Why hire loan officers? Examining delegated expertise*

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Abstract

Using rich data from a Chinese lender, I examine loan underwriting by developing a screening model of how loan officers behave. While loan officers can screen uncodified soft information, heterogeneity in risk preferences, screening ability, and beliefs about screening ability may distort their decisions. I recover these characteristics by developing a ML estimator that models the joint distribution of loan decisions and outcomes. I address potential endogeneity with the random assignment of borrower applications to loan officers. Using counterfactuals, I find that these characteristics distort loan decisions and are costly to the lender. Despite this, the average loan officer’s decisions can outperform an econometrician’s predictions by more than three times her pay.

Keywords: Lending market, Delegated expertise, Principal agent, Portfolio management

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1 Introduction

Many organizations such as universities, investment funds, and banks employ experts to screen uncodified subjective data that would otherwise be difficult to process. For example, admission counselors can read essays, fund managers can listen to conference calls, and loan officers can conduct interviews. However, this ability to interpret subjective information is costly. These agents require pecuniary compensation and also may have their own characteristics such as risk preferences or other biases that could distort their decisions. These characteristics could also create incentive conflicts that lead the agent to take actions different than the ones preferred by the principal.

I examine these issues using data from a Chinese lender that delegates loan decisions to expert loan officers. The lender specializes in unsecured loans to households and small businesses, and the lender hires loan officers to screen borrowers and to choose an approved loan amount. I am able to quantify the value of subjective screening by developing a structural model of how loan officers behave. The model features rich agent heterogeneity including differences in risk preferences, screening ability, and allows loan officers to have heterogeneous beliefs about said ability. Using the model primitives, I calculate their value to the lender by comparing their loan decisions to an econometrician’s predictions. Despite the many advantages afforded to the econometrician, I find that loan officers still outperform the econometrician by more than three times their pay.

These issues have important implications for the design of incentive schemes in principal agent relationships particularly in cases where information must be acquired and acted upon. Understanding the potential costs that result from idiosyncratic differences across agents could lead to interventions that mitigate the distortions inherent in subjective evaluation. In addition, by formally modeling the agent’s decisions, it is possible to consider interactions. For example, an agent’s risk preferences may attenuate some of the distortions due to heterogeneous beliefs. Moreover, as organizations increasingly rely on different methodologies to evaluate risks, it is important to develop a framework that allows for counterfactual comparisons between alternatives. Ultimately, the magnitude of the costs and the net benefit of subjective screening is an open empirical question. To the best of my knowledge, this is the first empirical study examining screening using a structural model.

Lending is a particularly interesting setting to study these issues for a number of reasons. First, in contrast to university admissions, the costs and benefits to the lender can be objectively quantified using loan profit and salary data. Second, agency costs that distort loan decisions have important negative effects on borrowers as well as lenders. For example, Banerjee and Newman (1993) find that a lack of credit could lead to poverty traps for borrowers, while Fan et al. (2013) and Nanda (2008) show that financial constraints for commercial lending also
negatively impact firm entry, profit, and survival.\textsuperscript{1} And third, lenders have a clear alternative to subjective evaluation. Since the 1980’s, lending markets worldwide have undergone drastic transformations from interview-based to risk-based pricing Johnson (2004). Today, while manual evaluation is still used in home mortgages Tzioumis and Gee (2013), business financing Agarwal and Ben-David (2014), and consumer loans Karlan and Zinman (2009), some financial products such as revolving credit exclusively use automated credit scoring for decisions. As a result, algorithmic lending provides a natural benchmark against which to assess the value of subjective evaluation.

Answering these questions requires overcoming a number of obstacles and places formidable demands on data. For example, developing a counterfactual lending model requires recovering the borrower’s repayment function, which itself is an important object of study. Because many loan decisions are decided with information generally unobserved to the econometrician, an omitted variables problem exists when estimating the repayment function. In particular, the marginal effect of loan size on repayment may be an endogenous object. To account for this, a literature has developed that focuses exclusively on exploring exogenous changes in loan terms to solve this causal inference problem (Karlan and Zinman 2009; Dobbie and Skiba 2013).

Furthermore, identifying differences across loan officers requires quasi-experimental variation to ensure similar ex-ante unobserved borrower attributes. Fortunately, the random assignment of borrower applications to loan officers overcomes both of these inference challenges. The random assignment of caseloads has been exploited by Abrams et al. (2012) to analyze prejudicial differences across justices in racial sentencing disparities, and used by Maestas et al. (2013) to instrument for disability benefits to identify impacts on employment. This study jointly explores both the differences across evaluators and uses those differences as an instrument in identifying a causal effect.

The differences across loan officers is modeled with rich heterogeneity. Loan officers are described by their risk preferences, screening ability, and beliefs about their screening ability. Some loan officers may even have inconsistent beliefs about their ability. This flexible specification nests overconfidence, underconfidence, and rational expectations that can be tested using model restrictions. The borrower’s stochastic risk level is determined by both screenable and unscreenable factors in contrast to studies that do not distinguish between the two. Loan officers screen applications and develop posterior beliefs about the borrower’s likelihood of repayment conditional on a signal the loan officer observes about the borrower. Given this updated belief and the compensation scheme, loan officers choose the size of the loan to approve to maximize their expected utility from lending.

The empirical strategy relies on rich data from a large Chinese lender. This dataset offers

\textsuperscript{1}Karlan and Zinman (2010) and Morduch (1998) also find negative impacts on job retention, income, and mental outlook from insufficient credit. However, the welfare effects are more ambiguous when examining certain kinds of high APR loans in developed countries. For example, Melzer (2011) finds that use of US payday lending leads to increased difficulty in repaying household bills.
an ideal setting to study these issues for a number of reasons. The data features detail at
the individual borrower level including all of the codified application variables available to
the lender. The exhaustive set of data allows me to construct an econometrician’s prediction
using the same information set that the lender would have had access to in the absence of
loan officers. Observed borrower attributes include the approved loan amount, loan terms,
demographics, education, financial, credit reports, self-reported survey data, and also include
home and workplace inspection variables totaling over 250 covariates. I also observe the full
monthly repayment stream including monthly payments, delinquencies, and penalty fees. By
incorporating late fees, I am able to construct a more comprehensive measure of loan profitability.

The structural model is able to attribute the differences in loan sizes and loan profits across
loan officers to their idiosyncratic characteristics. Specifically, I develop a maximum likelihood
estimator that models the joint distribution of loan sizes and loan profits. All else being equal,
loan officers that are more risk averse approve smaller loan sizes. Loan officers exhibiting greater
overconfidence approve loans with greater variation conditional on codified borrower attributes.
And all else equal, loan officers with greater screening ability have better performing loan
portfolios. The borrower repayment function is also recovered endogenously from the model.
Using the model primitives, I construct different counterfactual lending scenarios including the
econometrician’s prediction. By comparing to the status quo, I can use these counterfactuals to
measure the net value of subjective screening to the lender.

I preview three main results. First, there is substantial heterogeneity in risk preferences,
screening ability, and beliefs across loan officers. I further find that all of the loan officers exhibit
overconfidence where their loan decisions implies screening abilities that are much more accurate
than that shown by the data. These idiosyncratic differences across loan officers lead to large
effects on loan sizes and profits. Second, these differences distort loan decisions and impose costs
for the lender. Estimates suggest that the lender would be willing to pay ¥100 to ¥400 per
loan to mitigate their costs. For perspective, this is roughly equivalent to the per loan salary of
an additional two to seven loan officers. Third, despite these costs, the average loan officer is
able to outperform an econometrician’s predictions by more than three times her average pay.
Given the many advantages of the econometrician, this suggests that loan officers would have
also outperformed other econometric models developed by the lender at the time of origination.

This study sits at the intersection of a number of different literatures. The results provide
an empirical basis for models of delegated expertise. These are a form of principal agent models
that focuses on agents who are tasked with collecting, interpreting, and acting upon information.
Frequently applied to portfolio managers screening risky assets, the framework features both
information acquisition and an investment decision. With these two actions, the agents are
largely able to control both the scale and variance of their output, which is generally not the
case in the standard principal agent model (see Stracca 2006 for a survey). While most of the
research in this area has considered the optimum incentive contract (Demski and Sappington
1987; Bhattacharya and Pfleiderer 1985; Stoughton 1993), this is the first structural application of this framework.²

Loan officer screening behavior has also been considered before, generally in the context of randomized control trials or field experiments. Agarwal and Ben-David (2014), Cole et al. (2013), and Paravisini and Schoar (2013) test comparative statics about changes in the their compensation structure or information sets. They find that loan officers respond on multiple margins including the permissiveness, profitability, and volume of new loans. I contribute by casting their results into a model of how loan officers behave that can also be used for counterfactual analysis. Furthermore, I’m able to be very precise about modeling the differences between screenable risk and unscreenable risk. Unscreenable risk may be unpredictable shocks to repayment from business cycles to accidents. Ignoring this distinction may falsely inflate the value of loan screening.

I want to differentiate this study from others that focused on examining the effectiveness of automated credit scoring compared to loan officers. Einav et al. (2013) and Edelberg (2006) provide compelling evidence that credit scoring outperforms loan officers in isolation. The popularity of risk-based pricing across virtually all channels of retail credit attest to the effectiveness of automated methods to price codified risk. The comparison considered here is not to eliminate the machines, but to examine the additional value of experts working in conjunction with these machines.³

This study will also find evidence of inconsistent beliefs across loan officers indicating that many may be overconfident in their abilities. Other authors have also tried to find evidence of overconfidence, and their approach generally involves presupposing its existence and then testing model predictions that result. For example, Barber and Odean (2001) and Malmendier and Tate (2004) pre-classify agents as overconfident and then attribute differences in behavior to that assumption.⁴ My approach to identifying inconsistent beliefs is similar to a lab study. I am able to directly tie the loan officer’s rating of a borrower’s perceived risk to the borrower’s actual risk using loan outcome data. Screening ability and beliefs about said ability is identified jointly from the distribution of loan sizes and loan performance. In addition, I can explicitly incorporate the interaction between overconfidence and risk preferences. Goel and Thakor (2008) find that models that do not separately account for risk attitudes and overconfidence may confound identification of both.

The remaining sections are structured as follows. Section 2 describes the data and context

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²Misra and Nair (2011) and Paarsch and Shearer (2009) estimate structural models of behavior in the broader principal agent literature. Their research is also largely concerned with the effort policy function and not with additional forms of heterogeneity such as overconfidence.

³This also relates to a class of papers that uses counterfactual scenarios developed from structural models to make normative policy suggestions. For example, Cho and Rust (2008) and Mantrala et al. (2006) focus on optimal pricing strategies for an auto retailer.

⁴Another strategy explains certain market equilibrium as the optimal response to overconfident consumers. Grubb (2009) finds that overconfidence may explain some types of non-linear price schedules used by telecoms.
in more detail. Section 3 develops the structural model of the loan officer’s behavior. Section 4 presents the empirical strategy and intuition for identification of the model parameters. Section 5 uses the structural primitives of the loan officer and the borrower’s repayment function to evaluate counterfactual scenarios. Section 6 concludes.

2 Environment

I study a large Chinese lender with more than 40 sales branches located across the country. One of the lender’s main products is unsecured cash loans to households and small businesses. Average loan sizes are significantly higher than the microloans studied in the development literature and are slightly less than half of the average borrower’s annual salary income. Self-reported loan purposes range from weddings to home appliances to restaurant furnishings and office supplies. The borrowing population is not financially at-risk or subprime, and they have access to other financing options such as credit cards, home and vehicle loans, and other cash-based lenders. The credit card market in China is characterized by low rates of merchant take-up and high transaction fees. As a result, there has been a large growth in popularity of cash-based lending in China. See Ayyagari et al. (2010) for a more detailed survey of the Chinese financing industry.

2.1 Data

Table (1) presents some summary statistics for the data. The data period covers all loans made from December 2011 to January 2014 and includes 31,954 borrowers with application and repayment data. Because some loans have not yet completed, the repayment data is censored for about 22,000 borrowers. I discuss methods to accommodate data censoring in the empirical section. Average loan sizes are about ¥33,450, which is roughly $5,400 at current exchange rates. These loan amounts are substantial both in absolute terms and as a proportion of the average salary income of ¥71,000.7

Each loan is advertised with an APR and payment length, and different products are offered across locations based on the local competitive landscape. New products are introduced and

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5 In many parts of the developing world including China, the formal differences between small businesses and households are small. Morduch (1998) finds that small business loans are often used for consumption smoothing as well as investment purchases. The lender’s underwriting procedures between the two segments is similar. Lending to state owned enterprises and large firms is primarily handled by traditional banks.

6 Broecker (1990) finds that competition among different lenders could decrease the average credit-worthiness of a lender’s portfolio through adverse selection. In this environment, this concern is somewhat alleviated by credit agency reporting. Some of the reported information include credit applications, external loan terms, and historical repayment.

