The Welfare Effects of Law Enforcement in the Illegal Money Lending Market*

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November 8, 2021

Abstract

We estimate a structural model of borrowing and lending in the illegal money lending market using a unique panel survey of 1,090 borrowers taking out 11,032 loans from loan sharks. We use our model to estimate the welfare effects of a large enforcement crackdown that occurred during our sample period. The crackdown raised interest rates, lowered the volume of loans, and lowered the welfare of borrowers. The welfare of lenders that conduct harassment more frequently fell, but less-harsh lenders gained through the higher interest rates. We compare this strategy to an alternative policy of targeting borrowers. We find that targeting borrowers with medium ability to repay is more effective at lowering lender welfare than targeting those with low or high repayment ability.

Key words: Illegal Moneylending, Loan Sharks, Law Enforcement, Crime
JEL Codes: K42, G51

*Leong received a Singapore Ministry of Education Tier 1 grant for this research. The data used in this paper were collected by Leong who first obtained approval to collect this dataset by writing to the appropriate Singaporean authorities. He obtained ethics approval from the Nanyang Technological University (NTU) IRB. We thank Thomas Lemieux and seminar participants for their helpful comments. The usual caveat applies.

1 Introduction

Illegal money lending (IML), often referred to also as usury or loansharking, has been a widespread phenomenon across various countries for millennia. Laws banning individuals from charging excessive interest rates have existed at least as early as the Babylonian Code of Hammurabi from 1700 BC (Blitz and Long, 1965). However, a reliable quantification of the size of the current international IML market does not exist. This is because lenders are mostly part of organized criminal groups that operate under the radar of law enforcement, but also because borrowers are vulnerable individuals who fear both the consequences of reporting their loan sharks and the stigma of admitting their financial troubles. Among the few aggregate quantifications available are those of Savona and Riccardi (2015), who estimate that in Italy the annual revenue from IML amounts to 4.6 billion euros, which is roughly 16% of total annual revenues from illicit markets, and almost 30% compared to the total revenue from drugs markets. According to Payne et al. (2020), in 2004 approximately 310,000 households in Great Britain were in debt to an illegal lender. The fight against IML was also one of the key messages of the 1968 presidential campaign of Richard Nixon in the US (Seidl, 1968).

The lack of data implies that any quantification of the welfare effects of law enforcement in the IML market has not been possible so far. In this paper we are the first to overcome this challenge with novel and unique data, that allows us to estimate a structural model of the IML market in Singapore,[1] and to use the model to simulate the effect of law enforcement counterfactuals on borrower welfare and lender profits. We do this using a large survey of 11,032 loans from 1,090 different borrowers who took out loans from loan sharks. Our data detail many loan characteristics, such as the number of missed payments and types of harassment used by the lender. We also surveyed the characteristics of the

[1]The IML market is large in Singapore and in 2009 more than half of the crimes committed in Singapore are related to the IML market Singapore Police Force (2010). Furthermore, the transnational loanshark syndicates operating in Singapore also operate in other Asian countries, including Malaysia and China. Therefore Singapore is interesting context in which to study the IML market.

borrowers, such as their demographics and addictions.

Our counterfactuals evaluate the welfare effects of two kinds of policy interventions. First, we document that a crackdown on lenders that occurred during our sample period was highly successful at lowering the profits of harsh lenders and the surplus of borrowers, as well as at lowering the total volume of loans disbursed. Second, we show that removing borrowers from this market, either through offering formal market alternatives, rehabilitation or education programs, also hurts lenders, particularly if they focus on medium- and high-performing borrowers in terms of loan repayment time.

Our structural framework incorporates several features specific to the IML market, as well as aspects that are common in formal credit markets. In our model, borrowers choose between different lenders when they want to take out a loan. When a borrower approaches a lender, the lender decides whether to give them the loan. The lender decides this based on the expected profits from the loan, which depends on their estimate of the borrower's ability to repay, based on their performance in previous loans. When borrowers miss payments, the lender earns additional revenues in missed payment penalties, but incurs costs associated with harassing the borrower. Borrowers choose the lender to maximize their expected discounted payoffs. Borrowers exhibit hyperbolic discounting and low risk aversion, and obtain disutility from harassment. Borrower payoffs depend on the size of the loan, their expected number of missed payments, and the associated penalties and harassment from those missed payments. We structurally estimate the model using the observed loan outcomes in our data to evaluate the welfare effects of various market interventions.

Our borrower survey was conducted over two waves and contains loans from 2009-2016. In 2014, the authorities increased the resources targeting the IML market. This crackdown caused a large number of lenders to exit the market, often through arrest, which caused the interest rate in the market to increase from 20% over a six-week period to 35%. We use our estimated model to compute the welfare effects of this crackdown by simulating what would have happened had it occurred in 2009 instead of 2014. We find that the average loan size would have fallen by 38.8%, and the average borrower

surplus would have fallen by 67.4%. Although harassment costs increased by 141% for lenders, the higher interest rate led to higher profits from interest payments and penalties. Lenders are heterogeneous in how frequently they conduct harassment, and the welfare effect depends on their harshness. Those that conduct harassment the least gain from the crackdown as the interest rate increased, whereas the welfare of those that conduct harassment more frequently fell as their harassment costs increased substantially.

We compare this crackdown to an alternative policy that involves targeting the borrowers instead. We group borrowers into deciles by their repayment ability and consider removing each decile one at a time. The majority of loans in our data are taken out to fund either gambling losses, or drug or alcohol consumption. Gambling is widespread across the general population in Singapore, as well as in other Asian countries.[2] Borrowers could be removed in practice by offering rehabilitation strategies, a formal-market alternative, or education programs could deter them from borrowing.[3] We find that removing borrowers in the middle of the distribution lowers lender welfare the most. Borrowers with the highest repayment ability have smaller expected harassment costs, yet earn lenders little in missed payment penalties. Borrowers with the smallest repayment ability earn lenders the most in missed payment penalties, but lenders need to conduct more harassment to recover the loan. Due to these higher costs, lenders only give smaller loans to these borrowers. Borrowers in the middle of the distribution are the most profitable borrowers for lenders, and targeting these would be the most effective strategy at lowering lenders' profits.

While IML is considerably understudied due to lack of data, despite its significant importance among illicit markets, it shares some important simi-

[2]Over 50% of Singaporeans do some form of gambling (National Council on Problem Gambling, 2018), and this number is 78% for Hong Kong (Wong and So, 2003), 80% for India (Taxscan, 2020), 68% for Macau (Fong and Ozorio, 2005), 65% for Taiwan (Chang, 2009), and 42% for South Korea (Williams et al., 2013).

[3]Several governmental and non-governmental organizations provide these kinds of services to borrowers victims of loan sharks, both in Singapore (Credit Counseling Singapore - https://ccs.org.sg/) and in other countries (Stop Loan Sharks in the UK - https://www.stoploansharks.co.uk/).

larities and differences with more studied formal credit markets. In particular, the closest formal alternative to IML is that of payday loans, as both credit practices consist of small loans with very high interest rates and short maturities granted to vulnerable borrowers. As highlighted by Stegman (2007), these two forms of credit share some similarities. They are both likely to encourage habitual borrowing leading borrowers to a spiral of unaffordable debt. They are both widespread in developed economies, such as US, UK, and parts of Europe, and target mostly low-income individuals who can rarely access any other source of credit. They also share some standard features of credit markets, such as asymmetric information between borrowers and lenders over borrowers' repayment probability. In both settings, this information asymmetry can be reduced by lenders establishing long term relationships with borrowers. While adverse selection is likely to play a significant role in IML markets, moral hazard is unlikely to be relevant, due to the harsh punishments that borrowers are subject to in case of missed payments. In fact, evidence from our data rules out moral hazard as a potential friction. On the other hand, through a large-scale field experiment, Karlan and Zinman (2009) provide evidence of moral hazard being a significant friction in short-term high-cost loans in South Africa.

However, while payday loans are regulated and operate within the boundaries of the law, IML is an illegal market dominated by organized criminal groups. This implies that there are at least three substantial differences between the two types of lending that we explicitly incorporate in our structural model. First, as IML markets have no formal contracts, enforcement of repayment is done by lenders via costly harassment, often using destructive methods. In our setting, lenders often use public shaming as a tactic to force borrowers to repay, such as shouting at them in their neighborhood or workplace or by applying graffiti on their homes. Shaming has also been shown to be an effective method to enhance firm incentives in the US context (Johnson, 2020). While lenders also cause damage to borrowers' property when they miss payments, we do not find any evidence in our setting that lenders cause borrowers physical harm or torture. Lenders also sometimes force borrowers to

work for them to repay the loan. In most cases loan sharking is in fact aimed at debt-trapping borrowers to extract all of their resources. Moreover, these lenders face a reputational cost of not harassing, which would make them be perceived as weak.

Second, lenders in IML markets are part of large transnational criminal groups, whose core business is mostly drug dealing, and who use illegal lending to launder and hide their money. Lending is in fact a way for organized crime to disperse and conceal money from law enforcement, in case of a crackdown. It allows them to avoid having all their capital stored, while instead receiving a weekly income with interests from borrowers (Financial Conduct Authority, 2017). Differently from legal markets, criminal groups seem to coordinate on some loan contract terms and on dividing territorial areas of influence, while competing between each other to attract borrowers. In Singapore, the dominant criminal syndicates set the loan contract terms (interest rate, maturity, frequency of repayment installments) equivalently for all lenders, allowing them only to adjust the loan size within some limits. Moreover, given the underground nature of lenders, information frictions are likely to be considerably higher than in any formal market.

Third, the role of policymakers in IML markets is to find the most effective way of eradicating this phenomenon. This is usually done either directly targeting lenders, as it happened in Singapore in 2014, or providing assistance to vulnerable borrowers, offering them viable formal alternatives and convincing them to report loan sharks to the authorities.

Related Literature Our paper contributes to three main strands of the literature. The first is the growing field on the economics of illegal markets. This branch of the literature has notable contribution both in terms of theory (Becker et al., 2006; Galenianos et al., 2012) and empirics (Adda et al., 2014; Jacobi and Sovinsky, 2016; Galenianos and Gavazza, 2017; Leong et al., forthcoming), but is almost exclusively focused on drug markets. A few recent papers have tried to connect financing frictions with illegal activities, such as terrorism (Limodio, 2019), but none of these have direct access to illegal loan

contracts.[4] Together with Lang et al. (2021), we are the first to provide an empirical quantification of the market of illegal lending, leveraging unique and extensive survey data on a large fraction of illegal loan contracts in Singapore.[5]

The second contribution we make is to the literature on predatory lending practices. As mentioned, the closest lending context to ours is that of payday loans, despite being a formal market. A growing literature has investigated payday lending, especially in the US, showing that they do not alleviate economic hardship (Melzer, 2011), with the exception of reducing financial distress after a natural disaster (Morse, 2011). Using a field experiment, Bertrand and Morse (2011) find that information disclosure can induce borrowers to lower their use of high-cost debt, highlighting the cognitive biases that might characterize vulnerable payday borrowers. A related literature is also that of microfinance (Kaboski and Townsend, 2011, 2012; de Quidt et al., 2018) and informal lending (Aleem, 1990). Although these markets share features such as asymmetric information and relationship lending, there are at least three significant differences to IML. First, microcredit has the objective of fighting poverty and offering borrowers, mostly in rural areas in developing countries, a more viable financial channel compared to alternative credit means. IML is instead a predatory and extortionary practice that aims to exploit vulnerable borrowers, and is mainly widespread in urban areas in developed economies. Second, microfinance programs are mostly promoted by governments, NGOs, and non-profit organizations, while IML is dominated by large criminal organizations. Last, one of the main objectives of microcredit is to stimulate investment by households and small businesses (Kaboski and Townsend, 2011), while IML finances individuals' consumption and addictions,

[4]To our knowledge, Soudijn and Zhang (2013) is the only other study with access to any data on illegal loans. They describe the ledger of a single lender that was seized from a Dutch casino.

[5]Our paper uses the same dataset as Lang et al. (2021) supplemented by additional survey data we collected on ex-lenders in the market. They estimate the effects of the enforcement crackdown on loan-related variables (such as loan size, repayment duration and harassment) within borrower-lender pairs. In this paper we estimate a structural model of the IML market to compute the welfare effects on borrowers and lenders of the crackdown and other enforcement counterfactuals.

such as gambling and drug use. To sum up, microcredit represents a recent best practice to provide financial inclusion in developing countries, while IML is a criminal, old and global phenomenon that authorities strive to eradicate.

Finally, our paper also contributes to the growing area of structural models of financial markets. In recent years several papers have developed equilibrium frameworks of this kind, ranging from business loans (Crawford et al., 2018; Darmouni, 2020), mortgages (Allen et al., 2019; Benetton, 2021; Robles-Garcia, 2020; Buchak et al., 2020), consumer credit (Einav et al., 2012; Cuesta and Sepúlveda, 2019), credit cards (Nelson, 2020), deposits (Egan et al., 2017), insurance (Koijen and Yogo, 2016), and others. We provide the first model of a unique, relevant, and understudied lending market, that of loan sharking. Our modeling approach brings several novel features to this literature, specific of illegal money lending. First, lenders can harass borrowers to enforce repayment, and borrowers have a disutility from harassment. Second, lenders are not cash constrained and ultimately decide on the loan size to give. Third, borrowers are present-biased, often miss payments (but never strategically), and always end up repaying the loan.

2 Background and Data

2.1 Data Collection

We obtained our data by interviewing borrowers about their previous transactions with unlicensed lenders. Our loan-level data set is the same data used in Lang et al. (2021). We provide an overview of the data collection process here, but we refer the reader to Lang et al. (2021) for further details.

Our sample approximates a stratified random sample of borrowers who borrowed from loan sharks in Singapore. Similar to the strategy used by Blattman et al. (2017), we hired 48 survey enumerators who were previously involved in the unlicensed lending market. These enumerators initially went to locations where borrowers frequented and asked about the lenders they borrowed from. We estimate that we obtained information on the locations and operating

hours of approximately 90% of all lenders active at that time. From this list of lenders and operating times, we chose a set of random times and locations for the enumerators to visit to approach borrowers who had visited a lender to see if they would be willing to participate in a survey about the market. From this list of borrowers, we asked the enumerators to conduct interviews with a random 40% of the borrowers. Because borrowers received S$20-40 for participating, we did not interview the full list of borrowers for financial reasons.[6] Out of the list of 1,232 borrowers, the enumerators completed 1,123 interviews in the first wave. The first wave was conducted over 2011 to 2013, where we randomized the order in which borrowers were interviewed. To constrain the length of the interviews, enumerators asked these borrowers about the nine most recent transactions with loan sharks since 2009. Interviews were 1-2 hours long and were held in a café chosen by the respondent. 57.4% of borrowers reported nine loans and 97.2% reported at least six loans. The second wave interviews were conducted over 2015-2016. These interviews asked about the most recent two transactions since the interview in the first wave. 95.2% of borrowers reported on two loans. The reason we asked about fewer loans in the second wave was due to financial constraints. 1,090 of the original 1,123 were successfully reinterviewed. The main reason for why the remaining 33 borrowers could not be reinterviewed was because we were unable to make contact with them. We constrain our sample to the 1,090 borrowers who we successfully interviewed in both waves.

We believe the take-up rate of 91.1% in the first wave rules out any concerns for sample selection. We randomized our survey over several dimensions: the times and locations we asked enumerators to locate borrowers, as well as the time the borrowers were interviewed. Our sample does not contain once-off borrowers, but based on information from market participants these borrowers make up a very small fraction of all borrowers. As a developed country, Singapore offers many safety nets for individuals who have once-off medical emergencies or experience sudden unemployment. Such individuals can make use of these without having to resort to illegal money lenders.

[6] In 2009, US$1 was approximately S$1.38-1.45.

2.2 Loan Shark Syndicates

We also carried out interviews with previous loan sharks from Singapore (4), Malaysia (2) and China (13) to understand how lenders join the IML market in Southeast Asia and China. Based on these interviews, there are at least five transnational syndicates in operation in the region. These syndicates have branches in each country of operation throughout Asia. The syndicates recruit lenders via a formal interview process and vetting procedure. Once recruited, the syndicate provides the lender with a start-up loan of approximately S$50,000 (US$36,500) which they can use to lend out to borrowers. They also provide lenders with a database of potential borrowers that they can lend to.

