Essays on information asymmetries in lending

by

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DEDICATION

To Cristina, who has been endlessly patient while I labored for six years and never tired of hearing about loan officers, I could not have achieved this without you. And to Nico, who will soon begin his education just as his father finishes his, I hope that learning can be as rewarding in your life as it is in mine.

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ABSTRACT

I study information asymmetries in loan underwriting. In the first chapter, I develop a model of how loan officers interpret and use soft information in making decisions about the size of loans they give to applicants. The model emphasizes loan officer heterogeneity in risk preferences, ability, and beliefs about ability. I recover estimates of these loan officer characteristics using data on the joint distribution of loan decisions and outcomes. I find that loan officers differ across all three dimensions of heterogeneity, but that they are able to generate higher profits for the lender than would a mechanistic decision process that would solely utilize hard information. In the second chapter, I estimate the effect of moral hazard on loan default. I account for potential endogeneity by exploiting a natural experiment where borrower applications are randomly assigned as an instrument for loan sizes. I find that borrowers become more likely to default in response to larger loans, but the lender may be able to attenuate this additional risk with increased collection intensity on larger loans. In the third chapter, I examine peer effects arising from a coworker's default on the probability that a borrower will be late on loan payments. I rely on rich data detailing coworker relationships and time-varying fixed effects to control for correlated unobservables and endogenous group formation. I find that borrowers are more likely to be late with their payment when they have coworkers who default.

CHAPTER I

Why hire loan officers? Examining delegated expertise

1.1 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.[1] And third, lenders

[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

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

payday lending leads to increased difficulty in repaying household bills.

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 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. (2013b) 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

[2]Misra 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.

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 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.

[3] This 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.

[4] Another 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.

1.2 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.[5] 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.[6] 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.

1.2.1 Data

Table (1.1) 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

[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 creditworthiness 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.

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]

Table 1.1: Summary statistics

	Mean	Min	Max	Std dev
Loan terms				
Loan amount (¥000's)	33	5	60	12
Requested (¥000's)	124	3	300	103
Monthly payment (¥000's)	2.2	0.3	5.7	1.1
Payment length (Months)	25	12	36	7
APR (%)	48%	33%	62%	7%
Borrower attributes				
Estimated assets (¥000's)	587	1	7,358	1,337
Salary income (¥000's)	71	4	642	267
External debt (¥000's)	160	0	1,923	856
Age	38	18	58	9
Credit card utilization	41%	0%	100%	38%
Credit card limit (¥000's)	20	0	718	156
Proportion with credit card	76%			
Proportion female	28%			

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.

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 retired frequently at each of the various locations. Loan term lengths range from 12 to 36 months with the median at 24 months. The most common loan in my sample is a 24-month

[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.

fixed payment loan with an APR of 48%. This APR includes the nominal interest rate, application fees, and other ancillary maintenance fees.[8]

1.2.2 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.

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

[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.

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

[9] Some 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.

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] 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.

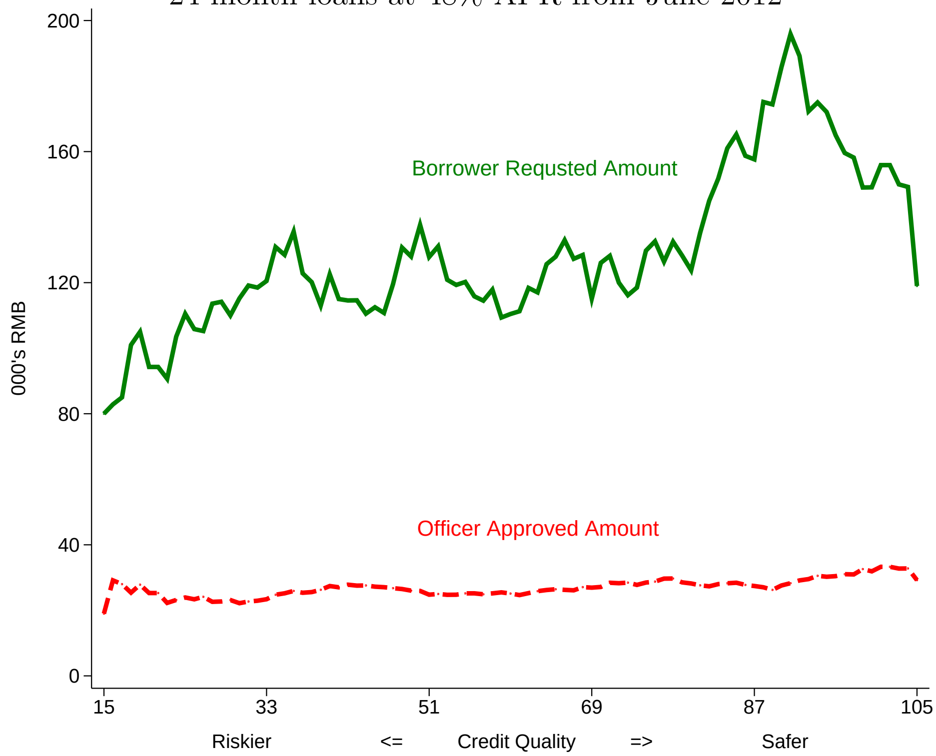
1.2.3 Requested amount

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.

[10] While 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.

[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.

Figure 1.2.1: 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.

Table (1.1) shows that the requested loan amount is generally three times the approved amount with a large amount of variation. Figure (1.2.1) 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

[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.

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 from higher future limits and a simpler approval process.[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.

[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.

1.3 Model of the loan officer

In this section, I develop a delegated expertise model following Stoughton (1993) and Bhattacharya 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 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.

1.3.1 Loan officer's objective

Figure (1.3.1) 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 $u\left(y_j\right) = -e^{-r_j y_j}$ where y_j is the loan officer's compensation net of effort costs. Compensation is given by a fixed salary α and a year end bonus that is directly proportional to loan profits $\beta \sum\limits_i \pi_{ij}$ where i indexes borrowers.[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.[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.

Figure 1.3.1: Loan officer's decision process

Effort choice

- Chooses a constant screening ability level for all borrowers.
- Screening ability determines the precision of a noisy signal.

2. Screening

- Screens soft information observed within a borrower's application.
- Develops posterior beliefs about the borrower's repayment function.

3. Loan choice

- Loan officer's compensation is proportional to loan profits.
- Chooses a loan size to maximize expected utility.

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

[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.

[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.

obedience where the loan officers are incentivized to maximize loan profits. Even without an explicit 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 β is not separately identified from $r_j\beta$. In other words, I cannot rule out that heterogeneous beliefs about β may also influence her decision.[16]

Loan officer j has screening ability σ_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 $y_j = \alpha + \beta \sum_i \pi_{ij} - cost_j\left(\sigma_j^2\right)$ where $cost_j\left(\sigma_j^2\right)$ is the disutility of the chosen screening ability in money. $cost_j\left(\sigma_j^2\right)$ is assumed to be convex and strictly decreasing with $cost_j\left(\sigma_j^2\right) > 0$ for any $\sigma_j^2 > 0$, $cost_j'\left(\sigma_j^2\right) < 0$, and $cost_j''\left(\sigma_j^2\right) > 0$. Combining everything, loan officers try to maximize their expected utility given by

[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.

$$EU\left[L_{ij}\right] = \int -e^{-r_j\left(\alpha+\beta\pi_{ij}-cost_j\left(\sigma_j^2\right)\right)} f\left(\pi\right) d\pi \tag{1.3.1}$$

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 $R_i L_{ij}$.[17] R_i is the ratio of the total present value of the loan if repaid in full to the value of the loan and is determined by the interest rate.[18] $\eta_i^*\left(L_{ij}\right)$ represents the proportion of the total that is ultimately repaid and is inclusive of penalty, application, early repayment, and late fees.[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 $\pi_{ij} = R_i L_{ij} \eta_i^*\left(L_{ij}\right) - L_{ij}$. This model is static in the sense that loan officers do not consider their prior portfolio composition when underwriting a new loan.[20]

The borrower's repayment proportion $\eta_i^*\left(L_{ij}\right)$ is composed of four parts: the loan amount L_{ij}, the codified hard information $\boldsymbol{x_i}$, the uncodified soft information u_i, and an exogenous unscreenable error ϵ_i. When choosing loan sizes, loan officers must balance the additional interest earned from loan increases with potentially higher delinquency rates. This delin-

[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.

[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%.

[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.

[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.

quency 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.[21]

The next component is hard information $\boldsymbol{x_i}$, 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.[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 u_i 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

[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.

[22]This understates the value of loan officers in two ways. One is that $\boldsymbol{x_i}$ 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.

[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.

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 ϵ_i shocks are distributed $N(0, \sigma_\epsilon^2)$ 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

$$\eta_i^* (L_{ij}) = \gamma L_{ij} + \boldsymbol{x_i'}\boldsymbol{\Gamma} + u_i + \epsilon_i \tag{1.3.2}$$

of the total present value $R_i L_{ij}$. The marginal effect γ is allowed to vary across different monthly payments so that two identical borrowers with different loan terms may have different repayment patterns. 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

[24] Without loss of generality, any portion of ϵ_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, 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 $\gamma = \gamma_L + \gamma_{MP} \frac{apr}{1-(1+apr)^{-N}} + \gamma_{PV} \frac{apr}{1-(1+apr)^{-N}} \frac{1-(1+i)^{-N}}{i}$.

[26] This follows from the exponential utility function without income effects.

loan officer's prior loan performance.

1.3.3 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 ω_{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 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

$$u_i|\omega_{ij} \sim N\left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_j^2}\omega_{ij}, \frac{\sigma_u^2\sigma_j^2}{\sigma_u^2+\sigma_j^2}\right) \tag{1.3.3}$$

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 σ_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.

[27] This follows from the conditional distribution of the normal distribution. The covariance between $u_i + \epsilon_i$ and ω_{ij} is σ_u^2 since u_i and δ_{ij} are assumed to be independent.

1.3.4 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 (1.3.3), the parametrized repayment function in equation (1.3.2), and the loan officer's utility, the optimal loan amount is given by

$$L_{ij}^* = k_j \times \left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R} + \frac{\sigma_u^2}{\sigma_u^2 + \sigma_j^2}\omega_{ij} \right) \tag{1.3.4}$$

where $k_j = \left[r_j \beta R \left(\frac{\sigma_u^2 \sigma_j^2}{\sigma_u^2 + \sigma_j^2} + \sigma_\epsilon^2 \right) - 2\boldsymbol{\gamma} \right]^{-1}$.[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, α is not identified and β 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 β. As mentioned

[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.

previously, one channel that I cannot rule out is that loan officers may have heterogeneous beliefs about the bonus rate β. These beliefs on β may interact with risk preferences. The intuition for identifying the other parameters is addressed in the empirical section.

1.3.5 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 σ_j^2 across different levels of hard information $\boldsymbol{x_i}$, 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

$$\sigma_j^{2*} = argmax \int\int EU\left[L_{ij}^{*}\left(\omega_{ij}\right)\right] dF_{\boldsymbol{x}} dF_{\omega|\sigma_j^2} \tag{1.3.5}$$

where $F_{\boldsymbol{x}}$ is the distribution of hard information across borrowers and $F_{\omega|\sigma_j^2}$ 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

$$\sigma_j^{2*} = \int \left(r_j \beta R \sigma_\epsilon^2 - 2\boldsymbol{\gamma}\right) \sigma_u^2 \left(\frac{\left(\frac{r_j}{2}\right)^{\frac{1}{2}} \beta R \left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R}\right) \sigma_u^2}{d_j} - r_j \beta R \left(\sigma_u^2 + \sigma_\epsilon^2\right) + 2\boldsymbol{\gamma} \right)^{-1} dF_{\boldsymbol{x}} \quad (1.3.6)$$

with the derivation in Appendix B.

σ_j^{2*} is increasing in the cost of effort parameter d_j indicating that higher cost of effort loan officers choose higher values of σ_j^2 and less screening ability. The effect of the bonus rate β on σ_j^{2*} is non-linear and non-monotonic.[30] Conditional on the other model parameters, the screening effort level σ_j^{2*} is isomorphic to the cost of effort parameter d_j for $\sigma_j^2 > 0$ and when the marginal 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 (1.3.6) during estimation. The derived expression can be considered as illustrative for how cost of effort d_j affects the screening effort level σ_j^2. This approach also avoids functional form assumptions for the cost of effort parametrization and the distribution of the borrower's hard information.[31] Another convenience is that this avoids some modeling difficulties. For example with behavioral overconfidence, loan officers may have inconsistent beliefs about

[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 γ approaches 0 and the compensation plan becomes linear in loan amounts, the bonus rate β disappears from equation (1.3.6). 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.

[31] 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.

their screening ability that interact in unclear ways with a separate ability choice.

1.3.6 Heterogeneous beliefs

Equation (1.3.4) 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 σ_j^2. 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.[32] Another explanation could be that loan officers have heterogeneous beliefs about the prior distribution of the soft information σ_u^2, which will not be separately identified from σ_j^2. 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

$$u_i|\omega_{ij} \sim N\left(\frac{\sigma_u^2}{\sigma_u^2 + c_j^2}\omega_{ij}, \frac{\sigma_u^2 c_j^2}{\sigma_u^2 + c_j^2}\right) \tag{1.3.7}$$

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

[32]Fisman 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.

beliefs is given by

$$L_{ij}^{*} = k_j \times \left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R} + \frac{\sigma_u^2}{\sigma_u^2 + c_j^2}\omega_{ij} \right) \tag{1.3.8}$$

where the updated officer effect is $k_j = \left[r_j \beta R \left(\frac{\sigma_u^2 c_j^2}{\sigma_u^2 + c_j^2} + \sigma_\epsilon^2 \right) - 2\boldsymbol{\gamma} \right]^{-1}$.

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]

1.4 Empirical strategy

Equations (1.3.2) and (1.3.8) jointly determine the borrower's repayment and the loan officer's loan decision respectively. These equations define an econometric model that can

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

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.

1.4.1 Endogenous loan sizes

Without an instrument, L_{ij} in equation (1.3.2) is an endogenous object. This is because loan amounts are decided after the loan officer observes a signal about soft information indicating that $E\left[u_i|L_{ij}\right] \neq 0$. 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, σ_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 $E\left[u_i|\sigma_u^2, r_j, c_j^2, \boldsymbol{x}_i, L_{ij}\right] = 0$.[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.

[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 1.2: First stage and test of correlated observables

	Dependent variable: loan amount				
21 Loan officer indicators					
Joint F-Test	17.18	18.91	19.48	19.59	22.57
P-Value	0.000	0.000	0.000	0.000	0.000
R^2	0.373	0.420	0.440	0.482	0.525
Loan officer mean loan amount	Dependent variable: loan Amount				
Coefficient	0.155	0.150	0.153	0.154	0.156
P-Value	0.000	0.000	0.000	0.000	0.000
R^2	0.367	0.413	0.433	0.476	0.518
Number of controls	78	84	85	129	265
Year by month, city, product	✓	✓	✓	✓	✓
Application variables		✓	✓	✓	✓
Internal credit quality			✓	✓	✓
Financial variables				✓	✓
Inspection variables					✓

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 only effect that loan officers have on repayment is through the choice of loan size.

Table (1.2) 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 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.[35] 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 $\frac{1}{N_j-1}\sum\limits_{-i} L_{ij}$. 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 (1.2) shows the results in the second panel for increasing collections of hard information. 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.

[35]Given 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.

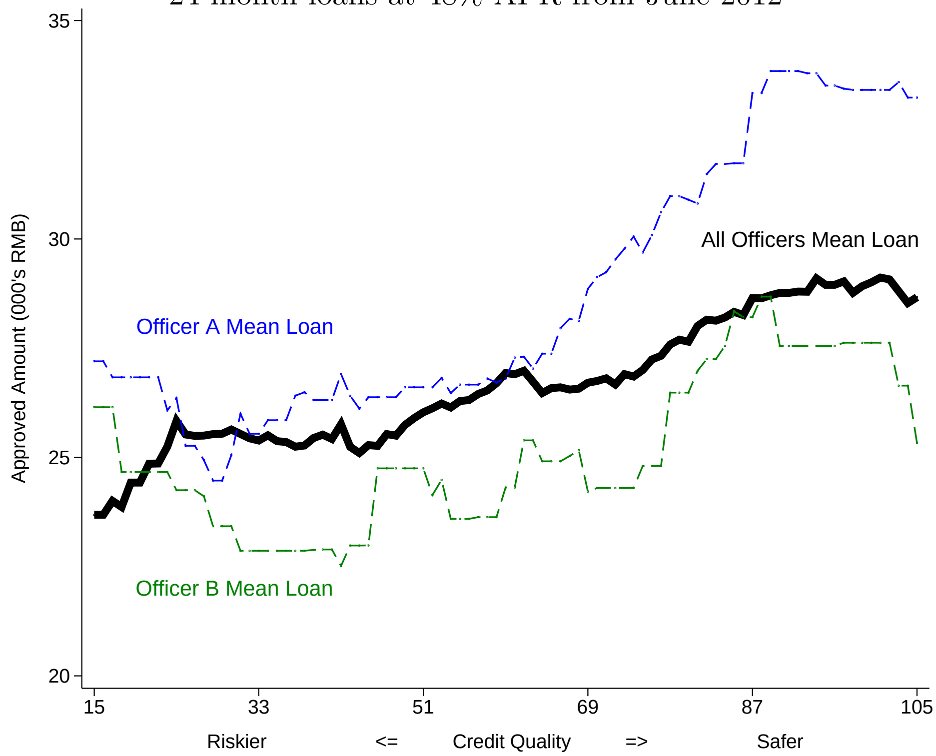
1.4.2 Censored repayment

Another empirical challenge is censoring in the borrower's repayment data. I do not observe the latent variable $\eta_i^*\left(L_{ij}^*\right)$ but a censored variable $\eta_i\left(L_{ij}^*\right)$ 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 $\eta_i\left(L_{ij}^*\right)$ I observe is given by

$$\eta_{ij}\left(L_{ij}^*\right) = \begin{cases} \eta_{ij}^*\left(L_{ij}^*\right) & if\ uncensored \\ \bar{\eta}_i < \eta_{ij}^*\left(L_{ij}^*\right) & if\ censored \end{cases} \tag{1.4.1}$$

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 $\eta_i^*\left(L_{ij}^*\right)$ 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 $\eta_i^*\left(L_{ij}^*\right)$ or L_{ij}^*.