7 Beyond direct deposited salary income, the lender counts many sources of additional income such as non-deposited salary, social security payments, business income, housing assistance, tax payments, and others. Detailed asset information such as housing, vehicles, and insurance policies are also collected to estimate net worth. There is also separate income accounting for certain worker types such as specialized employees or government workers whose primary compensation may be through reimbursement and payment in kind. The result is that individuals with low amounts of stated payroll may still be approved for large loans. For comparison, per capita GDP in Shanghai is ¥82,000, and is ¥38,000 for China as a whole.
Table 1: Summary statistics

<table>
<thead>
<tr>
<th>Loan terms</th>
<th>Mean</th>
<th>Min</th>
<th>Max</th>
<th>Std dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan amount (¥000's)</td>
<td>33</td>
<td>5</td>
<td>60</td>
<td>12</td>
</tr>
<tr>
<td>Requested (¥000's)</td>
<td>124</td>
<td>3</td>
<td>300</td>
<td>103</td>
</tr>
<tr>
<td>Monthly payment (¥000's)</td>
<td>2.2</td>
<td>0.3</td>
<td>5.7</td>
<td>1.1</td>
</tr>
<tr>
<td>Payment length (Months)</td>
<td>25</td>
<td>12</td>
<td>36</td>
<td>7</td>
</tr>
<tr>
<td>APR (%)</td>
<td>48%</td>
<td>33%</td>
<td>62%</td>
<td>7%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Borrower attributes</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimated assets (¥000's)</td>
<td>587</td>
<td>1</td>
<td>7,358</td>
<td>1,337</td>
</tr>
<tr>
<td>Salary income (¥000's)</td>
<td>71</td>
<td>4</td>
<td>642</td>
<td>267</td>
</tr>
<tr>
<td>External debt (¥000's)</td>
<td>160</td>
<td>0</td>
<td>1,923</td>
<td>856</td>
</tr>
<tr>
<td>Age</td>
<td>38</td>
<td>18</td>
<td>58</td>
<td>9</td>
</tr>
<tr>
<td>Credit card utilization</td>
<td>41%</td>
<td>0%</td>
<td>100%</td>
<td>38%</td>
</tr>
<tr>
<td>Credit card limit (¥000's)</td>
<td>20</td>
<td>0</td>
<td>718</td>
<td>156</td>
</tr>
<tr>
<td>Proportion with credit card</td>
<td>76%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Proportion female</td>
<td>28%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. APR is inclusive of application fees. Financial variables are from verified credit reports. Estimated assets include non-payroll sources, social security payments, vehicle and other durable goods as well as business income. Debt is the sum of the external debt load including credit, housing, and auto loans as identified by a credit report. As of August 2014, $1 is ¥6.18.

2.2 Loan process

The borrower’s first step is to fill out a loan application which includes identification, demographics, financial documents, and verified references. The borrower records the loan amount requested as well as the purpose of the loan. Following the application, local branch employees verify the borrower’s income, debt, and asset information using bank statements and credit reporting. The branch employees will also make home and workplace inspections to assess the borrower’s home environment. Data is collected on the number of TV sets, air conditioning units, square footage, and others which are photographed. One purpose of these somewhat unorthodox inspections is to find evidence of identity fraud or potential flight risk.

\[8\] Karlan and Zinman (2009) examine a similarly positioned unsecured cash-based lender in South Africa and find APR rates of over 200%. The overall default rate for the South African lender is 30% for first time borrowers. The studied lender’s overall default rate is less than 10%. The average APR for US credit cards is around 10-15% and may be much higher for payday cash loans.

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\[8\] Karlan and Zinman (2009)
The local branch employees collect a large amount of hard and soft information. I follow Petersen (2004) in defining hard information as quantitative, codified, and with no ambiguity in interpretation. Because the information is codified, the information can be inputted into a credit scoring model that can process the borrower’s average repayment risk. Examples of hard information include age, income, occupation, number of TV sets, and the lender’s measure of credit quality. This credit quality variable is itself an aggregation of a large amount of codified borrower attributes and is an internal measure of risk.

Petersen (2004) highlights that soft information on the other hand is either difficult or costly to codify. To process this type of information, the lender must rely on loan officers to manually screen the application. In addition, two loan officers may also have honest disagreements when interpreting soft information such as written notes, photographs, or the feel of the home when gauging a borrower’s repayment ability. Since I observe the exhaustive set of codified borrower attributes, I further define soft information as the uncodified data available to the loan officer but not to the lender or myself. The central tension is that loan officers can observe a noisy signal from soft information, while automated methods must form an expectation.

After the local branch employees gather the information, a local supervisor will make an approval decision on the loan. The approved application files are sent to the central headquarters where loan officers will choose the approved loan amount conditional on loan terms. Due to incomplete reporting standards from the different sales offices, I do not have information on rejections that happen before reaching central headquarters. The separation of the extensive and intensive margins on loan sizes is a unique institutional feature. One reason for separating authority is to minimize the potential costs of side payments at the branch level. There is no face to face contact between loan officers and the borrowers although it is possible for the loan officers to contact borrowers through other channels.

Once the central headquarters receives the application, it is randomly assigned to a loan officer for processing. My data include 21 loan officers but not all of the loan officers worked at all times. In practice, a batch of applications will enter the office and be distributed to loan officers without presorting.9 This assignment procedure is crucial for identification, which guarantees that each loan officer’s portfolio of borrowers has the same ex-ante distribution of uncodified attributes. Section 4 discusses this random assignment and the necessary assumptions in more detail. During screening, the loan officer observes the codified borrower attributes including the lender’s internal measure of credit quality as well as uncodified soft information. Once screening is complete, the loan officer chooses a loan amount given the interest rate and payment length.10

9Some loan products such as high net worth lending, college credit, or rapid turnaround loans do have specialized loan officers for screening. The underwriting teams for various products will have specific experience and training that is tailored for their loan products. For the unsecured cash loans considered here, no additional specialization occurs.

10While there is no explicit upper bound on loan size, the highest value I observe is ¥60,000. Loan officers may need to acquire supervisor approval for very large loan amounts although the exact threshold is not a codified rule. Ghosh et al. (2013) examine a model where pricing authority depends on the agent’s local knowledge.
I stress that the only lever that the loan officers have in adjusting the terms of the loan is in choosing the size. The other loan terms are fixed.

### 2.3 Requested amount

One unique feature of the application is that borrowers are asked to report a requested loan amount. If the approved loan size is larger than the borrower’s self-reported requested amount, then the full amount requested is approved. If the loan size is smaller, then the borrower is underfunded. The lender’s stated goal is to choose loan amounts based on the borrower’s repayment ability rather than trying to satisfy any liquidity demands.\(^{11}\) Once the determination is complete, the borrower may sign the terms of the loan with no further recourse for adjustment. The branch offices themselves play no part in adjusting loan terms beyond approving the borrower. The entire process from initial application to loan disbursement can take between 3 to 7 days. Loan officers process roughly 700 applications a year with the average file taking 30 to 40 minutes.

Table (1) shows that the requested loan amount is generally three times the approved amount with a large amount of variation. Figure (1) shows the average requested amount and approved amount for loans by credit quality, which is an internal measure of borrower quality. Higher values of credit quality indicate safer borrowers. The graph shows large and persistent differences between the amount that is requested and the amount that is ultimately funded.\(^{12}\) Over 90% of borrowers were approved for loan amounts smaller than requested. Loan officers say that they view the requested amount as a signal about the borrower’s repayment ability.

While such gaps could be the result of a strategic game where borrowers request larger loan amounts 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. Also, the average borrower may not be able to predict the loan officer’s lending behavior. While a very small proportion of borrowers reject loans because the amounts were too small, there were no cases where borrowers refused a loan for being too large. This gap is then suggestive of a large demand for borrowing that is constrained by the lender. Adams et al. (2009) examine a model where loans are constrained due to information asymmetries such as moral hazard. In addition to this effect, this study will attribute some of the constraints to idiosyncratic differences across loan officers.

The lender utilizes a variety of tools to incentivize repayment. Subsequent loans may come with more attractive terms including lower fees and reduced APR. Additional carrots also come

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\(^{11}\)This allocation mechanism mitigates the effect of adverse selection where borrowers with an ex-ante higher likelihood of default may request larger loan sizes in anticipation. In this setting, loan officers are able to directly condition on the borrower’s requested amount when making their decisions. This means that to the extent there is any cross-sectional relationship between requested loan amounts and defaults, then the correlation can be directly priced into the size of the loan.

\(^{12}\)The slope of credit quality on the approved amount is positive and significant, which is difficult to see at the scale of the graph.
Figure 1: Loan amounts and requested amounts by credit quality
24 month loans at 48% APR from June 2012

Notes: Sample includes 282 first-time borrowers from June 2012 borrowing a 24 month loan with an APR of 48%. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. Borrower applications are randomly assigned to loan officers. Credit quality is an internal measure of borrower quality from credit scoring - higher values indicate safer borrowers. For each level of credit quality, the average loan amount and requested amount is averaged over a bandwidth interval of 5.5 units of credit quality. As of August 2014, $1 is ¥6.18.

from higher future limits and a simpler approval process.\textsuperscript{13} Sticks may be collection calls from external collectors or litigation. Litigation may result in wage garnishments or court-modified repayment schedules. Accounts delinquent for more than 90 days or 3 payment periods are generally packaged and sold to collection agencies. The loan officer has no contact with the borrower after loan origination and she is not involved in collecting delinquent loans.

3 Model of the loan officer

In this section, I develop a delegated expertise model following Stoughton (1993) and Battacharya and Pfleiderer (1985). The framework is modeled after an investment manager who must acquire information about a risky asset and then must decide on an investment level conditional on that information. Borrowers, or the risky assets, have a large demand for credit

\textsuperscript{13}This lender was established in the last 4 years and over 98% of loans are made to first-time borrowers. Because secondary loans may come with additional information, I restrict all of my analysis to a borrower’s first loan.
limited only by their self-reported requested loan amount. Once given a loan, borrowers will begin to repay, and their stochastic repayment will be determined by both screenable and unscreenable factors. The screenable factors can be inferred from both hard and soft information. Since borrowers apply for a loan product with an advertised interest rate and payment length, I take the loan terms beyond loan size as given. Endogenizing the choice of loan products is beyond the scope of this paper.

In the absence of loan officers, the lender can only condition on the codified hard information when making decisions. However, the lender could do better by delegating decisions to loan officers. Loan officers can screen uncodified soft information about the borrower, which allows her to observe a noisy signal about his stochastic repayment. She then must decide on the size of a loan to approve taking into account the compensation structure, the information gathered, and the direct impact of increased loan sizes on his repayment. Loan officers are heterogeneous across three dimensions: risk preferences, screening ability, and beliefs about screening ability. These characteristics directly influence their loan decisions and may lead to distortions away from what the lender would prefer. I first introduce the model with rational expectations and without inconsistent beliefs before completing the full exposition.

3.1 Loan officer’s objective

Figure (2) illustrates the steps of the loan officer’s problem. Loan officers, who are indexed by \( j \), have an exponential utility function with heterogeneous risk preferences \( u(y_j) = -e^{-r_j y_j} \) where \( y_j \) is the loan officer’s compensation net of effort costs. Compensation is given by a fixed salary \( \alpha \) and a year end bonus that is directly proportional to loan profits \( \beta \sum_i \pi_{ij} \) where \( i \) indexes borrowers.\(^\text{14}\) One important caveat is that there is no explicit algorithm that ties loan performance to the year end bonus. The formula is not available to myself or to the loan officers.\(^\text{15}\) The year end bonus is determined from a performance review between the loan officers and their supervisors and can be considered as the outcome of a relational contract. While I do not have data on specific salaries or bonuses, the average salary is ¥42,000 and the average bonus is ¥3,000 to ¥4,000.

In practice, the compensation scheme is most likely non-linear exhibiting limited liability, deferred compensation over multiple calender periods, and variable bonus rates Cole et al. (2013). While the modeling of a linear bonus is admittedly an approximation for tractability, the structure is consistent with a reduced form model of career concerns or corporate obedience where the loan officers are incentivized to maximize loan profits. Even without an explicit

\(^\text{14}\)Maximizing an exponential utility function with a linear compensation scheme and normally distributed errors reduces to maximizing a mean variance utility function Misra et al. (2005). This mean variance utility form with heterogeneous risk parameter \( r_j \) is a second order approximation to any utility function.

\(^\text{15}\)The lender is vague about the bonus structure even to the loan officers themselves. One reason may be to avoid loan officers exploiting the scheme. See Berg et al. (2013) for evidence that loan officers may manipulate information to pass an approval threshold and increase their pay.
monetary incentive, non-pecuniary motivations such as competition with coworkers or fear of dismissal could lead her to behave as if she were maximizing expected utility from loan profits. Furthermore, conversations with the lender, supervisors, and the loan officers themselves indicate this is a reasonable approximation.

Although the average loan officer is screening 700 applications a year, she may still have reasons to be risk averse over individual loans. For example, a defaulted loan may warrant additional scrutiny from supervisors regardless of the performance of her remaining portfolio. This risk preference is designed to capture her internal tradeoff between the loan’s expected value and the variance. One detail that will be described more fully is that the bonus rate $\beta$ is not separately identified from $r_j$. In other words, I cannot rule out that heterogeneous beliefs about $\beta$ may also influence her decision.\textsuperscript{16}

Loan officer $j$ has screening ability $\sigma_j^2$ that determines her precision from a noisy signal about the borrower’s repayment risk. It is useful to think of this as an ability because it is assumed to be constant within a loan officer’s loan portfolio. This constant ability can be cast as the result of a prior effort choice since the constant screening ability is isomorphic to a loan officer specific cost of effort parameter. Net compensation is then given by $y_j = \alpha + \beta \sum_i \pi_{ij} - \text{cost}_j\left(\sigma_j^2\right)$ where $\text{cost}_j\left(\sigma_j^2\right)$ is the disutility of the chosen screening ability in money. $\text{cost}_j\left(\sigma_j^2\right)$ is assumed to be convex and strictly decreasing with $\text{cost}_j\left(\sigma_j^2\right) > 0$ for any $\sigma_j^2 > 0$, $\text{cost}'_j\left(\sigma_j^2\right) < 0$, and $\text{cost}''_j\left(\sigma_j^2\right) > 0$. Combining everything, loan officers try to maximize their expected utility given by

$$EU\left[L_{ij}\right] = \int -e^{-r_j\left(\alpha + \beta \pi_{ij} - \text{cost}_j\left(\sigma_j^2\right)\right)} f\left(\pi\right) d\pi \quad (1)$$

### 3.2 Loan profits

When borrower $i$ receives a loan of size $L_{ij}$, he will ultimately repay a proportion $\eta^*_i\left(L_{ij}\right)$ of the total $R_i L_{ij}$.\textsuperscript{17} $R_i$ is the ratio of the total present value of the loan if repaid in full to the value

\textsuperscript{16}Many loan officers believe that roughly 1\% of loan profits are ultimately returned to them as a bonus. Actual loan profitability data indicate this is a reasonable approximation.