Each syndicate has their own turf in the market. Lenders with one syndicate must pay fees to operate on the turf of another. The lenders we have interviewed reported that violence between lenders when competing for borrowers is very uncommon. All lenders have a lucrative business and have little incentive to physically attack other lenders for business.

There is some evidence from our data that these syndicates operated in a cartel-like nature for loan terms. As we will see, all loans in our data with lenders from different syndicates have the same structure, and the vast majority have the same interest rate at any given time. Therefore there is some evidence that syndicates coordinated. In other work, Leong et al. (forthcoming) find that drug-selling gangs have an external relations unit that talks to other gangs to work out differences and work together where possible. While we do not have direct evidence that the syndicates coordinated, given the observed market outcomes in the data it is a plausible explanation.

2.3 Standard Loan Structure

All loans issued by the loan sharks in our sample follow the same payment structure. We explain this structure using a S$1,000 principle as an example. In the early part of our sample, the nominal interest rate charged by almost all lenders was 20%. This means that for a S$1,000 loan, the borrower makes

repayments of S$200 per week for six weeks. A feature of this market is that the lender always takes the first payment from the borrower the moment the loan is issued. In effect, the borrower receives only S$800 when taking out the loan, and the loan has a 25% interest rate over a 5-week period.

If a borrower misses a payment in any week, the lender will harass the borrower and punish them financially. Harassment can involve anything from threatening text messages, to public shaming and to destruction of personal property. The way in which the lender imposes the financial penalty is by returning all previous payments made by the borrower back to them except one, and restarting the loan. This remaining payment kept by the lender is the financial penalty. In the context of the S$1,000 loan example, if the borrower had made 3 payments totaling S$600 but missed the fourth week's payment, the lender would return S$400 back to the borrower and keep the remaining $200 as a financial penalty. The lender then resets the loan and the borrower must make six payments each week starting in the following week. Thus when a loan resets, it takes at least six weeks to repay, compared to five weeks when the loan is first issued.

An example series of cashflows for a borrower who makes all of their payments and another who misses the fourth payment is shown in Table 1. In example 1, the borrower receives a net of S$800 in week 1, and makes five payments of S$200 over the next five weeks. The lender makes a profit of S$200. In example 2, the borrower misses the payment in week 4. The lender returns S$400 back to the borrower and retains the remaining S$200. The loan resets and the borrower must make six payments of S$200 each week for the next six weeks to repay the loan. The lender makes a profit of S$400, minus the cost of harassing the borrower.

This loan structure has the feature that borrowers who frequently miss payments can be caught in a never-ending debt spiral. To get out of the loan, the borrower must make six consecutive payments. In rarer cases where the loan lasts six to seven months, the lender will make the borrower work for them to pay off the remaining balance.

Week	Example 1	Example 2
1	Receive S$1,000 but pay S$200 immediately	Receive S$1,000 but pay S$200 immediately
2	Pay S$200	Pay S$200
3	Pay S$200	Pay S$200
4	Pay S$200	The borrower misses a payment. The lender returns S$400 to the borrower and keeps the remaining S$200 as a penalty. The lender harasses the borrower. The loan resets.
5	Pay S$200	Pay S$200
6	Pay S$200. Loan is complete.	Pay S$200
7		Pay S$200
8		Pay S$200
9		Pay S$200
10		Pay S$200. Loan is complete.

TABLE 1: Example repayment paths with a S$1,000 loan.

2.4 Enforcement Crackdown

Starting in 2014, there was an increase in enforcement efforts targeting the loan shark market. During this time, the police force was expanded with additional funding and law enforcement devoted more efforts to combat the loansharking market. From our interviews with ex-lenders, many lenders exited the market as a result of this crackdown. This includes lenders who were arrested, as well as those who chose to exit for fear of arrest. Market insiders claim that the number of active lenders in Singapore fell from approximately 1,100 to between 500-1,000 during 2014-2016.

As we will see, the enforcement crackdown affected typical loan contracts in a number of ways. Lenders began to charge higher interest rates to price the increased risk of arrest and the higher cost of harassment, disburse smaller loans to reduce the chance of missed payments and harassment, and increase the amount of harassment to reduce the probability of missed payments.

2.4.1 Alternative Explanations for Crackdown Effects

We provide now evidence that the change in outcomes that we observe from 2014 onwards is in fact due to the crackdown, and not due to other alternative explanations.

First, it is implausible that the transnational syndicates that fund the lenders reduced funding due to capital controls. Singapore dismantled all forms of capital controls many years prior to our data period. Furthermore, local operations did not need external funds, as more than 90% of all locally-issued loans were repaid in full with late fees within a short amount of time.

Second, the economic climate is also an implausible alternative explanation. Singapore's GDP per capita experienced steady growth from 2009-2015. A simple regression test shows that its per capita GDP growth did not exhibit a trend break coinciding with the enforcement increase. Therefore, it is unlikely that borrowers were unusually short of funds after 2014 or anticipated a change in the rate of income growth that would lead them to borrow more currently. Similarly, there is no reason to believe that lenders (or their suppliers) suddenly faced a higher opportunity cost of capital.

A third potential argument is that borrowers with bad habits were given worse loan terms over time as their bad habits intensified. These bad habits resulted in higher risk, and therefore higher interest rates that simply coincided with enforcement. However, we do not observe any decrease in eventual repayment after the crackdown.

Fourth, do the moneylenders pay "protection money" to corrupt police officers and crackdown resulted in a higher payment? It is challenging to obtain direct evidence on corrupt activities related to unlicensed money lending. However, Transparency International (2020) reports that Singapore was always consistently ranked one of the 10 most uncorrupted countries in the world in the past decade. Gallup (2020) report has ranked Singapore first for law and order from 2014 to 2020. According to Singapore's Corrupt Practices Investigation Bureau (2017), for the whole of government, there were only 20 public corruption cases in 2014, 15 in 2015, and 18 in 2016 that were investigated by it. Because the police force is a small subset of the whole of

government and only part of the police force is in charge of unlicensed money lending, the numbers of corruption cases related to unlicensed money lending that had been investigated in these years should be even smaller. Although the actual number of cases could be more than the cases that had been investigated, given Singapore's standing as it pertains to law and order, is unlikely that fees paid to corrupt police officers had caused loan prices to increase.

2.5 Features of the Loan Sharking Market

We now describe a number of features of the market that we observe in our data. We use these features as a foundation of the assumptions we make for our structural model.

Lender Features

Lender Feature 1: Almost all lenders charge the same interest rate at any given time. Before the enforcement crackdown in 2014, 88% of loans had a nominal rate of 20% and most of the other loans had a rate of 15%. After 2015, 89.6% of loans had a nominal rate of 35%, with the remaining either 30%, 40% or 50%. Figure 1 shows the median interest rate charged by lenders in our sample in each month. After the crackdown occurred in 2014, the interest rate increased in 5% increments throughout 2014 before stabilizing at 35%. Because almost all lenders charge the same interest rate at any given time, we assume lenders take the prevailing interest rate as given in our model.

Lender Feature 2: Loan sizes are often smaller than the loan size initially sought by the borrower. In our data we observe the loan size borrowers initially desired and the loan size they ended up receiving from the lender. When borrowers ask lenders for large loans, the lender may refuse the amount. Instead they may be only willing to lend the borrower a fraction of what they ask for. Before the crackdown, 59.6% of borrowers got the loan size they initially asked for, which on average was S$1,957. Borrowers obtaining smaller loans on average received 61% of what they initially asked for. After the crackdown, only 15.1% got the loan size they initially asked for, which on average was S$1,018,



FIGURE 1: Median nominal interest rate by month.

and the remaining got on average 48% of their initial desired amount. Histograms of the loan sizes as a proportion of the initial desired loan size before and after the crackdown are shown in Figure 2. When loan sizes are less than the desired loan size, they are often round fractions of the desired amount, such as one half or two thirds of the desired loan size. Approximately 1% of loans have a loan size larger than what the borrower asked for. However, we omit these loans from our analysis. The desired loan size also changed after the crackdown. Before the crackdown, the median desired loan size was S$1,500, whereas after the crackdown this fell to S$1,000.

In our model, we assume borrowers initially ask for their desired loan size. If the lender refuses, we assume they ask for a smaller loan. If the lender refuses this as well, they ask for an even smaller loan. We assume borrowers ask for two thirds, then one half, and finally one third of their initial desired loan size after being refused their initial desired loan size. This is because the vast majority of loan sizes are these common fractions of the initial desired loan size.

Lender Feature 3: Lenders are more likely to give larger loans to borrowers they have a previous history with and who performed better on their last loan. If a borrower performs well on a loan, lenders are more likely to give larger loan sizes to them in subsequent loans. The left panel of Figure 3 shows the average loan size as proportion of the borrower's desired loan size for different number

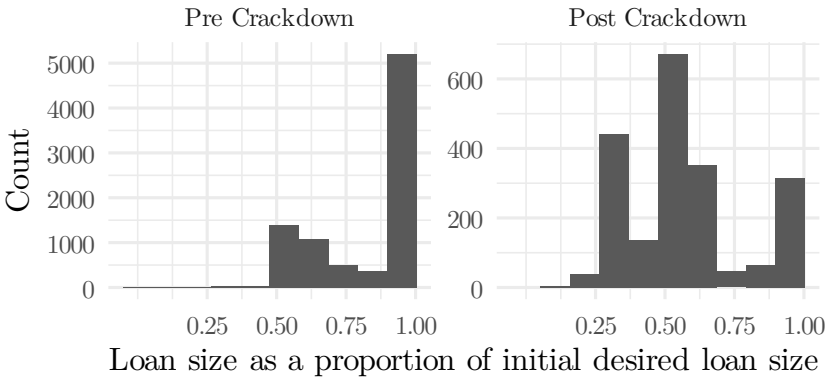


FIGURE 2: Loan sizes before and after the crackdown.

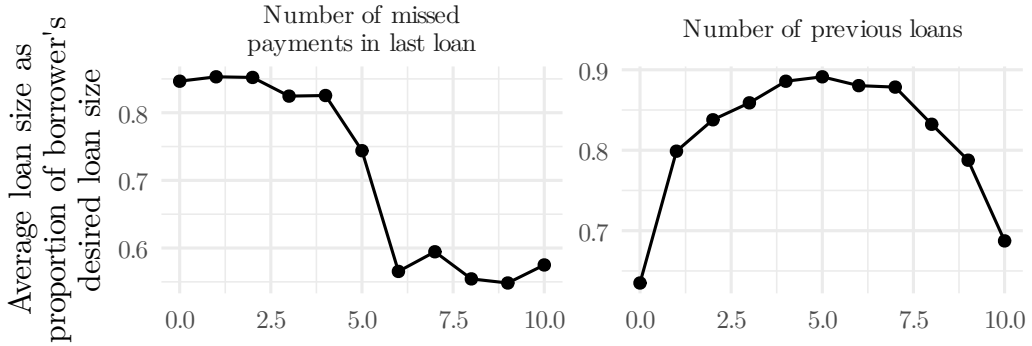


FIGURE 3: Loan sizes and relationship history.

of missed payments from their previous loan. If a borrower missed six or more payments in the previous loan, the average loan size is considerably smaller. If a borrower has developed a relationship with a lender with previous loans, the lender on average gives larger loan sizes. In the right panel of Figure 3 we see borrowers with longer histories obtain larger loans on average, except for serial borrowers who borrow very frequently. After seven previous loans, the average loan size begins to fall. In our model we incorporate the past performance and relationship history of a borrower in the lender's estimate of the borrower's ability to repay.

Lender Feature 4: Lenders use harassment methods to ensure borrowers

repay and some lenders are harsher than others. When a borrower misses a payment, the lender will conduct some form of harassment to pressure the borrower to repay. Harassment types can vary from making a phone call or sending a text message, to more severe forms, such as shaming and destruction of property. Lenders shame borrowers by threatening them in their neighborhood or workplace, or threatening their friends or family. Shaming methods are used in 15.6% of loans in our data. Destructive methods, which are used in 13.6% of loans, include splashing paint on the borrower's house or car, writing or putting graffiti in their home, or blocking the borrower's door by filling it with superglue or chaining it. The graffiti used by the lender may also include shaming details about the borrower. For example, the graffiti may be on the stairwell of an apartment building and read "OP" (owe money, pay money) with the apartment number of the borrower. The lender may also visit the borrower and threaten them in person. This kind of harassment occurs in 50.6% of loans.[7]

In our model, we differentiate between threatening phone calls and text messages to more severe kinds of harassment. Reminder calls and text messages happen in most loans when a borrower misses a payment. We consider these to be a standard part of all loans and do not incorporate it in our model. We assume these calls and text messages as costless for the lender to send and give no disutility to the borrower. The more severe forms, however, are costly for the lender in terms of the cost of hiring runners to conduct harassment, and the risk of arrest from doing so. We make this normalization because we cannot separately identify the expected cost of severe harassment and these reminder calls and text messages. Based on interviews with two ex-runners, splashing paint on someone's house costed between S$350-S$500 during the post-crackdown period. Locking a debtor's door or gate costed between S$120-S$150, and setting their house on fire costed between S$1,000-S$1,800. The severe forms also give the borrowers disutility.

Lenders do not use severe tactics every time borrowers miss a payment,

[7]In Table A.1 in the Online Appendix, we show the proportion of loans in our data where each form of harassment method was used.

but do so randomly to maintain their reputation and to ensure borrowers are incentivized to make repayments. Therefore in our modeling, we assume lenders harass borrowers with a certain probability after a borrower misses a payment. The only exception to this is when borrowers miss two payments in a row. According to our survey respondents, lenders will always conduct more severe forms of harassment when a borrower misses two payments in a row. This is because the lender does not have any payments made by the borrower to punish them financially. This is standard practice and common knowledge in the market. In our model, we therefore assume that if a borrower misses two payments in a row, they are harassed with a severe type of harassment with probability one. Conditional on the number of missed payments, lenders differ in how frequently they use the more severe harassment tactics. We refer to this as the lender's harshness and in our analysis we will group lenders of different harshness levels into three types: low, medium and high harshness.[8]

Lender Feature 5: Lenders are not cash constrained. Lenders who begin trading receive startup capital from the loan shark syndicate. Actively-trading lenders make large profits as there is virtually no default, high interest rates, and high revenue from missed payment penalties. Lenders do have costs for runners to help them get loans repaid, so unless borrowers have a very low repayment probability, lenders will make profits on a loan. From our interviews, we learned that lenders are always searching for new borrowers to lend to. The average lender will typically start with S$50,000 in cash to lend out for a day. If they lend out all of the cash before the end of the day, they can obtain additional cash within thirty minutes. Therefore in our modeling we do not model the lenders choosing which borrowers to lend to, but rather whether or not to lend to a borrower when approached.

Lender Feature 6: In rare cases, the lender requires the borrower to work for them to finish repaying the loan. The borrower works for the lender to finish repaying the loan in 8.7% of loans. This usually occurs when the loan is still unpaid after several months. Instead of continuing to reset the loan after

[8]We provide further details of how we classify lenders into types in A.3 in the Online Appendix.

missed payments, the lender will eventually require the borrower to work for them to complete the loan. In our modeling, we specify a terminal period after which the borrower must work for the lender to repay the loan. This terminal period is set to be 24 weeks after the initial loan is disbursed. In our data, 90% of loans are repaid within this timeframe.

Lender Feature 7: Lenders do not accept partial repayments. No borrower in our data ever experienced a lender that allowed partial repayments. Only one ex-lender we interviewed stated that shortly before he quit lending, he once accepted a partial payment which was S$20 short. Therefore in our model we assume borrowers can only make a payment if they have enough cash available for the entire amount due in a week.

Lender Feature 8: Lenders have imperfect information about a borrower's ability to repay. When a borrower borrows from a loanshark for the first time, the lender will ask the borrower to view their government-issued ID. The lender can then check the borrower's name against a large database of borrower information they have purchased from the black market or provided to them by the syndicate. This database gives the lender access to the borrower's Singpass. This is a digital ID containing various information about the borrower. This allows them to observe their formal sector income and basic sociodemographic information, such as their age and education. If the borrower is not in their database, they will require the borrower to provide the password for their Singpass to obtain this information. The lender also has information on the borrower's ability to repay from the borrower's performance on past loans. However, the lender is unable to observe the borrowers gambling, drug and alcohol addictions, gang member status or prior convictions. The exception to this is when a borrower asks for a loan while under the influence of alcohol, which occurred in 34% of loans in our data.