Figure 1.4.1: Average loan amount by credit quality
24 month loans at 48% APR from June 2012



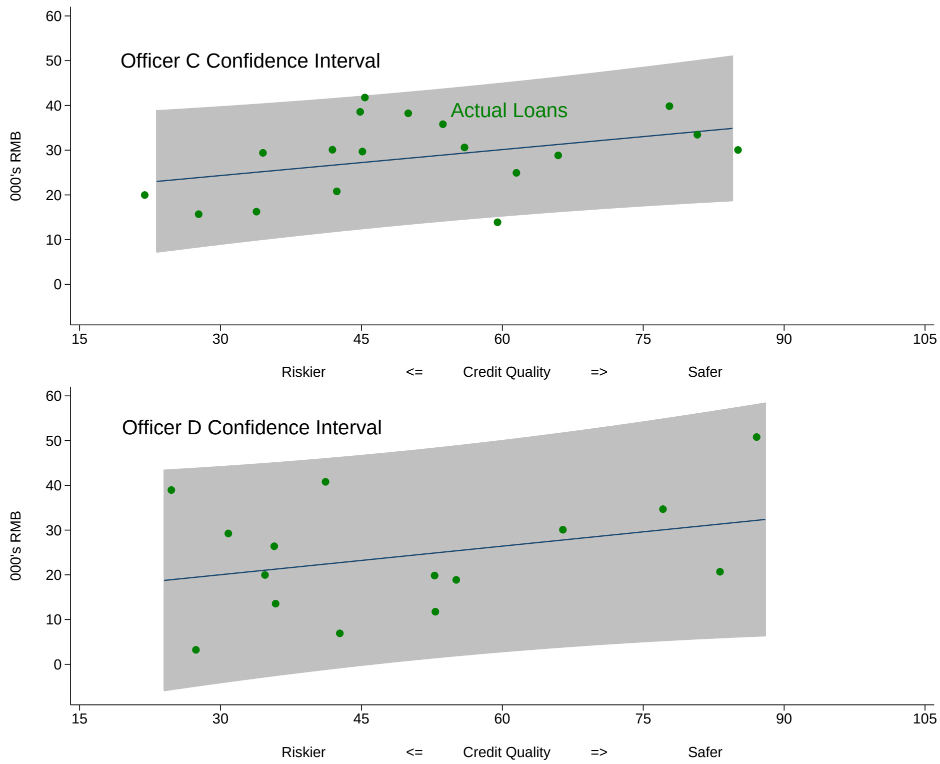
Notes: Sample includes 282 first-time borrowers from June 2012 borrowing a 24 month loan with an APR of 48%. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts are decided by the loan officers. Borrower applications are randomly assigned to loan officers. Credit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

1.4.3 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 $\boldsymbol{x_i}$, the distribution of loan sizes across all loan

[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.

Figure 1.4.2: Variance of loan size by credit quality
24 month loans at 48% APR from June 2012



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.

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 (1.4.1) 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 average loan amounts than Officer B for every level of risk. All else equal, Officer A is less risk averse than Officer B.[37]

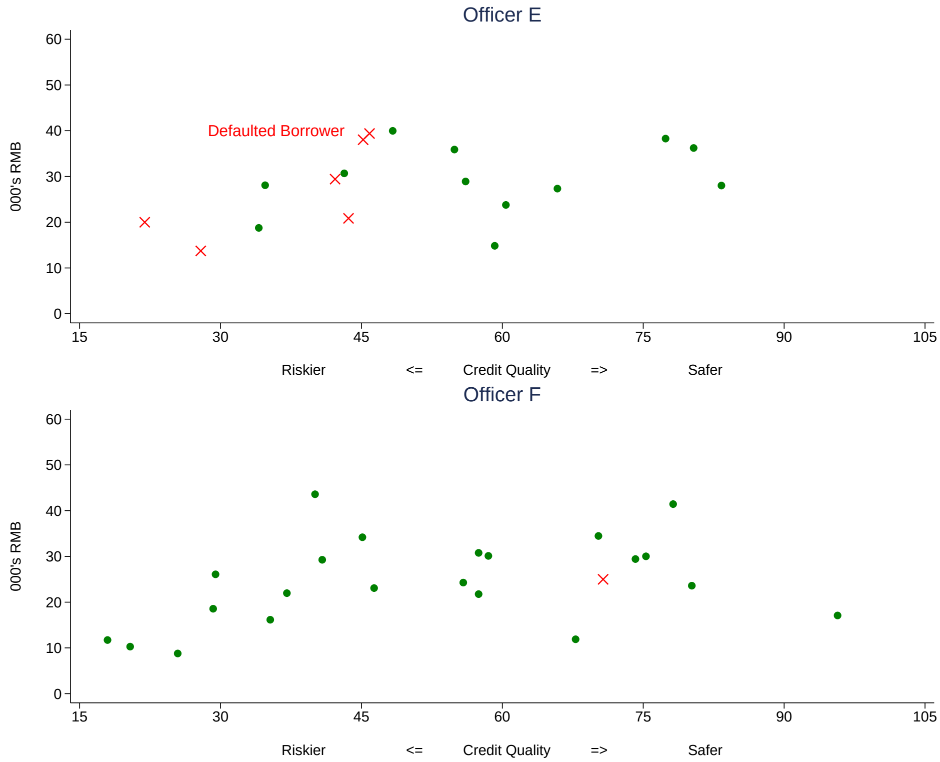
The variance of a loan officer's loan sizes identifies the loan officer's belief about her screening ability. Loan officers that believe that they have no ability to screen should have less variance of loan sizes conditional on hard information. This prediction is highlighted in Figure (1.4.2) that plots 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 ability loan officers should have worse performing loans. Figure (1.4.3) 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.[38]

[37]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.

[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.

Figure 1.4.3: Loan defaults by credit quality
24 month loans at 48% APR from June 2012



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.

1.4.4 Decomposing the variance of repayment

Some variables are difficult to identify. The variance of loan repayment recover the sum $\sigma_u^2 + \sigma_\epsilon^2$ 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 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 σ_u^2 and σ_ϵ^2. 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 σ_u^2. 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 $\Theta = \left(\Gamma, \gamma, r_j, \sigma_j^2, c_j^2, \sigma_u^2, \sigma_\epsilon^2\right)$, I estimate the adjusted set

$$\widetilde{\Theta} = \left(\Gamma, \gamma, \widetilde{r_j} = r_j\beta, \widetilde{\sigma_j^2} = \frac{\sigma_j^2}{\sigma_u^4} + \frac{1}{\sigma_u^2} - 1, \widetilde{c_j^2} = \frac{c_j^2}{\sigma_u^4} + \frac{1}{\sigma_u^2} - 1, \widetilde{\sigma_u^2} = 1, \widetilde{\sigma_\epsilon^2} = \sigma_u^2 + \sigma_\epsilon^2 - 1\right) \quad (1.4.2)$$

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 $\widetilde{c_j^2} < \widetilde{\sigma_j^2}$. 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]

[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

1.4.5 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 $\boldsymbol{x_i}$ is $P\left(L_{ij}^*, \eta_i | \Theta; \boldsymbol{x_i}, \bar{\eta_i}\right)$. This joint density can be written as the product of a conditional and a marginal using Bayes' rule, which gives $P\left(L_{ij}^* | \Theta; \boldsymbol{x_i}, \bar{\eta_i}\right) \times P\left(\eta_i | \Theta; L_{ij}^*, \boldsymbol{x_i}, \bar{\eta_i}\right)$. Since the stochastic piece in both expressions is additively normal, the likelihoods can be written as

$$\mathcal{L}\left(\Theta; L_{ij}^*, \eta_i\right) = \begin{cases} \frac{1}{\sigma_v}\phi\left(\frac{L_{ij}-w_{ij}}{\sigma_v}\right) \times \frac{1}{\sigma_{u+\epsilon|v}}\phi\left(\frac{\eta_{ij}-h_{ij}}{\sigma_{u+\epsilon|v}}\right) & if\ uncensored \\ \frac{1}{\sigma_v}\phi\left(\frac{L_{ij}-w_{ij}}{\sigma_v}\right) \times \Phi\left(\frac{h_{ij}-\bar{\eta_i}}{\sigma_{u+\epsilon|v}}\right) & if\ censored \end{cases} \tag{1.4.3}$$

where $w_{ij} = \boldsymbol{x_i'}\boldsymbol{\Gamma} k_j - \frac{k_j}{R}$, $\sigma_v^2 = k_j^2 \frac{\sigma_u^4\left(\sigma_u^2+\sigma_j^2\right)}{\left(\sigma_u^2+c_j^2\right)^2}$, $h_{ij} = \gamma L_{ij} + \boldsymbol{x_i'}\boldsymbol{\Gamma} + \frac{\sigma_u^2+c_j^2}{\left(\sigma_u^2+\sigma_j^2\right)k_j}\left(L_{ij}-w_{ij}\right)$, and $\sigma_{u+\epsilon|v}^2 = \frac{\sigma_u^2\sigma_j^2}{\sigma_u^2+\sigma_j^2} + \sigma_\epsilon^2$. 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]

1.5 Results and counterfactuals

In this section, I present the estimates for the adjusted model parameters $\widetilde{\Theta} = \left(\boldsymbol{\Gamma}, \boldsymbol{\gamma}, \widetilde{r_j}, \widetilde{c_j^2}, \widetilde{\sigma_j^2}, \widetilde{\sigma_\epsilon^2}\right)$. The parameters allow me to construct an econometrician's prediction without loan officers

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.

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 characteristics by adjusting their values. By comparing these counterfactuals with the status quo, I can recover the costs to the lender.

1.5.1 Borrower repayment function

Table (1.3) lists some of the estimates for the empirical repayment function $\eta_i^*\left(L_{ij}^*\right)$. Following equation (1.3.2), loan size, monthly payment, and the present value of full repayment all affect repayment through γ. 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 γ estimates are difficult to compare because of different interest rates and payment lengths, γ 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}.[41]

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

[41] The 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 (2014a) finds that a similar 1% increase in loan size leads to a .6% increase in the chance of default. Other estimates of γ 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 1.3: Estimates of the borrower repayment function

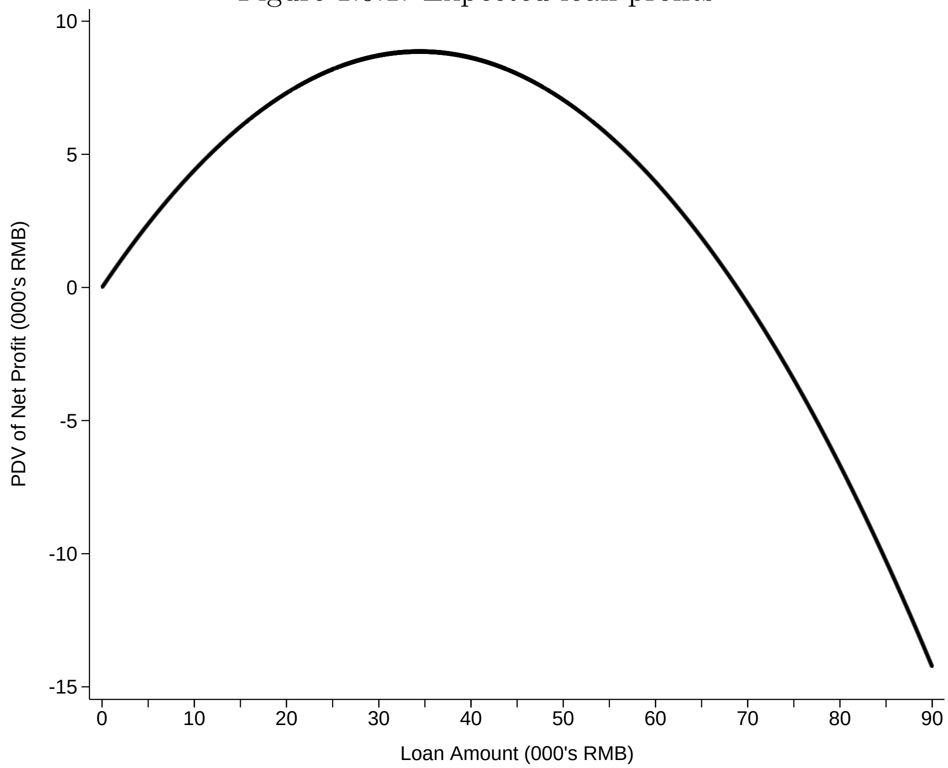
	Loan terms	
	Coefficient	P-Value
Loan amount	-0.016	0.000
Monthly payment	0.038	0.000
Present discounted value	0.006	0.000
Variance of soft information and error $\sigma_u^2 + \sigma_\epsilon^2$	0.115	0.000
γ for a 24 month loan with an APR of 48%.	-0.005	
	Selected hard information	
	Coefficient	P-Value
Payroll income	1.6e-5	0.000
External debt	1.1e-6	0.059
Credit card utilization	-0.008	0.101
Management position	0.024	0.000
Female indicator	0.002	0.071
Amount requested	1.7e-4	0.000
Dorm or rental indicator	-0.019	0.000
Credit quality	1.0e-5	0.838
Air conditioner units	0.004	0.001
Met family/coworkers	0.008	0.001

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.

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 (1.5.1) 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 (1.3) shows that there is still substantial

Figure 1.5.1: Expected loan profits



Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Borrower repayment parameters are from the main MLE specification. The average borrower is constructed by setting all covariates to their average values for a 24 month loan with an APR of 48%. The discount rate is set to the People's Bank of China base interest rate of 6%. As of August 2014, $1 is ¥6.18.

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 σ_u^2 increases relative to unscreenable risk σ_ϵ^2, 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 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]

1.5.2 Loan officer characteristics

Table (1.4) presents the estimates of the adjusted loan officer characteristics: risk preferences $\widetilde{r_j}$, screening belief $\widetilde{c_j^2}$, and screening ability $\widetilde{\sigma_j^2}$. Interpreting these estimates is difficult as they are functions of the bonus rate β and the variance of soft information σ_u^2. However, some conclusions can be drawn. The estimated values for $\widetilde{r_j} = r_j\beta$ are all positive indicating that all of the loan officers have positive risk preferences.[43] 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 (1.5) 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 (1.4) 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 $\widetilde{c_j^2} = \frac{c_j^2}{\sigma_u^4} + \frac{1}{\sigma_u^2} - 1$ is uniformly

[42] I 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.

[43] There are no constraints placed on $\widetilde{r_j}$ during estimation. Having a negative $\widetilde{r_j}$ may indicate risk loving behavior by some loan officers. 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.

Table 1.4: Estimates of the loan officer parameters

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

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 β and σ_u^2.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

less than adjusted screening ability $\widetilde{\sigma_j^2} = \frac{\sigma_j^2}{\sigma_u^4} + \frac{1}{\sigma_u^2} - 1$. 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 σ_j^2 constant, as c_j^2 increases, the variance of loan decisions 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 (1.5) shows specification tests for homogenous screening beliefs and for homogenous screening ability. Both of these nulls are rejected at the 10% level. Another specification

Table 1.5: Likelihood ratio tests

Null:	Likelihood ratio test $\mathcal{X}^2$	P-value
Loan officers have homogenous risk preferences $r_j = r \forall j$.	471	0.000
Loan officers have homogenous screening beliefs $c_j^2 = c^2 \forall j$.	31	0.051
Loan officers have homogenous screening ability $\sigma_j^2 = \sigma^2 \forall j$.	32	0.042
Loan officers have rational expectations $c_j^2 = \sigma_j^2 \forall j$.	446	0.000

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.

test is the rational expectations restriction that loan officers have accurate beliefs about their screening ability or $c_j^2 = \sigma_j^2$ 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.[44] 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.

1.5.3 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.[45] The status quo uses the estimated parameters and matches the

[44] The estimates are imprecise when claiming that individual loan officers are overconfident.

[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

observed loan decisions. Using the loan officer characteristics, I first invert equation (1.3.8) 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 (1.3.7).