\textsuperscript{17}$\eta^*_i\left(L_{ij}\right)$ is a latent variable, while $\eta_i\left(L_{ij}\right)$ is the observed variable due to censoring.
of the loan and is determined by the interest rate.\textsuperscript{18} \( \eta^*_i(L_{ij}) \) represents the proportion of the total that is ultimately repaid and is inclusive of penalty, application, early repayment, and late fees.\textsuperscript{19} This means that ultimately, some borrowers may return to the lender more than \( R_i L_{ij} \). The present value of loan profits is then given by \( \pi_{ij} = R_i L_{ij} \eta^*_i(L_{ij}) - L_{ij} \). This model is static in the sense that loan officers do not consider their prior portfolio composition when underwriting a new loan.\textsuperscript{20}

The borrower’s repayment proportion \( \eta^*_i(L_{ij}) \) is composed of four parts: the loan amount \( L_{ij} \), the codified hard information \( \mathbf{x}_i \), the uncodified soft information \( u_i \), and an exogenous unscreenable error \( \epsilon_i \). When choosing loan sizes, loan officers must balance the additional interest earned from loan increases with potentially higher delinquency rates. This delinquency could be due to factors under the borrower’s control as well as circumstance. For example, borrowers may have a greater incentive to default on larger loans through strategic default. They may also exert less effort on their own projects, or it could be that larger loan payments have a greater chance of pushing a borrower into delinquency.\textsuperscript{21}

The next component is hard information \( \mathbf{x}_i \), which contains all of the codified borrower data and loan terms. This includes demographics, financial variables, home inspection, workplace inspection, credit reporting data, and the borrower’s self-reported data including loan request and loan purpose. Loan officers are assumed to observe the effect of hard information and loan size on repayment without any ambiguity. This is to mimic the effect of credit scoring, which aggregates a large amount of codified borrower attributes.\textsuperscript{22}

The next part of \( \eta^*_i(L_{ij}) \) is stochastic, idiosyncratic to the borrower, and unobserved to the econometrician. Loan officers, however, can observe a noisy signal about this screenable portion of repayment \( u_i \). Loan officers rely on uncodified data to infer a borrower’s ability, personality, and job prospects. For convenience, I term the screenable but unobserved to the econometrician

\begin{equation}
PV_i = \frac{apr_i}{1-(1+apr_i)^{-N}} \times \frac{1-(1+i)^{-N}}{i} L_{ij} \quad \text{where} \quad apr_i \text{ is the monthly APR of the loan, } N \text{ is the payment length, and } i \text{ is the lender’s discount rate. } R_i \text{ is therefore given by } \frac{apr_i}{1-(1+apr_i)^{-N}} \times \frac{1-(1+i)^{-N}}{i} . \quad i \text{ is set at the People’s Bank of China base interest rate of 6%, and the official Chinese inflation rate is 2%}. \end{equation}

\textsuperscript{18}For a fixed stream of monthly payments, the present discounted value of a loan if repaid in full is given by \( PV_i = \frac{apr_i}{1-(1+apr_i)^{-N}} \times \frac{1-(1+i)^{-N}}{i} L_{ij} \) where \( apr_i \) is the monthly APR of the loan, \( N \) is the payment length, and \( i \) is the lender’s discount rate. \( R_i \) is therefore given by \( \frac{apr_i}{1-(1+apr_i)^{-N}} \times \frac{1-(1+i)^{-N}}{i} \). \( i \) is set at the People’s Bank of China base interest rate of 6%, and the official Chinese inflation rate is 2%.

\textsuperscript{19}One source of risk for the lender is early repayments. Borrowers financing a wedding may quickly repay the high interest loan as soon as the cash gifts are deposited. Even though the lender imposes sizable early repayment fees, over 50% of loans are completed early. The borrower’s decision to be late, to pay late fees, to pay early, to pay early payment fees, or to default is determined by a number of factors. Modeling the utility-maximizing repayment decision is outside the scope of this study and is not necessary for the counterfactual analysis. The repayment decision is treated in reduced form.

\textsuperscript{20}To the extent that loan officers care about portfolio composition, then the estimate of risk preferences may absorb some preferences towards correlation across loans.

\textsuperscript{21}This effect is also known as borrower moral hazard. See Gine et al. (2012) for a model that explicitly outlines the borrower’s repayment decision through a private action.

\textsuperscript{22}This understates the value of loan officers in two ways. One is that \( \mathbf{x}_i \) contains controls not used in credit scoring such as time effects, higher order terms, interacted terms, and fixed effects. The other is that loan officers are only needed to interpret uncodified soft information because all of the codified characteristics are assumed to already be incorporated via credit scoring. To the extent that loan officers have additional value to the lender in screening codified information, the bias will only increase the value of manual evaluation.
to be called soft information. Soft information is distributed \( N(0, \sigma_u^2) \) for all borrowers.\(^{23}\) Soft information is assumed to be uncorrelated with hard information, but will be correlated with the choice of the loan size.

The last component is an additive error, and represents shocks to repayment that are completely unscreenable and unpredictable at the time of loan origination. Examples include checks getting lost in the mail, unexpected health shocks, or unpredictable job loss. Loan officers cannot screen this portion of repayment, and must take an expectation over its distribution. These \( \epsilon_i \) shocks are distributed \( N(0, \sigma^2) \) and by definition are uncorrelated with hard or soft information.\(^{24}\) Without accounting for the distinction between screenable and unscreenable risk, the value of subjective evaluation may be overstated.

I further assume that each component is additively separable. Combining the effect of loan size, hard information, soft information, and the unscreenable error, the borrower will repay

\[
\eta_i^* (L_{ij}) = \gamma L_{ij} + x_i' \Gamma + u_i + \epsilon_i
\]

of the total present value \( R_i L_{ij} \). The marginal effect \( \gamma \) is allowed to vary across different monthly payments so that two identical borrowers with different loan terms may have different repayment patterns. \( \text{Adams et al. (2009)} \) find that some households are even more responsive to down payments than the borrowed amount indicating that accounting for short term liquidity effects such as monthly payments is crucial.\(^{25}\)

Since the total portfolio profit \( \sum_i \pi_{ij} \) is linear in individual profits and each borrower’s stochastic portion of repayment \( u_i + \epsilon_i \) is iid, maximizing utility from the entire loan portfolio is equivalent to maximizing the utility from each individual loan.\(^{26}\) As mentioned before, loan officers still have reasons to be risk averse over individual loans despite screening hundreds of borrowers. For example, a poor performing loan may attract attention regardless of the loan officer’s prior loan performance.

### 3.3 Screening signal

While screening, loan officers develop beliefs about the borrower’s screenable portion of repayment \( u_i \). After observing the file, loan officers observe a noisy signal \( \omega_{ij} \) about the soft information \( u_i \) such that \( \omega_{ij} = u_i + \delta_{ij} \). This signal is centered around the borrower’s \( u_i \) where the additive noise term \( \delta_{ij} \sim N \left( 0, \sigma_j^2 \right) \) is distributed according to the loan officer’s screening ability. This

\(^{23}\)Because of the prior loan decision at the branch level, this may be a posterior distribution that already conditions on the borrower meeting an approval threshold.

\(^{24}\)Without loss of generality, any portion of \( \epsilon_i \) that is correlated with soft information can be subsumed within soft information. Mean independence with the hard information is also without loss of generality as a constant term is included in hard information that captures the conditional expectation.

\(^{25}\)Conditional on the payment term \( N, \text{apr} \), and the discount rate \( i \), the monthly payment and present value of the loan are linear functions of loan size. The marginal effect of loan size on repayment can be re-written as

\[
\gamma = \gamma L + \gamma MP \frac{\text{apr}}{1-(1+\text{apr})^{-N}} + \gamma PV \frac{\text{apr}}{1-(1+\text{apr})^{-N}} \frac{1-(1+i)^{-N}}{i}.
\]

\(^{26}\)This follows from the exponential utility function without income effects.
idiosyncratic term represents noise in accurately predicting a borrower’s repayment even for a high ability loan officer. Loan officers that are more experienced, better trained, or exert more effort may have greater screening abilities and are better able to observe soft information.

Loan officers then develop a posterior belief about the distribution of soft information. This posterior is distributed

\[ u_i | \omega_{ij} \sim N \left( \frac{\sigma_u^2}{\sigma_u^2 + \sigma_j^2} \omega_{ij}, \frac{\sigma_u^2 \sigma_j^2}{\sigma_u^2 + \sigma_j^2} \right) \quad (3) \]

with a non-zero mean and a smaller variance conditional on the signal.\(^{27}\) Crucially, without loan officers, the lender must take an unconditional expectation over the distribution of \(u_i\). Loan officers with greater ability and a smaller \(\sigma_j^2\) view \(u_i\) with more precision than their peers. Because of the limited number of loan officers in my sample, my data does not have the power to estimate correlations between the various loan officer characteristics.

### 3.4 Optimal loan amount

With the parametrized repayment function, the optimal loan size \(L_{ij}^*\) can be solved for as a function of the loan officer’s structural parameters and the observed signal.\(^{28}\) Given the posterior belief in equation (3), the parametrized repayment function in equation (2), and the loan officer’s utility, the optimal loan amount is given by

\[ L_{ij}^* = k_j \times \left( x_i \Gamma - \frac{1}{R} + \frac{\sigma_u^2}{\sigma_u^2 + \sigma_j^2} \omega_{ij} \right) \quad (4) \]

where \(k_j = \left[ r_j \beta R \left( \frac{\sigma_u^2 \sigma_j^2}{\sigma_u^2 + \sigma_j^2} + \sigma_j^2 \right) - 2 \gamma \right]^{-1}\).\(^{29}\)

This \(k_j\) is termed the officer effect, and is composed of loan officer characteristics and the marginal effect of loan size. \(k_j\) multiplies the loan officer’s belief of repayment, which contains both hard information and soft information. Some of the costs of distortionary characteristics can be immediately seen. Loan officers with high risk preferences have a larger officer effect all else equal. This leads to excessively small loan sizes. The costs of these distortions are examined in the counterfactual section as alternate lending scenarios are constructed. Borrowers that are safer both due to hard information or soft information are given larger loans as expected.

Without additional information about the compensation scheme, \(\alpha\) is not identified and \(\beta\) cannot be separately identified from \(r_j \beta\). This is an unsurprising result given that the incentive scheme is modeled from career concerns with no explicit variation in \(\beta\). As mentioned previously,

\(^{27}\)This follows from the conditional distribution of the normal distribution. The covariance between \(u_i + \epsilon_i\) and \(\omega_{ij}\) is \(\sigma_u^2\) since \(u_i\) and \(\delta_{ij}\) are assumed to be independent.

\(^{28}\)This loan size can also be zero, but this is a rare with less than 1% of borrowers being denied at headquarters. This is because loan decisions are pre-approved already at the branch level before arriving at headquarters. I exclude borrowers that were denied credit at the headquarters.

\(^{29}\)Integrating the expected utility relies on the properties of the moment generating function of the normal distribution. See Appendix A for the derivation.
one channel that I cannot rule out is that loan officers may have heterogeneous beliefs about the bonus rate $\beta$. These beliefs on $\beta$ may interact with risk preferences. The intuition for identifying the other parameters is addressed in the empirical section.

### 3.5 Screening effort

Screening ability can be cast as the result of a prior effort choice by the loan officer. She must balance the cost of effort with the benefits of increased precision. I assume that she chooses a constant level of for all of her loans i.e. constant screening ability. While a more robust model may exhibit variation in screening effort $\sigma^2_j$ across different levels of hard information $x_i$, the constant effort choice allows for a more tractable estimation strategy. This interpretation is also consistent with a story where loan officers have many borrower applications to screen and limited time. Before even opening the application and observing the borrower’s hard information, she must decide on some amount of time to spend on each file.

Constant screening ability can be mapped to a heterogeneous cost of effort parameter $d_j$. While the two interpretations are isomorphic, it is still useful to motivate the screening ability as an effort choice that is subject to the lender’s compensation structure rather than as an immutable characteristic. Specifically, the loan officer is solving the maximization given by

$$\sigma^2_{j^*} = \arg\max \int \int EU \left[ L_{ij^*}^* (\omega_{ij}) \right] dF_x dF_{\omega|\sigma^2_j}$$

(5)

where $F_x$ is the distribution of hard information across borrowers and $F_{\omega|\sigma^2_j}$ is the conditional distribution of the signal given effort. The distributions are assumed to be independent. The first order condition gives the utility-maximizing effort level to be

$$\sigma^2_{j^*} = \int \left( r_j \beta R \sigma^2 \sigma^2 - 2\gamma \right) \sigma^2_u \left( \frac{r_j}{2} \beta R \left( x^2_i + \sigma^2 \sigma^2 \right) - r_j \beta R \left( \sigma^2 + \sigma^2 \right) + 2\gamma \right)^{-1} dF_x$$

(6)

with the derivation in Appendix B.