In our modeling, we assume the lender estimates the borrower's ability to repay using only information that is available to them. Because lenders are experienced in the market, we assume that on average their estimates are correct and they are not over-optimistic or pessimistic about new borrowers.

Lender Feature 9: Lenders do not require collateral for loans. Lenders

do not require borrowers to provide any assets as collateral. In our data, borrowers stated they only ever had to provide their government-issued ID or to provide access to their Singpass if the lender did not have access to this. However, the lender always returns the borrower's ID when they disburse the loan. Therefore the loans in our data are collateral-free.

Borrower Features

Borrower Feature 1: Borrowers frequently miss payments but almost always eventually repay. In our data, only 14.6% of loans are paid on time within 6 weeks, but 99.5% are eventually repaid. The median and modal loan is repaid after 12 weeks. Borrowers who do not finish repaying after the terminal week repay the loan by working for the borrower.

Borrower Feature 2: Borrowers often return to the same lenders they borrowed from in the past. When looking for a new lender, they settle for the first lender they find. Before the crackdown, 88% of loans were taken from lenders borrowers had previously borrowed from before. After the crackdown, this dropped to 75.5%. The primary reason for this drop was that lenders were no longer trading because they were arrested. In our sample, there were 711 active lenders before the crackdown, whereas there were only 401 active lenders after the crackdown. Those we have interviewed estimate that there were approximately 1,100 lenders in total before the crackdown, but after the crackdown there were 500-1,000. When borrowers look for a new lender, they usually are referred to one by their contacts. They typically will settle for the first lender they find as they want the cash as soon as possible. All the borrowers in our dataset stated that they considered less than or equal to one new lender for all transactions.

In our model, we assume borrowers choose between lenders when they want to take out a loan. We assume they only consider lenders they have previously borrowed from, as well as one additional new lender. We use the observed network of borrowers and lenders to choose this additional lender for each borrower such that they are likely lenders to be referred to them.

Borrower Feature 3: Borrowers do not have access to loans from the formal

sector. We asked the borrowers in our sample if they had access to loans in the formal sector. The answer was consistently no. Loan sharks are lenders of last resort and borrowers stated that they would not be borrowing from loan sharks if they had access to formal sector loans. Therefore in our model we do not include the formal sector in the borrower's consideration set when they want to take out a loan.

Borrower Feature 4: Borrowers do not strategically miss payments. Because of the threat of harassment and shaming, together with the fact that lenders almost always get the loans repaid eventually, borrowers almost always make a repayment when they can afford to. Only 5 of the 1,090 borrowers in our sample stated they had chosen not to pay when they could afford to. Borrowers we have interviewed have also told us that if a lender ever discovered that a borrower chose not to pay when they could afford to (for example, because they had a good gambling win), then the lender would use extra harassment methods to punish the borrower. Lenders often have contacts stationed in different areas where people gamble and would know if their borrowers had a good gambling win. From our survey evidence, it was common knowledge among borrowers that lenders would conduct very severe forms of harassment if they chose not to pay when they could afford to. Therefore in our model we assume that borrowers will always make a loan repayment when they have enough cash available to do so.

Borrower Feature 5: Borrowers are present-biased and have high discount rates. In our surveys, we asked borrowers how much they would need in ten months to be indifferent between it and S$800 in nine months. The median borrower said S$980, corresponding to an annual discount factor of 0.0875. To measure their quasi-hyperbolic discount factors, we also asked them what amount would they need in one month to be indifferent between it and S$500 now. The median borrower said S$700. Because future payments occur in weekly intervals, we use these responses to calculate the borrowers' weekly discount factors. We assume borrower i discounts payoffs w weeks in future with $\beta_i \delta_i^w$, where β_i is the present bias under quasi-hyperbolic discounting and δ_i is the weekly discount factor. The median borrower's weekly discount

factor δ_i is estimated to be 0.954 and the median present bias term β_i is 0.752. Only 9 of the 1,090 borrowers in our sample were not present biased.[9] Due to this large fraction of present biased borrowers, we refrain from modeling any dynamic consideration of borrowers beyond their current loan. This implies that borrowers, when repaying a loan, do not consider the potentially larger loan they could get in the future from the same lender, if they were to perform well on the current loan.

Borrower Feature 6: Borrowers have a low degree of risk aversion. We asked borrowers which to choose between a gamble and a certain alternative in three different scenarios. In each scenario, the gamble was S$1,000 with 50% probability and S$0 otherwise. The alternative was S$300, S$350, and S$400 with certainty, respectively. With S$300 as the certain amount, 80.3% chose the gamble. With S$350, 46.5% chose the gamble, and with S$400, only 7.6% chose the gamble. We also asked what their certainty equivalent amount was for a gamble with S$800 with 50% probability. The median borrower said S$500. We convert these responses into a coefficient of relative risk aversion for each borrower. The median value of this was 0.382.[10]

Borrower Feature 7: Borrowers usually borrow for gambling, drugs and alcohol. In our survey, we asked borrowers what their reason for borrowing was, where borrowers could give multiple responses per loan. 56.9% of loans were taken out for gambling-related purchases, for example, to pay a gambling debt from a loss. 47.9% of loans were taken out for drugs or alcohol. Often the money borrowed is used to treat friends for drinks. 55.3% of borrowers stated they regularly treat friends, 42.6% stated they occassionally do, and only 2.1% stated they never treat friends. In many Asian countries including Singapore, it is common for one person to pay for all the drinks and food for everyone at a table.[11]

[9] Details of these calculations are shown in A.4 in the Online Appendix.

[10] Details of these calculations are shown in A.5 in the Online Appendix.

[11] To a certain extent, whose turn it is to pay for the food and drinks in these settings rotates and there is a certain degree of randomness in when this occurs and the size of the bill. This can lead borrowers to unexpectedly require additional cash which they need to borrow.

Other reasons for taking out loans, such as paying rent or medical emergencies, were much less common.[12] Because the majority of loans are used to pay back gambling debt or fund drug and alcohol consumption, we take the amount that the borrower desires to borrow as given in our model.

Borrower Feature 8: Borrowers mainly use their own income to repay loans. Borrowers stated that their own income was the main source of cash used to repay loans in 83.6% of loans. In contrast, borrowers said their main source of cash to repay was from another loanshark in only 1.6% of loans. In 5.5% of loans, borrowers borrowed from either friends or family.

Borrowers do not frequently borrow from one lender to repay another. Lenders under the same syndicate may share information on borrowers to improve their joint profitability. If a borrower wanted to take out a loan from one lender to repay another, the new lender may already have the information on the borrower's debt and reject their loan request. Furthermore, if borrowers were frequently taking out small loans in order to make repayments on existing loans when they were short cash, we would observe many small loans in our data. Before the crackdown, 83.7% of loan sizes were between S$500 and S$2,000. With the prevailing 20% interest rate, weekly loan repayments would be between S$100 and S$400 for the majority of loans. However, less than 1% of loans are for amounts less than or equal to S$400 in this period, incidating that borrowers were not taking out loans to make repayments for loans with other lenders.

Therefore, because the borrower's own income is the main source of funds for repayment, we do not model model borrowers deciding to take out additional loans to repay outstanding loans.

Borrower Feature 9: Most borrowers spend frequently and do not have savings. All borrowers in our sample have zero savings. They all stated that if they had savings, they would not borrow from loan sharks. Only 54 of the 1,090 borrowers stated they would save some of their money from windfall income. Therefore in our modeling, we assume that borrowers do not save the money lenders return to them when they miss a payment and the loan resets.

[12] A table of these reasons is shown in Table A.2 in the Online Appendix.

2.6 The Modal Loan

Before we discuss our model, we further clarify the structure of this market and how a typical loan goes in reality by describing how the modal loan in our data proceeds in practice.

A borrower is gambling at the casino and runs out of money. The borrower needs a loan to continue gambling.[13] The borrower decides between different lenders to ask for a loan and decides on one they borrowed from in the past.[14] The borrower leaves the casino to go to the café where this lender operates. The borrower asks for S$1,000 from the lender. The lender asks to see the borrower's ID card to check their own records, both the past loan history and information from the borrower's Singpass that the lender purchased from the black market. The lender deems the loan profitable and returns the ID card to the borrower.[15] The lender hands S$800 in cash to the borrower, keeping the remaining S$200 as the first payment.[16] The borrower then returns to the casino and continues gambling.

One week later, the borrower gives the lender the second payment of S$200 according to the repayment schedule. In week 3 when the next payment is due, the borrower had just had some bad gambling losses and cannot make the payment. The lender calls the borrower and threatens them but does not resort to any severe harassment methods. The lender returns S$200 to the borrower, keeps the remaining S$200 the borrower had paid and resets the loan. In the next two weeks (weeks 4 and 5) the borrower succeeds in making a payment, but again fails to make the payment in week 6. This time the lender conducts a more severe form of harassment and visits them at their home to threaten them.[17] The lender returns S$200 back to the borrower, keeping the remaining S$200 they have paid and resets the loan a second time. The borrower then makes six consecutive payments each week in weeks 7 to 12 and

[13] 56.9% of loans were taken out for gambling-related reasons.

[14] 86% of loans are taken with a previous lender.

[15] The modal desired loan size and actual loan size is S$1,000.

[16] The modal interest rate and prevailing pre-crackdown rate is 20%.

[17] Severe harassment methods are used in 50.6% of loans. Visiting the borrower's home is the most common severe form, present in 42.9% of loans.

finishes paying off the loan.[18]

2.7 External Validity

To assess the external validity of our setting and analysis, we rely on interviews with former lenders in Singapore (4), Malaysia (2), China (13) and two with experience in both Singapore and China. All agree that transnational syndicates control almost the entire Southeast Asian and Chinese markets and that there are at least five syndicates (some suggest ten to fifteen). These syndicates, headquartered in Guangdong, China, focus on the highly developed parts of these countries such as Shenzhen, Shanghai, Kuala Lumpur, and Singapore. Consequently, our findings should apply more broadly to this enormous market. They do not operate in poor rural regions where money lending presumably resembles informal lending in developing countries.

According to these informants, the operating model is similar across countries, possibly because international law enforcement cooperation forces syndicates to cooperate transnationally.[19] Lenders share a common database and receive similar advice from the syndicates, and therefore, target similar borrowers in all markets: individuals excluded from the formal financial sector with bad habits but who are likely to repay loans with minimal harassment. Purportedly, 70% of the individuals in the database have at least one known bad habit. Likewise, lenders operate in similar locations, such as at gambling dens in China and near gambling outlets in Singapore. The two lenders who operated in both Singapore and China confirmed the cross-border similarities.

No matter the country of operation, including Singapore, all loan sharks working with transnational syndicates face low barriers to entry and exit. A potential lender does not need to fulfill any particular demographic require-

[18]The modal loan has two missed payments and takes 12 weeks to repay.

[19]Our setting is similar to other countries in many ways, and as a result, we argue our results have validity in other countries. Many countries, including Britain, China, Japan and Malaysia, have announced nationwide crackdown on loan sharks. Countries that have adopted a harsh stance for such offenses have a combined population of over 1.5 billion. Therefore the behavior of the lenders regarding the harsh penalties for illegal money lending may be similar in these other countries.

ment (including nationality), have any minimum financial standing or a pre-existing affiliation with these organizations to join this trade. For example, if a Singaporean wants to become a lender in China, he will first have to pass a verbal interview and security screening to ensure he is not a law enforcement officer in Singapore. If the interviewer deems that he can be successful, he will be provided with the necessary resources to enter China legally. He will be interviewed in China again. If successful, he will be given the necessary resources to start his business in China. For example, one branch office in Shenzhen sourced about 40% of its members from overseas.[20]

Lenders can also move across countries freely with assistance from the branch office. For example, Singaporean lenders typically move to China or Malaysia once they believe they are at risk of detection. Branch offices are always looking for new lenders as they do not have enough manpower to keep up with their expanding business operations. While the branch offices do reach out to potential lenders proactively, interested parties can also go through existing lenders, the dark web or underground chat groups to obtain referrals to the branch offices. Typically, 5 out of 10 new lenders proactively seek out branch offices. There is no barrier to exit. As long as the interest on the startup loan is paid off, the lender hands over all existing customers to the syndicate and does not divulge any gang related information to authorities, he is free to leave.

Lenders across all countries also target the same type of borrowers because they have access to the same database and advice from the syndicates. The syndicates have already pre-identified the most profitable borrowers, who are individuals excluded from the formal financial sector with bad habits and who are likely to repay loans with minimal harassment. The type of physical areas that lenders choose to operate in is also similar across countries. For example, the lenders we interviewed waited in gambling dens in China for potential clients, whereas lenders in Singapore opted to wait near gambling outlets. Our informants do not know of any lenders that "did not earn a lot of money

[20] According to market insiders, this is roughly the same or slightly less for other Asian nations.

in this business." Lender typically start turning a profit within 3 months or less after they start operating. Typically, lenders do not compete with one another to issue loans because the pool of borrowers exceeds the number of lenders operating in the market.

3 Model

3.1 Overview

We now describe our model which captures the features of this market described above. We first provide an informal overview of our model before describing it formally. In our model, borrowers exogenously receive a desire to borrow a particular sum of money, for example, because they lost money while gambling. The borrower can choose between different lenders they have borrowed from before, search for a new lender they have no history with, or not take out any loan. If the borrower chooses to take out a loan with a particular lender, they make weekly repayments according to the standard loan structure described above. Each period, the borrower earns cash that can be used for consumption and loan repayments. These cashflows are stochastic and borrowers can only make their weekly payment if their cash on hand is at least as large as the installment. Missing a payment involves a financial penalty, as well as the possibility of severe harassment from the lender. Borrowers will always make a payment when they can afford to, because of the threat of harassment and the resetting property of the loan structure. The loan ends when the borrower has made six consecutive payments. If the loan is not fully repaid after a terminal week, the loan contract ends. The lender will make the borrower work for the lender to repay the remaining balance which incurs further disutility for the borrower.

When a borrower approaches a lender, the lender chooses whether or not go give out the loan. The lender uses available information about the borrower from their past performance to estimate their ability to repay. If the lender believes that a borrower is likely to miss many payments, the lender earns

more via missed payment penalties, but incurs more harassment costs. The lender only gives out the loan if they expect to make a profit on it. If the lender rejects a borrower, the borrower can ask the lender for a smaller loan size. If they reject that as well, the borrower will ask for an even small loan size, until the lender rejects all offers.

While all lenders charge the same nominal interest rate at any given time, lenders differ in harshness and how likely they are willing to lend to the borrower, which depends on the borrower's relationship history with them and on borrower's observable characteristics. Borrowers take expectations of the size of the loan they will receive from the lender when choosing a lender. Furthermore, when choosing a new lender, borrowers do not know the harshness of the lender and take expectations of how harsh they will be. Borrowers have constant relative risk aversion utility on consumption and discount the future with quasi-hyperbolic discounting. The borrower then chooses a lender to borrow from that maximizes their expected present discounted value of utility.

This market features very limited competition between lenders, which explains why we do not explicitly incorporate it into our model. There are three main reasons that support this modeling strategy. First, as described in Section 2.2, the syndicates that control the market and hire the lenders coordinate on several margins, imposing to all lenders the same interest rate, the same maturity and loan structure, the same forms of financial penalty, and similar harassment methods. This implies that lenders have little margin left to compete between each other. This form of cartel-like agreements is a typical feature of illicit market products. Second, as discussed in Section 2.5, borrowers often return to the same lenders they borrowed from in the past, which implies that poaching borrowers from each other is not a common practice among lenders. Third, lenders are not cash constrained and their harassment methods make sure that borrowers always repay, so they have little incentive to reject borrowers that approach them, which also limits borrowers' search among lenders and the extent of competition.

We now describe the model formally and in greater detail.

3.2 Setup

In the market there are I borrowers and L lenders. At each time period t, the nominal interest rate r_t is fixed and borrowers and lenders take it as given. At time t, borrower i exogenously receives a need to borrow an amount of money $L_{it}^{\star}$. The borrower can choose to borrow from a number of different lenders or choose the outside option of not taking out a loan at all. Let $\mathcal{L}_{it} \subset \{1, \ldots, L\}$ be the set of lenders borrower i can choose from at time t. This includes lenders the borrower has borrowed from before who are still active, as well as a new lender they have no history with. If borrower i chooses lender $\ell \in \mathcal{L}_{it}$ and asks for a loan of size $L_{i\ell t} = L_{it}^{\star}$, lender ℓ decides whether to give the borrower the loan or not. If the lender rejects, the borrower asks for a smaller loan.