Specifically for each loan officer, the officer effect k_j is calculated using the adjusted parameters where $k_j^{S.Q} = \left[\widetilde{r}_j R_i \left(\frac{\widetilde{c}_j}{1+\widetilde{c}_j} + \widetilde{\sigma}_\epsilon^2\right) - 2\boldsymbol{\gamma}\right]^{-1}$ and the posterior belief is given by

$$\frac{\sigma_u^2}{\sigma_u^2 + c_j^2}\omega_{ij} = L_{ij}^*/k_j^{S.Q} - \boldsymbol{x_i'}\boldsymbol{\Gamma} + \frac{1}{R_i} \tag{1.5.1}$$

Because loan officers are overconfident, the correct posterior mean of soft information is not given by equation (1.5.1). Using the adjusted parameters, the correct posterior can be expressed as

$$\frac{\sigma_u^2}{\sigma_u^2 + \sigma_j^2}\omega_{ij} = \underbrace{\frac{\sigma_u^2 + c_j^2}{\sigma_u^2 + \sigma_j^2}}_{\frac{1+\widetilde{c}_j^2}{1+\widetilde{\sigma}_j^2}} \times \underbrace{\frac{\sigma_u^2}{\sigma_u^2 + c_j^2}\omega_{ij}}_{Eqn\,1.5.1} \tag{1.5.2}$$

which gives the expected profit conditional on the soft information signal to be

$$E\left[\pi_i^{S.Q}|\omega_{ij}\right] = R_i L_{ij}^{S.Q}\left(\gamma L_{ij}^{S.Q} + \boldsymbol{x_i'}\boldsymbol{\Gamma} + \frac{\sigma_u^2}{\sigma_u^2 + \sigma_j^2}\omega_{ij}\right) - L_{ij}^{S.Q} \tag{1.5.3}$$

$E\left[\pi_i^{S.Q}|\omega_{ij}\right]$ can be compared to the econometrician's prediction $E\left[\pi_i^{Econometrician}\right]$ to re-

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.

cover the value of loan officers.

1.5.4 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 (1.3.2), the profit-maximizing loan amount for an econometrician with access to only the hard information is given by

$$L_i^{Econometrician} = (-2\boldsymbol{\gamma})^{-1}\left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R_i}\right) \tag{1.5.4}$$

Contrast this with the loan officer's loan amount in equation (1.3.8). The econometrician's effect $(-2\boldsymbol{\gamma})^{-1}$ 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

$$E\left[\pi_i^{Econometrician}\right] = R_i L_i^{Econometrician}\left(\gamma L_i^{Econometrician} + \boldsymbol{x_i'}\boldsymbol{\Gamma}\right) - L_i^{Econometrician} \tag{1.5.5}$$

[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 1.6: Counterfactuals compared to econometrician

	Additional loan amount (¥000's)	Additional loan profit (¥000's)
Status quo with estimated parameters.	-4.56 ***	0.21 *
	(1.63)	(0.11)
Loan officers with $r_j = r_{min}$.	-0.57	0.32 ***
	(1.00)	(0.04)
Loan officers with $c_j^2 = \sigma_j^2$.	-4.62 ***	0.35 ***
	(1.64)	(0.12)
Loan officers with $\sigma_j^2 = \sigma_{min}^2$	-4.54 ***	0.64 ***
	(1.63)	(0.13)

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.

Table (1.6) 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 repayment behavior, which allows the econometrician to make an in-sample prediction using ex-post data.[47] 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.[48] 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 (1.5.2) 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.

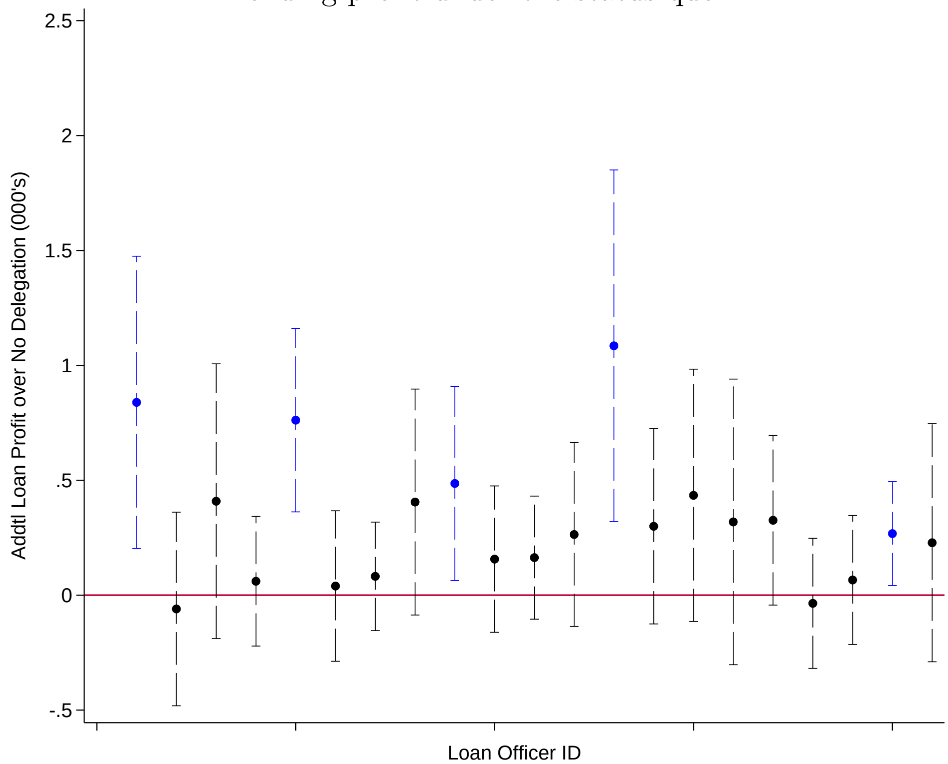
1.5.5 Minimum estimated risk aversion

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. 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 $\widetilde{r_j} = r_j\beta$ is a scalar multiple of the bonus rate β, the loan officer with the lowest value of r_j also has the lowest value of $\widetilde{r_j}$ after the monotonic transformation. Each officer effect is given by $k_j^{MinRA} = \left[r_{\widetilde{Min}} R \left(\frac{\widetilde{c_j^2}}{1+\widetilde{c_j^2}} + \widetilde{\sigma_\epsilon^2} \right) - 2\gamma \right]^{-1}$. Af-

[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.

Figure 1.5.2: Status quo versus the econometrician
Lending profit under the status quo.

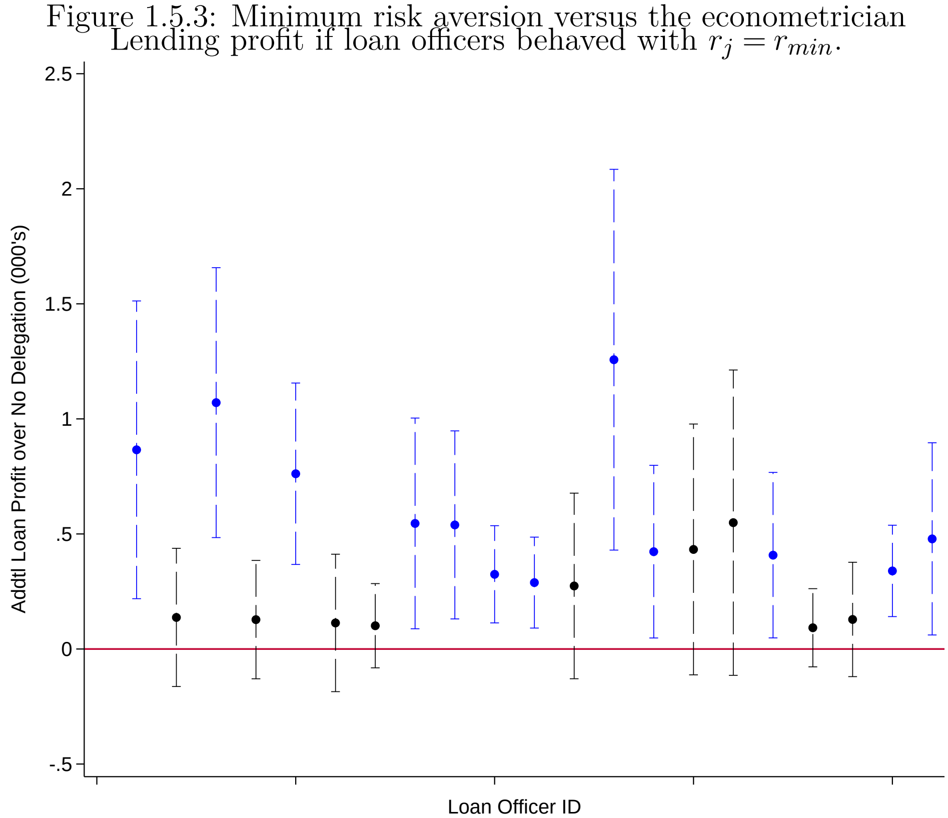


Notes: 95% confidence interval constructed from bootstrapped standard errors. Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Borrowers apply for a loan amount with a set APR and payment length. Approved loan amounts 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.

ter solving for the original signal in equation (1.5.1), the updated loan amount and expected loan profits are given similarly to equations (1.3.8) and (1.5.3).

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 1.5.3: Minimum risk aversion versus the econometrician



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 (1.6) 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 (1.5.3) 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.

1.5.6 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_j. Because the adjusted overconfidence $\widetilde{c_j^2} = \frac{c_j^2}{\sigma_u^4} + \frac{1}{\sigma_u^2} - 1$ has the same functional form as the adjusted screening effort $\widetilde{\sigma_j^2} = \frac{\sigma_j^2}{\sigma_u^4} + \frac{1}{\sigma_u^2} - 1$, a loan officer with rational expectations has $\widetilde{c_j^2} = \widetilde{\sigma_j^2}$. The officer effect is given by $k_j^{NoOC} = \left[\widetilde{r}_j R\left(\frac{\widetilde{\sigma_j^2}}{1+\widetilde{\sigma_j^2}} + \widetilde{\sigma_\epsilon^2}\right) - 2\boldsymbol{\gamma}\right]^{-1}$. The updated loan amount is given by

$$L_{ij}^{NoOC} = k_j^{NoOC}\left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R_i} + \frac{\sigma_u^2}{\sigma_u^2 + \sigma_j^2}\omega_{ij}\right) \tag{1.5.6}$$

where the adjusted signal can be calculated from equation (1.5.2) and expected profit is similar to equation (1.5.5).

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_j 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.

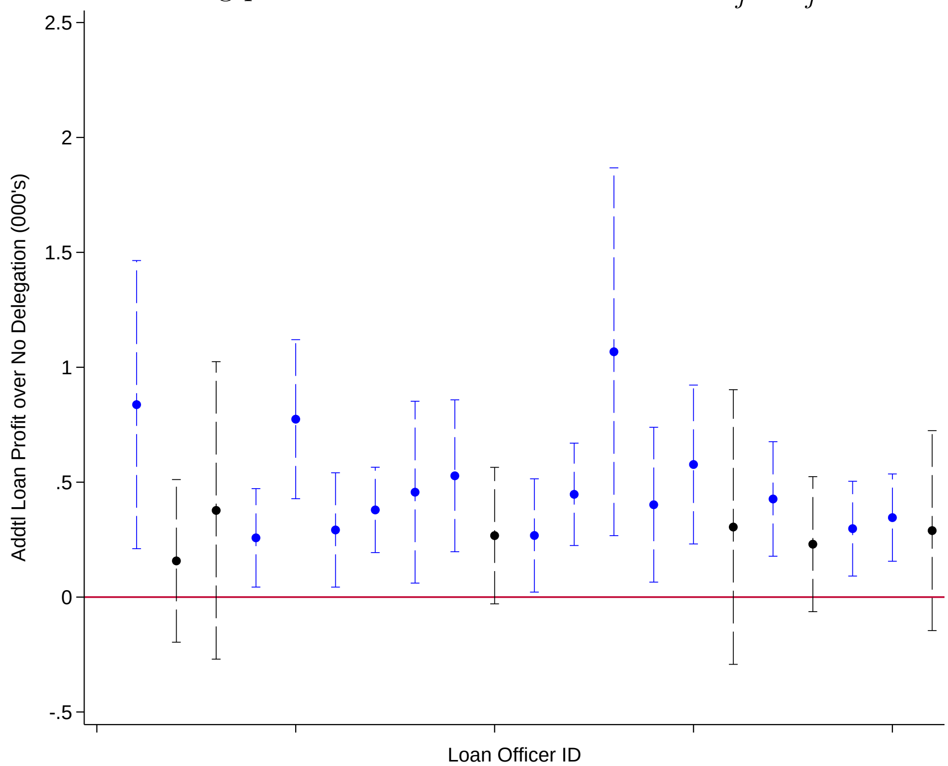
Table (1.6) shows that the impact on average loan amounts decreases but is not statistically significant. Profits, however, are ¥350 larger. Loan officers now contribute 5.5 times their compensation in additional annual profits over the econometrician. Profits are also ¥140 higher than the status quo indicating large costs imposed by overconfidence. Figure (1.5.4) 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.

1.5.7 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

[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.

Figure 1.5.4: Rational expectations versus the econometrician
Lending profit if loan officers behaved with $c_j^2 = \sigma_j^2$.



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 no overconfidence. 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.

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 σ_j^2 must also have the lowest adjusted $\tilde{\sigma}_j^2$ from the change of variables. Since the realization of ω_{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 $\frac{\sigma_u^2}{\sigma_u^2+\sigma_j^2}\omega_{ij} \sim N\left(0, \frac{\sigma_u^4}{\sigma_u^2+\sigma_j^2}\right)$, while a signal coming from a loan officer with screening ability σ_{Min}^2 would be distributed

$$\frac{\sigma_u^2}{\sigma_u^2+\sigma_{Min}^2}\omega_{ij}^{High} \sim N\left(0, \frac{\sigma_u^4}{\sigma_u^2+\sigma_{Min}^2}\right) \tag{1.5.7}$$

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

$$\frac{\sigma_u^2}{\sigma_u^2+\sigma_{Min}^2}\omega_{ij}^{High} \sim \underbrace{\sqrt{\frac{\sigma_u^2+\sigma_j^2}{\sigma_u^2+\sigma_{Min}^2}}}_{\sqrt{\frac{1+\tilde{\sigma}_j^2}{1+\tilde{\sigma}_{Min}^2}}} \times \underbrace{\frac{\sigma_u^2}{\sigma_u^2+\sigma_j^2}\omega_{ij}^{S.Q}}_{Eqn\,1.5.2} \tag{1.5.8}$$

This normalizes the value of the counterfactual signal ω_{ij}^{High} without having to draw a new stochastic value. The benefit to this approach instead of simulating from the distribution in equation (1.5.7) is that this allows for a consistent comparison with the status quo. As σ_{Min}^2 approaches σ_j^2, the counterfactual values equal the status quo. The loan officer's biased posterior can be calculated as

$$\frac{\sigma_u^2}{\sigma_u^2+c_j^2}\omega_{ij}^{High} = \underbrace{\frac{\sigma_u^2+\sigma_{Min}^2}{\sigma_u^2+c_j^2}}_{\frac{1+\tilde{\sigma}_{Min}^2}{1+\tilde{c}_j^2}} \times \underbrace{\frac{\sigma_u^2}{\sigma_u^2+\sigma_{Min}^2}\omega_{ij}^{High}}_{Eqn\,1.5.8} \tag{1.5.9}$$

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

$$\begin{aligned} L_{ij}^{High} &= k_j^{S.Q}\left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \tfrac{1}{R_i} + \tfrac{\sigma_u^2}{\sigma_u^2+c_j^2}\omega_{ij}^{High}\right) \\ E\left[\pi_i^{High}|\omega_{ij}^{High}\right] &= RL_{ij}^{High}\left(\gamma L_{ij}^{High} + \boldsymbol{x_i'}\boldsymbol{\Gamma} + \tfrac{\sigma_u^2}{\sigma_u^2+\sigma_{Min}^2}\omega_{ij}^{High}\right) - L_{ij}^{High} \end{aligned} \tag{1.5.10}$$

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 (1.6) 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 (1.5.5) shows this effect for each loan officer and finds that almost all of the loan officers are above the Mendoza line.[50]

1.5.8 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

[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.

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[51], training, and compensation. Equation (1.3.6) shows that the effect of the bonus rate β 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.

1.6 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

[51] Ackerberg and Botticini (2002) find that matching between principals and agents may be important in determining the optimal structure of contracts.

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.

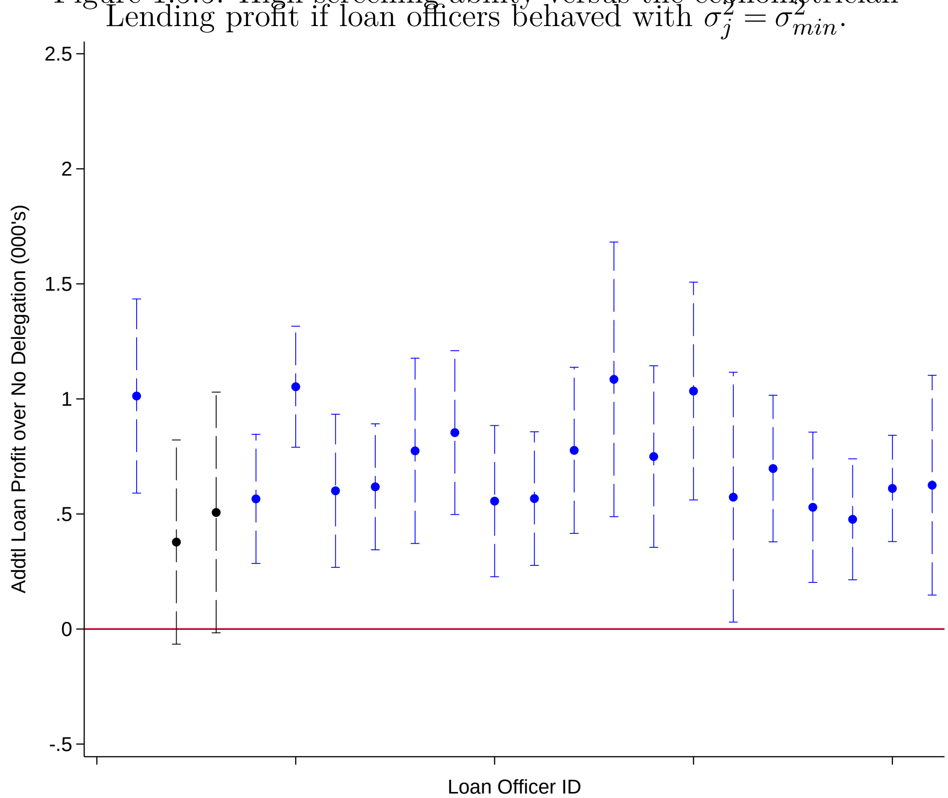
First, there was substantial heterogeneity in risk preferences, screening ability, and beliefs about screening ability across loan officers. I further found that loan officers were uniformly risk averse and overconfident. These characteristics led to large distortions in average loan amounts and loan 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 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.[52] 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.