$\sigma^2_{j^*}$ is increasing in the cost of effort parameter $d_j$ indicating that higher cost of effort loan officers choose higher values of $\sigma^2_j$ and less screening ability. The effect of the bonus rate $\beta$ on $\sigma^2_{j^*}$ is non-linear and non-monotonic.\(^{30}\) Conditional on the other model parameters, the screening effort level $\sigma^2_{j^*}$ is isomorphic to the cost of effort parameter $d_j$ for $\sigma^2_j > 0$ and when the marginal

---

\(^{30}\) Under certain conditions, Holmstrom and Milgrom (1987) established that the linear compensation scheme is the optimum incentive contract for principal agent models. For delegated expertise models however, Stoughton (1993) and Bhattacharya and Pfleiderer (1985) find that linear contracts suffer from the irrelevance result where the agent’s optimum effort level is not a function of a linear bonus. To see this, note that as $\gamma$ approaches 0 and the compensation plan becomes linear in loan amounts, the bonus rate $\beta$ disappears from equation (6). An agent can always undo the incentive effects of a linear scheme because the agent has costless control of a linear action $L_{ij}$ after realization of the signal Stracca (2006). Stoughton (1993) instead propose a quadratic contract that asymptotically approximates the optimal incentive scheme. The compensation plan I use is linear in profits but quadratic in loan amounts. This distinction enables the lender to motivate effort and avoid the irrelevance result.
effect $\gamma < 0$. For interior solutions of loan size, this is likely to be the case or loan sizes would increase without bound.

To simplify the model and the calculation of the ML gradient, I do not rely on equation (6) during estimation. The derived expression can be considered as illustrative for how cost of effort $d_j$ affects the screening effort level $\sigma^2_j$. This approach also avoids functional form assumptions for the cost of effort parametrization and the distribution of the borrower’s hard information.\footnote{Misra and Nair (2011) are able to non-parametrically identify the policy effort function with an assumption that the observed sales is monotonic in effort. Since the loan officer’s output is the return of a noisy asset, further structure needs to be placed on the model to recover the policy function.} Another convenience is that this avoids some modeling difficulties. For example with behavioral overconfidence, loan officers may have inconsistent beliefs about their screening ability that interact in unclear ways with a separate ability choice.

### 3.6 Heterogeneous beliefs

Equation (4) makes sharp predictions about low ability loan officers, who should update and realize that their screening ability is low. These loan officers should discount the signals that they observe and weigh more heavily the borrower’s hard information such as income or debt levels. In the limiting case, a loan officer with no ability to screen soft information should behave as the lender with no variation in loan sizes conditional on hard information. In addition, the model also implies that low ability loan officers should achieve lower levels of profit than their high ability peers because of the lower quality of their screening signal. This ties a sharp relationship between a loan officer’s variance of loan sizes with loan performance.

Allowing for a more flexible empirical relationship will serve as the motivation for introducing inconsistent beliefs. For example, heterogeneous beliefs allow a loan officer who has a large amount of variance in her loan decisions to also have poor loan performance i.e. guessing randomly. Forcing rational expectations may instead erroneously attribute a high variance to high ability. With rational expectations, I also do not require data on the performance of the loans to estimate the model. The distribution of loan decisions is enough to pin down both risk preferences and screening ability. With data on loan performance, I can allow for more rich behavior and greater heterogeneity.

Moore and Healy (2008) describe one form of overconfidence as an excessive precision in beliefs. In lab studies, McKenzie et al. (2008) find that participant’s 90% confidence intervals include the true value only half of the time. This indicates that many people may be overconfident in their estimates. I interpret these results to mean that loan officers may also be overconfident and behave as if their screening signal is more accurate than the true value. I allow for inconsistent beliefs where a loan officer believes that her screening ability is $c_j^2$ rather than $\sigma^2_j$. This flexible specification allows for overconfidence, underconfidence, and the rational
expectations case. I will also be able to formally reject rational expectations as a restriction on the full model using a likelihood ratio test.

I am agnostic about the underlying cause of this inconsistency. For examples, loan officers may not know their ability and are guessing, they may be pretending to be of a different type, or the loan officers could receive random preference shocks for some borrowers. Another explanation could be that loan officers have heterogeneous beliefs about the prior distribution of the soft information $\sigma^2_u$, which will not be separately identified from $\sigma^2_j$. This will be expanded upon in the empirical section. Having heterogeneous beliefs about the prior is another form of overconfidence, and ultimately I make no distinction between these alternative mechanisms. This addition to the model allows for richer screening behaviors than simply Bayesian updating.

Loan officers with inconsistent beliefs falsely perceive the posterior distribution to instead be

$$u_i | \omega_{ij} \sim N \left( \frac{\sigma^2_u \omega_{ij}}{\sigma^2_j + c^2_j}, \frac{\sigma^2_j}{\sigma^2_u + c^2_j} \right) \quad (7)$$

If $c^2_j < \sigma^2_j$, this means that she believes her screening signal to be more precise than her actual precision. If $c^2_j > \sigma^2_j$, this means that the loan officer must be underconfident, while $c^2_j = \sigma^2_j$ indicates rational expectations. The updated optimal loan amount allowing for inconsistent beliefs is given by

$$L^*_{ij} = k_j \times \left( x_i \Gamma - \frac{1}{R} + \frac{\sigma^2_u \omega_{ij}}{\sigma^2_j + c^2_j} \right) \quad (8)$$

where the updated officer effect is

$$k_j = \left[ r_j \beta R \left( \frac{\sigma^2_c \omega_{ij}}{\sigma^2_u + c^2_j} + \sigma^2_k - \frac{\sigma^2_k}{\sigma^2_u + c^2_j} \right) \right]^{-1}.$$

All else equal, loan officers that are more overconfident have a larger variance of loan decisions conditional on hard information. This variance now identifies what the loan officer thinks of her screening ability, while her actual screening ability is identified from the performance of her loans. Another distortionary cost is that overconfident loan officers view the borrower’s soft information with some bias, which results in excessively large loans for safer borrowers. The officer effect $k_j$ is also larger, which interacts with risk preferences. Since overconfidence increases the officer effect, it may offset some of the costs of risk aversion. For a risk averse loan officer, overconfidence mitigates the tendency to choose small loan amounts. In some cases with an especially risk averse loan officer, overconfidence may actually increase profits. This is also why it is crucially important to perform this decomposition because by themselves each characteristic may distort loan decisions, but taken together, they may mutually attenuate.33

32Fisman et al. (2012) find some evidence that loan officers originate loans at higher rates for borrowers from similar backgrounds. However, the variance of these random preference shocks would also have to be heterogeneous across loan officers since the empirical model rejects homogenous beliefs.

33This is also why the separate identification of overconfidence apart from risk aversion has traditionally been difficult Goel and Thakor (2008).
4 Empirical strategy

Equations (2) and (8) jointly determine the borrower’s repayment and the loan officer’s loan decision respectively. These equations define an econometric model that can be estimated using maximum likelihood. Before deriving the likelihood, I highlight three main challenges to estimation: endogenous loan sizes, censored repayment histories, and identification of the loan officer characteristics. I address these in turn.

4.1 Endogenous loan sizes

Without an instrument, $L_{ij}$ in equation (2) is an endogenous object. This is because loan amounts are decided after the loan officer observes a signal about soft information indicating that $E[u_i|L_{ij}] \neq 0$. One solution is to rely on the application assignment process as an instrument for exogenous changes in loan amounts. The intuition is that ex-ante identical borrowers are assigned to different loan officers with different preferences for lending. However, instead of relying on indicators for each loan officer or the average loan size, the model suggests a set of ideal instruments. The heterogeneous loan officer characteristics $r_j$, $\sigma_j^2$, and $c_j^2$ are by definition uncorrelated with the borrower’s actual soft information $u_i$, but correlated with the borrower’s loan amount.

This means that the differences in repayment across loan officers can be causally attributed to these characteristics. The necessary assumption is that the uncodified soft information cannot be correlated with the loan officer’s characteristics conditional on codified hard information $E[u_i|\sigma_u^2, r_j, c_j^2, x_i, L_{ij}] = 0$.\(^\text{34}\) This assumption is supported by the random assignment of borrower applications to loan officers. And because borrowers are not involved in collecting delinquent loans, there is a natural exclusion restriction. Loan collection is handled entirely by the local branch offices with no contact from the original loan officer. The only effect that loan officers have on repayment is through the choice of loan size.

Table (2) provides evidence that loan officers are heterogeneous and approve different loan sizes. The specifications can be thought of as a first stage and show an F-test for the equality of loan officer indicators. Despite including hundreds of controls accounting for hard information such as year by month effects, city controls, application variables, and extensive financial and inspections variables, loan officers are still heterogeneous with respect to loan sizes. The large test statistic across all specifications indicates that the random assignment of loan officers has sufficient correlation with loan sizes. These differences also lead to variation in loan profits across loan officers.

Furthermore, it is not necessary that the assignment be unconditionally random. The identification assumption is still valid as long as the borrowers are randomly assigned conditional on

\(^\text{34}\)One possible violation is if loan officers collaborate with each other. For example, a loan officer on a particularly hard to read application may consult with others. The data does not allow me to identify collaboration in this way, but the large workload should preclude this type of joint inspection from frequently occurring.
Table 2: First stage and test of correlated observables

<table>
<thead>
<tr>
<th>Loan officer indicators</th>
<th>Dependent variable: loan amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>Joint F-Test</td>
<td>17.18 18.91 19.48 19.59 22.57</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.000 0.000 0.000 0.000 0.000</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.373 0.420 0.440 0.482 0.525</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Loan officer mean loan amount</th>
<th>Dependent variable: loan Amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>0.155 0.150 0.153 0.154 0.156</td>
</tr>
<tr>
<td>P-Value</td>
<td>0.000 0.000 0.000 0.000 0.000</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.367 0.413 0.433 0.476 0.518</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of controls</th>
<th>78 84 85 129 265</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year by month, city, product</td>
<td>✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Application variables</td>
<td>✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Internal credit quality</td>
<td>✓ ✓ ✓</td>
</tr>
<tr>
<td>Financial variables</td>
<td>✓ ✓</td>
</tr>
<tr>
<td>Inspection variables</td>
<td>✓</td>
</tr>
</tbody>
</table>

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Top panel shows the first stage test of correlation between loan officers and loan amounts. Second panel shows the test of correlated observables. Mean loan amount is the loan officer’s average loan amount excluding borrower $i$ or $\frac{1}{N_j-1} \sum_{-i} L_{ij}$. Application variables include loan amount requested, loan purpose, and transformations. Internal credit quality is an internal measure of borrower quality from credit scoring. Financial variables include income, wealth, taxes, social security, credit reports, external debt, and transformations. Inspection variables include home financing, home living arrangement, extensive occupation details, home furnishing, tenure in workplace, payment length dummies, and others. As of August 2014, $1 is ¥6.18.

the observed hard information. Loan officers may specialize in borrowers from specific cities or time windows, but they cannot specialize in cases with particularly high or low values of soft information $u_i$ within those categories. This assumption can be examined using a test for correlated observables. The rationale is that if observable attributes are not correlated with a loan officer’s portfolio, than it is less likely that unobservable attributes are correlated.

When examining the approval rates for disability examiners, Maestas et al. (2013) suggest such a test. I construct a loan officer’s average loan amount excluding borrower $i$ as $\frac{1}{N_j-1} \sum_{-i} L_{ij}$. By examining the regression of $L_{ij}$ on this variable along with additional covariates, I can test for correlated observables. This is because only borrower attributes that are correlated with the loan officer’s average loan amount should change its coefficient when added to the regression. Table (2) shows the results in the second panel for increasing collections of hard information.

---

35Given the volume of cases, it would be difficult and impractical for a pre-screener to give the borrowers with lower than expected $u_i$ to certain loan officers. The lender asserts that applications are not pre-sorted beyond time and city. This is because loan officers do not all work at the same time and applications from the same branch office may be frequently batched together. The lender does rely on separate underwriting departments for its other products such as high net worth loans or college loans.
The stable values across specifications provides evidence that loan officers do not specialize in observed borrower types beyond time and city. Extending the logic, this also supports the assumption that loan officers do not specialize within borrower types either.

4.2 Censored repayment

Another empirical challenge is censoring in the borrower’s repayment data. I do not observe the latent variable \( \eta^*_ij(L^*_ij) \) but a censored variable \( \bar{\eta}_i(L^*_ij) \) because many of the outstanding loans have not yet completed by the end of the study period. The data include 26 months of loans from 2011 to 2014 where the most common loan has a term length of 24 months. I have repayment data for those loans through 2014, and observe roughly 9,500 completed loans. I account for the remainder by estimating with a Tobit specification. Specifically, if \( \bar{\eta}_i \) is the current proportion of payments made, then the repayment \( \eta_i(L^*_ij) \) I observe is given by

\[
\eta_{ij}(L^*_ij) = \begin{cases} 
\eta^*_{ij}(L^*_ij) & \text{if uncensored} \\
\bar{\eta}_i < \eta^*_{ij}(L^*_ij) & \text{if censored}
\end{cases}
\]

For example, if the data period ends with a borrower making 6 of 12 required payments, then \( \eta_{ij} = \bar{\eta}_i = .5 \) ignoring adjustments due to discounting. The likelihood function accounts for the fact that \( \eta^*_{ij}(L^*_ij) \) is weakly greater since the lender would not refund payments back to the borrower. Uncensored contracts are those where no further payments are expected and include completed contracts and defaulted borrowers.\(^{36}\) With the lender engaged throughout the year, the censoring point only depends on the date of origination and is assumed to not be correlated with \( \eta^*_{ij}(L^*_ij) \) or \( L^*_ij \).