We first describe the expected payoffs for the lender if they were to give the borrower a loan of size $L_{i\ell t}$, and then discuss the lender's optimal choice. We then describe the borrower's optimal choice of lender.

3.3 Lenders

3.3.1 Repayment Probabilities

Each week w after a loan from lender ℓ is disbursed the time t, borrower i has cash $m_{i\ell tw}$ available to make repayments. We assume this is generated according to a truncated normal distribution:

$$m_{i\ell tw} = \max\left\{0, m_{i\ell t} + \nu_{i\ell tw}\right\} \qquad \text{where } \nu_{i\ell tw} \sim \mathcal{N}\left(0, \sigma_i^2\right) \tag{1}$$

Each week, borrowers have $m_{i\ell t}$ available plus a stochastic component $\nu_{i\ell tw}$ whose variance can vary by borrower (for example, because they gamble more frequently). This weekly cashflow can vary across different lenders, because borrowers may make more effort to have cash available for lenders with different relationship capital or lenders which harass more often.

With a loan of size $L_{i\ell t}$, the borrower must make weekly repayments of $r_t L_{i\ell t}$ throughout the course of the loan. The borrower can only make a pay-

ment if their available cash in a week exceeds $r_t L_{i\ell t}$ as lenders do not accept partial payments. We assume borrowers cannot strategically default on a payment, and thus they will always make a payment if they can afford to. The probability that the borrower can make a payment in any week is given by:

$$p^{m}_{i\ell t}\left(L_{i\ell t}\right) = \Phi\left(\frac{m_{i\ell t} - r_t L_{i\ell t}}{\sigma_i}\right)$$

where $\Phi\left(\cdot\right)$ is the cumulative distribution function of the normal distribution. Lenders have imperfect information about the process for $m_{i\ell tw}$. We assume that the lender believes the borrower earns $\widetilde{m}_{i\ell tw}$ each week, where

$$\widetilde{m}_{i\ell tw} = \max\left\{0, \widetilde{m}_{i\ell t} + \widetilde{\nu}_{i\ell tw}\right\} \qquad \text{where } \nu_{i\ell tw} \sim \mathcal{N}\left(0, \widetilde{\sigma}_i^2\right)$$

Given this, the lender's belief that a borrower can make a payment in any week is given by:

$$p^{\widetilde{m}}_{i\ell t}\left(L_{i\ell t}\right) = \Phi\left(\frac{\widetilde{m}_{i\ell t} - r_t L_{i\ell t}}{\widetilde{\sigma}_i}\right)$$

3.3.2 Lender Expected Payoffs

If the lender disburses a loan of size $L_{i\ell t}$ to the borrower, in week 1 their payoff from the loan is the cash outflow from disbursing the loan:

$$\widetilde{u}_{i\ell t1}\left(L_{i\ell t}\right) = -\left(1 - r_t\right) L_{i\ell t}$$

The reason the lender only disburses $\left(1 - r_t\right) L_{i\ell t}$ instead of $L_{i\ell t}$ is because the lender keeps the first payment at the moment of disbursing the loan.

In the second week, the lender believes the borrower will make the payment with probability $p^{\widetilde{m}}_{i\ell t}$. If the borrower makes the payment, the lender receives a cash inflow of $r_t L_{i\ell t}$.

When a borrower misses a payment, the lender harasses the borrower. This could involve lighter forms of harassment such as remind phone calls or text messages, but could also involve more severe harassment, such as shaming or damaging their property. When a borrower misses a payment, the lender

uses more severe forms of harassment with probability $p^{\eta}_{i\ell t}$. The probability of harassment can differ by lender, as some lenders are harsher than others. The probability of harassment may also depend on the length of the borrower-lender relationship, and whether it is before or after the crackdown. If a borrower misses two payments in a row, we assume the lender uses a severe form of harassment with probability one, because she cannot punish the borrower resetting the loan anymore.

We assume lighter forms of harassment are costless for the lender, but the more severe forms are costly. Inflicting harassment is costly because the lender often must pay runners to conduct harassment for them. It is also risky and can land the lender in jail. We assume the expected cost of harassment for lender ℓ at time t is $\kappa_{\ell t}$.[21] This can vary over time, as the authorities increased their enforcement efforts, as well as over lenders, as some are on average harsher than others.

Together, the expected payoff in week 2 is then:

$$\mathbb{E}\left[\widetilde{u}_{i\ell t2}\left(L_{i\ell t}\right)\right] = p^{\widetilde{m}}_{i\ell t}\left(L_{i\ell t}\right) r_t L_{i\ell t} - \left(1 - p^{\widetilde{m}}_{i\ell t}\left(L_{i\ell t}\right)\right) p^{\eta}_{i\ell t}\kappa_{\ell t}$$

If the borrower misses payments in a later week, then the lender must return a portion of the borrower's previous payments to them and reset the loan. For example, if the borrower misses a payment in week 4, the lender has a cash outflow of two payments, and the loan resets. If the borrower misses two payments in a row, the lender has no cash from the borrower to financially punish them. Instead, the lender inflicts harassment on the borrower with probability one. There is a terminal week W after which the loan ends regardless if the loan is fully repaid or not. If this period is reached, the lender makes the borrower work for them to repay the loan. If the borrower has completed paying off the loan by making six consecutive payments before the terminal week, the loan ends and cashflows and harassment cease.

[21] We can interpret the expected cost of harassment as being the sum of two components, $\kappa_{\ell t} = c^{\eta}_{\ell t} + p^{K}_{\ell t} K_{\ell t}$, where $c^{\eta}_{\ell t}$ is the monetary cost of conducting harassment, $p^{K}_{\ell t}$ is the probability of being arrested while harassing, and $K_{\ell t}$ is the lender's disutility of going to jail.

To define the lender's payoff in each possible case, we define the payment counter $n_{i\ell tw}$ as the number of consecutive payments made before week w. Using this, we can define the lender's expected payoff in each possible case for weeks $w \in \{2, \ldots, W-1\}$:

$$\widetilde{u}_{i\ell tw}\left(L_{i\ell t}\right) = \begin{cases} r_t L_{i\ell t} & \text{if } n_{i\ell tw} < 6 \text{ and } \widetilde{m}_{i\ell tw} \geq r_t L_{i\ell t} \\ -\kappa_{\ell t} & \text{if } n_{i\ell tw} = 0 \text{ and } \widetilde{m}_{i\ell tw} < r_t L_{i\ell t} \\ -\left(n_{i\ell tw} - 1\right) r_t L_{i\ell t} - p^{\eta}_{i\ell t}\kappa_{\ell t} & \text{if } n_{i\ell tw} \in \{1, \ldots, 5\} \text{ and } \widetilde{m}_{i\ell tw} < r_t L_{i\ell t} \\ 0 & \text{if } n_{i\ell tw} = 6 \end{cases}$$

In the first case, the loan is not fully repaid ($n_{i\ell tw} < 6$), the borrower makes the payment and the lender receives $r_t L_{i\ell t}$. In the second case, the borrower misses two payments in a row and the lender harasses the borrower with probability one. In the third case, the borrower misses a payment and the lender must return $\left(n_{i\ell tw} - 1\right) r_t L_{i\ell t}$ back to the borrower. They inflict harassment with probability $p^{\eta}_{i\ell t}$ at an expected cost $\kappa_{\ell t}$. In the final case, the loan is already fully repaid ($n_{i\ell tw} = 6$) and there are no more cashflows between the borrower and lender. In the case where the loan is still unpaid by the terminal week W, the lender is still able to recover the remaining balance of the loan by making the borrower do work for them.[22]

The lender discounts future weeks with a weekly discount factor of $\widetilde{\delta}$. The expected present discounted value of disbursing a loan of size $L_{i\ell t}$ is then:

$$\widetilde{V}_{i\ell t}\left(L_{i\ell t}\right) = -\left(1 - r_t\right) L_{i\ell t} + \mathbb{E}\left[\sum_{w=2}^{W} \widetilde{\delta}^{w-1} \widetilde{u}_{i\ell tw}\left(L_{i\ell t}\right)\right]$$

3.3.3 Lender's Choice to Disburse Loan

If a lender is approached by a borrower desiring to borrower $L_{i\ell t}$, the lender compares the expected discounted value of payoffs from the loan $\widetilde{V}_{i\ell t}\left(L_{i\ell t}\right)$ to the outside option, which is given by $\widetilde{\varepsilon}_{i\ell t}$. We assume $\widetilde{\varepsilon}_{i\ell t}$ is distributed logistically. The lender disburses the loan if $\widetilde{V}_{i\ell t}\left(L_{i\ell t}\right) > \widetilde{\varepsilon}_{i\ell t}$.

[22] We describe the exact specification for the lender's payoff in this special case in the Online Appendix A.7.1.

3.4 Borrowers

We first describe the payoffs of a borrower from a loan of size $L_{i\ell t}$ from lender ℓ. We then discuss the borrower's optimal choice of lender.

3.4.1 Borrower Expected Payoffs from a Loan

If borrower i has an outstanding loan with lender ℓ at time t, they earn cash each week which can be used for repayments according to equation (1). Borrowers have constant relative risk aversion utility over consumption each week, and can differ in their coefficient of relative risk aversion, γ_i. In the first week, the borrower consumes their available cash $m_{i\ell t1}$ and the disbursed loan $(1 - r_t) L_{i\ell t}$. We assume the borrower takes out the loan before the weekly cash shock $\nu_{i\ell tw}$ is realized. Therefore, the borrower's expected utility in week 1 is:

$$\mathbb{E}\left[u_{i\ell t1}\left(L_{i\ell t}\right)\right] = \mathbb{E}\left[\frac{\left[m_{i\ell t1} + (1 - r_t) L_{i\ell t}\right]^{1-\gamma_i} - 1}{1 - \gamma_i}\right]$$

In week 2, the borrower is able to make the repayment with probability $p^m_{i\ell t}\left(L_{i\ell t}\right)$. If the borrower misses the payment, the borrower will be harassed by the lender. We assume that lighter forms of harassment such as phone calls and text messages give the borrower no disutility, but that more severe forms, which occur with probability $p^\eta_{i\ell t}\left(L_{i\ell t}\right)$, give the borrower an expected disutility $\chi_{i\ell t}$. This can differ by lender because different lenders may use different harassment methods.

The expected payoff in week 2 from the loan is then:

$$\begin{aligned}\mathbb{E}\left[u_{i\ell t2}\left(L_{i\ell t}\right)\right] =& p^m_{i\ell t}\left(L_{i\ell t}\right)\mathbb{E}\left[\frac{\left[m_{i\ell t2} - r_t L_{i\ell t}\right]^{1-\gamma_i} - 1}{1 - \gamma_i}\middle| m_{i\ell t2} \geq r_t L_{i\ell t}\right] \\ &+ \left[1 - p^m_{i\ell t}\left(L_{i\ell t}\right)\right]\left[\mathbb{E}\left[\frac{m_{i\ell t2}^{1-\gamma_i} - 1}{1 - \gamma_i}\middle| m_{i\ell t2} < r_t L_{i\ell t}\right] - p^\eta_{i\ell t}\chi_{i\ell t}\right]\end{aligned}$$

If the borrower misses a payment in a later week, the lender returns all but one of the previous payments made and resets the loan. The lender retains one payment as a financial penalty. If the borrower misses two payments in a

row, the borrower receives harassment with probability one.

We can define the borrower's expected payoff in each possible case for all weeks between the first and terminal week, $w \in \{2, \ldots, W-1\}$, as:

$$u_{i\ell tw}\left(L_{i\ell t}\right) =$$
$$\begin{cases} \mathbb{E}\left[\frac{[m_{i\ell tw}-r_t L_{i\ell t}]^{1-\gamma_i}-1}{1-\gamma_i}\middle| m_{i\ell tw} \geq r_t L_{i\ell t}\right] & \text{if } n_{i\ell tw} < 6 \text{ and } m_{i\ell tw} \geq r_t L_{i\ell t} \\ \mathbb{E}\left[\frac{m_{i\ell tw}^{1-\gamma_i}-1}{1-\gamma_i}\middle| m_{i\ell tw} < r_t L_{i\ell t}\right] - \chi_{i\ell t} & \text{if } n_{i\ell tw} = 0 \text{ and } m_{i\ell tw} < r_t L_{i\ell t} \\ \mathbb{E}\left[\frac{[m_{i\ell tw}+(n_{i\ell tw}-1)r_t L_{i\ell t}]^{1-\gamma_i}-1}{1-\gamma_i}\middle| m_{i\ell tw} < r_t L_{i\ell t}\right] - p_{i\ell t}^{\eta}\chi_{i\ell t} & \text{if } n_{i\ell tw} \in \{1,\ldots,5\} \text{ and } m_{i\ell tw} < r_t L_{i\ell t} \\ \mathbb{E}\left[\frac{m_{i\ell tw}^{1-\gamma_i}-1}{1-\gamma_i}\right] & \text{if } n_{i\ell tw} = 6 \end{cases}$$

In the first case, the borrower is able to make the payment and consumes their remaining income. In the second case, the borrower misses two payments in a row and is harassed with probability one. In the third case, the borrower misses a payment and the lender returns $(n_{i\ell tw}-1)\, r_t L_{i\ell t}$ to them and resets the loan. We assume the borrower consumes this extra cash immediately and does not save it for payments in following weeks.[23] The borrower also is harassed with probability $p_{i\ell t}^{\eta}$. In the final case, the loan is already fully repaid and the borrower consumes their entire cash from that week. If the loan is still unpaid by the terminal week W, the borrower must work for the lender to repay the loan.[24]

Borrower i discounts expected payoffs w weeks in the future with a discount factor $\beta_i \delta_i^w$. The term $\delta_i \in (0,1)$ is the weekly discount factor and $\beta_i \in (0,1]$ denotes the degree of present bias of borrower i. The expected present discounted value of borrowing from lender ℓ with a loan of size $L_{i\ell t}$ is then:

$$v_{i\ell t}\left(L_{i\ell t}\right) = \mathbb{E}\left[u_{i\ell t1}\left(L_{i\ell t}\right) + \sum_{w=2}^{W} \beta_i \delta_i^{w-1} u_{i\ell tw}\left(L_{i\ell t}\right)\right]$$

[23] This is based on the low savings rate observed by the borrowers in our data and from interviews we have carried out.

[24] We specify the exact payoffs in this case in the Online Appendix A.7.2.

3.4.2 Borrower Expected Payoffs from a Lender

The borrower does not observe the lender's value of the outside option, $\widetilde{\varepsilon}_{i\ell t}$. Therefore, when a borrower is choosing a lender, they are uncertain about whether the lender will give them their desired loan amount. If the lender refuses to lend $L_{it}^{\star}$ to the borrower, the borrower will ask for a smaller amount. they will continue asking for smaller amounts until the lender either accepts or has rejected all the loan requests. We assume the borrower asks for loans with different sizes in the following order: $L_{it}^{\star}$, then $\frac{2}{3}L_{it}^{\star}$, then $\frac{1}{2}L_{it}^{\star}$, then finally $\frac{1}{3}L_{it}^{\star}$. If the lender refuses all requests, the borrower leaves without a loan. We denote $\mathfrak{L}_{it} = \left\{0, \frac{1}{3}L_{it}^{\star}, \frac{1}{2}L_{it}^{\star}, \frac{2}{3}L_{it}^{\star}, L_{it}^{\star}\right\}$ as the set of possible loan sizes the borrower could receive.

We assume the lender's outside option is independent across requests and define $p_{i\ell t}^{L}\left(L_{i\ell t}\right)$ as the probability that borrower i will receive a loan of size $L_{i\ell t}$ from lender ℓ at time t if they approach them.

If a borrower takes out a loan with a lender for the first time, then they also do not know the lender's harshness. They only learn this after they have taken out the loan. The repayment probabilities, loan sizes and harassment probabilities differ by the lender's harshness type. Each lender type k is one of "low", "medium" or "high", where "low" is the least harsh type of lender. All lenders of the same type are equally harsh conditional on the time period, loan size and relationship history. We denote by $v_{i\ell(k)t}\left(L_{i\ell(k)t}\right)$ the borrower's expected discounted payoff from a loan of size $L_{i\ell(k)t}$ from lender ℓ if lender ℓ was type k. The probability that lender ℓ of type k will give the borrower a loan of size $L'_{i\ell(k)t}$ is given by $p_{i\ell(k)t}^{L}\left(L'_{i\ell(k)t}\right)$. We denote by $\pi_{\ell t}^{k}$ the prior probability that lender ℓ is of type k at time t.