[52] 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.

Figure 1.5.5: High screening ability versus the econometrician



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.

CHAPTER II

Decomposing moral hazard in lending: evidence from China

2.1 Introduction

Since the seminal work of Akerlof (1970), economists have known that asymmetric information imposes costs on markets. One such market is lending where moral hazard effects can lead to loan rationing and credit constraints Stiglitz and Weiss (1981). To remedy these costs, policymakers and researchers have suggested a variety of tools such as increased collection and repayment incentives. However, the choice and success of various policy interventions depends on the magnitude of the effect of moral hazard and whether the existing techniques are effective. An important obstacle to empirical work is the supply side response that may confound estimates of moral hazard. The complication is that default is an equilibrium outcome due to both borrowers and the lender. Borrowers may be more likely to default on larger loans, but the lender may could reduce this effect with greater collection intensity. Policymakers and researchers that wish to understand the costs of asymmetric information must isolate the borrower effect apart from the lender's response.

I examine these issues using data from a large Chinese lender that specializes in providing unsecured cash loans to households and small businesses. I exploit a natural experiment where borrower applications are randomly assigned to loan officers to accommodate potential endogeneity in loan sizes. I separate the lender's response by recognizing that the decision to first become late on payments doesn't include collection intensity, while the ultimate decision to default incorporates collection. By comparing the causal effects from both outcomes, I can isolate the effect of moral hazard on default. To the best of my knowledge, this is the first paper studying moral hazard in lending that accounts for this distinction.

Lending is a particularly important setting in which to study information asymmetries for a number of reasons. One is that moral hazard result in credit constraints that can have negative costs 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.[53] Another important factor is the government's involvement and regulation in lending, screening, and collection practices. By understanding the costs of asymmetric information, more effective policy interventions can be implemented.

Isolating the effect of moral hazard on default requires overcoming a number of obstacles and places formidable demands on data. Loan decisions are frequently made after observing borrower attributes that are uncodified and unavailable to the econometrician. This creates an omitted variables problem leading to endogeneity of loan sizes. Estimation requires exogenous variation in loan sizes for causal inference. I accomplish this by comparing the

[53] 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.

delinquency behavior of ex-ante identical borrowers who were randomly assigned to different loan officers. Similar to Abrams et al. (2012) or Maestas et al. (2013) in studying judicial sentencing disparities and disability benefits, idiosyncratic differences across loan officers lead to quasi-experimental variation in loan amounts that is orthogonal to unobserved borrower attributes.

However, these approaches may not account for collection strategies. For example, Dobbie and Skiba (2013) find a negative effect of moral hazard on default in the market for payday lending, which indicates that borrowers become less risky with increases in loan sizes. One explanation is that borrowers are in fact riskier when given larger unsecured loans, but the lender is able to attenuate its effects with greater collection intensity. My approach in isolating the borrower's moral hazard on default is to exploit the difference between late payments and defaulted loans. The rationale is that the causal effect of loan size on *default* pools two effects: increased borrower incentives to not repay and collection intensity, while the effect of loan size on *late payments* only captures the former. Differencing the two gives an estimate of each component.

The empirical strategy relies on rich data from a large Chinese lender. This dataset offers an ideal setting to decompose the effect of moral hazard. The data features detail at the individual borrower level including all of the codified application variables available to the lender. 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 repayment stream including monthly payments, delinquencies, and penalty fees. The repayment data pins down when borrowers first missed payments and when the lender ultimately wrote off the loan through default.

I preview some main results. First, I find a significant effect of moral hazard where borrowers given a ¥1,000 larger loan are 1.5% more likely to be late on payments indicating that borrowers become riskier in response to larger loan sizes. Second, the causal effect of loan size on default indicates that borrowers given a ¥1,000 larger loan are only .5% more likely to default. I attribute the difference to the lender's collection intensity towards larger loans. Ignoring this interaction leads to a much smaller effect of moral hazard. In the case where borrowers may be accidentally late and would have repaid even in the absence of collection, the 1.5% estimate can be considered an upper bound for the effect of moral hazard on default since not all of those borrowers would have defaulted. Lastly, following the strategy of Adams et al. (2009), I find that the borrowers actually approved for larger loans were 1.5% less likely to be late. This effect could be due to advantageous selection by borrowers or effective underwriting by the lender. Together, the selection and incentive effects of loan sizes leads to no correlation with delinquency.

This paper fits into a growing literature that attempts to identify the effect of moral hazard on default in credit markets. These studies focus on different identification strategies to account for the endogeneity of loan sizes. Dobbie and Skiba (2013) use a regression discontinuity approach around loan eligibility cutoffs to find little evidence of moral hazard and potentially even negative effects. Karlan and Zinman (2009) conduct a randomized field experiment varying an offer rate to find strong evidence of the effects of moral hazard. Adams et al. (2009) use a borrower's self-selected down payment and extensive controls to account for selection and find large effects of moral hazard. Gine et al. (2012) examine the effect of a specific repayment incentive of fingerprinting on default and find that collection leads to decreased moral hazard.

This paper contributes through a number of dimensions. The first is a research design not previously used in this literature that estimates a causal effect from idiosyncratic differences in approved loan amounts across different loan officers. Additionally, I separate the supply side collection response from the borrower's moral hazard on default. This is related to a large literature in healthcare that studies how medical utilization is a combined decision by both the patient and the physician. Hu et al. (2014) and Ho and Pakes (2013) show evidence that physicians' prescribing and referring behavior changes in response to cost sharing changes. By ignoring that healthcare utilization and loan default are equilibrium outcomes, policy interventions could be misguided. The remaining sections are structured as follows. Section 2 describes the data and context in more detail. Section 3 presents the theoretical framework for moral hazard, while Section 4 shows the estimation strategy and assumptions for identification. Section 5 discusses the results and possible confounds to identification, and section 6 concludes.

2.2 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.[54] The lender utilizes both automated credit scoring through proprietary technology as well as subjective evaluation with manual loan officer screening. Loan officers make a loan amount decision given a holistic reading of the credit score and other uncodified data.[55] Approved loan sizes are significantly higher than the microloans studied in the development

[54]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.

[55]Wang (2014b) study the loan officer's decisions and finds that subjective screening adds considerable value to automated credit scoring.

literature and are slightly less than half of the average borrower's salary income on average.

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 has access to other financing options such as credit cards, home and vehicle loans, and other cash-based lenders.[56] 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 in recent years. See Ayyagari et al. (2010) for a more detailed survey of the Chinese financing industry.

2.2.1 Data

Table (2.7) 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.[57]

[56]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 adverse selection on observable characteristics concern is somewhat alleviated by extensive information reporting. Applications to different lenders and outstanding loans are reported to credit monitoring agencies. Some of the additional reported information include credit card usage and limits, external loan terms, and historical repayment schedules.

[57]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 have large sources of income. For

Table 2.7: Summary statistics

	Mean	Min	Max	Std dev
Loan terms				
Loan amount (¥000's)	33	5	60	12
Requested (¥000's)	124	3	300	103
Monthly payment (¥000's)	2.2	0.3	5.7	1.1
Payment length (Months)	25	12	36	7
APR (%)	48%	33%	62%	7%
Borrower attributes				
Estimated assets (¥000's)	587	1	7,358	1,337
Salary income (¥000's)	71	4	642	267
External debt (¥000's)	160	0	1,923	856
Age	38	18	58	9
Credit card utilization	41%	0%	100%	38%
Credit card limit (¥000's)	20	0	718	156
Proportion with credit card	76%			
Proportion female	28%			

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.

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 retired frequently at each of the various locations. Loan term lengths range from 12 to 36 months with the median at 24 months. The most common loan in my sample is a 24-month fixed payment loan with an APR of 48%. This APR includes the nominal interest rate, application fees, and maintenance fees.[58]

comparison, per capita GDP in Shanghai is ¥82,000, and is ¥38,000 in China as a whole.

[58]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.

2.2.2 Credit scoring and manual screening

The borrower's first step is to fill out a loan application which includes identification, demographics, financial documents, and verified references. Some of the self-reported data include the purpose of the loan and the amount that the borrower is requesting. Following submission, local branch employees verify the borrower's income, debt, and asset information using bank statements and credit reports. The branch employees will also make home and workplace inspections to assess the borrower's home environment. The application process collects a large amount of information both codified and subjective. Survey information is collected on the number of TV sets, air conditioning units, square footage, number of family members, and others which are photographed and detailed in notes.

Codified information is entered into the lender's proprietary credit scoring model. Some examples include age, income, occupation, number of TV sets, and the square footage of the borrower's home. I also include the outcome of the lender's credit scoring model, which is a variable called credit quality that is an aggregation of a large amount of borrower attributes. The uncodified subjective data is used by loan officers to holistically screen borrowers and determine risk in conjunction with the objective information. This includes written notes, photographs, or local knowledge about a borrower's purchasing habits from bank statements. Differences in how loan officers process this kind of information lead to variation in loan decisions.

Once the branch employees gather the information from interviews and inspections, the application is approved or denied by a local branch supervisor. Approved applications are sent to the central headquarters where loan officers will screen the loan and choose the approved loan size. 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 feature in this setting. One reason that the lender gives in 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 one of 21 loan officers for processing. In practice, a batch of applications will enter the office and be distributed to loan officers without presorting.[59] This assignment procedure will be crucial in identification of the borrower's moral hazard on default, which guarantees that each loan officer's portfolio of borrowers has the same ex-ante distribution of subjective uncodified attributes. Idiosyncratic differences in how loan officers screen and make loan decisions provides exogenous variation in loan sizes. Loan officers process roughly 700 applications a year with the average file taking 30 to 40 minutes. Section 3 discusses this random assignment and the necessary assumptions in more detail. During screening, the loan officer observes all of the codified attributes including the borrower's credit quality as well as the uncodified subjective data such as photographs or notes.

After screening, the loan officer chooses a loan amount given the interest rate and payment length.[60] I stress that the only lever that the loan officers have in adjusting the terms of the

[59]Some 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 during distribution.

[60]While 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 delegated pricing authority and find that the amount of authority available to the agent depends on the agent's local knowledge.

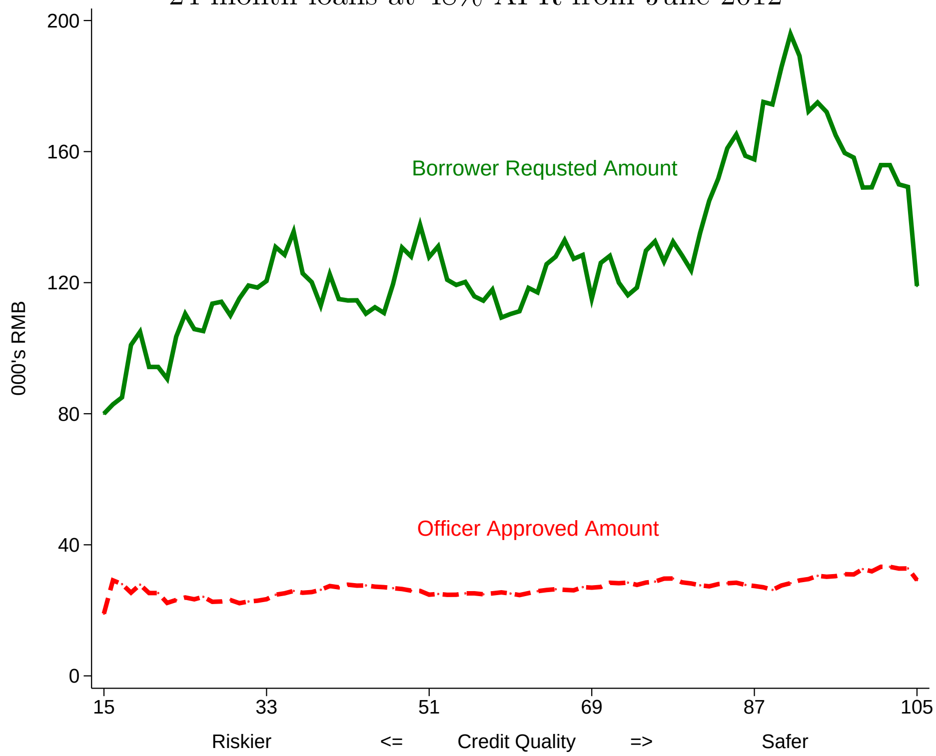
loan is in choosing the size. The other loan terms including the interest rate and payment length are fixed. Once the determination is complete, the borrower may sign the terms of the loan with no further recourse for adjustment. The sales offices themselves play no part in adjusting loan terms. The entire process from initial application to loan disbursement can take between 3 to 7 days.

2.2.3 Requested amount

One unique feature of the application is that borrowers are asked to report a requested loan amount. If the loan officer's chosen loan size is larger than the borrower's requested amount, then the full amount requested is approved. If the approved loan amount is less than the requested, then the borrower is underfunded and credit constrained. The lender's stated goal is to choose loan amounts based on the borrower's repayment ability rather than trying to satisfy borrower liquidity demands. This allocation mechanism mitigates the effect of adverse selection where borrowers with an ex-ante higher likelihood of delinquency 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 to potentially mitigate any selection effects. To the extent there is any cross-sectional relationship between self-reported requested amounts and defaults, then the correlation can be accounted for similarly to the borrower's other attributes such as income.

Another important point is that this requested amount may not represent a borrower's true underlying demand for loans, and there may be a signaling or strategic mechanism involved in the decision. Table (2.7) shows that the requested loan amount is generally three times the approved amount with a large amount of variation. Figure (2.2.1) shows the average

Figure 2.2.1: Loan amounts and requested amounts by credit quality
24 month loans at 48% APR from June 2012



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 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.

requested amount and approved amount for loans by credit quality, which is an internal measure of borrower quality from credit scoring. 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 funded.[61] Over 90% of borrowers were approved for loan amounts smaller than requested.

[61] The slope of credit quality on the approved amount is positive and significant, which is difficult to see at the scale of the graph.

2.2.4 Repayment incentives

Borrowers are late when their payment is not received by their due date. Accounts delinquent for more than 90 days or 3 payment periods are in default, and generally packaged and sold to external collectors or written off. To prevent default, the lender utilizes a variety of tools to mitigate moral hazard and incentivize repayment. Subsequent loans may come with more attractive terms including lower fees and reduced APR. Additional carrots also come from higher future loan amounts and a simpler approval process.[62] The lender also uses sticks to deter default, some of which scale with loan size and some that do not.

As soon as borrowers are late, automated messages and recorded calls are placed to the borrower. The deterrence effect of these collection practices do not scale with the size of the loan. However, some of the lender's tools do rise in intensity with loan sizes. After 3 days of missed payments, the lender begins charging penalty fees and the borrower is considered in arrears. Further actions include reporting to credit agencies and collection calls by collectors. The intensity of some of these actions rises with the size of the loan. For example, larger loans receive additional scrutiny by the collections department with a greater frequency of collection calls, a higher chance of litigation, and a smaller chance to be written off.[63] Because the collections team is rewarded both on the number of loans recovered as well as the total amount, collectors also may exert greater effort when contacting the borrower. Many collectors will call family members and friends to exert additional repayment pressure. The calls, notices, and collection intensity is not observed, but it is possible to see their impact on repayment patterns. The loan officer has no contact with the borrower after loan

[62] 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.

[63] For especially egregious borrowers who are late on large payments, their names are published in city newspapers and along public corridors to increase social stigma and incentivize repayment.

origination and the loan officer is not involved in collecting delinquent loans.

2.3 Framework

The goal of this study is to examine the degree of moral hazard present. Moral hazard directly increases the incentives to default from higher loan sizes, while collection intensity may alter the repayment decision. Separating these two effects is difficult because both lead to a correlation between loan sizes and delinquency. Default could be due to factors directly under the borrower's control as well as environmental factors where the borrower has little volition. The channel could be through strategic default where all else equal, borrowers are more likely to walk away from repayment and declare bankruptcy for larger loans. The mechanism could also be entirely outside of the borrower's control such as higher monthly payments pushing a borrower into default given stochastic shocks to income.

The causal effect could also be negatively related to risk. For some borrowers, increasing returns from loan sizes may actually decrease the probability of default although the joint correlation has to be weakly positive for equilibrium credit constraints Dobbie and Skiba (2013). Both the sign and magnitude therefore depend on the concavity of the returns from loan sizes versus the costs of default. Another effect that changes with the size of the loan is collection efforts. Without accounting for this supply side response, any estimate of the causal effect pools the effects of moral hazard and collection intensity. For late loans, the lender could exert greater effort on collecting larger loans which attenuates the effects of moral hazard. On the other hand, the lender could also engage in the inverse strategy and exert greater effort in collecting smaller loans. The reasoning could be that larger loans are easier to sell to third party collection agencies. This strategy would actually upward bias estimates of the effects of moral hazard on default because the data would exhibit more defaults for larger loans. The goal of the empirical section is to examine the relationship between loan amounts and delinquency and separate moral hazard from the lender's collection intensity.