4.3 Loan officer characteristics

I next give some intuition for the identification of the loan officer parameters. Since borrower applications are randomly assigned to loan officers, the distribution of unobserved borrower attributes \( u_i + \epsilon_i \) across loan officers is ex-ante identical. If all loan officers were identical, then conditional on the hard information \( x_i \), the distribution of loan sizes across all loan officers should be the same. However, heterogeneity in loan officer characteristics leads to differences in loan decisions. For example, heterogeneity in risk preferences lead some loan officers to approve larger loan amounts.

This prediction can be seen using the actual borrower data to examine differences in approved loan amounts across loan officers. Figure (3) plots the average loan amount for loan officers against the internal measure of credit quality where higher values indicate safer borrowers. For comparable loans made with the same loan terms in the same month, Officer A approves larger

\(^{36}\)I rely on the lender’s definition of a defaulting loan being 90 days past due or three payment periods. After the 90 day mark, the loans are usually packaged and sold to collections agencies. In some cases, delinquent loans go to litigation.
average loan amounts than Officer B for every level of risk. All else equal, Officer A is less risk averse than Officer B.\footnote{In practice, maximum likelihood identifies all of the loan officer characteristics and the borrower repayment function jointly using the full distribution rather than just these moments. For example, the absolute level of risk aversion is also determined from the borrower’s repayment function since risk neutral lending is where marginal profit is equal to 0.}

The variance of a loan officer’s loan sizes identifies the loan officer’s belief about her screening ability. Loan officers that believe that they have no ability to screen should have less variance of loan sizes conditional on hard information. This prediction is highlighted in Figure (4) that plots a scatter of loans approved by two officers in the same month and same terms against credit quality. With the bands representing 95% confidence intervals, Officer D has a greater spread in her loan decisions than Officer C at every level of risk. All else equal, Officer D must be more overconfident than Officer C.

The loan officer’s actual screening ability can be seen with how her loans perform where low
Notes: Sample includes first-time borrowers from June 2012 examined by 2 loan officers. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. Borrower applications are randomly assigned to loan officers. Credit quality is an internal measure of borrower quality from credit scoring - higher values indicate safer borrowers. For each level of credit quality, the loan officer’s loans are plotted with a 95% confidence interval. As of August 2014, $1 is ¥6.18.

ability loan officers should have worse performing loans. Figure (5) shows a scatter of defaulted and completed loans against credit quality for two loan officers. Note that loan performance includes default, late fees, early repayment fees, and other ancillary fees so that profitability is not determined solely by default. However, this is a useful visual proxy to understand the relationship. For comparable loans, Officer F has higher performing loans than Officer E showing that Officer F must have greater screening ability than Officer E all else equal.\textsuperscript{38}

4.4 Decomposing the variance of repayment

Some variables are difficult to identify. The variance of loan repayment recover the sum $\sigma_u^2 + \sigma_t^2$ but not the individual components. This is because there is no observable source of variation affecting one and not the other. The principle difficulty is trying to decompose the variance into

\textsuperscript{38}I do not impose a correlation structure between loan officer characteristics, and each loan officer’s characteristics may be correlated in different ways. With only 21 loan officers, it would be difficult to recover parameters that are identified across loan officers.
Notes: Sample includes first-time borrowers from June 2012 examined by 2 loan officers. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. Borrower applications are randomly assigned to loan officers. Credit quality is an internal measure of borrower quality from credit scoring - higher values indicate safer borrowers. Defaulted loans are delinquent for more than 2 payment periods. As of August 2014, $1 is ¥6.18.

a portion that is screenable versus unscreenable. If there was a loan officer that could perfectly observe the soft information $u_i$ without any overconfidence, then the loan decisions of that loan officer would be able to separate $\sigma^2_u$ and $\sigma^2_\epsilon$. However, without such a perfect loan officer, I can only recover the composite and not the component pieces. For this reason, the counterfactual exercises also cannot model a loan officer that has a perfectly accurate signal.

Instead of relying on functional form assumptions or placing additional structure on the model, I consider a different approach. I use a change of variables that allows me to estimate the model parameters as functions of the underlying variance of soft information $\sigma^2_u$. This change rewrites the model using a reduced set of parameters but with an identical likelihood function with the proof in Appendix C. Instead of the parameter set $\Theta = (\Gamma, \gamma, r_j, \sigma^2_j, c^2_j, \sigma^2_u, \sigma^2_\epsilon)$, I estimate the adjusted set

$$\tilde{\Theta} = \left( \Gamma, \gamma, \tilde{r}_j = r_j \beta, \tilde{\sigma}^2_j = \frac{\sigma^2_j}{\sigma^2_u} + 1, \tilde{c}^2_j = \frac{c^2_j}{\sigma^2_u} + 1, \tilde{\sigma}^2_u = 1, \tilde{\sigma}^2_\epsilon = \sigma^2_u + \sigma^2_\epsilon - 1 \right)$$

(10)

This normalization has three main benefits. The first is that it removes the need to specify
how much of the variance is screenable versus unscreenable, but still allows for the model to accommodate the distinction. Screening models that do not account for this difference implicitly assume that evaluators can observe signals that occur after origination such as an unpredictable shock. This means that all else equal, increases in the variance of repayment for any reason strictly increase the value of evaluators versus automated methods. Second, the change of variables is monotonic so that loan officers that are overconfident in the original parameter set where $c_j^2 < \sigma_j^2$ are still overconfident in the adjusted set $\tilde{c}_j^2 < \tilde{\sigma}_j^2$. This allows straightforward comparisons both within and across loan officers. Last and most importantly, this change still allows for counterfactual lending models that change the loan officer’s behavior.\(^{39}\)

4.5 Maximum likelihood

Deriving the actual likelihood function is straightforward. For ease of exposition, I write the likelihood in terms of the full set of parameters and not the adjusted set. Appendix C contains the derivation of their equality. The probability of observing $L_{ij}^*$ and $\eta_i \left( L_{ij}^* \right)$ conditional on the censoring point $\bar{\eta}_{i}$ and hard information $x_i$ is $P \left( L_{ij}^*; \eta_i | \Theta; x_i, \bar{\eta}_i \right)$. This joint density can be written as the product of a conditional and a marginal using Bayes’ rule, which gives $P \left( L_{ij}^* | \Theta; x_i, \bar{\eta}_i \right) \times P \left( \eta_i | \Theta; L_{ij}^*, x_i, \bar{\eta}_i \right)$. Since the stochastic piece in both expressions is additively normal, the likelihoods can be written as

$$L \left( \Theta; L_{ij}^*, \eta_i \right) = \begin{cases} \frac{1}{\sigma_v} \phi \left( \frac{L_{ij}^* - w_{ij}}{\sigma_v} \right) \times \frac{1}{\sigma_{u+v}} \phi \left( \frac{\eta_i - h_{ij}}{\sigma_{u+v}} \right) & \text{if uncensored} \\ \frac{1}{\sigma_v} \phi \left( \frac{L_{ij}^* - w_{ij}}{\sigma_v} \right) \times \Phi \left( \frac{h_{ij} - \bar{\eta}_i}{\sigma_{u+v}} \right) & \text{if censored} \end{cases} \tag{11}$$

where $w_{ij} = x_i' \Gamma k_j - k_j$, $\sigma_v^2 = k_j^2 \frac{\sigma_j^2 (\sigma_j^2 + \sigma_v^2)}{(\sigma_j^2 + c_j^2)}$, $h_{ij} = \gamma L_{ij} + x_i' \Gamma + \frac{\sigma_v^2 + c_j^2}{(\sigma_j^2 + c_j^2)} k_j (L_{ij} - w_{ij})$, and $\sigma_{u+v}^2 = \frac{\sigma_j^2 \sigma_v^2}{\sigma_j^2 + c_j^2} + \sigma_v^2$. This likelihood function is a Tobit model with an endogenous regressor and an observation-specific censoring point. Estimation relies on an analytic gradient and Hessian using a modified Newton-Raphson search algorithm.\(^{40}\)

5 Results and counterfactuals

In this section, I present the estimates for the adjusted model parameters $\tilde{\Theta} = \left( \Gamma, \gamma, \tilde{\gamma}_j, \tilde{c}_j, \tilde{\sigma}_j^2, \tilde{\sigma}_\epsilon^2 \right)$. The parameters allow me to construct an econometrician’s prediction without loan officers and based entirely on the codified hard information. By comparing the status quo to this prediction, I observe the net value of delegating to loan officers compared to an automated decision. I can also examine counterfactuals designed to mitigate the distortionary costs of the loan officer

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\(^{39}\)In addition to not being able to assemble a perfect loan officer, I also cannot examine counterfactuals that vary the composition of screenable versus unscreenable risk. I can however perform counterfactuals that increase or decrease the overall amount of variance.

\(^{40}\)I do not present a proof for global concavity of the likelihood, however, different initial values converged to a stable estimate.
characteristics by adjusting their values. By comparing these counterfactuals with the status quo, I can recover the costs to the lender.

5.1 Borrower repayment function

Table (3) lists some of the estimates for the empirical repayment function $\eta^*_i \left(L^*_ij\right)$. Following equation (2), loan size, monthly payment, and the present value of full repayment all affect repayment through $\gamma$. Higher borrowed amounts decrease repayment, while a higher monthly payment increases the proportion returned. With an average repayment proportion around 80%, it is not surprising that higher monthly payments lead to greater loan recovery all else equal.

While the individual $\gamma$ estimates are difficult to compare because of different interest rates and payment lengths, $\gamma$ for the most common loan type with a 24 month loan and an APR of 48% is -.5%. In other words, an increase of ¥10,000 in the size of the loan leads to a decrease of 5% of the total payment $R_iL_{ij}$.

To put this into context, a loan of size ¥34,450 for 24 months at an APR of 48% has a total present value of ¥49,500. This is the value of the loan if the borrower repays in full each period without incurring any penalty late fees or paying early fees. By extending an additional ¥1,000 to this borrower, two effects occur. One is that additional interest is earned on the marginal loan increase, but this change may be offset by the fall in repayments on the inframarginal repayments. These two effects can be seen in Figure (6) where past a point, marginal profit decreases. The lender’s average loan amount for these terms indicate that the marginal loan amount may be profitable. Karlan and Zinman (2010) attribute marginal loan profitability to overly conservative risk assessment, which I take this as further motivation that risk preferences may explain this gap.

The variance estimate of $u_i + \epsilon_i$ of .115 in Table (3) shows that there is still substantial variation in repayment conditional on hard information. As this variance increases, more of the variation in repayment cannot be screened by hard information alone. However, this does not necessarily imply that loan officers increase in value with a greater variance. As the variance of screenable risk $\sigma^2_u$ increases relative to unscreenable risk $\sigma^2_\epsilon$, the screening value of loan officers increases as more of the variation can be screened. However, the breakdown between these component pieces is not identified.

Some of the additional covariates are also of interest. Managers and women all repay at above average rates. Dorm or rental indicators in China generally imply young, migrant, or

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41The magnitude can be compared to the literature, but the comparison is not straightforward because most studies investigate the impact on default and not repayment. In addition, differences in institutional setting make cross-country comparisons difficult. Despite this concerns, the estimates are roughly consistent. In the US subprime auto financing market, Adams et al. (2009) find that a 1% increase in loan amounts leads to a 1.6% increase in the chance of default. By running the same specification with default instead of repayment on the same sample, Wang (2014) finds that a similar 1% increase in loan size leads to a .6% increase in the chance of default. Other estimates of $\gamma$ find either very small or sometimes positive magnitudes. Dobbie and Skiba (2013) find that increases in loan size lead to a slight decrease in default when examining US payday lenders. However, their estimates cannot reject no change.
Table 3: Estimates of the borrower repayment function

<table>
<thead>
<tr>
<th>Loan terms</th>
<th>Coefficient</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan amount</td>
<td>-0.016</td>
<td>0.000</td>
</tr>
<tr>
<td>Monthly payment</td>
<td>0.038</td>
<td>0.000</td>
</tr>
<tr>
<td>Present discounted value</td>
<td>0.006</td>
<td>0.000</td>
</tr>
<tr>
<td>Variance of soft information and error $\sigma^2_u + \sigma^2_\epsilon$</td>
<td>0.115</td>
<td>0.000</td>
</tr>
</tbody>
</table>

$\gamma$ for a 24 month loan with an APR of 48%: -0.005

Selected hard information

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Payroll income</td>
<td>1.6e-5</td>
</tr>
<tr>
<td>External debt</td>
<td>1.1e-6</td>
</tr>
<tr>
<td>Credit card utilization</td>
<td>-0.008</td>
</tr>
<tr>
<td>Management position</td>
<td>0.024</td>
</tr>
<tr>
<td>Female indicator</td>
<td>0.002</td>
</tr>
<tr>
<td>Amount requested</td>
<td>1.7e-4</td>
</tr>
<tr>
<td>Dorm or rental indicator</td>
<td>-0.019</td>
</tr>
<tr>
<td>Credit quality</td>
<td>1.0e-5</td>
</tr>
<tr>
<td>Air conditioner units</td>
<td>0.004</td>
</tr>
<tr>
<td>Met family/coworkers</td>
<td>0.008</td>
</tr>
</tbody>
</table>

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. Borrower repayment parameters are from the main MLE specification. The monthly payment varies with payment length and APR. PDV is the total repayment if the loan is repaid in full and includes fees. Additional controls include year by month, city, product fixed effects, and additional application, financial, and inspection variables. As of August 2014, $1 is ¥6.18.