If the lender type is unknown, the borrower takes expectations over possible lender types, and possible loan sizes for each type. If the type is known, the borrower takes expectations only over the possible loan sizes. We denote by $h_{i\ell t} \in \mathbb{N}$ the number of loans borrower i has taken out with lender ℓ in the past

before time t. The expected discounted payoff of choosing lender ℓ is then:

$$V_{i\ell t} = \begin{cases} \sum_{k=1}^{K} \pi_{\ell t}^{k} \left[\sum_{L'_{i\ell(k)t} \in \mathfrak{L}_{it}} p_{i\ell(k)t}^{L} \left(L'_{i\ell(k)t} \right) v_{i\ell(k)t} \left(L'_{i\ell(k)t} \right) \right] + \varepsilon_{i\ell t} & \text{if } h_{i\ell t} = 0 \\ \sum_{L'_{i\ell t} \in \mathfrak{L}_{it}} p_{i\ell t}^{L} \left(L'_{i\ell t} \right) v_{i\ell t} \left(L'_{i\ell t} \right) + \varepsilon_{i\ell t} & \text{if } h_{i\ell t} > 0 \end{cases}$$

where $\varepsilon_{i\ell t}$ is a Type I extreme value borrower-lender-time-specific match value shock. If the borrower chooses the outside option of not taking out a loan, they obtain the following payoff:

$$V_{i0t} = \mathbb{E} \left[\frac{m_{i0t1}^{1-\gamma_i} - 1}{1-\gamma_i} + \sum_{w=2}^{W} \beta_i \delta_i^{w-1} \frac{m_{i0tw}^{1-\gamma_i} - 1}{1-\gamma_i} \right] + \varepsilon_{i0t}$$

where ε_{i0t} a Type I extreme value shock to the match value of the outside option. When taking the outside option, the borrower simply consumes their weekly cash, m_{i0tw}, each week.

3.4.3 Lender Choice

The borrower chooses the lender or outside option which maximizes their payoff. The borrower chooses lender $\ell \in \{0\} \cup \mathcal{L}_{it}$ if $V_{i\ell t} > \max_{\ell' \in \mathcal{L}_{it} \setminus \{\ell\}} V_{i\ell' t}$. Let $\bar{V}_{i\ell t}$ and $\bar{V}_{i0t}$ be the expected present discounted value of choosing lender ℓ and the outside option respectively excluding the match value shocks. Before the realization of the match value shock, the probability of choosing lender ℓ is then given by:

$$\Pr \left(V_{i\ell t} > \max_{\ell' \in \{0\} \cup \mathcal{L}_{it} \setminus \{\ell\}} V_{i\ell' t} \right) = \frac{\exp \left(\bar{V}_{i\ell t} \right)}{\sum_{\ell' \in \{0\} \cup \mathcal{L}_{it}} \exp \left(\bar{V}_{i\ell' t} \right)}$$

Although we model the borrower's choice of lender as a complex dynamic problem, we note that due to the high level of present bias and high discount rate present in our sample, borrowers weight the initial utility of receiving the loan much higher than the following repayments and harassment. However, we do not believe borrowers are cognitively impaired or use biased and simple heuristics we deciding to take out a loan. Borrowers in this market take out

loans very frequently and understand how loans are structured. In our surveys we asked borrowers mathematical questions about the loan structure and only 2 of the 1,090 borrowers answered questions incorrectly.

4 Estimation

We estimate the components of our model in a series of steps using maximum likelihood and simulated maximum likelihood. We discuss each of these in turn.

4.1 Borrower Weekly Repayment Probabilities

We model the borrower's cashflow $m_{i\ell t}$ and the lender's expectation of the borrower's cashflow $\widetilde{m}_{i\ell t}$ as a linear function of borrower characteristics, the lender type, the lending history, whether the loan was sought under the influence of alcohol, and whether it is pre- or post-crackdown:

$$m_{i\ell t} = \boldsymbol{x}_{i\ell t}^{m} \cdot \boldsymbol{\theta}^{m}$$
$$\widetilde{m}_{i\ell t} = \boldsymbol{x}_{i\ell t}^{\widetilde{m}} \cdot \boldsymbol{\theta}^{\widetilde{m}}$$

The parameterizations of $m_{i\ell t}$ and $\widetilde{m}_{i\ell t}$ differ in that the lender does not use unobservable borrower characteristics to form their estimate of the borrower's repayment probability. For example, we include the borrower's drug addictions and gang affiliation in our parameterization of $m_{i\ell t}$ but not $\widetilde{m}_{i\ell t}$. Instead, the lender relies more heavily on the past lending relationship to form their beliefs. We also add the borrower's weekly income to $m_{i\ell t}$ and $\widetilde{m}_{i\ell t}$.

We model the variance of the stochastic component of the borrower's cashflow σ_i as a function of the borrower's gambling habits:

$$\sigma_i = \boldsymbol{x}_i^{\sigma} \cdot \boldsymbol{\theta}^{\sigma}$$

We normalize the constant term in $\boldsymbol{\theta}^{\sigma}$ to 1 as it is not separately identified from the constant term in $\boldsymbol{\theta}^{m}$. This means that for borrowers that do not

gamble, we normalize $\sigma_i = 1$. As these habits are unobserved by the lender, we normalize $\widetilde{\sigma}_i = 1$ for all borrowers.

To estimate $\boldsymbol{\theta}^m$, $\boldsymbol{\theta}^\sigma$, and $\boldsymbol{\theta}^{\widetilde{m}}$ we use the observed number of weeks to repay and the number of missed payments. We do this separately for the probabilities from the borrower's perspective and the lender's perspective. While we observe the total number of weeks to repay and the total number of missed payments, we do not observe the exact weeks when these missed payments occurred. Therefore we estimate the repayment probability parameters by maximizing the likelihood of observing the exact number of weeks and missed payments according to our model. The probability that the borrower completes the loan in w weeks with f missed payments according to our model is:

$$C_f^w \left[p_{i\ell t}^m \left(L_{i\ell t}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right)\right]^{w-f-1} \left[1 - p_{i\ell t}^m \left(L_{i\ell t}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right)\right]^f \tag{2}$$

where C_f^w is the number of possible ways a borrower can miss f payments in w weeks under the structure of the loan.[25]

The probability that the loan reaches the terminal period unpaid is:

$$1 - \sum_{w=1}^{W} \sum_{f=0}^{w} C_f^w \left[p_{i\ell t}^m \left(L_{i\ell t}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right)\right]^{w-f-1} \left[1 - p_{i\ell t}^m \left(L_{i\ell t}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right)\right]^f$$

Let $w_{i\ell t}$ be the observed number of weeks to repay and let $f_{i\ell t}$ be the observed number of missed payments. Furthermore, let $d_{i\ell t} \in \{0, 1\}$ denote whether the borrower failed to complete the loan by the terminal week W. The probability

[25] For example, there is only one way to complete a loan in 10 weeks with 1 missed payment: missing the payment in week 4. However, there are 2 ways to complete a loan in 10 weeks with 2 missed payments: missing weeks 2 and 4 or missing weeks 3 and 4. We provide further details on C_f^w in Section A.8 in the Online Appendix.

of observing $(w_{i\ell t}, f_{i\ell t}, d_{i\ell t})$ according to the model is then:

$$\begin{aligned} &L_{1i\ell t}\left(\boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right) = \\ &\quad \left(1 - d_{i\ell t}\right) C_{f_{i\ell t}}^{w_{i\ell t}} \left[p_{i\ell t}^m\left(L_{i\ell t}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right)\right]^{w_{i\ell t} - f_{i\ell t} - 1} \left[1 - p_{i\ell t}^m\left(L_{i\ell t}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right)\right]^{f_{i\ell t}} \\ &\quad + d_{i\ell t}\left(1 - \sum_{w=1}^{W}\sum_{f=0}^{w} C_f^w \left[p_{i\ell t}^m\left(L_{i\ell t}, \boldsymbol{\theta}^m\right)\right]^{w-f-1} \left[1 - p_{i\ell t}^m\left(L_{i\ell t}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right)\right]^f\right) \end{aligned}$$

We estimate $\boldsymbol{\theta}^m$ and $\boldsymbol{\theta}^\sigma$ with maximum likelihood:

$$\left(\widehat{\boldsymbol{\theta}}^m, \widehat{\boldsymbol{\theta}}^\sigma\right) = \underset{\boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma}{\arg\max} \sum_{i=1}^{I}\sum_{t \in \mathcal{T}_i} \log\left(L_{1i\ell t}\left(\boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right)\right)$$

where $\mathcal{T}_i$ is the set of time periods we observe borrower i taking out loans.

We define the likelihood $L_{2i\ell t}\left(\boldsymbol{\theta}^{\widetilde{m}}\right)$ for the lender's estimate of the borrower's repayment probability analogously, where we replace $p_{i\ell t}^m\left(L_{i\ell t}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right)$ with $p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \boldsymbol{\theta}^{\widetilde{m}}\right)$.[26]

4.2 Probability of Harassment

We allow the probability of harassment to vary by lender type, pre- and post-crackdown, the loan size, and the length of the borrower-lender relationship. We parameterize the harassment probability, $p_{i\ell t}^\eta$, as:

$$p_{i\ell t}^\eta\left(\boldsymbol{\theta}^\eta\right) = \Phi\left(\boldsymbol{x}_{i\ell t}^\eta \cdot \boldsymbol{\theta}^\eta\right)$$

To estimate $\boldsymbol{\theta}^\eta$ we use whether or not severe harassment was used in the loan, and the observed number of missing payments, length of time to repay, and whether the loan reached the terminal week. In our data, we observe if harassment was used at the loan level, but we do not observe the exact number of times harassment was used. For example, for a loan with three missed payments, we may observe if the lender splashed paint on the borrower's home and harassed a family member. However, we do not observe if these tactics were

[26] We specify the likelihood explicitly in section A.9 in the Online Appendix.

used on separate occassions for different missed payments, or if these tactics were used at the same time in response to a single missed payment. Therefore we estimate the harassment probability using the likelihood that harassment is used at least once given the observed number of missed payments.

Recall that if a borrower misses one payment, the lender will harass the borrower with probability $p^{\eta}_{i\ell t}(\boldsymbol{\theta}^{\eta})$. If the borrower misses two payments in a row, the lender will harass the borrower with probability 1 after the second missed payment. We do not observe in our data if a borrower missing multiple payments ever missed two payments in a row. We use the number of missed payments combined with the number of possible ways a loan can have two missed payments in a row given the time taken to repay to estimate the harassment probability. We denote by $\mathfrak{h}_{i\ell t} \in \{0,1\}$ whether or not harassment was used at least once in a loan and we denote by $\Pr(\mathfrak{h}_{i\ell t}=1|w_{i\ell t}, f_{i\ell t}, d_{i\ell t}, \boldsymbol{\theta}^{\eta})$ the probability of harassment occurring at least once given $w_{i\ell t}$, $f_{i\ell t}$ and $d_{i\ell t}$. This is given by:

$$\begin{aligned}
&\Pr(\mathfrak{h}_{i\ell t}=1|w_{i\ell t}, f_{i\ell t}, d_{i\ell t},) = \\
&\quad (1-d_{i\ell t})\left(\frac{\widehat{\widehat{C}}^{w_{i\ell t}}_{f_{i\ell t}} + \left(C^{w_{i\ell t}}_{f_{i\ell t}} - \widehat{\widehat{C}}^{w_{i\ell t}}_{f_{i\ell t}}\right)\left(1-[1-p^{\eta}_{i\ell t}(\boldsymbol{\theta}^{\eta})]^{f_{i\ell t}}\right)}{C^{w_{i\ell t}}_{f_{i\ell t}}}\right) \\
&+ d_{i\ell t}\left(\frac{\widehat{\widehat{C}}^{d}_{f_{i\ell t}} + \left(C^{d}_{f_{i\ell t}} - \widehat{\widehat{C}}^{d}_{f_{i\ell t}}\right)\left(1-[1-p^{\eta}_{i\ell t}(\boldsymbol{\theta}^{\eta})]^{f_{i\ell t}}\right)}{C^{d}_{f_{i\ell t}}}\right)
\end{aligned}$$

Here, C^{w}_{f} is the same as in equation (2): it is the number of ways a loan can finish in w weeks with f missed payments. The other terms $\widehat{\widehat{C}}^{w}_{f}$, C^{d}_{f} and $\widehat{\widehat{C}}^{d}_{f}$ are defined as follows. $\widehat{\widehat{C}}^{w}_{f}$ is the number of ways a loan can have two missed payments in a row when finishing in w weeks with f missed payments. C^{d}_{f} is the number of ways a loan can reach the terminal week with f missed payments. Finally, $\widehat{\widehat{C}}^{d}_{f}$ is the number of ways a loan can have two missed payments in a row when reaching the terminal week with f missed payments.

For some examples of how this formula works, suppose a borrower finishes a loan with no missed payments ($f_{i\ell t} = 0$). Then the harassment probability is zero. This is because $\widehat{\widehat{C}}_0^w = 0$: there are no possible ways for two missed payments in a row if the borrower does not miss a payment. If the borrower finishes a loan with only one missed payment, the harassment probability is $p_{i\ell t}^{\eta}(\boldsymbol{\theta}^{\eta})$. This is because $\widehat{\widehat{C}}_1^w = 0$ as there are no possible ways to finish a loan with two missed payments in a row when there is only one missed payment. If the borrower finishes a loan in 9 weeks with 2 missed payments, the harassment probability is 1. This is because there is only 1 way to finish a loan with 9 weeks with 2 missed payments: to miss in both weeks 2 and 3. Thus the only way a loan can finish in 9 weeks with 2 missed payments is with two missed payments in a row, so $\widehat{\widehat{C}}_1^9 = C_2^9 = 1$. Finally, if the borrower finishes a loan in 10 weeks with 2 missed payments, the harassment probability is $\left(1 + \left(1 - \left[1 - p_{i\ell t}^{\eta}(\boldsymbol{\theta}^{\eta})\right]^2\right)\right)/2$. This is because a loan that finishes in 10 weeks either had a missed payment in weeks 2 and 4 or weeks 3 and 4. So $C_2^{10} = 2$ and $\widehat{\widehat{C}}_2^{10} = 1$. Therefore either there were two separate missed payments or two missed payments in a row, with both equally likely according to the model.

The likelihood of observing the harassment observed in the data is then:

$$\begin{aligned} L_{3i\ell t}(\boldsymbol{\theta}^{\eta}) =& \mathfrak{h}_{i\ell t} \Pr\left(\mathfrak{h}_{i\ell t} = 1 | w_{i\ell t}, f_{i\ell t}, d_{i\ell t}, \boldsymbol{\theta}^{\eta}\right) \\ &+ \left(1 - \mathfrak{h}_{i\ell t}\right)\left[1 - \Pr\left(\mathfrak{h}_{i\ell t} = 1 | w_{i\ell t}, f_{i\ell t}, d_{i\ell t}, \boldsymbol{\theta}^{\eta}\right)\right] \end{aligned}$$

We estimate $\boldsymbol{\theta}^{\eta}$ with maximum likelihood.

4.2.1 Lender Harassment Cost

We parameterize the expected cost of harassment, $\kappa_{\ell t}$, as follows:

$$\kappa_{\ell t} = \sum_{k=1}^{K} \left(\theta_{k(\ell)}^{\kappa} + \theta_{k(\ell)}^{\kappa,post} Post_t\right)$$

We allow the harassment cost to vary across lender types, k, and before and after the crackdown, where $Post_t = 1$ after the crackdown. We group these

parameters into $\boldsymbol{\theta}^{\kappa} = \left(\{\theta^{\kappa}, \theta^{\kappa,post}\}_{k=1}^{K}\right)$.