2.4 Empirical strategy

The first step is to specify an empirical model of default.

$$D_i = \gamma L_{ij} + \boldsymbol{x_i'}\boldsymbol{\Gamma} + \epsilon_i \tag{2.4.1}$$

D_i is a 0/1 indicator for a delinquency event such as late payments or default, L_{ij} is the loan size chosen by loan officer j for borrower i, $\boldsymbol{x_i}$ is a vector of borrower attributes and loan terms including self-reported items, and ϵ_i is a stochastic shock that is observed to loan officers but not to the econometrician.

The moral hazard parameter of interest is γ, which is the direct causal effect of loan size on the chance of delinquency. Larger values of γ mean that borrowers respond to larger loan sizes by becoming more risky and more likely to default. Identifying the causal effect is challenging because loan amounts are not randomly assigned. L_{ij} is decided in combination with the borrowers requested amount and the loan officer's decisions. This means that L_{ij} and ϵ_i may be correlated because L_{ij} is decided after screening ϵ_i, which indicates that the unobserved attributes are not mean zero $E\left[\epsilon_i | L_{ij}, \boldsymbol{x_i}, q_i\right] \neq 0$.

Following Adams et al. (2009), γ in equation (2.4.1) without controlling for endogeneity pools two effects. One is the causal effect, and the other is the correlation between loan amounts and delinquency induced by selection and matching. If the correlation is positive, then it indicates either advantageous selection by borrowers for loan sizes or the lender is able to match larger loans to safer borrowers.[64] This leads to a downward bias for γ if endogeneity is not taken into account. With a suitable instrument, then comparing the OLS and IV estimates of γ returns both the causal effect and the aggregate loan selection factors. Fortunately, the random assignment of borrower applications to loan officers provides such an instrument.

2.4.1 Endogeneity

Without an instrument, L_{ij} is endogenous and correlated with the unobserved ϵ_i. One solution to identifying the causal effect is to use the random assignment of borrower applications to loan officers as exogenous variation in loan amounts. The intuition is that observably identical borrowers are assigned to different loan officers with different propensities for approving loan sizes. Idiosyncratic differences in how loan officers screen, process, and approve borrowers are assumed to be orthogonal to each borrower's unobserved shock to repayment ϵ_i. This suggests that the loan officer's average approved loan amount is a strong candidate for an instrument.

With an instrument, average differences in delinquency across loan officers can be causally attributed to differences in their average loan amount. The identifying assumption is that ϵ_i cannot be correlated with the loan officer's average loan amount conditional on observable borrower attributes.[65] This assumption is supported by the random assignment of borrower

[64] These two mechanisms are not separated given this data. In the Adams et al. (2009) setting, this is also a concern as individual salespeople may steer certain types of borrowers to different kinds of products irrespective of their own selection.

[65] One possible violation is if loan officers collaborate with each other. For example, a loan officer on

Table 2.8: First stage

	Dependent variable: loan amount				
$MeanLoan_{itj}$	0.261***	0.252***	0.257***	0.239***	0.252***
	(0.0416)	(0.0416)	(0.0403)	(0.0407)	(0.0398)
R^2	0.369	0.415	0.435	0.477	0.520
Number of controls	78	84	85	129	265
Year by month, city, product	✓	✓	✓	✓	✓
Application variables		✓	✓	✓	✓
Internal credit quality			✓	✓	✓
Financial variables				✓	✓
Inspection variables					✓

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Table shows the first stage between the loan officer's average decision and loan sizes. $MeanLoan_{ij}$ is the loan officer's average loan amount in a given month excluding borrower i and is given by $\frac{1}{N_{tj}-1}\sum_{-i} L_{itj}$. 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. Standard errors are clustered at the loan officer level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

applications to loan officers. And because loan officers are not involved in collecting delinquent loans, there is an exclusion restriction. Loan collection is handled entirely by the local branch offices and external collectors with no contact from the original loan officer. The only effect that loan officers have on delinquency is through the choice of loan size.

Following Maestas et al. (2013), a candidate for an instrument is the loan officer's average loan amount within a month window.[66] The average loan amount can be constructed to

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 precludes this type of joint inspection from frequently happening.

[66] This allows loan officers to change their lending behavior month to month. The variation comes from shocks to their lending preferences across months.

exclude borrower i so that the individual-specific instrument is defined as

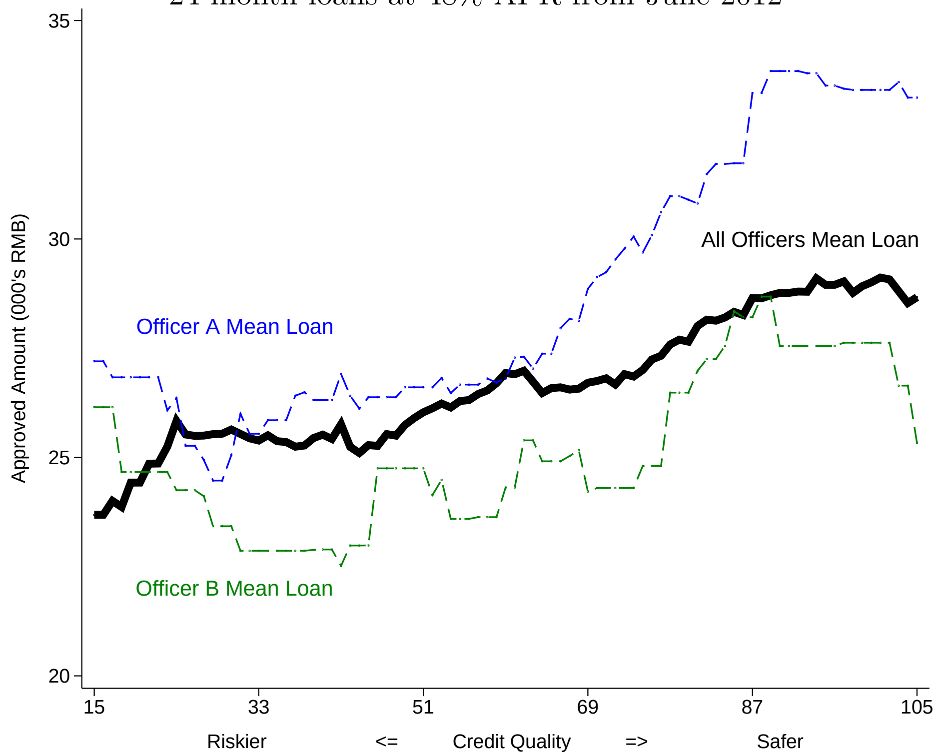
$$MeanLoan_{itj} = \frac{1}{(N_{tj} - 1)} \sum_{k \neq i} L_{ktj} \tag{2.4.2}$$

where N_{tj} is the loan officer's total number of cases within a month window. This instrument by construction cannot be correlated with the borrower specific portion of ϵ_i. Any potential endogeneity comes from factors within ϵ_i that are correlated across borrowers. The intuition for this instrument can be seen in figure (2.4.1), which plots the average loan amount for two different loan officers for all of their loans against credit quality. Credit quality is the lender's internal measure of borrower risk and is an aggregation of a large amount of codified borrower attributes. Despite borrower applications being randomly assigned across loan officers, Officer B still approves a smaller loan amount at every level of risk.

Table (2.8) is the first stage of the approved loan size on this instrument. The Z-score around 6 across specifications supports the rank assumption that $MeanLoan_{itj}$ has sufficient correlation with the the borrower's approved loan amount. Despite including hundreds of controls accounting for year by month effects, city controls, application variables, and extensive financial and inspections variables, $MeanLoan_{itj}$ is still highly predictive of loan sizes due to idiosyncratic differences in screening, processing, and approving borrowers. Significance still holds whether the errors are clustered at the loan officer or loan officer month level.

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 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

Figure 2.4.1: Average loan amount 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 loan officer's average loan amount is averaged over a bandwidth interval of 5.5. As of August 2014, $1 is ¥6.18.

values of ϵ_i *within* those categories.[67] This assumption can be examined with 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

[67]Given 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.

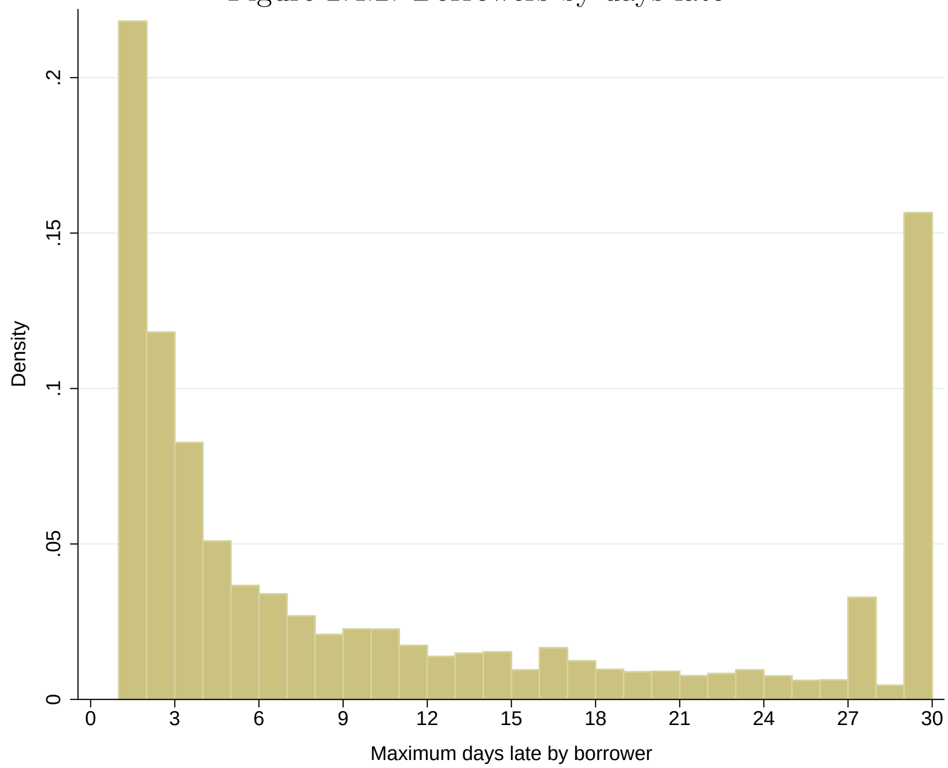
such a test. By examining the regression of L_{ij} on $MeanLoan_{itj}$ along with additional covariates, I can test for correlated observables. This is because only borrower attributes that are correlated with $MeanLoan_{itj}$ should change its coefficient when added to the regression. The stable values across specifications in table (2.8) provide 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* observed borrower types either.

2.4.2 Separating moral hazard and collection intensity

After accounting for endogeneity, there is an additional difficulty in estimating γ. The causal effect itself is a composite of both the borrower's increased moral hazard and the lender's increased collection intensity. Even without any moral hazard, there could be a relationship between default and loan size if the lender exerts differential collection intensity towards larger loans. The direction of the bias depends on the lender's strategic choice of collection and is not ex-ante obvious. Collection activities that are invariant to the size of the loan will not bias γ and instead be subsumed into the constant term. Only collection efforts that rise or fall with the size of the loan will confound estimates of γ. I account for the lender's response by relying on the distinction between late loans versus defaulted loans.

As soon as a payment is overdue, automated messages are placed to the borrower. These collection efforts continue and are invariant to the amount in arrears until the third day, at which point the penalty grace period expires. From this point, fees are levied and a series of collection efforts including calls to family members, friends, and other references will follow. Depending on the amount of time delinquent, collection visits may occur. These calls and

Figure 2.4.2: Borrowers by days late



Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Emails and automated reminder calls are placed as soon as the borrower is late, but penalty interest does not begin until the borrower is three days past due. Once this occurs, collection agents contact the borrower to encourage repayment. Borrowers late by more than 30 days are aggregated to 30. Loans are written off and in default past 90 days overdue.

visits escalate in frequency given time and the repayment outstanding. The lender also employs newspapers and billboards to advertise certain delinquent borrowers to the public. After 90 days overdue, the loans are usually written off and sold to external collectors or referred to litigation. Figure (2.4.2) shows a histogram of the number of days late conditional on a borrower being late. Many late borrowers are converted back to their payment schedules throughout the delinquency period as the lender exerts collection efforts. I define late loans as three days past due to separate collection that is invariant to loan size and collection that may scale with the loan.

The borrower's increased risk results in more borrowers becoming late on payments, but ultimately, the lender can convert many late borrowers back to their regular payment schedule. γ in equation (2.4.1) where late payments is the outcome variable includes only the effect of moral hazard on default, while γ in equation (2.4.1) with default as the outcome also pools the collection intensity. The identifying assumption is that late borrowers would not have repaid their loans absent collection notices. If this assumption holds, then the causal effect of increased loan size on late payments is the moral hazard effect.

One potential confound is that some borrowers are late by accident and would not have defaulted even without reminders from the lender. Two institutional features address this concern. One is that the three day grace period gives borrowers time to submit payments that were missed on accident. The other is that all of the payments for all borrowers are directly debited from the borrower's bank account with no need for physical mailing of the monthly payment. The borrower's primary bank account must have low funds for the borrower to be overdue. These two features decrease the probability that late payments are unplanned. The histogram in Figure (2.4.2) shows that many borrowers repay their loans within the first three days. Longer lasting delinquent borrowers are likely to not be accidental. It may also be possible that borrowers are late strategically in order to repay at a later date. This could be due to liquidity constraints or pay cycles that are not matched to the loan's payment dates. Due to late penalty fees, it is unlikely that this is a profitable strategy for the borrower. The late fees would be higher than the interest on an additional loan covering the missed payment. To the extent that borrowers may default for these other reasons, then the estimate of moral hazard can be considered an upper bound since some portion of delinquent borrowers might still have been accidental.

2.4.3 Empirical default model

I use the probit specification as the main model of delinquency risk. I account for endogeneity by instrumenting for L_{ij} using $MeanLoan_{itj}$ and the full set of exogenous regressors $Z_{itj} = (\boldsymbol{x_i}, MeanLoan_{itj})$. The probit specification is given by

$$D_i = \Phi\left(\gamma L_{ij} + \boldsymbol{x_i'}\boldsymbol{\Gamma} + \epsilon_i\right) \tag{2.4.3}$$

$$L_{ij} = \beta Z_{itj} + \upsilon_i \tag{2.4.4}$$

where D_i is in indicator for delinquency such as late payments or default. The two equations are estimated jointly using maximum likelihood.

Another hurdle is censoring in the repayment variable 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 7,000 completed loans. I account for this by including extensive controls on the number of payments completed, payments remaining, and the proportion of payments completed into the borrower's observed attributes $\boldsymbol{x_i}$. I perform three different robustness checks on the sensitivity of results to censoring. One methodology only estimates on the full sample of uncensored loans, and another method also includes all completed and defaulted.[68] I also estimate with a Cox proportional hazard model, which can directly account for censoring by modeling the instantaneous probability of default.

The Cox proportional hazards model exhibits a number of attractive features. The model is

[68] An uncensored loan is one in which I have observed the total number of repayment periods. A loan completed early 3 months into a 24 month payment term would only be uncensored if I observed all 24 payment periods.

flexible, semi-parametric, and is able to handle data censoring. The model specifies that the instantaneous probability of delinquency at time t conditional on the loan surviving until time t is given by $h(t|\boldsymbol{x_i}, L_{ij}) = h_0(t)\,exp\left(\gamma L_{ij} + \boldsymbol{x_i'}\boldsymbol{\Gamma}\right)$. This hazard rate is composed of two parts: an unparametrized baseline rate that is allowed to vary flexibly, and a proportional hazard component that shifts the overall hazard rate multiplicatively. Because payment length varies considerably in the sample from a low of 12 months to a high of 36 months, time is cast as the percentage of loan payments made instead of calender time. For example, $t = 0$ would be the start of the loan, $t = .5$ would be 50% of payments made, and $t = 1$ would be full completion.

While the Cox model can accommodate censoring, it suffers from a number of weaknesses. The required assumption is that changes in the proportional hazard shift the baseline multiplicatively and have no other impact on the baseline. This is a strong assumption not present in the linear probability model or the probit. In addition, accounting for endogeneity is more difficult. Since the Cox model is non-linear, standard methods for implementing instrumental variables are not as efficient as a control function approach Wooldridge and Imbens (2007). Estimation follows a two-step control function procedure. In the first step, L_{ij} is regressed on the exogenous covariates and the instrument $MeanLoan_{itj}$. The predicted residuals from this first stage are entered linearly into the Cox model as another explanatory variable in the likelihood function. The reasoning of the control function is that the predicted residual controls for the portion of L_{ij} that is correlated with the endogenous errors. By including the control function, the remaining variation in L_{ij} can be considered orthogonal to the error.

2.5 Results

Table (2.9) shows the estimates for the probit model. The displayed coefficients are marginal effects on the probability of the delinquency outcome with all covariates set to their mean values. Column (1) displays the regression without controlling for the endogeneity of loan sizes. Column (2) uses $MeanLoan_{itj}$ as an instrument for loan sizes with late payment as the outcome, and column (3) uses default as the delinquency outcome. Without an instrument, column (1) indicates that higher loan amounts lead to a small and statistically insignificant causal effect on the chance of a late payment. This effect is biased because the borrowers given larger loans may be safer (or riskier) than their peers all else equal.

