Fixed	Y	Y	Y	Y	Y	Y
Officer Fixed	N	Y	N	Y	N	Y
R2	0.055	0.056	0.056	0.057	0.102	0.103
N	33,879	33,879	26,113	26,113	7,766	7,766

Panel B

Std of Soft Info		Loan Processing Time (Min)	
salient (n= 7,766)	0.17	salient (n= 7,766)	77
non-salient (n=26,113)	0.12	non-salient (n=26,113)	68

Note: Panel A reports results from regressions of loan profit on soft information. The dependent variable is the loan repayment ratio, a measure of profit, defined as (total repayment – loan size)/loan size. Soft Info is $s_{i,t}$ estimated in equation (3) using the decomposition method in section 3.3.2. Control variables include all codified borrower characteristics. Column (1) and (2) are taken from Table 2. Column (3) and (4) are results on a subsample in which borrowers have no salient information. Column (5) and (6) are results on a subsample in which borrowers have at least one salient accounting variable. An accounting variable is defined as salient if its value falls into 5% in the left tail of the distribution of that variable across all borrowers. T-stats are in parentheses. Standard errors are clustered by loan officers. Panel B reports the standard deviation of $s_{i,t}$ and average loan processing time (minutes) in the salient and non-salient samples.

*** significance at 1% level

** significance at 5% level