We estimate the lender harassment costs using the observed loan sizes in the data. Given a trial value of $\boldsymbol{\theta}^{\kappa}$ and the estimated repayment probabilities, $p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}\right)$ and harassment probabilities $p_{i\ell t}^{\eta}\left(\widehat{\boldsymbol{\theta}}^{\eta}\right)$, we can calculate the expected present discounted value of a loan for the lender, $\widetilde{V}_{i\ell t}\left(L_{i\ell t}, \boldsymbol{\theta}^{\kappa}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^{\eta}\right)$. We assume the lender's weekly discount factor is $\widetilde{\delta} = 0.999$, corresponding to an annual discount factor of 0.95.[27] Due to the very large number of possible loan repayment paths, we do not calculate this expected value exactly. Instead we simulate 10,000 repayment paths using the lender's estimate of the repayment probability and take the average lender payoff.[28]

Given the logistic distribution assumption on the lender's outside option, the probability that the lender will give the borrower their full desired loan size is:

$$p_{i\ell t}^{L}\left(L_{it}^{\star}, \boldsymbol{\theta}^{\kappa}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^{\eta}\right) = \frac{\exp\left(\widetilde{V}_{i\ell t}\left(L_{it}^{\star}, \boldsymbol{\theta}^{\kappa}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^{\eta}\right)\right)}{1 + \exp\left(\widetilde{V}_{i\ell t}\left(L_{it}^{\star}, \boldsymbol{\theta}^{\kappa}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^{\eta}\right)\right)}$$

The probability that the lender will reject $L_{it}^{\star}$, but accept a smaller loan size is shown in A.10 in the Online Appendix for all other loan sizes, giving $p_{i\ell t}^{L}\left(L_{i\ell t}, \boldsymbol{\theta}^{\kappa}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^{\eta}\right)$ for all $L_{i\ell t} \in \mathfrak{L}_{it}$.

The likelihood is the probability of the lender choosing the loan size we observe in the data:

$$L_{4i\ell t}\left(\boldsymbol{\theta}^{\kappa}\right) = p_{i\ell t}^{L}\left(L_{i\ell t}, \boldsymbol{\theta}^{\kappa}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^{\eta}\right)$$

We estimate $\boldsymbol{\theta}^{\kappa}$ with simulated maximum likelihood.

[27] This is a common annual discount factor used in empirical settings, such as in Holmes (2011), Dunne et al. (2013) and Collard-Wexler (2013). We have also elicited the discount factor from two ex-lenders and found them to be consistent with this assumption.

[28] We have computed the expectation exactly to confirm that our simulation approach is accurate. However, because this calculation is very computationally expensive and needs to be calculated many times in estimation, we choose to use the simulation approach.

4.3 Borrower Harassment Disutility

4.3.1 Parameterization

The final estimation step is to estimate the borrower harassment disutility parameters. We parameterize $\chi_{\ell t}$ as follows:

$$\chi_{\ell t} = \sum_{k=1}^{K} \left(\theta^{\chi}_{k(\ell)} + \theta^{\chi,post}_{k(\ell)} Post_t \right)$$

We allow the disutility from harassment to vary by lender type, and we allow this to change after the crackdown. We group these parameters into $\boldsymbol{\theta}^{\chi} = \left(\{\theta^{\chi}, \theta^{\chi,post}\}_{k=1}^{K} \right)$.

In order to calculate a borrower's choice probabilities over time, we also need to specify their consideration sets of lenders, potential loan instances, and priors of the harshness level of new lenders in the consideration sets. We discuss each of these in turn before discussing the calculation of the choice probabilities.

4.3.2 Borrower Consideration Sets

For each borrower in the data we observe the lender they actually chose to borrow from, but we do not observe all the lenders they compare the payoffs of borrowing from for each loan. For the borrower's consideration set at each point in time $\mathcal{L}_{it}$, we assume that they choose between five options: the lender they actually chose, the last two lenders they borrowed from, a new lender they never borrowed from before, and the outside option of not taking out a loan.[29] If the borrower does not have history with other lenders, we add additional new lenders so that all borrowers have five options in their consideration sets.[30] Because borrowers do not have access to formal sector loans, these types of loans are not part of their consideration set.

[29] All the borrowers in our dataset stated that they considered less than than or equal to one new lender for all transactions.

[30] For the first two lenders a borrower borrowed from, we take the first three lenders they actually borrowed from, the outside option and an additional new lender.

For the new lenders, we use the network of lenders to choose a lender close to the borrower's own lender network. The result of this approach is if i's lenders also frequently lend to borrower i', then i's additional lender is one of i''s lenders.[31]

4.3.3 Borrower Potential Loans

In our data we observe the loans the borrowers actually took out, but we do not observe instances where borrowers chose the outside option. That is, instances where they considered taking out a loan but chose not to. Motivated by the literature in the estimation of dynamic entry models (Ryan, 2012; Collard-Wexler, 2013), we introduce potential loan instances for each borrower. We construct these based on the median time interval between loans for each borrower, over the time they were active taking out loans. We do this separately before and after the crackdown, as their loan frequency may change after the crackdown. For a simple example of this approach, suppose we observe a borrower taking out loans in July 2009, January 2010, July 2010, and July 2011. The time intervals are 6, 6, and 12 months. The median number of months is therefore 6 months. For this borrower, we would assume that loan instances arrive every 6 months and they chose the outside option in January 2011. This procedure leads to the average borrower choosing the outside option approximately 4 times, which means the outside option is chosen approximately 40.2% of the time.

4.3.4 Borrower Priors on Lender Harshness

For borrowers borrowing from a lender for the first time, we must specify their prior on the lender being each harshness type. According to our data, borrowers know if the lender they borrowed from were either a small, medium or large lender. Medium-and large-sized lenders are more likely to be harsher and are informative about a lender's harshness for borrowers taking out a loan with them for the first time. We assume the borrower's prior on the probability

[31] The details of this network approach are shown in A.11 in the Online Appendix.

of lender ℓ being type k at time t, $\pi_{\ell t}^{k}$ is equal to the proportion of lenders of that size who are type k in our sample at time t.

4.3.5 Computing the Expected Payoff from a Lender

Given a guess of $\boldsymbol{\theta}^{\chi}$ and estimates $\widehat{\boldsymbol{\theta}}^{m}$, $\widehat{\boldsymbol{\theta}}^{\sigma}$, $p_{i\ell t}^{\eta}\left(\widehat{\boldsymbol{\theta}}^{\eta}\right)$ and $p_{i\ell t}^{L}\left(L_{i\ell t}, \widehat{\boldsymbol{\theta}}^{\kappa}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^{\eta}\right)$, we can calculate the expected payoff of each lender, $\bar{V}_{i\ell t}\left(\boldsymbol{\theta}^{\chi}, \widehat{\boldsymbol{\theta}}^{m}, \widehat{\boldsymbol{\theta}}^{\sigma}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^{\eta}, \widehat{\boldsymbol{\theta}}^{\kappa}\right)$, and the outside option for each borrower. This involves calculating the expected payoff from a loan for each possible loan size and each possible harshness level for new lenders for each lender in the borrower's consideration set. We also calculate the value of the outside option for each borrower.

Due to the large number of possible paths, combined with a large number of different lenders, harshness levels and loan sizes, we compute these expected payoffs via simulation. We use 10,000 paths to calculate these expected payoffs. We first calculate the expected payoff $\mathbb{E}\left[u_{i\ell tw}\left(L_{i\ell t}\right)\right]$ in each possible state for each week. We numerically evaluate the conditional and unconditional expectations in these expressions using Gauss-Hermite quadrature with 200 nodes.[32] We then simulate 10,000 repayment paths for each possible loan using the borrower's repayment probabilities. Using $p_{i\ell t}^{L}\left(L_{i\ell t}, \widehat{\boldsymbol{\theta}}^{\kappa}, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^{\eta}\right)$, we calculate the expected payoff of a lender given a harshness level, and we use the priors $\pi_{\ell t}^{k}$ to calculate the expected payoff of a lender when the harshness level is unknown to the borrower.[33]

4.3.6 Likelihood

To identify the borrower's harassment disutility we use the borrower's observed choice of lender in the data. The likelihood is the probability of choosing the

[32] We provide further details of this numerical integration procedure in the Online Appendix A.12.

[33] Similar to the case with the lender's payoffs, we have calculated the borrower's expected payoffs without simulation (except for the Gauss-Hermite quadrature step) for a smaller value of the terminal week W to confirm the validity of our simulation approach.

lender the borrower actually chose in the data:

$$L_{5i\ell t}\left(\boldsymbol{\theta}^{\chi},\widehat{\boldsymbol{\theta}}^{m},\widehat{\boldsymbol{\theta}}^{\sigma},\widehat{\boldsymbol{\theta}}^{\widetilde{m}},\widehat{\boldsymbol{\theta}}^{\eta},\widehat{\boldsymbol{\theta}}^{\kappa}\right)=\frac{\exp\left(\bar{V}_{i\ell t}\left(\boldsymbol{\theta}^{\chi},\widehat{\boldsymbol{\theta}}^{m},\widehat{\boldsymbol{\theta}}^{\sigma},\widehat{\boldsymbol{\theta}}^{\widetilde{m}},\widehat{\boldsymbol{\theta}}^{\eta},\widehat{\boldsymbol{\theta}}^{\kappa}\right)\right)}{\sum_{\ell'\in\{0\}\cup\mathcal{L}_{it}}\exp\left(\bar{V}_{i\ell' t}\left(\boldsymbol{\theta}^{\chi},\widehat{\boldsymbol{\theta}}^{m},\widehat{\boldsymbol{\theta}}^{\sigma},\widehat{\boldsymbol{\theta}}^{\widetilde{m}},\widehat{\boldsymbol{\theta}}^{\eta},\widehat{\boldsymbol{\theta}}^{\kappa}\right)\right)}$$

We estimate $\boldsymbol{\theta}^{\chi}$ with simulated maximum likelihood.

We note that it would be in principle possible to estimate the full vector of parameters $\boldsymbol{\theta}=\left(\boldsymbol{\theta}^{m},\boldsymbol{\theta}^{\sigma},\boldsymbol{\theta}^{\widetilde{m}},\boldsymbol{\theta}^{\eta},\boldsymbol{\theta}^{\kappa},\boldsymbol{\theta}^{\chi},\right)$ jointly using the products of the five likelihood functions. We prefer to estimate our parameters separately for the following reasons. Due to differences in the average probabilities in each of the likelihoods, the different likelihoods are scaled differently, which gives a different weight to each term. Joint estimation leads to greater weight being placed on likelihoods with smaller probabilities, such as the repayment probabilities. Secondly, the variation in the data that identifies each of the parameters is clearer under separate estimation. Therefore we chose to estimate our parameters in a series of steps, rather than jointly.

5 Estimation Results

The parameter estimates are presented in Tables 2 and 3. Column (1) of Table 2 shows the estimates of the borrower repayment probability parameters, $\boldsymbol{\theta}^{m}$ and $\boldsymbol{\theta}^{\sigma}$.[34] We can see that after the crackdown, borrowers have lower repayment probabilities. In fact, from the borrowers' perspective, the cashflow drops by S$544, while from the lenders' perspective it reduces by S$379. This is partially explained by the lower harassment probabilities after the crackdown, as borrowers had less incentives to make their payments each week. Borrowers borrowing from a lender for the first time have a lower repayment probability, partially explained by those borrowers not having any relationship capital to lose with that lender. Borrowers with some relationship capital are better able to repay, but those with many previous loans are worse. This is because

[34]Based on the modeling approach described in Section 3.3.1, the estimated coefficients in Table 2 can be interpreted in S$ terms when multiplied by 1,000.

	Borrower (1)		Lender (2)	
	$\boldsymbol{\theta}_m$ estimates		$\boldsymbol{\theta}_{\tilde{m}}$ estimates	
Constant	0.823	(0.134)	0.360	(0.087)
Medium harshness lender	0.036	(0.020)	0.010	(0.013)
High harshness lender	0.029	(0.020)	0.001	(0.014)
Post Crackdown	−0.544	(0.025)	−0.379	(0.016)
Medium harshness lender × Post Crackdown	0.019	(0.040)	0.020	(0.027)
High harshness lender × Post Crackdown	−0.019	(0.034)	0.001	(0.023)
No lending history	−0.697	(0.032)	−0.536	(0.021)
Number of previous loans	0.036	(0.008)	0.023	(0.005)
Number of previous loans squared	−0.003	(0.001)	−0.002	(0.000)
Number of missed payments in last loan	−0.084	(0.003)	−0.061	(0.002)
Asked for loan under influence of alcohol	−0.032	(0.015)	−0.024	(0.010)
Age	−0.002	(0.007)	0.008	(0.005)
Age squared	0.000	(0.000)	0.000	(0.000)
Malaysian (relative to Singapore Chinese)	0.052	(0.023)	0.124	(0.014)
Indian (relative to Singapore Chinese)	−0.022	(0.023)	0.068	(0.015)
Female	0.104	(0.024)	0.137	(0.015)
Married (relative to single)	0.020	(0.032)	−0.008	(0.021)
Divorced (relative to single)	0.060	(0.032)	0.015	(0.022)
Has children	−0.055	(0.030)	−0.051	(0.020)
Secondary education	−0.009	(0.020)	−0.035	(0.013)
Number of previous convictions	−0.026	(0.008)		
Current gang member	0.107	(0.025)		
Previously gang member	0.036	(0.017)		
Occasional drug user (relative to non-user)	−0.037	(0.023)		
Frequent drug user (relative to non-user)	−0.006	(0.025)		
Very Frequent drug user (relative to non-user)	0.122	(0.030)		
Regular drinker (relative to non-drinker)	0.031	(0.020)		
Frequent drinker (relative to non-drinker)	0.031	(0.022)		
Frequently uses sex workers	−0.024	(0.031)		
	$\boldsymbol{\theta}_\sigma$ estimates			
Constant	1.000	–	1.000	–
Occasional gambler (relative to non-gambler)	0.575	(0.030)		
Frequent gambler (relative to non-gambler)	0.562	(0.031)		
Very Frequent gambler (relative to non-gambler)	0.542	(0.027)		

Standard errors in parentheses. The 1st column shows the estimates of $\boldsymbol{\theta}_{\tilde{m}}$ which determine the lender's belief in the borrower's weekly repayment probability. The 2nd column shows the estimates of $\boldsymbol{\theta}_m$ and $\boldsymbol{\theta}_\sigma$ which determine the weekly repayment probabilities from borrower's perspective.

TABLE 2: Weekly repayment probability parameter estimates.

borrowers who borrow very often are worse at repaying. Borrowers who asked for the loan under the influence of alcohol have lower repayment ability. Female borrowers on average perform better, as well as those who have never been to prison. Those involved in a gang perform better, because they may have access to more money-making opportunities. Very frequent drug users also perform better, as these heavy users typically also sell drugs. We also estimate that

gamblers have a higher variance in income, compared to non-gamblers.

Column (2) of Table 2 shows the estimate's for the lender's estimate of the repayment probability. These are similar to column (1), and most values have either the same sign or are not statistically different from zero in either case. The difference between these estimates and those in column (1) is that the lender does not observe certain borrower characteristics, such as their addictions, prior convictions, or gang member status.[35]

The parameter estimates relating to harassment are shown in Table 3. Column (1) shows the estimates of the harassment probability parameters, $\boldsymbol{\theta}^{\eta}$. Harsher lenders are more likely to conduct harassment, and after the crackdown, low- and medium-harshness lenders become less likely to conduct harassment. High-harshness lenders, however, increase their harshness after the crackdown. This suggests an asymmetric response in harshness across lenders after the crackdown. While least harsh lenders prefer reducing harassment to minimize the likelihood of arrest, harsher lenders prefer instead to increase harassment to reduce the chance of missed payments, given their lower harassment cost. The harassment probability increases with the loan size, as lenders have a greater incentive to make borrowers repay. Finally, lenders conduct less harassment with new borrowers, and conduct harassment more frequently with borrowers they have had more loans with.

Column (2) shows the estimates of the lender harassment cost parameters, $\boldsymbol{\theta}_{\kappa}$. Harsher lenders have a lower harassment cost, and the harassment cost increases for all lender types after the crackdown. These parameter estimates can be interpreted in terms of S$1,000, so the average cost of harassment increased by S$151 after the crackdown. Based on interviews with ex-runners on the costs of harassment, our estimates are consistent with the typical harassment costs lenders face.

Column (3) shows the borrower harassment disutility parameters, $\boldsymbol{\theta}^{\chi}$. The harassment disutility is lower for high-harshness lenders, because these lenders

[35] We note that we find very little evidence of assortative matching between borrowers of higher repayment abilities and lender types. After controlling for pre- and post-crackdown, the difference in the average weekly repayment probabilities of loans with each lender type differ by less than one percentage point. The average weekly repayment probability is 73.9%.