Column (2) displays the effect of moral hazard on late payments controlling for the endogeneity of loan sizes with $MeanLoan_{itj}$ as an instrument. The estimate can be interpreted as a ¥1,000 increase in loan amounts leads to a 1.5% higher chance of a loan being late. However, when examining defaults, the effect is substantially smaller. Column (3) shows the effect on default indicating that a ¥1,000 higher loan amount increases the chance of default by .5%. If the lender exerted the same collection intensity to all loans, then there should be no difference in the two estimates. If the lender instead favored collecting smaller loans, then the coefficient in column (3) may even be larger than column (2). The coefficients indicate that the lender is increasing collection intensity on larger loans which conforms with the lender's stated procedures. One potential confound may be that borrowers are late accidentally and do not intend to default even without any collection. If these borrowers are still late despite the 3 day grace period and large penalty fees, then the moral hazard effect may be upward biased. In other words, this may be an upper bound.

The estimate can be compared to the literature, although the comparison is again not straightforward since differences in institutional setting make cross-country comparisons difficult. Despite the difficulties, 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. Other estimates 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. One possible interpretation of this result is that the authors are instead examining the composite causal effect including collection. Payday lenders may be effective at convincing late borrowers to resume repayment and avoid default.

Some of the other borrower attributes are also of interest. Column (2) shows that borrowers that ask for more, don't have credit cards, regular employees, or males are all riskier than their counterparts. Older borrowers also become delinquent at greater rates. The difference between column (2) and column (3) shows that some borrower types respond to collection differently than others. For example, while females are less likely to become late, they seem to respond less to collection than males. This could be because females are less susceptible to social pressures or that collection agents use comparatively lighter methods to collect from females. One added difficulty in interpreting some borrower attributes is that the lender's internal measure of risk is already an aggregation of many borrower types such as income.

Adams et al. (2009) note that the cross sectional correlation in column (1) includes both the causal effect and the loan assignment process. This assignment includes both the borrower's selection and the lender's approval effects. Borrowers demand loans for many reasons such as true liquidity demand, anticipated moral hazard Einav et al. (2013a), strategic signaling, or cheap talk. The lender approves loan sizes due to the screening decisions of their loan officers given the amount that borrowers request so that loan assignment includes both factors. By subtracting the causal effect from column (1), I can recover a measure of the aggregate selection effects. Differencing column (2) from (1) indicates that borrowers receiving a ¥1,000 loan were 1.5% less likely to become late on payments. This indicates an advantageous selection either caused by the safer borrowers demanding larger loans or the lender's underwriting efforts approving safer borrowers to larger loans. The exact mechanism is not pinned down with this data due to possible strategic action on the borrower's requested amount.

2.5.1 Robustness

Alternative specifications also support the estimates from the probit model. Table (2.10) uses the linear probability model and displays similar results. Column (2) estimates with $MeanLoan_{itj}$ as an instrument using 2SLS to find that a ¥1,000 causally increases late payments by 1.5%. Using an alternative measure for late payments, column (4) finds that the total number of late periods is also increasing with the size of the loan. Note that continuous late periods past three months results in default. Column (5) finds that if collection efforts are included, then the marginal effect is mitigated to .8%. This is consistent with the main results suggesting that collection can attenuate the effects of moral hazard on default. Differencing column (2) from (1) or differencing column (4) from (3) also shows that loan sizes are advantageously selected and given to safer borrowers.

Table (2.11) displays alternative specifications to examine censoring in the data. The top panel shows the probit model estimated off of only uncensored loans. Uncensored loans are those for which the full number of repayment months has been observed regardless of the loan status. With 3,799 uncensored observations, column (2) gives an estimate of 1.7% which is reduced to a statistically insignificant 1% when examining default as the outcome. Compared to column (1), the borrowers given larger loans still indicate advantageous selection. This pattern is repeated when examining uncensored, defaulted, and completed loans in the middle panel. The estimate in column (5) is mitigated in column (6) although the two values are much closer. This is most likely due to the sample selection issues of over-sampling from defaulted loans and selecting on the left hand side variable. The last panel shows the Cox proportional hazard model which directly accounts for censoring by modeling the instantaneous delinquency risk using survival methods. The hazard ratios show that a ¥1,000 larger loan leads to a 10% greater chance of late payments, and only a 8% chance of default. There is still evidence of advantageous selection when compared to column (7). While the direction of the effects is comparable, the difference in magnitude could be due to the more restrictive parametric assumptions of the Cox model.

The additional evidence conforms with the probit that borrowers become riskier when given larger loans, but the effect is attenuated by the lender so that many delinquent borrowers resume repayment. Additionally, the cross-sectional correlation between loan sizes and late payments is uniformly smaller than the causal effect across all specifications. Loan assignment seems to be advantageous where safer borrowers are given larger loans. This could be due to safer borrowers demanding larger loans or effective underwriting mechanisms leading to good matches.

2.6 Conclusion

In this paper, I have presented evidence of private information operating through moral hazard. I identified the effect of moral hazard on default by relying on exogenous variation in loan sizes due to the random assignment of borrower applications to loan officers. Idiosyncratic differences in how loan officers screen, process, and approve borrowers led to variation in average loan amounts. This exogenous variation identified the causal impact of larger loan amounts on delinquency. By exploiting the differences between late and defaulted loans, I also accounted for the effectiveness of the lender's collection intensity towards larger loans. The rationale is that the causal effect of loan size on *default* includes two effects: increased moral hazard on default and increased collection. However, the causal effect of loan size on *late loans* only captures the former. By differencing the two specifications, I can get an estimate of the component pieces. I found that although borrowers given larger loans are 1.5% more likely to become late, that effect decreases to .5% when examining defaults. I concluded that greater collection effort may have been effective at reducing this tendency.

These results highlight the difficulty of evaluating costs in other markets as well. For example, increased healthcare utilization observed in aggregate data is a joint decision that is driven by both the patient and the physician. There may be a bias in estimates without accounting for the confounding supply side response. Another important insight is that private information may be mitigated with the tools identified by theory. Given the prevalence of markets featuring moral hazard, these results speak to the benefits of increased information screening and greater dynamic incentives. Automated credit scoring, manual loan officer screening, and rising collection intensity are largely able to offset many of the costs of asymmetric information. A better understanding of how these mechanisms actually mitigate is an important area for future research.

Table 2.9: Effect of loan size on delinquency with probit

	(1) Probit **Late indicator**	(2) Probit with IV **Late indicator**	(3) Probit with IV **Default indicator**
Loan size (000's)	0.000421	0.0150***	0.00454**
	(0.000295)	(0.00364)	(0.00223)
Requested (000's)	-4.27e-05	0.000184***	3.92e-05
	(2.74e-05)	(6.69e-05)	(3.35e-05)
Credit score	-3.67e-05	-5.52e-05	-2.59e-05
	(0.000208)	(0.000218)	(0.000121)
APR (%)	-0.000895	0.285	0.228
	(0.353)	(0.358)	(0.187)
Salary (000's)	1.10e-06	-2.66e-05	-6.23e-06
	(1.75e-05)	(1.69e-05)	(9.22e-06)
Credit card (1/0)	-0.0165*	-0.0248***	-0.0140***
	(0.00918)	(0.00937)	(0.00537)
CC utilization (%)	0.0113	0.0198	0.00641
	(0.0223)	(0.0232)	(0.0113)
Debt level (000's)	-3.48e-06	-6.61e-06	-1.70e-06
	(3.58e-06)	(4.05e-06)	(1.77e-06)
Manager (1/0)	0.000491	-0.0322***	-0.00144
	(0.00816)	(0.0117)	(0.00548)
Female (1/0)	-0.0783***	-0.0765***	-0.0196***
	(0.00606)	(0.00614)	(0.00365)
Homeowner (0/1)	-0.0210*	0.00822	0.00761
	(0.0118)	(0.0140)	(0.00767)
Age	-0.00325***	-0.00359***	-0.00121***
	(0.000771)	(0.000773)	(0.000448)
Observations	31,954	31,954	31,954

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Displayed coefficients for the probit are marginal effects on the probability of the outcome with all covariates set to their mean value. Additional controls include year by month, city, product fixed effects, and additional application, financial, and inspection variables. Loans are late if payment is not received within 3 days after the due date. Loans are in default is payment is not received 90 days past the due date. As of August 2014, $1 is ¥6.18. Standard errors are clustered at the loan officer level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2.10: Effect of loan size on delinquency with linear probability model

	(1) OLS **Late indicator**	(2) 2SLS **Late indicator**	(3) OLS **Total late periods**	(4) 2SLS **Total late periods**	(5) 2SLS **Default indicator**
Loan size (000's)	0.000299	0.0146***	0.000236	0.0454**	0.00763***
	(0.000260)	(0.00392)	(0.00191)	(0.0207)	(0.00281)
Requested (000's)	-3.88e-05	0.000182***	-0.000557***	0.000139	8.06e-05*
	(2.38e-05)	(6.89e-05)	(0.000167)	(0.000507)	(4.49e-05)
Credit score	0.000121	0.000101	5.89e-05	-2.84e-06	0.000172
	(0.000172)	(0.000190)	(0.00150)	(0.00152)	(0.000146)
APR (%)	-0.442	-0.163	-6.698***	-5.819***	-0.333
	(0.308)	(0.333)	(2.153)	(2.211)	(0.234)
Salary (000's)	2.25e-06	-2.51e-05	0.000166	7.92e-05	-8.13e-06
	(1.55e-05)	(1.61e-05)	(0.000157)	(0.000162)	(1.28e-05)
Credit card (1/0)	-0.0126	-0.0213**	-0.164**	-0.192***	-0.0162**
	(0.00796)	(0.00854)	(0.0663)	(0.0684)	(0.00641)
CC utilization (%)	0.0122	0.0206	-0.0324	-0.00599	0.0137
	(0.0184)	(0.0202)	(0.147)	(0.149)	(0.0136)
Debt level (000's)	-1.76e-06	-4.98e-06**	-1.90e-05**	-2.92e-05**	-2.13e-06
	(1.32e-06)	(2.52e-06)	(8.11e-06)	(1.36e-05)	(1.44e-06)
Manager (1/0)	0.00355	-0.0280**	-0.0523	-0.152*	-0.00355
	(0.00706)	(0.0113)	(0.0510)	(0.0810)	(0.00721)
Female (1/0)	-0.0652***	-0.0665***	-0.425***	-0.429***	-0.0209***
	(0.00524)	(0.00546)	(0.0436)	(0.0441)	(0.00370)
Homeowner (0/1)	-0.0181*	0.00993	-0.112	-0.0236	0.0128
	(0.0106)	(0.0128)	(0.0858)	(0.104)	(0.00906)
Age	-0.00280***	-0.00327***	-0.0255***	-0.0270***	-0.00156***
	(0.000650)	(0.000681)	(0.00566)	(0.00568)	(0.000525)
Observations	31,954	31,954	31,954	31,954	31,954

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Additional controls include year by month, city, product fixed effects, and additional application, financial, and inspection variables. Loans are late if payment is not received within 3 days after the due date. Loans are in default is payment is not received 90 days past the due date. As of August 2014, $1 is ¥6.18. Standard errors are clustered at the loan officer level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table 2.11: Effect of loan size on delinquency with alternative censoring

	(1)	(2)	(3)
Probit - Uncensored	**Late indicator**	**Late indicator with** $MeanLoan_{itj}$	**Default indicator with** $MeanLoan_{itj}$
Loan size (000's)	-0.00142	0.0173**	0.0104
	(0.000924)	(0.00760)	(0.00814)
Requested (000's)	-0.000233**	0.000199	7.92e-05
	(9.91e-05)	(0.000200)	(0.000189)
Observations	3,799	3,799	3,799
	(4)	(5)	(6)
Probit - Uncensored, defaulted, & completed	**Late indicator**	**Late indicator with** $MeanLoan_{itj}$	**Default indicator with** $MeanLoan_{itj}$
Loan size (000's)	0.000995	0.0284***	0.0250***
	(0.000844)	(0.00446)	(0.00554)
Requested (000's)	-0.000126	0.000428***	0.000252
	(9.61e-05)	(0.000128)	(0.000154)
Observations	6,872	6,872	6,872
	(7)	(8)	(9)
Cox proportional hazard	**Late indicator**	**Late indicator with** $MeanLoan_{itj}$	**Default indicator with** $MeanLoan_{itj}$
Loan size (000's)	1.004***	1.107***	1.082***
	(0.00133)	(0.0253)	(0.0182)
Requested (000's)	1.000**	1.001***	1.001***
	(0.000110)	(0.000390)	(0.000283)
Observations	31,954	31,954	31,954

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. "Uncensored loans" are loans where the full payment term has been observed. "Uncensored, defaulted, & completed loans" are loans that are uncensored, defaulted, or were completed early. The cox proportional hazard uses $MeanLoan_{itj}$ as a control function to control for endogeneity. Displayed coefficients for the probit are marginal effects on the probability of the outcome with all covariates set to their mean value. Displayed coefficients for the Cox model are hazard ratios. Additional controls include year by month, city, product fixed effects, and additional application, financial, and inspection variables. Loans are late if payment is not received within 3 days after the due date. Loans are in default is payment is not received 90 days past the due date. As of August 2014, \$1 is ¥6.18. Standard errors are clustered at the loan officer level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

CHAPTER III

Learning by defaulting

3.1 Introduction

Social (peer) effects are a key factor in lending markets with effects on adoption, liability, and repayment Breza (2013). Peer effects spread information about the costs and benefits of loan default across borrowers. This could lead to updated perceptions about the ease of default, the degree of stigma, or the burden of collection efforts among a borrower's peer group. Policymakers and researchers have long been interested in studying how interventions targeting one borrower may causally affect his or her peers. Recognizing the importance of information diffusion and social factors, many lenders take advantage of group liability and social pressure to increase repayment Karlan and Gine (2007). The efficacy of different policy prescriptions depends on the existence of peer effects and its empirical magnitude. However, estimates of peer effects may capture many unrelated confounding factors.

Identifying peer effects involves formidable obstacles including endogenous group formation, correlated unobservables, and reflection as highlighted by Manski (1993). These challenges make it difficult to separate peer effects without sufficiently rich data and sharp research design. For example, peer groups may form based on unobservable factors that are correlated with repayment behavior. This endogenous formation may result in group members that are similar in unobserved ways and susceptible to the same delinquency patterns. Post group formation, common shocks may also impact an entire peer group at once and directly change the incentives for repayment. Furthermore, it is difficult to avoid a simultaneity problem where members may also influence the group leading to a reflection effect. Policymakers and researchers that wish to quantify the magnitude of peer effects must overcome these challenges.

I study peer effects using data from a large Chinese lender that specializes in providing unsecured cash loans to households and small businesses. I rely on several attractive institutional features for identification. These include the time difference between initial delinquency and default; micro data that incorporates rich borrower attributes, workplace groups, and repayment histories; and a natural experiment where borrower applications are randomly assigned. I overcome the reflection problem by relying on the past number of defaults in a borrower's work group, which avoids issues of simultaneity because the past defaults of others are not affected by the borrower's current decision to repay. My methodology accounts for correlated unobservables and endogenous group formation in two ways. One is with a large collection of borrower attributes and fixed effects, and the other is an instrumental variables strategy that provides exogenous variation in the chance of default.

To account for the endogeneity of the peer group's default behavior, I rely on the random assignment of borrower applications to loan officers. Loan officers using sophisticated underwriting technologies and subjective interviews are able to screen borrowers and adjust loan sizes. However, differences across loan officers in how they screen, process, and approve borrowers lead to exogenous differences in loan sizes and default risk for borrowers Wang (2014a). By using the loan officer's average loan sizes for other borrowers, I can instrument for both the loan amount and the peer group's default rate. Similar to Abrams et al. (2012) or Maestas et al. (2013) in studying judicial sentencing disparities and disability benefits, idiosyncratic differences across loan officers lead to quasi-experimental variation that is orthogonal to unobserved shocks. As an additional check against a weak instrument, I also utilize an alternate approach with time varying fixed effects and find similar results.

The empirical strategy relies on rich data from a large Chinese lender. This dataset offers an ideal setting to study peer effects. The data features detail at the individual borrower level including all of the codified application variables available to the lender. 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 repayment stream including monthly payments, delinquencies, and penalty fees. The repayment data pins down when borrowers first missed payments and when the lender ultimately wrote off the loan through default 90 days later. I find large and consistent peer effects across an array of specifications. I find that a coworker defaulting increases the chance of a late payment by 3.2%. This effect increases as the coworker spends additional time in delinquency indicating that the strength of the peer effect may rise over time.

Lending is a particularly important setting in which to study peer effects for a number of reasons. One is that correlated defaults across borrowers may result in credit constraints that can have negative costs on borrowers as well as lenders Karlan and Gine (2007). 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.[69] Peer effects are also especially prominent in lending with correlated defaults found in mortgage markets and microfinance Guiso et al. (2009). Another important factor is the widespread use of repayment interventions that take advantage of social pressure such as group liability. By understanding the nature of peer effects, more effective policy interventions can be implemented and regulated.

This paper fits into a growing literature that attempts to study peer effects in credit markets. These studies use different identification strategies to overcome empirical challenges. Breza (2013) rely on different incentives to default based on payments remaining in the loan cycle to find strong evidence of peer effects. Peers that move from full default to full repayment increase the probability of repayment by 10 to 15 percentage points. Karlan and Gine (2007) use a field experiment to modify liability from group to individual and find little effect of group liability on repayment rates. However, they find simultaneous changes in loan sizes, approval rates, and monitoring. Accounting for these corresponding changes in loan terms is another unique challenge in lending. Guiso et al. (2009) use survey data to find that borrowers are more likely to default on their mortgage payments if they know of someone who has previously defaulted.