Transient workers, and it is not surprising that their repayment rates are correspondingly lower than average. Some of the home inspection items such as air conditioner units or conversations with family and coworkers also indicate that household wealth and openness are associated with higher rates of repayment.42

5.2 Loan officer characteristics

Table (4) presents the estimates of the adjusted loan officer characteristics: risk preferences $\tilde{r}_j$, screening belief $\tilde{c}_j^2$, and screening ability $\tilde{\sigma}_j^2$. Interpreting these estimates is difficult as they are functions of the bonus rate $\beta$ and the variance of soft information $\sigma_u^2$. However, some conclusions can be drawn. The estimated values for $\tilde{r}_j = r_j \beta$ are all positive indicating that all of the loan

42I urge caution when interpreting the coefficients on hard information since many of the included variables are higher order terms, interactions, or functions of existing variables. For instance, the lender’s credit quality variable is itself a function of salaried income and other attributes such as education. The purpose of this exercise is to mimic a predictive model and not to assign causal interpretations to borrower attributes apart from the size of the loan.
officers have positive risk preferences.\footnote{There are no constraints placed on $\tilde{r}_{ij}$ during estimation. Having a negative $\tilde{r}_{ij}$ may indicate risk loving behavior by some loan officers. \textit{Agarwal and Ben-David (2014)} find that some loan officers take excessive risks given that their screening effort conveys little information. These excessive risks may be erroneously attributed to risk aversion if overconfidence is not allowed.} This means that the marginal loan amount is profitable for all of the loan officers. Another conclusion is that there is substantial heterogeneity across loan officers in risk preferences. Table (5) displays a likelihood ratio test for a restricted model of homogenous risk preferences for all loan officers. The data is sufficient to reject this null.

The second and third columns in Table (4) shows the estimate of screening beliefs and screening ability for all of the loan officers. The change of variables still allows comparisons to be made between these loan officers. Adjusted overconfidence $\tilde{c}_j^2 = \frac{c_j^2}{\sigma_u^2} + \frac{1}{\sigma_u^2} - 1$ is uniformly less than adjusted screening ability $\tilde{\sigma}_j^2 = \frac{\sigma_j^2}{\sigma_u^2} + \frac{1}{\sigma_u^2} - 1$. All of the loan officers are overconfident indicating that the loan officers behave as if their screening ability is much more precise than shown by the data. It is informative to characterize how an underconfident loan officer would behave. Holding screening ability $\sigma_j^2$ constant, as $c_j^2$ increases, the variance of loan decisions
Table 4: Estimates of the loan officer parameters

<table>
<thead>
<tr>
<th>Officer #</th>
<th>Risk preferences</th>
<th>Screening beliefs</th>
<th>Screening ability</th>
</tr>
</thead>
<tbody>
<tr>
<td>#1</td>
<td>0.004</td>
<td>124.9 ***</td>
<td>129.7 *</td>
</tr>
<tr>
<td>#2</td>
<td>0.011 ***</td>
<td>476.5</td>
<td>1917.0</td>
</tr>
<tr>
<td>#3</td>
<td>0.018 ***</td>
<td>96.4 ***</td>
<td>107.8 **</td>
</tr>
<tr>
<td>#4</td>
<td>0.010 ***</td>
<td>262.4 ***</td>
<td>753.2 *</td>
</tr>
<tr>
<td>#5</td>
<td>0.001</td>
<td>151.6 ***</td>
<td>181.1 **</td>
</tr>
<tr>
<td>#6</td>
<td>0.009 ***</td>
<td>294.2 **</td>
<td>968.2</td>
</tr>
<tr>
<td>#7</td>
<td>0.005 **</td>
<td>440.0 ***</td>
<td>1767.0</td>
</tr>
<tr>
<td>#8</td>
<td>0.008 ***</td>
<td>186.5 ***</td>
<td>324.1</td>
</tr>
<tr>
<td>#9</td>
<td>0.006 **</td>
<td>199.7 ***</td>
<td>320.5 *</td>
</tr>
<tr>
<td>#10</td>
<td>0.010 ***</td>
<td>243.3 ***</td>
<td>550.2 **</td>
</tr>
<tr>
<td>#11</td>
<td>0.010 ***</td>
<td>267.8 ***</td>
<td>620.4 **</td>
</tr>
<tr>
<td>#12</td>
<td>0.005 *</td>
<td>289.5 **</td>
<td>744.0</td>
</tr>
<tr>
<td>#13</td>
<td>0.010 ***</td>
<td>78.9 ***</td>
<td>87.7 *</td>
</tr>
<tr>
<td>#14</td>
<td>0.008 ***</td>
<td>210.8 ***</td>
<td>434.1 *</td>
</tr>
<tr>
<td>#15</td>
<td>0.001</td>
<td>223.2 ***</td>
<td>444.8</td>
</tr>
<tr>
<td>#16</td>
<td>0.015 ***</td>
<td>196.9 **</td>
<td>272.2</td>
</tr>
<tr>
<td>#17</td>
<td>0.006 **</td>
<td>268.0 *</td>
<td>555.1</td>
</tr>
<tr>
<td>#18</td>
<td>0.010 ***</td>
<td>297.1 ***</td>
<td>1026.0 **</td>
</tr>
<tr>
<td>#19</td>
<td>0.007 ***</td>
<td>462.7</td>
<td>1708.0</td>
</tr>
<tr>
<td>#20</td>
<td>0.007 ***</td>
<td>288.7 ***</td>
<td>583.6 **</td>
</tr>
<tr>
<td>#21</td>
<td>0.011 ***</td>
<td>200.7 ***</td>
<td>389.6</td>
</tr>
</tbody>
</table>

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Estimates are from the main MLE specification and are the adjusted variables in terms of $\beta$ and $\sigma^2_u$.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

conditional on hard information will decrease, loan sizes will decrease, and loan repayment will decrease as well. Underconfident loan officers therefore have smaller but worse performing loans.

Table (5) shows specification tests for homogenous screening beliefs and for homogenous screening ability. Both of these nulls are rejected at the 10% level. Another specification test is the rational expectations restriction that loan officers have accurate beliefs about their screening ability or $c^2_j = \sigma^2_j$ for all of the loan officers. The likelihood ratio test rejects this hypothesis convincingly showing that loan officers seem to be overconfident about their screening ability. A model that does not allow for inconsistent beliefs would attribute the poor loan performance of some low ability loan officers to excessive variance in loan repayments. Together, these results provide evidence that there is heterogeneity in risk preferences, screening beliefs, and screening ability. Furthermore, loan officers are overconfident about their screening ability. However, to measure the value of these loan officers, it is necessary to construct counterfactuals.

\footnote{The estimates are imprecise when claiming that individual loan officers are overconfident.}
Table 5: Likelihood ratio tests

<table>
<thead>
<tr>
<th>Null:</th>
<th>Likelihood ratio test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loan officers have homogenous risk preferences $r_j = r \forall j$.</td>
<td>$X^2 = 471$ P-value 0.000</td>
</tr>
<tr>
<td>Loan officers have homogenous screening beliefs $c_j^2 = c^2 \forall j$.</td>
<td>$X^2 = 31$ P-value 0.051</td>
</tr>
<tr>
<td>Loan officers have homogenous screening ability $\sigma_j^2 = \sigma^2 \forall j$.</td>
<td>$X^2 = 32$ P-value 0.042</td>
</tr>
<tr>
<td>Loan officers have rational expectations $c_j^2 = \sigma_j^2 \forall j$.</td>
<td>$X^2 = 446$ P-value 0.000</td>
</tr>
</tbody>
</table>

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Likelihood ratio test statistics are on the parameter estimates from the main MLE specification.

5.3 Status quo lending profits

The model can calculate expected loan profits in the status quo for each of the loan officer’s approved loans. Using these, I can compare to the econometrician’s prediction as well as alternative counterfactuals.\textsuperscript{45} The status quo uses the estimated parameters and matches the observed loan decisions. Using the loan officer characteristics, I first invert equation (8) for the biased signal that the loan officer must have observed. This signal is a function of her characteristics, the borrower’s hard information, and the approved loan amount. This signal relates both the loan officer’s belief about expected profit as well as the loan’s actual expected profit through equation (7).

Specifically for each loan officer, the officer effect $k_j$ is calculated using the adjusted parameters where $k_j^{S,Q} = \left( \frac{\sigma_u^2}{\sigma_u^2 + c_j^2} \right)^{-1}$ and the posterior belief is given by

$$\frac{\sigma_u^2}{\sigma_u^2 + c_j^2} \omega_{ij} = L_{ij}^*/k_j^{S,Q} - x_i^\prime \Gamma + \frac{1}{R_i}$$ \textbf{(12)}

Because loan officers are overconfident, the correct posterior mean of soft information is not given by equation (12). Using the adjusted parameters, the correct posterior can be expressed as

$$\frac{\sigma_u^2}{\sigma_u^2 + c_j^2} \omega_{ij} = \frac{\sigma_u^2 + c_j^2}{\sigma_u^2 + \sigma_j^2} \times \frac{\sigma_u^2}{\sigma_u^2 + c_j^2}$$ \textbf{Eqn 12} \textbf{(13)}

\textsuperscript{45}It is possible to use the realized profits instead of the expected profits for the status quo. This approach is unattractive because many loans are censored and do not have realized profits. This also maintains consistent comparisons with the expected profits from the counterfactuals. A simulation approach that calculates the expected profits for counterfactual borrowers also is not possible. This is because I cannot separate soft information from the exogenous error, and therefore cannot simulate alternative borrowers.
which gives the expected profit conditional on the soft information signal to be

\[
E \left[ \pi_i^{S,Q} | \omega_{ij} \right] = R_i L_i^{S,Q} \left( \gamma L_i^{S,Q} + x_i' \Gamma + \frac{\sigma_u^2}{\sigma_u^2 + \sigma_j^2} \omega_{ij} \right) - L_i^{S,Q} \tag{14}
\]

\(E \left[ \pi_i^{S,Q} | \omega_{ij} \right]\) can be compared to the econometrician’s prediction \(E \left[ \pi_i^{\text{Econometrician}} \right]\) to recover the value of loan officers.

### 5.4 Econometrician’s prediction

The structural model allows for counterfactual lending under different scenarios. One is to examine an econometrician’s prediction without delegating to loan officers and relying only on the codified hard information. How would loan sizes and loan profits change if an econometrician made decisions without the distortionary characteristics faced by loan officers?\(^{46}\) Given equation (2), the profit-maximizing loan amount for an econometrician with access to only the hard information is given by

\[
L_{i}^{\text{Econometrician}} = (-2\gamma)^{-1} \left( x_i' \Gamma - \frac{1}{R_i} \right) \tag{15}
\]

Contrast this with the loan officer’s loan amount in equation (8). The econometrician’s effect \((-2\gamma)^{-1}\) is much larger than the officer effect \(k_j\) due to risk neutral lending. The econometrician has consistent beliefs about his lack of screening ability and must take an expectation over soft information unlike the overconfident loan officer. This results in no loan variation conditional on hard information.

For each loan, expected loan profits can be calculated as

\[
E \left[ \pi_i^{\text{Econometrician}} \right] = R_i L_i^{\text{Econometrician}} \left( \gamma L_i^{\text{Econometrician}} + x_i' \Gamma \right) - L_i^{\text{Econometrician}} \tag{16}
\]

Table (6) compares the econometrician’s expected profit with the status quo. The average loan amount is ¥38,000, which is 14% higher than the status quo amount of ¥33,450. This large gap is unsurprising given the higher risk preferences of the individual loan officers. However, average loan profits are about ¥200 higher and significant at the 10% level. The average loan officer screens 700 applications per year, which results in roughly ¥140,000 in additional yearly profits over the econometrician. With an annual pay of ¥45,000, loan officers outperform the econometrician by more than three times their pay.

Despite the distortionary costs of heterogeneous characteristics, loan officers are still profitable compared to an econometrician’s prediction. The econometrician enjoys unfair advantages in this comparison. One advantage is making loan decisions after observing the borrower’s actual

\(^{46}\)Heider and Inderst (2012) examine a model where competition between lenders causes lenders to disregard soft information and rely solely on observable characteristics. The role of the loan officer changes to a salesperson prospecting for borrowers rather than as evaluators. Berger et al. (2005) find that the costs of collecting soft information rise with the size of the lender. Past a certain volume, lenders may not find it worthwhile to continue to collect soft information.
Table 6: Counterfactuals compared to econometrician

<table>
<thead>
<tr>
<th>Status quo with estimated parameters.</th>
<th>Additional loan amount (¥000’s)</th>
<th>Additional loan profit (¥000’s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-4.56 ***</td>
<td>0.21 *</td>
</tr>
<tr>
<td></td>
<td>(1.63)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Loan officers with $r_j = r_{min}$.</td>
<td>-0.57</td>
<td>0.32 ***</td>
</tr>
<tr>
<td></td>
<td>(1.00)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Loan officers with $\sigma^2_j = \sigma^2_{j}$.</td>
<td>-4.62 ***</td>
<td>0.35 ***</td>
</tr>
<tr>
<td></td>
<td>(1.64)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Loan officers with $\sigma^2_j = \sigma^2_{min}$.</td>
<td>-4.54 ***</td>
<td>0.64 ***</td>
</tr>
<tr>
<td></td>
<td>(1.63)</td>
<td>(0.13)</td>
</tr>
</tbody>
</table>

Notes: Bootstrapped standard errors in parenthesis. Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. Econometrician’s prediction is risk neutral lending based only on hard information. The econometrician’s average loan amounts equal ¥38,000 and average profits are ¥11,000. For each counterfactual, each borrower’s loan amount is re-optimized and expected profit is calculated. As of August 2014, $1 is ¥6.18.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

...repayment behavior, which allows the econometrician to make an in-sample prediction using ex-post data. Another is that the econometrician has access to time and area effects, access to prohibited controls such as gender, and is allowed to be risk neutral. With these advantages, the econometrician is likely to outperform automated algorithms that the lender would have had access to at the time of origination.