	Harassment Probability Parameters (1)	Lender Harassment Cost Parameters (2)	Borrower Harassment Disutility Parameters (3)
Constant	−1.888	0.493	4.955
	(0.084)	(0.020)	(0.085)
Medium harshness lender	0.360	−0.065	0.284
	(0.057)	(0.028)	(0.082)
High harshness lender	0.718	−0.127	−1.131
	(0.056)	(0.026)	(0.076)
Post Crackdown	−0.316	0.151	−2.531
	(0.134)	(0.024)	(0.108)
Medium harshness lender × Post Crackdown	0.241	0.005	−0.420
	(0.303)	(0.038)	(0.123)
High harshness lender × Post Crackdown	0.723	0.004	0.155
	(0.195)	(0.032)	(0.098)
Loan size (in S$1,000s)	0.112		
	(0.020)		
No lending history	−0.337		
	(0.122)		
Number previous loans	0.106		
	(0.028)		
Number previous loans squared	−0.008		
	(0.002)		

Standard errors in parentheses.

TABLE 3: Harassment Probability, Cost and Disutility Parameters.

use less severe forms of harassment very frequently, whereas medium-harshness lenders use more severe forms but with less frequency. The harassment disutility decreased after the crackdown, as lenders use harassment more cautiously and used less severe forms due to the risk of arrest. A simple back of the envelope calculation results in borrowers' monetary disutility from harassment, in the pre-crackdown period for low harshness lenders, of approximately S$8,380.

In Table A.8 in the Online Appendix we show how well our model is able to match our data. We simulate loans at the estimated parameters and find that the model is able to match the average number of weeks, number of missed payments, harassment levels and loan sizes on aggregate.

6 The Welfare Effects of Law Enforcement

6.1 Crackdown on Lenders

We use our model estimates to compute the effects of the crackdown on borrower and lender welfare and on the average size of disbursed loans. Because the crackdown caused many lenders to exit the market, we estimate the effect of the crackdown by computing payoffs as if the crackdown happened at the beginning of our sample period. Our sample period spans 2009-2016 and the crackdown occurred in 2014. In this counterfactual simulation, we assume the crackdown happened at the beginning of 2009 instead of 2014, and the effects of the crackdown persisted throughout the entire sample period. We then compare the payoffs and loan sizes between 2009 and 2013 to the baseline scenario of no crackdown to calculate the effect of the increase in enforcement.

We therefore use the variation in outcomes between pre and post crackdown to recover the change in structural parameters that the crackdown induces, and then use the model to simulate a scenario where the crackdown was implemented also in the pre period. We favor this approach relative to comparing welfare before and after the crackdown, because it allows us to compare welfare changes for the same loan instances for each borrower. We also prefer to simulate the crackdown in the early part of the sample rather than undoing the crackdown in the later part of the sample, because we have a considerably larger number of loans in the pre crackdown period.

If a lender exited the market (either voluntarily or due to arrest) in the 2014-2016 period, we remove that lender from all borrowers' consideration sets and replace them accordingly with other lenders that did not exit. We also set the nominal interest rate for 2009-2013 to 35%, the prevailing rate in the post-crackdown period. We also observe that the desired loan sizes of borrowers fell by 45.7% after the crackdown. Because these are treated as exogenous in our model, we scale these down accordingly in 2009-2013. Finally, we use the post-crackdown values for all parameters throughout the entire sample period.

The results of this counterfactual experiment are summarized in Table 4. Because the crackdown increased the interest rate from 20% to 35%, the total

	Baseline	Earlier Crackdown	% Difference
Total lender surplus (in S$m)	18.50	19.93	+7.69%
Low harshness Lender surplus (in S$m)	7.10	11.96	+68.52%
Medium harshness lender surplus (in S$m)	5.73	3.29	−42.52%
High harshness lender surplus (in S$m)	5.68	4.67	−17.72%
Total interest payments (in S$m)	20.22	33.58	+66.10%
Total harassment costs (in S$m)	5.51	13.28	+140.81%
Average loan size (in S$000)	1.36	0.83	−38.80%
Average borrower surplus (in S$000)	0.72	0.24	−67.43%
Average amount paid (in S$000)	3.15	3.77	+19.56%
Average number of weeks	13.98	17.93	+28.21%
Average number of missed payments	3.42	6.10	+78.59%
Average number of times harassed	1.31	2.71	+106.63%

TABLE 4: Welfare effects if the crackdown occurred at the beginning of the sample period.

surplus of lenders increased by 7.7%. However, if we examine the change in surplus for different lender types, we see that the welfare of harsher lenders fell from the crackdown. Only the welfare of low-harshness lenders increased. These lenders benefited from the higher interest rate, but were less effected by the increased cost of harassment as they harass less frequently. Because their surplus increases substantially, their increase dominates the decrease in surplus for medium- and high-harshness lenders.

The crackdown caused the volume of disbursed loans to decrease, with the average loan size falling by 39%. Borrower surplus fell markedly from the crackdown, where we observe a 67.4% decrease. We convert borrower surplus to dollar values by calculating a certainty equivalent amount for each borrower. That is, the amount of money a borrower would need to receive each week over the W weeks to be indifferent between it and the option value of borrowing from lenders. When the crackdown occurs, borrowers receive smaller loans, yet pay more for them with higher interest payments. They also miss more payments, leading to more harassment.

Overall, the crackdown was successful at lowering the volume of loans, reducing the incentives for borrowers to borrow from this market, and hurting

the profits of medium- and high-harshness lenders.

In Table A.9 in the Online Appendix, we decompose the effects of the crackdown by imposing each of the changes one by one. If only the interest rate increases but harassment costs and other effects of the crackdown are unchanged, then the lenders' surplus increases by 50.7%. Lenders give larger loans but borrowers miss more payments and are harassed more often. Overall borrower surplus decreases by 21.4%. If we only impose the post-crackdown parameter values which affect the repayment probabilities and harassment probabilities, costs and disutilities, then the welfare of borrowers and lenders decrease. However, borrower surplus does not decrease as much as the earlier crackdown case because the interest rate remains at 20%. If we only consider the effect of lender exit and arrests, borrower surplus decreases by only 2%. These exits and arrests destroys some of the relationship capital built by borrowers, but have only a small effect on their welfare.

6.2 Targeting Borrowers

As an alternative market intervention, we consider the effect of removing different types of borrowers on lender welfare. We sort borrowers by their average loan repayment probability and group them into ten groups such that the sum of the desired loan size within each group is approximately equal. Thus each group, or decile, has a similar size in terms of loan demand but differ by their repayment ability. We consider the effect of removing each of these groups in turn on lender welfare and other loan outcomes. These borrowers could be removed in practice by either offering them formal-market alternatives, providing rehabilitation for their gambling and drug use, or educating them on the perils of borrowing from loan sharks.

The results of this counterfactual experiment are shown in Figure 4. We find that removing the worst borrowers (decile 1) is the least effective at lowering lender welfare. This is because these borrowers are more costly for lenders to serve as they miss many payments, leading to high harassment costs. Lenders often reject loans to these borrowers and only give them smaller

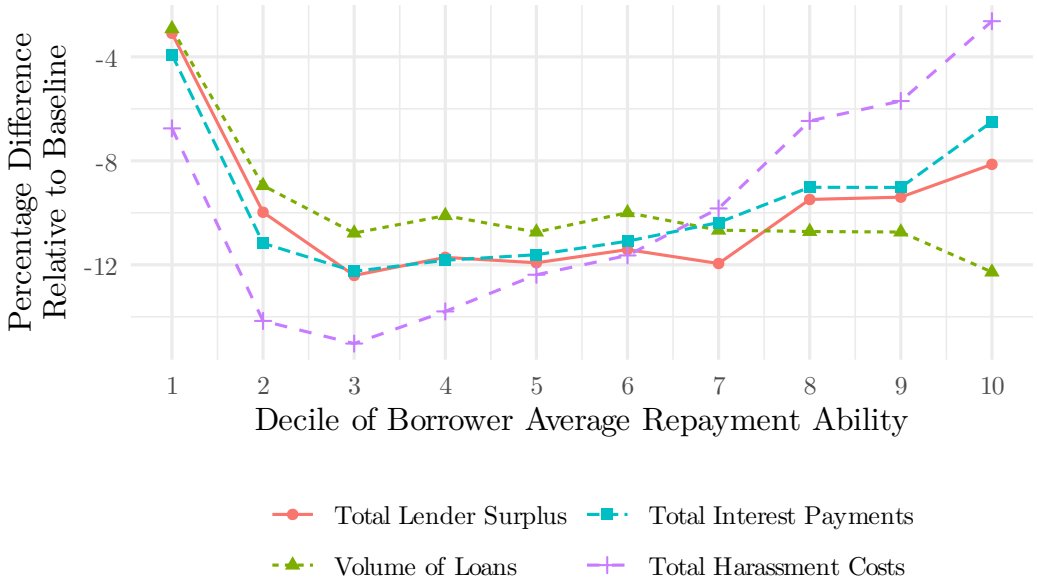


FIGURE 4: Welfare effects of targeting borrowers on lenders.

loan sizes such that they are better able to repay them. Removing borrowers from the middle of the distribution, between deciles 3 and 7, hurts lenders the most. These borrowers are the most profitable for the lender because they miss a small number of payments, leading to greater payment penalty revenue for the lender, but do not miss too many payments such that they need to be harassed very frequently. Removing the borrowers with the highest repayment ability (decile 10) lowers the volume of loans the most, but does not impact the lenders' profits as much. This is because these borrowers do not miss many payments and earn the lenders less in interest payment revenue, although they are also less costly to serve. Therefore targeting borrowers in the center of the repayment ability distribution is the most effective at hurting lender profits.

The characteristics of borrowers that represent the best and worst borrowers can be seen in the parameter estimates in Table 2. Targeting borrowers with a higher ability to repay, apart from the very highest, is the most effective strategy to affect lenders. Those with a gang affiliation, who are often selling drugs, have a higher repayment ability. Therefore enforcement efforts

targeting drug pushers also can have a large knock-on effect on the lenders in the loan shark market.

7 Conclusion

Illegal money lending has been prevalent across many societies throughout history for millennia, and laws attempting to curb loansharking have existed as long written records exist. However, due to a lack of high-quality data on loansharking, empirical studies of this illegal market are scarce. We use highly detailed survey data from over one thousand borrowers to estimate a structural model of the illegal money lending market in Singapore. We use this model to evaluate the welfare effects of a large enforcement crackdown that occurred in this market during our sample period, and to evaluate alternative policy interventions. We find that the crackdown was highly successful at lowering the payoffs of harsh lenders and borrowers in this market, as well as lowering the total volume of loans disbursed. Removing borrowers from the market, either through offering formal market alternatives, rehabiliation or education programs, also hurts lenders, particularly if they focus on medium- and high-performing borrowers in terms of loan repayment time.

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A.1 Harassment Methods

Table A.1 shows the frequency of different harassment methods used by loan sharks in the loans in our data. Multiple harassment methods were possible for each loan and hence the proportions do not sum to one.

Harassment Method Type	Proportion of Loans
Verbal threat	0.429
Shout at borrower in his/her neighborhood	0.020
Stalk borrower in a public venue and shout at him/her	0.001
Harass borrower in his/her workplace	0.003
Splash paint or kerosene in borrower's building	0.059
Harass borrower's family members or friends	0.021
Harass neighbors	0.023
Body attack or torture	0.000
Use or threat to use ID(s) in lender's hand for crime	0.018
Phone harassment or reminder call	0.511
Send letter, note or threatening message	0.269
Throw flowerpot at borrower	0.007
Scribble on borrower's property	0.066
Graffiti on borrower's property	0.030
Knock borrower's door or gate	0.173
Block borrower's door (e.g. putting superglue in key holes)	0.003
Visiting borrower's home	0.011
Visiting borrower's workplace	0.018
Scratch & splash paint on borrower's car	0.000

TABLE A.1: Harassment methods used by loan sharks.

A.2 Reasons for Taking out Loans

Table A.2 shows the reasons borrowers gave for taking out loans. Borrowers could give multiple responses per loan and hence the proportions do not sum to one.

A.3 Classifying Lenders into Types

Because we do not observe lender characteristics directly, we classify lenders into types based on the observed frequency of different types of harassment conditional on the number of missed payments and the borrowers taking out the loan. We regress a dummy for if severe harassment was used on dummies for the number of missed payments, borrower dummies and lender dummies. We include separate lender dummies for pre- and post-crackdown to allow

Reason	Proportion of Loans
Paying rent	0.046
Children's education	0.029
Paying hospital fees	0.012
Buying alcohol or drugs	0.479
Gambling or buying lottery tickets	0.551
Treating friends	0.144
Business needs	0.049
Others	0.006
Paying bills	0.213
Sex worker, girlfriend, or KTV	0.130
Child medical fee	0.005
Paying gambling debt	0.132
Paying credit card debt	0.047
Paying lender	0.343
Paying company creditor	0.034
Holidays or special celebrations	0.021
Loan sharing with friends in need	0.008
Supporting family	0.004
Marriage	0.001
Vehicle	0.002
Guarantor for others	0.004
Pay debts for others	0.004
Renovations	0.001
Lawyer fees	0.001
Paying other debt	0.019
Bank loan installment	0.012
Helping Friend to Borrow	0.000

TABLE A.2: Reasons for taking out loans.

these to change after the increase in enforcement. We then classify lenders into low, medium and high types based on the values of the estimated fixed effects. We do this in such a way that the volume of loans from each lender type is approximately equal.

High-type lenders conduct harassment more often than low-type lenders both before and after the crackdown. Before the crackdown, high-type lenders were the most common, representing 43% of lenders. After the crackown, low

	Proportion with harassment		Number of lenders	
	Pre	Post	Pre	Post
Lender type	(1)	(2)	(3)	(4)
Low type	0.34	0.65	281	195
Medium type	0.53	0.86	103	52
High type	0.74	0.95	289	150

Columns (1) and (2) show the share of loans that had harassment for each lender type before and after the crackdown, respectively. Columns (3) and (4) show the number of lenders of each type before and after the crackdown, respectively.

TABLE A.3: Lender types.

type lenders became dominant at 49%. These figures are shown in Table A.3.

A.4 Borrower Weekly Discount Rates and Present Bias

We calculate each borrower's weekly discount factor and present bias factor as follows. In the survey, we asked borrowers what they would need to receive in ten months to be equivalent to receiving S$800 in nine months. Let X_i^δ be the amount stated by borrower i for this question. We assume that this the X_i^δ that solves:

$$\beta_i \delta_i^{\left(\frac{9}{12} \times \frac{365.25}{7}\right)} 800 = \beta_i \delta_i^{\left(\frac{10}{12} \times \frac{365.25}{7}\right)} X_i^\delta$$

where δ_i is the weekly discount factor and β_i is the present-bias term. Thus the weekly discount factor for borrower i is:

$$\delta_i = \left(\frac{800}{X_i^\delta}\right)^{12 \times \frac{7}{365.25}} \tag{3}$$

In the survey, we also asked borrowers what they would need to receive in one month to be equivalent to receiving S$500 now. Let X_i^β be the amount stated by borrower i for this question. We assume that this the X_i^β that solves:

$$\beta_i \delta_i^{\left(\frac{1}{12} \times \frac{365.25}{7}\right)} X_i^\beta = 500$$

Using the δ_i from equation (3) and solving for β_i yields:

$$\beta_i = \left(\frac{500}{X_i^{\beta}}\right) \frac{1}{\delta_i^{\left(\frac{1}{12} \times \frac{365.25}{7}\right)}} = \left(\frac{500}{X_i^{\beta}}\right) \left(\frac{800}{X_i^{\delta}}\right)$$

A.5 Borrowers' Coefficients of Relative Risk Aversion

We calculate each borrower's coefficient of relative risk aversion as follows. In our survey, we asked borrowers to choose between a gamble and a certain amount in three different scenarios. In each scenario there was a gamble which was to win S$1,000 with 50% probability and S$0 otherwise. The alternative in each scenario was a varying certain amount. These were S$300, S$350, and S$400. The borrower's utility function is $u(c) = (c^{1-\gamma_i} - 1) / (1 - \gamma_i)$, where γ_i is the coefficient of relative risk aversion.