I contribute to this literature in a number of ways. First, I study a population that is not financially at risk or subprime; this population is more representative of an average borrower than the microloan borrowers studied in other contexts. Second, I employ a rich dataset featuring extensive borrower attributes and repayment data. In contrast to other

[69] 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.

studies that use a historical group characteristic to account for simultaneity, I have access to individual data to construct a measure of group delinquency that exclude the borrower. Making this adjustment allows for consistent estimation even in the presence of fixed or random effects Bollinger and Gillingham (2012). Lastly, I also account for the endogeneity of loan sizes using instrumental variables. Allowing the individual loan amount to also be endogenous is important because any instrument for group delinquency is likely to also be correlated with individual loan sizes Angrist and Pischke (2009).

The remaining sections are structured as follows. Section 2 describes the data and context in more detail. Section 3 shows the estimation strategy and assumptions for identification. Section 4 discusses the results and possible confounds to identification, and section 5 concludes.

3.2 Environment

I study a large Chinese lender with more than 40 branches located across the country. One of the lender's main products is unsecured cash loans to households and small businesses.[70] The lender utilizes both automated credit scoring through proprietary underwriting technology as well as subjective evaluation with manual loan officer screening. Loan officers make a loan size decision given a holistic reading of the credit score and other uncodified data.[71] Approved loan sizes are significantly higher than the microloans studied in the development literature and are slightly less than half of the average borrower's salary income on average.

[70] 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.

[71] Wang (2014b) study the loan officer's decisions and finds that subjective screening adds considerable value to automated credit scoring alone.

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 has access to other financing options such as credit cards, home and vehicle loans, and other cash-based lenders.[72] 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 in recent years. See Ayyagari et al. (2010) for a more detailed survey of the Chinese financing industry.

3.2.1 Data

Table (3.12) 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. Estimation takes advantage of the panel nature of monthly payment periods for a total of 445,093 observations. 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.[73]

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

[72] 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 extensive information reporting. Applications to different lenders and outstanding loans are reported to credit monitoring agencies. Some of the additional reported information include credit card usage and limits, external loan terms, and historical repayment schedules.

[73] 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 have large sources of income. For comparison, per capita GDP in Shanghai is ¥82,000, and is ¥38,000 in China as a whole.

Table 3.12: Summary statistics

	Mean	Min	Max	Std dev
Loan terms				
Loan amount (¥000's)	33	5	60	12
Requested (¥000's)	124	3	300	103
Monthly payment (¥000's)	2.2	0.3	5.7	1.1
Payment length (Months)	25	12	36	7
APR (%)	48%	33%	62%	7%
Borrower attributes				
Estimated assets (¥000's)	587	1	7,358	1,337
Salary income (¥000's)	71	4	642	267
External debt (¥000's)	160	0	1,923	856
Age	38	18	58	9
Credit card utilization	41%	0%	100%	38%
Credit card limit (¥000's)	20	0	718	156
Proportion with credit card	76%			
Proportion female	28%			

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.

retired frequently at each of the various locations. Loan term lengths range from 12 to 36 months with the median at 24 months. The most common loan in my sample is a 24-month fixed payment loan with an APR of 48%. This APR includes the nominal interest rate, application fees, and maintenance fees.[74]

3.2.2 Credit scoring and manual scoring

The borrower's first step is to fill out a loan application which includes identification, demographics, financial documents, and verified references. Some of the self-reported data

[74] 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.

include the purpose of the loan and the amount that the borrower is requesting. Following submission, local branch employees verify the borrower's income, debt, and asset information using bank statements and credit reports. The branch employees will also make home and workplace inspections to assess the borrower's home environment. Survey information is collected on the number of TV sets, air conditioning units, square footage, number of family members, and others which are detailed in notes and photographs.

The application process collects a large amount of information both objective and subjective. The difference is that objective data is codified while subjective data is uncodified or costly to codify. Another important distinction is that all of the codified data is observable to the econometrician while the uncodified data is only observable to the loan officers. I also include the outcome of the lender's credit scoring model, which is a variable called credit quality that is an aggregation of a large amount of borrower attributes. The uncodified subjective data is used by loan officers to holistically screen borrowers and determine risk in conjunction with the objective information. This includes written notes, photographs, or local knowledge about a borrower's purchasing habits from bank statements. By reviewing this type of information, loan officers can respond to shocks to repayment that are unobserved to the econometrician.

Once the branch employees gather the information from interviews and inspections, the application is approved or denied by a local branch supervisor. Approved applications are sent to central headquarters where loan officers will screen the loan and choose the approved loan size. 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 feature in this setting. One reason that the lender gives in 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 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 one of 21 loan officers for processing. In practice, a batch of applications will enter the office and be distributed to loan officers without presorting.[75] This assignment procedure will be crucial in identification of peer effects because it guarantees that each loan officer's portfolio of borrowers has the same ex-ante distribution of subjective uncodified attributes. Idiosyncratic differences in how loan officers screen and make loan decisions provides exogenous variation in both loan sizes and the probability of default. This latter mechanism is through a moral hazard effect where greater loan amounts may causally increase the chance of strategic default Adams et al. (2009). Loan officers process roughly 700 applications a year with the average file taking 30 to 40 minutes.

After screening, the loan officer chooses a loan amount given the interest rate and payment length.[76] 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. Once the determination is complete, the borrower may sign the terms of the loan with no further recourse for adjustment. The sales offices themselves play no part in adjusting loan terms. The entire process from initial application to loan disbursement can take between 3 to 7 days.

[75]Some 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 during distribution.

[76]While 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 delegated pricing authority and find that the amount of authority available to the agent depends on the agent's local knowledge.

3.2.3 Peer repayment incentives

Peer groups can be defined in a number of ways including self-reported, geographic proximity, social status, or workplace association. My data offers detailed information on the name and address of the borrower's workplace. By performing a match based on name, address, and industry type, I am able to form over 2,000 workplace groups with more than one borrower. This includes common workplaces such as restaurants, factories, and offices. While the lender does not explicitly use any repayment incentives at the group level such as group liability, many of the costs and benefits of default could be opaque to inexperienced borrowers. These include social stigma, annoyance of collection activities, or the ease of discharging debt. Borrowers could become more or less risky after learning from the experiences of their coworkers.

Borrowers are first late when their monthly loan payment is not received by their due date. Accounts delinquent for more than 90 days or 3 payment periods are in default and generally packaged and sold to external collectors or written off. To prevent default, 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 from higher future loan amounts and a simpler approval process.[77] Sticks include automated messages, collection calls, penalty fees, and reporting to credit agencies. [78] Many collectors will call family members and friends to exert additional repayment pressure. The loan officer has no contact with the borrower after loan origination and the loan officer is not involved in collecting delinquent loans.

[77]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.

[78]For especially egregious borrowers who are late on large payments, their names are published in city newspapers and along public corridors to increase social stigma and incentivize repayment.

3.3 Empirical strategy

The goal of the empirical section is to quantify the direct effect of a coworker defaulting on the chance of a late payment. To solidify terms, the first step is to specify an empirical model of default

$$Late_{it} = \gamma L_{ij} + \delta D_{it} + \boldsymbol{x_i'}\boldsymbol{\Gamma} + \eta_{it} + \epsilon_{it} \tag{3.3.1}$$

where $Late_{it}$ is an indicator for borrower i's loan status at time t, L_{ij} is the borrower's loan amount approved by loan officer j, and D_{it} is the total number of defaults across the borrower's work group at time t. The $\boldsymbol{x_i}$ is a vector of borrower attributes including all of the codified variables available to the lender and also includes fixed effects for time, city, and industry. γ represents the borrower's moral hazard from higher loan sizes and reflects the increased risk induced by higher loan amounts. η_{it} are correlated shocks across a work group, and ϵ_{it} is an idiosyncratic borrower specific shock to the chance of being late. It is without loss of generality that the unobserved component to repayment can be separated into a portion correlated across peer groups and a borrower specific term.

δ is the causal parameter of interest, but may not be consistently estimated if the group default characteristic D_{it} is correlated with the unobserved shock η_{it} within a peer group. This could be the case if borrowers select peer groups based on unobserved common attributes such as borrowers who tend to be forgetful selecting friends who are also forgetful. Borrowers in the same coworker groups may form based on common traits, skills, and personalities. Another concern is correlated unobservable shocks that impact the entire group at once, which could be falsely attributed to a peer effect. These shocks could include a business shock to everyone at a single workplace, other macroeconomic trends, or local geographic shocks to a workplace. Borrowers may also simultaneously impact their peer group's decision to default, which is known as reflection. Additionally, L_{ij} may also be endogenous as loan officers observe ϵ_{it} before deciding loan sizes. Without accounting for these challenges, δ is not identified Manski (1993).

3.3.1 Reflection

One method to address the reflection problem is to use the past actions of the group instead of contemporaneous actions Bollinger and Gillingham (2012). This is accomplished by examining the distinction between late payments and defaults. Payments are first late as borrowers miss a payment, and are only classified as in default after being late for 3 or more payment periods or 90 days. The reasoning is that borrowers are not able to diffuse knowledge about the costs and benefits of collection activities, social stigma, or ease of default until the borrower actually goes through the delinquency process. After being late for months, the borrower would have had a chance to inform his coworkers about the lender's collection techniques and any other associated costs. Conversely, the decision to stop repaying a loan could react immediately to additional knowledge. Additional specifications increase the definition of default to 4 or 5 payment periods to examine if the peer effect changes with time.

Other situations that may naturally have this time delay include installation of solar panels, online purchases, or project evaluations. Another problem is that historical group actions could still include lagged dependent actions. Angrist and Pischke (2009) suggest modifying D_{it} to exclude the repayment patterns of borrower i, which is only possible with individual data. Hartmann et al. (2008) notes that by not excluding borrower i, the estimates from a dynamic panel may be biased. This is because D_{it} by definition includes lagged dependent variables, which may affect consistency in the presence of fixed effects. In this setting, this adjustment is automatic since borrowers are removed at default so D_{it} cannot include borrower i's past defaults. Excluding borrower i removes the influence of borrower specific random shocks ϵ_{it}, but this change still does not control for the correlated unobservables η_{it} at the workplace level.

3.3.2 Correlated unobservables

η_i is determined by two kinds of correlated unobservables across a peer group. One is that peer groups could form due to endogenous factors such as shared tendencies or traits, and another is that common shocks could affect an entire group at once. The former problem is unobservable factors that create the group while the latter is correlated shocks that affect the group post-formation. With peer groups defined by occupation, certain industries may attract certain types of individuals that are more likely to not repay. For example, migrant laborers working for agricultural or manufacturing firms may find it more worthwhile to strategically default on their loan obligations. Workers in the same company may also be exposed to similar company shocks that decrease profitability, wages, and increase the chance of delinquency.

My methodology to account for these factors is twofold. The first is a large collection of over 250 borrower attributes, fixed effects for area, industry, and time to absorb geographic and industry shocks. These attributes cover all aspects of the borrower's financial position, home arrangement, and workplace details. An additional robustness check on the main specification relies on time-varying workplace controls to absorb correlated shocks. The second approach is to use the random assignment of borrower applications to loan officers as exogenous variation. There are two endogenous regressors in equation (3.3.1). D_{ij} is endogenous because η_{it} is correlated across borrowers, and L_{ij} may be endogenous because unobserved components to repayment $\eta_{it} + \epsilon_{it}$ are observed by loan officers before a loan size decision. Even though the focus is on estimating D_{ij}, L_{ij} must also be in equation (3.3.1) because any suitable instrument for D_{ij} is likely to also be correlated with L_{ij}.

The intuition for identification is that observably identical borrowers are assigned to different loan officers with different propensities for approving loan sizes. Idiosyncratic differences in how loan officers screen, process, and approve borrowers are assumed to be orthogonal to each borrower's unobserved shock ϵ_{it} or the correlated η_{it}. This suggests that the loan officer's average approved loan amount is a strong candidate for an instrument.[79] I construct instruments following Maestas et al. (2013) who use average approval rates of disability examiners as instruments.

One instrument is the average loan amount of loan officer j excluding borrower i in month t

$$MeanLoan_{itj} = \frac{1}{(N_{tj} - 1)} \sum_{k \neq i} L_{kj} \tag{3.3.2}$$

where N_{tj} is the loan officer's total number of cases in month t.[80] The other instrument is the average loan amount of the peer group's loan officers in month t excluding all borrowers in the same group

[79] 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 precludes this type of joint inspection from frequently happening.

[80] This allows loan officers to change their lending behavior month to month. The variation comes from shocks to their lending preferences across months.

$$PeerLoan_{itj} = \frac{1}{N_{tZ}} \sum_{j \in Z_{itj}} L_{kj} \tag{3.3.3}$$

where Z_{itj} is the set of cases excluding the peer group in month t, and N_{tZ} is the count of the group in month t. Both of these instruments exclude the borrower specific loan sizes. A single peer group could have more than one loan officer. The data includes approximately 2,500 separate workplace groups with more than 1 worker. And of those, over 90% have between 2 and 4 workers.

3.3.3 IV assumptions

Differences across loan officers lead to quasi-exogenous shocks to loan sizes and to delinquency. Loan officers are not involved in collecting delinquent loans which satisfies an exclusion restriction. Loan collection is handled entirely by the local branch offices and external collectors with no contact from the original loan officer. The only effect that loan officers have on a borrower's chance of late payment is through the choice of loan size. The instrument $PeerLoan_{ij}$ acts on workplace default through a moral hazard effect. Wang (2014a) show that loan sizes have a direct causal effect on the probability of repayment. Borrowers that are approved higher loan amounts become riskier all else equal. The mechanism could be strategic default or simply that higher monthly payments causally increase the chance of missed payments.

Table (3.13) is the first stage regression of the endogenous regressors D_{it} and L_{ij} on the exogenous variables and instruments. Despite including hundreds of controls accounting for year by month effects, city controls, application variables, and extensive financial and inspections variables, the instruments are predictive due to idiosyncratic differences in screening,

Table 3.13: First stage

	Dependent variable: loan amount				
$MeanLoan_{itj}$	0.261***	0.252***	0.257***	0.239***	0.252***
	(0.0416)	(0.0416)	(0.0403)	(0.0407)	(0.0398)
R^2	0.369	0.415	0.435	0.477	0.520
	Dependent variable: delinquent peers				
$PeerLoan_{itj}$	0.000376*	0.000368*	0.000368*	0.000359*	0.000336*
	(0.000218)	(0.000218)	(0.000216)	(0.000211)	(0.000210)
R^2	0.008	0.008	0.008	0.010	0.018
Number of controls	78	84	85	129	265
Year by month, city, product	✓	✓	✓	✓	✓
Application variables		✓	✓	✓	✓
Internal credit quality			✓	✓	✓
Financial variables				✓	✓
Inspection variables					✓

Notes: Data includes 31,954 first-time borrowers from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Table shows the first stage between the loan officer's average decision and loan sizes. $MeanLoan_{itj}$ is the loan officer's average loan amount excluding borrower i and is given by $\frac{1}{N_j-1}\sum_{-i} L_{ij}$. $PeerLoan_{itj}$ is the loan officer's average loan amount excluding borrower i's peer group. Each peer group may have multiple loan officers. 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. Standard errors clustered at loan officer level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

processing, and approving borrowers. The high Z-score across specifications supports the rank assumption that $MeanLoan_{ij}$ has sufficient correlation with the borrower's approved loan amount. $PeerLoan_{ij}$ is not as strongly correlated with the peer group's default status. To account for this, an additional robustness check is performed that includes time varying workplace postal code effects.

Furthermore, it is not necessary that the assignment be entirely random. The identification assumption is still valid as long as the borrowers are randomly assigned *conditional* on the observed borrower attributes. 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 $\eta_{it} + \epsilon_{it}$ *within* those categories.[81] This assumption can be examined with 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. By examining the regression of L_{ij} on $MeanLoan_{ij}$ along with additional covariates, I can test for correlated observables. This is because only borrower attributes that are correlated with $MeanLoan_{ij}$ should change its coefficient when added to the OLS regression. The stable values across specifications in table (3.13) 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. $PeerLoan_{ij}$ also demonstrates stability in coefficients across the different specifications.

3.4 Results

Table (3.14) shows the results of the 2SLS IV estimates which show a strong relationship between a borrower's likelihood of delinquency and coworker defaults. The analysis only focuses on first time borrowers since secondary loans may have different loan terms and also include additional information unobserved to the econometrician. The main specification is shown in column (1) with the point estimate for δ found to be .032 with the standard errors clustered at the borrower level.[82] This means that an additional default in the bor-

[81] Given 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.

[82] Results remain significant if clustered at the loan officer or loan officer month level.

rower's work group increases the chance of a payment being late by 3.2%. Controlling for a large collection of borrower attributes including industry effects, borrowers learn from their coworkers and become riskier as their coworkers default.

This result also conforms with the estimates in the literature which find consistent evidence that borrowers respond to the repayment patterns of their peers. Specifically, repayment or delinquency within a peer group accentuates the behavior of its members. Breza (2013) finds that as a borrower's peer group moves from default to repayment, the borrower is roughly 10 to 15 percent more likely to repay. Guiso et al. (2009) find evidence that mortgage borrowers become riskier when their peers walk away from their mortgages indicating that the spread of information about default makes borrowers riskier. Gine et al. (2011) study a mass default of Muslims in India and find that borrowers in groups with overall higher levels of Muslims are riskier. In this setting, the diffusion mechanism could be more experience and information about social stigma, ease of discharging debt, or the costs of collection efforts.