Despite these advantages, loan officer decisions are still more profitable. However, this value varies across loan officers. Figure (7) compares the status quo to the econometrician for all of the loan officers individually. While some loan officers may not outperform the econometrician, some are extremely valuable although the estimates are imprecise. The loan officers are all profitable according to net present value, but some may not outperform the econometrician.

5.5 Minimum estimated risk aversion

Another set of counterfactuals are designed to mitigate the distortionary costs of loan officer characteristics. One example is to examine lending if loan officers behaved with less risk aversion.

---

47 If the econometrician’s model included individual borrower indicators, then it would outperform any screening model.
48 Misra et al. (2005) consider a model where the principal may also have risk preferences.
Notes: 95% confidence interval constructed from bootstrapped standard errors. Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. Status quo lending is with the estimated parameters. Econometrician’s prediction is risk neutral lending based only on hard information. Each borrower’s loan amount is re-optimized and expected profit is calculated. As of August 2014, $1 is ¥6.18.

Specifically, I construct a lending model where all of the loan officers behave with risk preferences equal to that of the least risk averse loan officer. The procedure first requires calculating an updated officer effect $k_j$ and then recalculating the loan amount $L_{ij}^{MinRA}$. Since the adjusted risk aversion estimate $\tilde{r}_j = r_j \beta$ is a scalar multiple of the bonus rate $\beta$, the loan officer with the lowest value of $r_j$ also has the lowest value of $\tilde{r}_j$ after the monotonic transformation. Each officer effect is given by $k_j^{MinRA} = \left[r_{Min} R \left(\frac{\tilde{c}_j^2}{1+c_j^2} + \tilde{\sigma}_e^2\right) - 2\gamma\right]^{-1}$. After solving for the original signal in equation (12), the updated loan amount and expected loan profits are given similarly to equations (8) and (14).

This change increases average loan sizes and profits since the original loan amount was approved with higher risk preferences. However, this effect is not ambiguously beneficial to the lender and it could be possible that some loans actually see a decrease in expected profit. To see this, suppose an extremely overconfident loan officer received a signal about the borrower’s soft
information. Overconfidence leads her to erroneously believe the borrower is low risk, but this tendency is counteracted by risk aversion which decreases average loan amounts. By behaving with less risk aversion, the distortion created by overconfidence may dominate the risk aversion effect. The result may be that some loan amounts are excessively large and less profitable than otherwise. The effectiveness of the counterfactual on loan profits is then largely an empirical question.

Figure 8: Additional profit over econometrician
Lending profit if loan officers behaved with $r_j = r_{min}$.

Notes: 95% confidence interval constructed from bootstrapped standard errors. Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. Counterfactual lending is if all loan officers behaved with the minimum estimated risk aversion. Econometrician’s prediction is risk neutral lending based only on hard information. Each borrower’s loan amount is re-optimized and expected profit is calculated. As of August 2014, $1 is ¥6.18.

Table (6) reports that the average loan size of ¥37,440 is significantly higher than the status quo, and statistically indistinguishable from the econometrician’s prediction. This is expected as loan amounts increase. Profits are ¥320 higher for every loan. With 700 applications a year, this counterfactual brings an additional profit of ¥224,000 above the econometrician. This is about five times the average loan officer’s compensation. Compared to the status quo, this is roughly ¥110 more per loan. This is the cost to the lender of risk preferences, which over the course of a year is the pay of an additional two loan officers. Figure (8) shows the profit comparison
for individual loan officers versus the econometrician. The majority now statistically outperform the econometrician with some achieving additional profits of over ¥1,000 per loan.

5.6 Rational expectations

Another counterfactual is to look at changes in loan sizes and loan profits if loan officers behaved with rational expectations. This imposes $c_j^2 = \sigma_j^2$ for all loan officers. The procedure for determining counterfactual loan profits follows the counterfactual on risk aversion, which requires calculating an updated officer effect $k_{ij}$. Because the adjusted overconfidence $\tilde{c}_j^2 = \frac{c_j^2}{\sigma_u^2} + \frac{1}{\sigma_u^2} - 1$ has the same functional form as the adjusted screening effort $\tilde{\sigma}_j^2 = \frac{\sigma_j^2}{\sigma_u^2} + \frac{1}{\sigma_u^2} - 1$, a loan officer with rational expectations has $c_j^2 = \sigma_j^2$. The officer effect is given by $k_{ij}^{NoOC} = \left(\tilde{r}_j R \left(\frac{\tilde{\sigma}_j^2}{\sigma_u^2} + \tilde{\sigma}_j^2\right) - 2\gamma\right)^{-1}$. The updated loan amount is given by

$$L_{ij}^{NoOC} = k_{ij}^{NoOC} \left(x_i^\prime \Gamma - \frac{1}{R_i} \frac{\sigma_u^2}{\sigma_u^2 + \sigma_j^2} \omega_{ij}\right) \tag{17}$$

where the adjusted signal can be calculated from equation (13) and expected profit is similar to equation (16).

Without overconfidence, average loan sizes must decrease but so might profits due to two effects. The first is because an overconfident loan officer has a larger officer effect $k_{ij}$ due to the smaller $c_j^2$. Overconfidence attenuates the effect of risk preferences so that by reducing overconfidence, loan amounts and profits may decrease further.\(^{49}\) The second effect is because overconfidence also changes the posterior belief $\frac{\sigma_u^2}{\sigma_u^2 + \sigma_j^2} \omega_{ij}$. This also interacts with risk preferences so that with accurate beliefs about screening ability, risky borrowers are given larger loans and safer borrowers are given smaller loans. This is another important reason for this decomposition.

A naive lender that blindly implements rational expectations could decrease profits without accounting for risk preferences.

Table (6) shows that the impact on average loan amounts decreases but is not statistically significant. Profits, however, are ¥350 larger. Loan officers now contribute 5.5 times their compensation in additional annual profits over the econometrician. Profits are also ¥140 higher than the status quo indicating large costs imposed by overconfidence. Figure (9) shows that most loan officers now beat the econometrician. However, the point estimate for some of the loan officers decreases due to less overconfidence. For example, loan officer 3 sees her profits decrease by more than ¥30 per loan. For particularly high levels of risk aversion, some amount of overconfidence may be profitable.

\(^{49}\)Even with a precise signal, it may be possible that some loan officers are not willing to increase loans to the point where marginal profit equals zero. This fear may be driven by herd behavior or career concerns where a failing loan given to an observably risky borrower may be blamed on the loan officer. See Borenstein et al. (2012) for a career concerns model where the agent willfully deviates from the profit-maximizing outcome to avoid possible blame.
5.7 Highest estimated screening ability

One last counterfactual compares loan amounts and profits when loan officers have greater screening ability. If all loan officers had the highest estimated screening ability, then screening would be more precise. The procedure begins by recognizing that the officer effect $k_j$ does not change from the status quo since $k_j$ is not directly a function of screening ability but of screening beliefs. The loan officer with the lowest value of $\sigma_j^2$ must also have the lowest adjusted $\tilde{\sigma}_j^2$ from the change of variables. Since the realization of $\omega_{ij}$ changes with greater screening ability, a different approach must be taken in calculating the adjusted signal. The adjusted signal in the status quo is distributed $\frac{\sigma^2}{\sigma^2 + \sigma_j^2} \omega_{ij} \sim N \left( 0, \frac{\sigma^2}{\sigma^2 + \sigma_j^2} \right)$, while a signal coming from a loan officer with screening ability $\sigma^2_{Min}$ would be distributed...
\[
\frac{\sigma^2_u}{\sigma^2_u + \sigma^2_{Min}} \omega_{ij}^{High} \sim N \left( 0, \frac{\sigma^4_u}{\sigma^2_u + \sigma^2_{Min}} \right)
\]

(18)

To maintain consistent comparisons with the status quo, I rescale the original signal instead of redrawing from the updated distribution.

\[
\frac{\sigma^2_u}{\sigma^2_u + \sigma^2_{Min}} \omega_{ij}^{High} \sim \sqrt{\frac{\sigma^2_u + \sigma^2_j}{\sigma^2_u + \sigma^2_{Min}}} \times \frac{\sigma^2_u}{\sigma^2_u + \sigma^2_j} \omega_{ij}^{S,Q}
\]

(19)

This normalizes the value of the counterfactual signal \( \omega_{ij}^{High} \) without having to draw a new stochastic value. The benefit to this approach instead of simulating from the distribution in equation (18) is that this allows for a consistent comparison with the status quo. As \( \sigma^2_{Min} \) approaches \( \sigma^2_j \), the counterfactual values equal the status quo. The loan officer’s biased posterior can be calculated as

\[
\frac{\sigma^2_u}{\sigma^2_u + C^2_j} \omega_{ij}^{High} = \sqrt{\frac{\sigma^2_u + \sigma^2_{Min}}{\sigma^2_u + \sigma^2_j}} \times \frac{\sigma^2_u}{\sigma^2_u + \sigma^2_{Min}} \omega_{ij}^{High}
\]

(20)

The loan officer’s updated loan amount and expected profit is given by

\[
E \left[ \pi^H_{ij} | \omega_{ij}^{High} \right] = RL_{ij}^{High} \left( \gamma L_{ij}^{High} + \omega_{ij}^{High} \omega_{ij}^{S,Q} \right) - L_{ij}^{High}
\]

(21)

This change should not affect average loan sizes since a more accurate signal leads to larger loans for safer borrowers and smaller loans for riskier borrowers. Average profits increase because loan officers are more effective at screening. Table (6) finds that average profits are ¥640 higher in the counterfactual case indicating that loan officers contribute 10 times their pay in additional profits compared to the econometrician. This is now ¥430 more per loan than the status quo, which is the yearly equivalent of hiring an additional seven loan officers. The lender should be willing to hire seven additional loan officers to increase screening ability to the maximum estimated level. Figure (10) shows this effect for each loan officer and finds that almost all of the loan officers are above the Mendoza line.\(^{50}\)

\(^{50}\)An expression in baseball that gives the batting average where players below this threshold cannot contribute positively to the team regardless of other strengths. The loan officer would have to contribute about ¥65 per loan above the econometrician to equal her average ¥45,000 compensation.
Figure 10: Additional profit over econometrician
Lending profit if loan officers behaved with $\sigma_j^2 = \sigma_{\text{min}}^2$.

Notes: 95% confidence interval constructed from bootstrapped standard errors. Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. Counterfactual lending is if all loan officers behaved with the highest estimated screening effort. Econometrician’s prediction is risk neutral lending based only on hard information. Each borrower’s loan amount is re-optimized and expected profit is calculated. As of August 2014, $1 is ¥6.18.

5.8 Implementation

Implementing these counterfactuals may be difficult. Because these depend on knowing the parameters of the individual loan officers, there may be a ratchet effect as loan officers vary their behavior anticipating that the lender is learning about them Gibbons (1987). In addition, the composition of the loan officers may change in response to these attempts to alter their behavior Lazear (2000). With that said, some of the counterfactuals may be possible to implement with post-origination scaling if the lender could hold constant their behavior. For example, one way to mitigate risk preferences is to increase each loan based on the loan officer’s officer effect $k_j$. This requires that loan officers report truthfully, which may require compensation according to the initial loan decision.

For rational expectations, if simply informing the loan officer of her behavioral bias is insufficient, then it may also be possible to use ex-post adjustments. Overconfidence leads loan officers
to exaggerate the precision of their signal. The lender could intervene by compressing loan amounts so that larger loans are reduced and smaller loans are increased. As long as the loan officer still has the incentives to truthfully report the initial decision, then it could be possible to reduce this distortion. However, care must be taken so that the design can account for offsetting interactions between risk preferences and overconfidence. Increasing screening ability may be much more difficult and require structural changes in hiring\textsuperscript{51}, training, and compensation. Equation (6) shows that the effect of the bonus rate $\beta$ on the optimal choice of ability to be non-linear and non-monotonic, which could be one method to induce greater ability.

Increasing the bonus rate may also exacerbate the costs of risk preferences since greater profit sharing encourages less risk. In addition, the costs of inducing additional ability may not be profitable for the lender and could be much larger than the benefits. Another possibility is to potentially increase the amount of hard information and reduce soft information by codifying more of the collected data as in Berg et al. (2013) or collecting more information. This could reduce the amount of information that loan officers need to screen, which may lead to more precise signals. An alternate policy may be to have additional loan officers screen the same borrower provided that loan officers can communicate their soft information to each other without ambiguity.

6 Conclusion

This paper has examined the value of delegating loan decisions to loan officers exhibiting three sources of heterogeneity: risk preferences, screening ability, and beliefs about screening ability. To weigh the costs and benefits, I developed a structural model where loans officers were delegated two choices. The first was a costly screening decision used to analyze uncodified soft information unobserved by credit scoring, and the second was a loan size choice that incorporated both soft and hard information. The model featured multiple dimensions of heterogeneity, recovered the borrower’s repayment, and accounted for potential endogeneity with the random assignment of borrower applications to loan officers. I found three main results.

First, there was substantial heterogeneity in risk preferences, screening ability, and beliefs about screening ability across loan officers. I further found that loan officers were uniformly risk averse and overconfident. These characteristics led to large distortions in average loan amounts and loan profits. Second, delegating to loan officers was more profitable than relying on an econometrician’s prediction based only on hard information. Estimates showed that the average loan officer with an annual compensation of ¥45,000 contributed ¥147,000 more in annual profits compared to the econometrician despite the econometrician’s many advantages. This effect was heterogeneous with some loan officers unable to contribute additional value, while others were

\textsuperscript{51} Ackerberg and Botticini (2002) find that matching between principals and agents may be important in determining the optimal structure of contracts.
extremely valuable. Lastly, these characteristics distorted loan decisions and were very costly for the lender. These costs were the equivalent of hiring an additional two to seven loan officers.

I view these results as highlighting the value of expert loan officers even when decisions can be based on a large amount of hard information. These benefits are especially pronounced in settings with limited formal credit histories such as personal or small business loans. This is evident from the rise in popularity of peer to peer lenders such as Prosper or Lending Club that use subjective evaluation to augment their existing credit metrics. This is not to say that delegating to experts is always valuable compared to alternative decision-making processes. For example, Gruber (1996) finds that passive investment management generally outperforms active managers in mutual funds. In addition, some contexts prohibit extensive collection of soft information such as appearance and demographic. With that said, despite the costs, these loan officers were very profitable.

More broadly, an insight of this paper is that it is difficult to evaluate expertise without jointly modeling a number of factors both environmental and innate. Consideration must be given to the information collection process, the expert’s preferences, the efficacy of the alternative decision model, and the compensation scheme. On this last point, this research also highlights the importance of incentive schemes in principal agent relationships beyond pecuniary benefits. Agents in all settings may respond to soft incentives such as career concerns much more than just pay. Beyond lending, this work provides a valuable framework that is useful in evaluating experts working elsewhere in program evaluation or assessment. I view the study of this type of decision-making as an important avenue for further study.

Another reason to hire experts could be to avoid directly specifying a rule that may skirt regulation. For example, some universities may use admissions counselors to implement racial policies that would be controversial if programmed explicitly in an automated model.
References


Appendix

A Optimal loan size

Conditional on the hard information \( x_i \), the observed signal \( \omega_{ij} \), and the loan officer’s characteristics, loan officers choose \( L_{ij}^* \) to maximize their expected utility. Utility is given by \( u(y_j) = -e^{-r_jy_j} \) where \( y_j = \alpha + \beta \sum_i \pi_{ij} - cost_j \left( \sigma_j^2 \right) \). \( r_j \) is risk aversion, \( c_j^2 \) is the overconfidence, and \( \sigma_j^2 \) is screening ability. The borrower’s repayment function is given by equation (2).

\[
EU[L_{ij}] = -e^{r_j \left( \alpha + \beta \sum_i \pi_{ij} + \beta R_i L_{ij} \left( \gamma L_{ij} + x_i' r \right) - \beta L_{ij} - cost_j \left( \sigma_j^2 \right) \right)} \int e^{-r_j \beta (u_i + e_i)} dF_x
\]

If \( x \) is normally distributed, then \( \int e^{tx} f(x) dx = e^{t \mu_x + \frac{1}{2} t^2 \sigma_x^2} \) by the moment generating function where the posterior mean and variance are given by equation (13).

\[
= -e^{r_j \left( \alpha + \beta \sum_i \pi_{ij} + \beta R_i L_{ij} \left( \gamma L_{ij} + x_i' r \right) - \beta L_{ij} - cost_j \left( \sigma_j^2 \right) + \beta R_i L_{ij} \frac{\sigma_j^2}{\sigma_u^2 + c_j^2} \omega_{ij} - \frac{r_j}{2} \left( \beta R_i L_{ij} \right)^2 \left( \frac{\sigma_j^2}{\sigma_u^2 + c_j^2} + \sigma_x^2 \right) \right)}
\]

Maximizing the above expression is equivalent to maximizing the expression inside the inner parenthesis.

\[
L_{ij}^* = \left[ r_j \beta R_i \left( \frac{\sigma_j^2 c_j^2}{\sigma_u^2 + c_j^2} + \sigma_x^2 \right) - 2 \gamma \right]^{-1} \left( x_i' \Gamma - \frac{1}{R_i} + \frac{\sigma_j^2}{\sigma_u^2 + c_j^2} \omega_{ij} \right)
\]

B Choice of ability

Cost of effort is parametrized as \( cost_j \left( \sigma_j^2 \right) = \frac{d_j^2}{\sigma_j^2} \) and is a decreasing function of a cost of effort term \( d_j \). Once screening effort is chosen, a signal \( \omega_{ij} \) is observed, and the optimal loan amount is given by equation (4). Loan officers do not recognize that they are overconfident when choosing screening effort. Solving backwards from the optimal loan amount, the indirect utility function is given by \( v(\omega_{ij}) = EU \left[ L_{ij}^* (\omega_{ij}) \right] \). The expected utility of this function can be expanded using a first order Taylor expansion.

\[
EU \left[ \sigma_j^2 \right] = \int \int v(\omega_{ij}) dF_x dF_{\omega|\sigma_j^2} \\
\approx \int E \left[ v(\bar{\omega}) + \frac{dv(\bar{\omega})}{d\omega} (\omega_{ij} - \bar{\omega}) \right] dF_x \\
= \int v(\bar{\omega}) dF_x \\
= -e^{r_j \left( \alpha + \beta R_i L_{ij}^* \left( \gamma L_{ij}^* + x_i' r \right) - \beta L_{ij}^* - cost_j \left( \sigma_j^2 \right) - \frac{r_j}{2} \left( \beta R_i L_{ij}^* \right)^2 \left( \frac{\sigma_j^2 c_j^2}{\sigma_u^2 + c_j^2} + \sigma_x^2 \right) \right)} dF_x
\]
Maximizing this expression is equivalent to maximizing the the term inside the parenthesis

\[
\begin{align*}
\cos \theta_j (\sigma_j^2) &= \int \frac{\partial L_{ij}^*}{\partial \sigma_j^2} \left( 2 \beta R_i \Gamma - \beta - r_j (\beta R_i)^2 \frac{r_j \sigma_j^2}{\sigma_j^2 + \sigma_j^2} \right) - \frac{r_j}{2} \left( \beta R_i \Gamma - \frac{1}{R_i} \right) \left( \frac{r_j}{2} \beta R_i \sigma_j^2 \right) dF_x \\
&= \int \frac{\partial L_{ij}^*}{\partial \sigma_j^2} \beta R_i \left( x_i' \Gamma - \frac{1}{R_i} + \frac{L_{ij}^*}{L_j} \right) \left( 2 \gamma - r_j \beta R_i \left( \frac{r_j^2 \sigma_j^2}{\sigma_j^2 + \sigma_j^2} \right) \right) - \frac{r_j}{2} \left( \beta R_i \Gamma - \frac{1}{R_i} \right) \left( \frac{r_j}{2} \beta R_i \sigma_j^2 \right) dF_x \\
&= \int \frac{\partial L_{ij}^*}{\partial \sigma_j^2} \beta R_i \left( x_i' \Gamma - \frac{1}{R_i} + \frac{L_{ij}^*}{k_j} \right) - \frac{r_j}{2} \left( \beta R_i \Gamma - \frac{1}{R_i} \right) \left( \frac{r_j}{2} \beta R_i \sigma_j^2 \right) dF_x \\
&= \int -\frac{r_j}{2} \left( \beta R_i \Gamma - \frac{1}{R_i} \right) \left( \frac{r_j}{2} \beta R_i \sigma_j^2 \right) dF_x \\
\end{align*}
\]

where the last step is because \( L_{ij}^* (\omega_{ij}) = k_j \left( x_i' \Gamma - \frac{1}{R_i} \right) \).

\[
\frac{d^2}{\sigma_j^2} = \int \frac{r_j}{2} \left( \beta R_i \Gamma - \frac{1}{R_i} \right) \left( \frac{r_j}{2} \beta R_i \sigma_j^2 \right) dF_x \\
\frac{d_j}{\sigma_j^2} = \int \left( \frac{r_j}{2} \right) \beta R_i \left[ \frac{r_j \beta R_i \left( \frac{r_j^2 \sigma_j^2}{\sigma_j^2 + \sigma_j^2} \right)}{2} - 2 \gamma \right] \left( x_i' \Gamma - \frac{1}{R_i} \right) \left( \frac{r_j}{2} \beta R_i \sigma_j^2 \right) dF_x \\
= \int \left( \frac{r_j}{2} \right) \beta R_i \left( x_i' \Gamma - \frac{1}{R_i} \right) \sigma_j^2 \left[ \frac{r_j \beta R_i \sigma_j^2}{2} + \left( r_j \beta R_i \sigma_j^2 - 2 \gamma \right) \left( \sigma_j^2 + \sigma_j^2 \right) \right] dF_x
\]

Cross multiplying gives

\[
\frac{\int \left( \frac{r_j}{2} \right) \beta R_i \left( x_i' \Gamma - \frac{1}{R_i} \right) \sigma_j^2 dF_x}{d_j} = r_j \beta R_i \left( \sigma_j^2 + \sigma_j^2 \right) - 2 \gamma + \left( r_j \beta R_i \sigma_j^2 - 2 \gamma \right) \sigma_j^2
\]

Simplifying gives the final optimal screening effort to be

\[
\sigma_j^{2*} = \int \left( r_j \beta R_i \sigma_j^2 - 2 \gamma \right) \sigma_j^2 \left( \frac{\left( \frac{r_j}{2} \right) \beta R_i \left( x_i' \Gamma - \frac{1}{R_i} \right) \sigma_j^2}{d_j} - r_j \beta R_i \left( \sigma_j^2 + \sigma_j^2 \right) + 2 \gamma \right) dF_x
\]

C Change of Variables

Since I have no variation separating soft information \( \sigma_j^2 \) from \( \sigma_j^2 \), I perform a change of variables to transform the parameter set \( \left( \Gamma, \gamma, r_j, \sigma_j^2, c_j^2, \sigma_u^2, \sigma_e^2 \right) \) to \( \left( \Gamma, \gamma, \tilde{r}_j, \tilde{\sigma}_j^2, \tilde{c}_j^2, \tilde{\sigma}_u^2, \tilde{\sigma}_e^2 \right) \) where
\[ r_j = r_j \beta \]
\[ c_j^2 = \frac{c_j^2}{\sigma_u^2} + \frac{1}{\sigma_u^2} - 1 \]
\[ \sigma_j^2 = \frac{\sigma_j^2}{\sigma_u^2} + \frac{1}{\sigma_u^2} - 1 \]
\[ \sim_\sigma^2 = 1 \]
\[ \sim_\epsilon^2 = \sigma_u^2 + \sigma_\epsilon^2 - 1 \]

The likelihood in equation (11) can be written entirely as functions of \( k_j, \sigma_v^2, w_{ij}, \sigma_{u+\epsilon|v}, \) and \( h_{ij} \). I show that these functions can be written in terms of the adjusted parameters.

\[ k_j = \left[ r_j \beta R_i \left( \frac{\sigma_u^2 c_j^2}{\sigma_u^2 + c_j^2} + \sigma_\epsilon^2 \right) - 2 \gamma \right]^{-1} = \left[ \sim_{r_j} R_i \left( \frac{\sim_{c_j^2}}{1+c_j^2} + \sim_{\epsilon_2} \right) - 2 \gamma \right]^{-1} = \sim_k_j \]
\[ \sigma_v^2 = \frac{k_j^2 (1+\sim_\epsilon^2)}{(1+c_j^2)^2} = \sim_1 \]
\[ w_{ij} = x'_i \Gamma k_j - \frac{k_j}{\sim_k_j} = x'_i \Gamma k_j - \frac{k_j}{\sim_k_j} = w_{ij} \]
\[ \sigma_{u+\epsilon|v}^2 = \left( \frac{1}{\sim_k_j} \right) = \sigma_{u+\epsilon|v}^2 \]
\[ \sim_{h_{ij}} = \gamma \sim_{L_{ij}} + x'_i \Gamma \left( \frac{1}{\sim_k_j} \right) \left( L_{ij} - \sim_{w_{ij}} \right) = \gamma \sim_{L_{ij}} + x'_i \Gamma + \frac{1+\sim_{\epsilon_2}}{(1+c_j^2)} \sim_{k_j} \left( L_{ij} - \sim_{w_{ij}} \right) = \sim_{h_{ij}}. \]

These can be inverted to solve for the original parameters so that

\[ r_j = \frac{\sim_{r_j}}{\beta} \]
\[ c_j^2 = \sigma_u^2 \sim_{c_j^2} + \sigma_u^2 - \sigma_u^2 \]
\[ \sigma_j^2 = \sigma_j^2 \sigma_u^4 + \sigma_u^4 - \sigma_u^2 \]
\[ \sigma_\epsilon^2 = 1 + \sigma_\epsilon^2 - \sigma_u^2 \]