Additional specifications find that this peer effect is strengthening over time which supports the assumption that the diffusion of information across a peer group depends on length of experience. When a borrower is first late, he or she has not had a chance to internalize the costs and benefits. This experience only accrues after a length of time in default subject to bureaucracy and collection efforts. Column (2) defines the peer group default with a month lag. Put another way, the group characteristic defines default as 4 payment periods delinquent rather than 3, while column (3) defines default as 5 payment periods delinquent. Borrowers that had an additional default in their work group defined this way are 3.6% more likely to be late with their payments. This effect grows to 4.1% with a two month lag since the coworker's default. This suggests that borrowers respond to the information diffusion more strongly over time although the increases are within the margin of error.

Column (4) uses time varying fixed effects for the company's postal code to account for correlated shocks instead of the instrument $PeerLoan_{ij}$ in the event that $PeerLoan_{ij}$ is a possible weak instrument. Time varying fixed effects for each company in the data would be too computationally burdensome so the company postal codes are interacted with year indicators. The alternative specification is consistent with the main results that a coworker's default increases the borrower's chance of delinquency. Regression result shows that an additional default in the borrower's work group leads to a 2.4% higher chance of a late payment using time varying fixed effects.

The coefficient on loan amount is also of interest. This parameter is commonly known as the borrower's moral hazard and represents the increased delinquency risk from higher loan sizes. The common difficulty with identifying this parameter is that loan officers can observe borrower attributes that the econometrician cannot so standard OLS techniques are biased. By controlling for this endogeneity with $MeanLoan_{ij}$ as an instrument, the estimate indicates a strong and statistically significant causal effect. The moral hazard estimate can be interpreted as a ¥1,000 increase in loan amounts leads to a .5% higher chance of any payment being late.

The moral hazard estimate can be compared to the literature, although the comparison is again not straightforward since differences in institutional setting make cross-country comparisons difficult. Additionally, the observation unit is the monthly payment level rather than borrower level. Despite the difficulties, the estimates are roughly consistent in sign. 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. Other estimates find either very small or sometimes positive magnitudes for moral hazard. Dobbie and Skiba (2013) find that increases in loan size lead to a slight *decrease* in default when examining US payday lenders.

Wang (2014a) use the same data and find a 1.5% increased chance of being delinquent at all. The discrepancy results from allowing a single borrower to have multiple instances of being late.

3.5 Conclusion

In this paper, I have presented evidence of peer effects operating through workplace groups. I identified peer effects by exploiting rich data that allowed me to identify workplaces, see repayment histories, and control for hundreds of borrower attributes. I overcame reflection, endogenous group formation, correlated unobservables, and endogenous loan sizes using unique institutional features of my data. By recognizing the time difference between late loans and defaulted loans, I controlled for simultaneity of the group default variable. I accounted for correlated unobservables and endogenous loan sizes with a natural experiment where borrower applications were randomly assigned to loan officers. The random assignment provided me with quasi-experimental variation in both loan sizes and group default likelihood. Additionally, the methodology of using microdata to exclude the borrower's own delinquency from the group characteristic allowed for consistent estimation of peer effects even in the presence of fixed effects. These techniques can be generalized to other settings such as education or judicial sentencing.

I found consistent evidence of peer effects where an additional default by a coworker increased the probability of a payment being late by 3.2%. This effect increased with time so that borrowers that have a coworker delinquent for 5 payment periods are 4.1% more likely to become late on payments. The diffusion of knowledge and experience may increase over time as borrowers learn of the social stigma, ease of discharging debt, or the costs of collection efforts. These results highlight the importance of peer effects in lending and have implications for structuring repayment incentives such as group liability and social pressure. Furthermore, policymakers and lenders should be concerned about possible systemic issues that may arise when borrowers default and pass information to their peer group.

Table 3.14: Effect of group default on delinquency

	(1) Late payment	(2) Late payment	(3) Late payment	(4) Late payment
Coworker defaults 3 mo	0.032*			0.024***
	(0.19)			(0.0027)
Coworker defaults 4 mo		0.036*		
		(0.21)		
Coworker defaults 5 mo			0.041*	
			(0.23)	
Loan size (000's)	0.0047***	0.0047***	0.0047***	0.0053***
	(0.00059)	(0.00059)	(0.00059)	(0.0011)
Requested (000's)	-0.000060***	-0.000060***	-0.000060***	-0.000084***
	(9.5e-06)	(9.5e-06)	(9.5e-06)	(0.000018)
Credit score	0.000086***	0.000087***	0.000087***	0.00016***
	(0.000032)	(0.000032)	(0.000032)	(0.000049)
APR (%)	0.21***	0.21***	0.21***	0.20***
	(0.029)	(0.029)	(0.029)	(0.043)
Salary (000's)	-7.7e-06***	-7.7e-06***	-7.7e-06***	-0.000015***
	(2.6e-06)	(2.6e-06)	(2.6e-06)	(4.1e-06)
Credit card (1/0)	-0.0066***	-0.0066***	-0.0066***	-0.0062***
	(0.0016)	(0.0016)	(0.0016)	(0.0020)
CC utilization (%)	-0.0013	-0.0013	-0.0013	0.0029
	(0.0029)	(0.0029)	(0.0029)	(0.0039)
Debt level (000's)	-8.8e-07**	-8.8e-07**	-8.8e-07**	-8.2e-07**
	(3.5e-07)	(3.5e-07)	(3.5e-07)	(3.7e-07)
Manager (1/0)	-0.016***	-0.016***	-0.016***	-0.014***
	(0.0021)	(0.0021)	(0.0022)	(0.0029)
Female (1/0)	-0.020***	-0.020***	-0.020***	-0.022***
	(0.0010)	(0.0011)	(0.0011)	(0.0011)
Homeowner (0/1)	0.00053	0.00053	0.00052	0.0013
	(0.0020)	(0.0020)	(0.0020)	(0.0029)
Age	-0.0012***	-0.0012***	-0.0012***	-0.00097***
	(0.00012)	(0.00012)	(0.00012)	(0.00016)
Observations	445,093	445,093	445,093	445,093
Time controls	Year by month	Year by month	Year by month	Year by month
Area controls	City	City	City	Postal code by year

Notes: Data includes 31,954 first-time borrowers with 445,093 monthly payment periods from December 2011 to January 2014 across more than 40 branches examined by 21 loan officers. Loans are late if payment is not received within 3 days after the due date. Coworker default 3 months defines default as 3 payment periods without payment. Default 5 mo is 5 payment periods without payment. Additional controls include year by month, city, industry, product fixed effects, and additional application, financial, and inspection variables. As of August 2014, $1 is ¥6.18. Standard errors are clustered at the borrower level.
*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

APPENDICES

APPENDIX A
Optimal loan size

Conditional on the hard information $\boldsymbol{x_i}$, the observed signal ω_{ij}, and the loan officer's characteristics, loan officers choose L_{ij}^* to maximize their expected utility. Utility is given by $u(y_j) = -e^{-r_j y_j}$ 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 σ_j^2 is screening ability. The borrower's repayment function is given by equation (1.3.2).

$$EU[L_{ij}] \quad = \quad -e^{-r_j\left(\alpha+\beta\sum_{-i}\pi_{ij}+\beta R_i L_{ij}\left(\gamma L_{ij}+\boldsymbol{x_i'}\boldsymbol{\Gamma}\right)-\beta L_{ij}-cost_j\left(\sigma_j^2\right)\right)} \int e^{-r_j\beta(u_i+\epsilon_i)} dF_\pi$$

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 (1.5.2).

$$= \quad -e^{-r_j\left(\alpha+\beta\sum_{-i}\pi_{ij}+\beta R_i L_{ij}\left(\gamma L_{ij}+\boldsymbol{x_i'}\boldsymbol{\Gamma}\right)-\beta L_{ij}-cost_j\left(\sigma_j^2\right)+\beta R_i L_{ij}\frac{\sigma_u^2}{\sigma_u^2+c_j^2}\omega_{ij}-\frac{r_j}{2}\left(\beta R_i L_{ij}\right)^2\left(\frac{\sigma_u^2 c_j^2}{\sigma_u^2+c_j^2}+\sigma_\epsilon^2\right)\right)}$$

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

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

APPENDIX 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 ω_{ij} is observed, and the optimal loan amount is given by equation (1.3.4). 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 $v\left(\omega_{ij}\right) = EU\left[L_{ij}^*\left(\omega_{ij}\right)\right]$. The expected utility of this function can be expanded using a first order Taylor expansion.

$$
\begin{aligned}
EU\left[\sigma_j^2\right] &= \int\int v\left(\omega_{ij}\right) dF_{\boldsymbol{x}} dF_{\omega|\sigma_j^2} \\
&\approx \int E\left[v\left(\bar{\omega}\right) + \frac{dv\left(\bar{\omega}\right)}{d\omega}\left(\omega_{ij} - \bar{\omega}\right)\right] dF_{\boldsymbol{x}} \\
&= \int v\left(\bar{\omega}\right) dF_{\boldsymbol{x}} \\
&= \int -e^{-r_j\left(\alpha + \beta R_i L_{ij}^*\left(\gamma L_{ij}^* + \boldsymbol{x_i'}\boldsymbol{\Gamma}\right) - \beta L_{ij}^* - cost_j\left(\sigma_j^2\right) - \frac{r_j}{2}\left(\beta R_i L_{ij}^*\right)^2\left(\frac{\sigma_u^2\sigma_j^2}{\sigma_u^2+\sigma_j^2} + \sigma_\epsilon^2\right)\right)} dF_{\boldsymbol{x}}
\end{aligned}
$$

Maximizing this expression is equivalent to maximizing the the term inside the parenthesis

$$
\begin{aligned}
cost_j'\left(\sigma_j^2\right) &= \int \frac{\partial L_{ij}^*}{\partial \sigma_j^2}\left(2\beta R_i \boldsymbol{\gamma} L_{ij}^* + \beta R_i \boldsymbol{x_i'}\boldsymbol{\Gamma} - \beta - r_j \left(\beta R_i\right)^2 L_{ij}^*\left(\frac{\sigma_u^2\sigma_j^2}{\sigma_u^2+\sigma_j^2}+\sigma_\epsilon^2\right)\right) - \frac{r_j}{2}\left(\beta R_i L_{ij}^*\right)^2\left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_j^2}\right)^2 dF_{\boldsymbol{x}} \\
&= \int \frac{\partial L_{ij}^*}{\partial \sigma_j^2}\beta R_i\left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R_i} + L_{ij}^*\left(2\boldsymbol{\gamma} - r_j\beta R\left(\frac{\sigma_u^2\sigma_j^2}{\sigma_u^2+\sigma_j^2}+\sigma_\epsilon^2\right)\right)\right) - \frac{r_j}{2}\left(\beta R_i L_{ij}^*\right)^2\left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_j^2}\right)^2 dF_{\boldsymbol{x}} \\
&= \int \frac{\partial L_{ij}^*}{\partial \sigma_j^2}\beta R_i\left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R_i} - \frac{L_{ij}}{k_j}\right) - \frac{r_j}{2}\left(\beta R_i L_{ij}^*\right)^2\left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_j^2}\right)^2 dF_{\boldsymbol{x}} \\
&= \int -\frac{r_j}{2}\left(\beta R_i L_{ij}^*\right)^2\left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_j^2}\right)^2 dF_{\boldsymbol{x}}
\end{aligned}
$$

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

$$
\begin{aligned}
\frac{d_j^2}{\sigma_j^4} &= \int \frac{r_j}{2}\left(\beta R_i L_{ij}^*\right)^2\left(\frac{\sigma_u^2}{\sigma_u^2+\sigma_j^2}\right)^2 dF_{\boldsymbol{x}} \\
\frac{d_j}{\sigma_j^2} &= \int \left(\frac{r_j}{2}\right)^{\frac{1}{2}}\beta R_i\left[r_j\beta R\left(\frac{\sigma_u^2\sigma_j^2}{\sigma_u^2+\sigma_j^2}+\sigma_\epsilon^2\right) - 2\boldsymbol{\gamma}\right]^{-1}\left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R_i}\right)\frac{\sigma_u^2}{\sigma_u^2+\sigma_j^2} dF_{\boldsymbol{x}} \\
&= \int \left(\frac{r_j}{2}\right)^{\frac{1}{2}}\beta R_i\left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R_i}\right)\sigma_u^2\left[r_j\beta R_i\sigma_u^2\sigma_j^2 + \left(r_j\beta R_i\sigma_\epsilon^2 - 2\boldsymbol{\gamma}\right)\left(\sigma_u^2+\sigma_j^2\right)\right]^{-1} dF_{\boldsymbol{x}}
\end{aligned}
$$

Cross multiplying gives

$$
\frac{\int\left(\frac{r_j}{2}\right)^{\frac{1}{2}}\beta R_i\left(\boldsymbol{x_i'}\boldsymbol{\Gamma} - \frac{1}{R}\right)\sigma_u^2 dF_{\boldsymbol{x}}}{d_j} = r_j\beta R_i\left(\sigma_u^2+\sigma_\epsilon^2\right) - 2\boldsymbol{\gamma} + \left(r_j\beta R_i\sigma_\epsilon^2 - 2\boldsymbol{\gamma}\right)\frac{\sigma_u^2}{\sigma_j^2}
$$

Simplifying gives the final optimal screening effort to be

$$\sigma_j^{2*} = \int \left(r_j \beta R_i \sigma_\epsilon^2 - 2\boldsymbol{\gamma} \right) \sigma_u^2 \left(\frac{\left(\frac{r_j}{2}\right)^{\frac{1}{2}} \beta R_i \left(\boldsymbol{x_i'} \boldsymbol{\Gamma} - \frac{1}{R} \right) \sigma_u^2}{d_j} - r_j \beta R_i \left(\sigma_u^2 + \sigma_\epsilon^2 \right) + 2\boldsymbol{\gamma} \right)^{-1} dF_{\boldsymbol{x}}$$

APPENDIX C
Change of Variables

Since I have no variation separating soft information σ_u^2 from σ_ϵ^2, I perform a change of variables to transform the parameter set $\left(\Gamma,\gamma,r_j,\sigma_j^2,c_j^2,\sigma_u^2,\sigma_\epsilon^2\right)$ to $\left(\Gamma,\gamma,\widetilde{r_j},\widetilde{\sigma_j^2},\widetilde{c_j^2},\widetilde{\sigma_u^2},\widetilde{\sigma_\epsilon^2}\right)$ where

$$
\begin{aligned}
\widetilde{r_j} &= r_j\beta \\
\widetilde{c_j^2} &= \frac{c_j^2}{\sigma_u^4}+\frac{1}{\sigma_u^2}-1 \\
\widetilde{\sigma_j^2} &= \frac{\sigma_j^2}{\sigma_u^4}+\frac{1}{\sigma_u^2}-1 \\
\widetilde{\sigma_u^2} &= 1 \\
\widetilde{\sigma_\epsilon^2} &= \sigma_u^2+\sigma_\epsilon^2-1
\end{aligned}
$$

The likelihood in equation (1.4.3) can be written entirely as functions of k_j, σ_v^2, w_{ij}, $\sigma_{u+\epsilon|v}^2$, and h_{ij}. I show that these functions can be written in terms of the adjusted parameters.

$k_j=\left[r_j\beta R_i\left(\frac{\sigma_u^2c_j^2}{\sigma_u^2+c_j^2}+\sigma_\epsilon^2\right)-2\boldsymbol{\gamma}\right]^{-1}=\left[\widetilde{r_j}R_i\left(\frac{\widetilde{c_j^2}}{1+\widetilde{c_j^2}}+\widetilde{\sigma_\epsilon^2}\right)-2\boldsymbol{\gamma}\right]^{-1}=\widetilde{k_j}$

$\sigma_v^2=k_j^2\frac{\sigma_u^4\left(\sigma_u^2+\sigma_j^2\right)}{\left(\sigma_u^2+c_j^2\right)^2}=\widetilde{k_j^2}\frac{1+\widetilde{\sigma_j^2}}{\left(1+\widetilde{c_j^2}\right)^2}=\widetilde{\sigma_v^2}$

$$w_{ij} = \boldsymbol{x_i'}\boldsymbol{\Gamma} k_j - \frac{k_j}{R} = \boldsymbol{x_i'}\boldsymbol{\Gamma}\widetilde{k_j} - \frac{\widetilde{k_j}}{R} = \widetilde{w_{ij}}$$

$$\sigma^2_{u+\epsilon|v} = \frac{\sigma_u^2\sigma_j^2}{\left(\sigma_u^2+\sigma_j^2\right)} + \sigma_\epsilon^2 = \frac{\widetilde{\sigma_j^2}}{1+\widetilde{\sigma_j^2}} + \widetilde{\sigma_\epsilon^2} = \widetilde{\sigma^2_{u+\epsilon|v}}$$

$$h_{ij} = \gamma L_{ij} + \boldsymbol{x_i'}\boldsymbol{\Gamma} + \frac{\sigma_u^2+c_j^2}{\left(\sigma_u^2+\sigma_j^2\right)k_j}\left(L_{ij}-w_{ij}\right) = \gamma L_{ij} + \boldsymbol{x_i'}\boldsymbol{\Gamma} + \frac{1+\widetilde{c_j^2}}{\left(1+\widetilde{\sigma_j^2}\right)\widetilde{k_j}}\left(L_{ij}-\widetilde{w_{ij}}\right) = \widetilde{h_{ij}}.$$

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

$$\begin{aligned}
r_j &= \widetilde{r_j}/\beta \\
c_j^2 &= \sigma_u^4\widetilde{c_j^2} + \sigma_u^4 - \sigma_u^2 \\
\sigma_j^2 &= \widetilde{\sigma_j^2}\sigma_u^4 + \sigma_u^4 - \sigma_u^2 \\
\sigma_\epsilon^2 &= 1 + \widetilde{\sigma_\epsilon^2} - \sigma_u^2
\end{aligned}$$

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