We assume a baseline wealth of zero, which for the borrowers in our sample is a close approximation. Let $\bar{c} \in \{0.3, 0.35, 0.4\}$ be the certain amount in S$1,000s. A borrower indifferent between the certain amount $\bar{c}$ and the gamble which wins S$1,000 with probability 0.5 and S$0 otherwise has a coefficient of relative risk aversion, $\gamma_{\bar{c}}$, that satisfies:

$$\frac{\bar{c}^{1-\gamma_{\bar{c}}} - 1}{1 - \gamma_{\bar{c}}} = 0.5 \times \frac{1^{1-\gamma_{\bar{c}}} - 1}{1 - \gamma_{\bar{c}}} + \frac{1}{2} \times \frac{0^{1-\gamma_{\bar{c}}} - 1}{1 - \gamma_{\bar{c}}}$$

Canceling terms yields::

$$\bar{c}^{1-\gamma_{\bar{c}}} = 0.5$$

Solving for $\gamma_{\bar{c}}$ yields:

$$\gamma_{\bar{c}} = 1 - \frac{\log(0.5)}{\log(\bar{c})} = 1 + \frac{\log(2)}{\log(\bar{c})}$$

These indifference points are $\gamma_{\bar{c}} \in \{0.424, 0.340, 0.244\}$ for $\bar{c} \in \{0.3, 0.35, 0.4\}$. We use the survey data to give borrowers a coefficient of relative risk aversion as follows. If borrower i would take the gamble with $\bar{c} = 0.3$ but the certain amount at $\bar{c} = 0.35$, we assume $\gamma_i = \frac{\gamma_{0.3} + \gamma_{0.35}}{2}$. Similarly, if borrower i would

Coefficient	Number of Borrowers
0.195	83
0.292	417
0.382	374
0.806	216

TABLE A.4: Number of borrowers with each possible coefficient of relative risk aversion.

take the gamble with $\bar{c} = 0.35$ but the certain amount at $\bar{c} = 0.4$, we assume $\gamma_i = \frac{\gamma_{0.35}+\gamma_{0.4}}{2}$. If borrower i would always take the gamble, we assume $\gamma_i = \gamma_{0.4} - \frac{\gamma_{0.35}-\gamma_{0.4}}{2}$. If borrower i would always take the certain amount, we assume $\gamma_i = \gamma_{0.3} + \frac{\gamma_{0.3}-\gamma_{0.35}}{2}$. Thus we assume an upper and lower bound on their level of risk aversion. However, borrowers at the extremes are a minority. A table of the number of borrowers with each value is shown in Table A.4. The majority of borrowers would take the gamble over the certain S$300, but would take the certain S$400 over the gamble.

A.6 Summary of Model Notation

Tables A.5 and A.6 summarize the notation we use in our modeling. We order the terms alphabetically, split by Greek and Latin letters.

A.7 Terminal Week Payoffs

A.7.1 Lender

If the borrower reaches the terminal week W, the borrower is made to work for the lender to finish paying off the loan. This gives the lender an immediate payoff of the outstanding amount plus a mean-zero shock $\xi_{i\ell t}$. This shock captures that sometimes the lender does not have a suitable job for the borrower and earns less than the amount outstanding, whereas other times the lender has a very lucrative and valuable task that is worth more than the amount outstanding.

β_i	Borrower i's present bias factor (quasihyperbolic discounting).
γ_i	Borrower i's coefficient of relative risk aversion.
δ_i	Borrower i's weekly discount factor.
$\widetilde{\delta}$	The lender's weekly discount factor (same for all lenders).
$\varepsilon_{i\ell t}$	Borrower's lender-specific match value shock.
$\widetilde{\varepsilon}_{i\ell t}\left(L_{i\ell t}\right)$	Lender's value of their outside option.
$\kappa_{\ell t}$	Lender's expected cost of harassment.
$\boldsymbol{\theta}$	Vector of structural parameters: $\boldsymbol{\theta} = \left(\boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma, \boldsymbol{\theta}^{\widetilde{m}}, \boldsymbol{\theta}^\eta, \boldsymbol{\theta}^\kappa, \boldsymbol{\theta}^\chi, \right)$
$\nu_{i\ell tw}$	Borrower's shock to their weekly cashflow, where $\nu_{i\ell tw} \sim \mathcal{N}\left(0, \sigma_i^2\right)$
$\widetilde{\nu}_{i\ell tw}$	Borrower's shock to their weekly cashflow from the lender's perspective, where $\widetilde{\nu}_{i\ell tw} \sim \mathcal{N}\left(0, \widetilde{\sigma}_i^2\right)$
$\pi_{\ell t}^k$	Prior probability lender ℓ is type k at time t.
$\chi_{\ell t}$	Borrower's disutility from harassment.
C_f^w	Number of possible combinations a borrower can complete a loan in w weeks with f missed payments.
$\widehat{\widehat{C}}_f^w$	Number of possible ways a borrower can miss two payments in a row in a loan finishing in w weeks with f missed payments.
C_f^d	Number of ways a loan can reach the terminal week W with f missed payments.
$\widehat{\widehat{C}}_f^d$	Number of ways a loan can have two missed payments in a row that reached the terminal week with f missed payments.
$d_{i\ell t}$	Indicator for whether borrower i failed to repay by the terminal week.
$h_{i\ell t}$	Number of times borrower i has borrowed from lender ℓ before time t.
$\mathfrak{h}_{i\ell t}$	Indicator for whether severe harassment was used in a loan.
$L_{i\ell t}$	Loan size.
$L_{it}^\star$	Borrower i's initial desired loan size.
$\mathcal{L}_{it}$	Borrower's consideration set of lenders.
$\mathfrak{L}_{it}$	Set of possible loan sizes given $L_{it}^\star$.
$m_{i\ell tw}$	Borrower's cash generated in week w, $m_{i\ell t} = \max\left\{0, m_{i\ell t} + \nu_{i\ell t}\right\}$
$\widetilde{m}_{i\ell tw}$	Lender's estimate about the borrower's cash generated in week w, $\widetilde{m}_{i\ell t} = \max\left\{0, \widetilde{m}_{i\ell t} + \widetilde{\nu}_{i\ell t}\right\}$

TABLE A.5: Summary of notation: Part 1.

The expected payoff to the lender in the terminal week in each possible

$n_{i\ell tw}$	Payment counter. The number of consecutive payments made before week w.
$p^{\eta}_{i\ell t}$	Probability of harassment from a missed payment.
$p^{L}_{i\ell t}\left(L_{i\ell t}\right)$	The probability a borrower will receive a loan of size $L_{i\ell t}$ from lender ℓ at time t.
$p^{m}_{i\ell t}\left(L_{i\ell t}\right)$	Borrower's weekly repayment probability.
$p^{\widetilde{m}}_{i\ell t}\left(L_{i\ell t}\right)$	Lender's estimate of the borrower's weekly repayment probability.
r_t	Nominal interest rate at time t (same across lenders).
$\mathcal{T}_i$	Set of time periods borrower i takes out loans.
$u_{i\ell tw}\left(L_{i\ell t}\right)$	Borrower's payoff in week w of the loan.
$\widetilde{u}_{i\ell tw}\left(L_{i\ell t}\right)$	Lender's payoff in week w of the loan.
$v_{i\ell t}\left(L_{i\ell t}\right)$	Borrower's expected present discounted value of a loan from lender ℓ with loan size $L_{i\ell t}$.
$V_{i\ell t}$	Borrower i's expected present discounted value of a loan from lender ℓ.
$\bar{V}_{i\ell t}$	Borrower i's expected present discounted value of a loan from lender ℓ excluding the match value shock $\varepsilon_{i\ell t}$.
$\widetilde{V}_{i\ell t}\left(L_{i\ell t}\right)$	Lender ℓ's expected present discounted value of a loan from borrower i with loan size $L_{i\ell t}$.

TABLE A.6: Summary of notation: Part 2.

case is given by:

$$\widetilde{u}_{i\ell tW}\left(L_{i\ell t}\right)=\begin{cases} r_t L_{i\ell t} & \text{if } n_{i\ell tW}=5 \text{ and } \widetilde{m}_{i\ell tW}\geq r_t L_{i\ell t} \\ 6r_t L_{i\ell t}-\kappa_{\ell t} & \text{if } n_{i\ell tW}=0 \text{ and } \widetilde{m}_{i\ell tW}<r_t L_{i\ell t} \\ \left(6-n_{i\ell tW}\right) r_t L_{i\ell t}-p^{\eta}_{i\ell t}\kappa_{\ell t} & \text{if } n_{i\ell tW}\in\{1,\ldots,5\} \text{ and } \widetilde{m}_{i\ell tW}<r_t L_{i\ell t} \\ \left(5-n_{i\ell tW}\right) r_t L_{i\ell t} & \text{if } n_{i\ell tW}\in\{0,\ldots,4\} \text{ and } \widetilde{m}_{i\ell tW}\geq r_t L_{i\ell t} \\ 0 & \text{if } n_{i\ell tW}=6 \end{cases}$$

In the first case, the borrower manages to make the final payment in the terminal week and doesn't have to work for the lender. In the second case, the borrower has not made any payments towards the loan and must work to repay the loan in full. Because of two missed payments in a row, the lender inflicts harassment with probability 1. In the third case, the loan is partially repaid. The borrower misses a payment and must work to repay the remaining $\left(6-n_{i\ell tW}\right) r_t L_{i\ell t}$ outstanding on the loan. Because of the missed payment, the lender additionally harasses the borrower with probability $p^{\widetilde{\eta}}_{i\ell t}$. In the fourth

case, the borrower makes a payment in week W and only has to work to repay the remaining $(5 - n_{i\ell tW})\, r_t L_{i\ell t}$ on the loan. In the final case, the loan is already fully paid by week W.

A.7.2 Borrower

If the loan is unpaid upon reaching the terminal week, the borrower must work for the lender. This gives the borrower disutility because the lender requires them to complete undesirable tasks. The expected level of disutility from this depends on the amount outstanding on the loan. Borrowers we have interviewed stated the expected disutility from this is between 8-10 times the expected disutility from missing a payment. Based on this information, we assume the expected disutility from working for the lender is:

$$\left[8 + 2\left(\frac{5 - \mathbb{1}\left\{m_{i\ell tW} \geq r_t L_{i\ell t}\right\} - n_{i\ell tW}}{5}\right)\right] p_{i\ell t}^{\eta} \chi_{i\ell t}$$

If the borrower has not made any payments towards the loan, the expected disutility is $10 p_{i\ell t}^{\eta} \chi_{i\ell t}$. If they only have one outstanding payment, the disutility is $8 p_{i\ell t}^{\eta} \chi_{i\ell t}$.

The expected payoff to the borrower in the terminal week in each possible case is given by:

$$u_{i\ell tW}(L_{i\ell t}) =$$
$$\begin{cases} \mathbb{E}\left[\frac{[m_{i\ell tW} - r_t L_{i\ell t}]^{1-\gamma_i} - 1}{1-\gamma_i} \middle| m_{i\ell tW} \geq r_t L_{i\ell t}\right] & \text{if } n_{i\ell tW} = 5 \text{ and } m_{i\ell tW} \geq r_t L_{i\ell t} \\ \mathbb{E}\left[\frac{m_{i\ell tW}^{1-\gamma_i} - 1}{1-\gamma_i} \middle| m_{i\ell tW} < r_t L_{i\ell t}\right] - \left(10 p_{i\ell t}^{\eta} + 1\right) \chi_{i\ell t} & \text{if } n_{i\ell tW} = 0 \text{ and } m_{i\ell tW} < r_t L_{i\ell t} \\ \mathbb{E}\left[\frac{m_{i\ell tW}^{1-\gamma_i} - 1}{1-\gamma_i} \middle| m_{i\ell tW} < r_t L_{i\ell t}\right] - \left(9 + 2\left(\frac{5 - n_{i\ell tW}}{5}\right)\right) p_{i\ell t}^{\eta} \chi_{i\ell t} & \text{if } n_{i\ell tW} \in \{1, \ldots, 5\} \text{ and } m_{i\ell tW} < r_t L_{i\ell t} \\ \mathbb{E}\left[\frac{[m_{i\ell tW} - r_t L_{i\ell t}]^{1-\gamma_i} - 1}{1-\gamma_i} \middle| m_{i\ell tW} \geq r_t L_{i\ell t}\right] - \left(8 + 2\left(\frac{4 - n_{i\ell tW}}{5}\right)\right) p_{i\ell t}^{\eta} \chi_{i\ell t} & \text{if } n_{i\ell tW} \in \{0, \ldots, 4\} \text{ and } m_{i\ell tW} \geq r_t L_{i\ell t} \\ \mathbb{E}\left[\frac{m_{i\ell tW}^{1-\gamma_i} - 1}{1-\gamma_i}\right] & \text{if } n_{i\ell tW} = 6 \end{cases}$$

In the first case, the borrower manages to make the final payment at the terminal week and avoids having to work for the lender. In the second case, the borrower reaches the terminal week with no part of the loan paid and receives the largest possible disutility: an expected harassment cost of $\chi_{i\ell t}$ from two missed payments in a row and an expected disutility of $10 p_{i\ell t}^{\eta} \chi_{i\ell t}$

from working for the lender to recover the full value of the loan. In the third case, the borrower does not make a payment in the final week an receives the expected disutility from a missed payment of $p_{i\ell t}^{\eta}\chi_{i\ell t}$ and must work for the lender to repay the loan. The fourth case is similar except the borrower makes a payment in the terminal week and avoids the missed payment disutility. Finally, if the loan is fully repaid by week W, the borrower simply consumes her cash from that week.

A.8 Repayment Path Probabilities

In this section we discuss the interpretation of the likelihood of the repayment probabilities. For ease of notation in this section, let $p_{i\ell t}$ be the weekly repayment probability for borrower i with a loan from lender ℓ at time t. If the loan is finished in week $w \geq 8$, we know that six consecutive payments were made following one missed payment. The probability of this part of the path is $p_{i\ell t}^{6}\left(1-p_{i\ell t}\right)$. We only need to consider the probability of the events preceding this final missed payment. For this part we need the probability of missing $f-1$ payments in the preceding $w-8$ weeks. In general this would be given by the binomial probability $\frac{(w-8)!}{(f-1)!(w-7)!}p_{i\ell t}^{w-f-7}\left(1-p_{i\ell t}\right)^{f-1}$. To get the probability of the entire path, we take the product of the two probabilities:

$$\begin{aligned} & p_{i\ell t}^{6}\left(1-p_{i\ell t}\right)\frac{(w-8)!}{(f-1)!\,(w-7)!}p_{i\ell t}^{w-f-7}\left(1-p_{i\ell t}\right)^{f-1} \\ & =\frac{(w-8)!}{(f-1)!\,(w-7)!}p_{i\ell t}^{w-f-1}\left(1-p_{i\ell t}\right)^{f} \end{aligned}$$

However, it is possible that the binomial coefficient contains paths that include 6 consecutive payments before week w, the end date of the loan. This is not possible as otherwise the loan would finish before week w. Therefore we compute an adjusted coefficient that removes these combinations. Table A.7 shows values of C_f^w for a range of values of w and f. We can see that starting in week 8 the combinations are part of Pascal's triangle, but combinations are removed when the number of missed payments is small relative to the number of weeks. With this adjustment, the probability of repaying a loan in w weeks

	Missed payments												
Weeks	0	1	2	3	4	5	6	7	8	9	10	11	12
1	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0	0
6	1	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	1	0	0	0	0	0	0	0	0	0	0	0
9	0	1	1	0	0	0	0	0	0	0	0	0	0
10	0	1	2	1	0	0	0	0	0	0	0	0	0
11	0	1	3	3	1	0	0	0	0	0	0	0	0
12	0	1	4	6	4	1	0	0	0	0	0	0	0
13	0	0	5	10	10	5	1	0	0	0	0	0	0
14	0	0	5	15	20	15	6	1	0	0	0	0	0
15	0	0	4	20	35	35	21	7	1	0	0	0	0
16	0	0	3	23	55	70	56	28	8	1	0	0	0
17	0	0	2	24	77	125	126	84	36	9	1	0	0
18	0	0	1	23	98	201	251	210	120	45	10	1	0
19	0	0	0	20	115	295	451	461	330	165	55	11	1
20	0	0	0	15	125	400	741	911	791	495	220	66	12

TABLE A.7: Example values of C_f^w for different values of w and f.

with f missed payments is:

$$C_f^w p_{i\ell t}^{w-f-1} \left(1 - p_{i\ell t}\right)^f$$

This probability also includes the final case of repaying a loan in 6 weeks with no missed payments, which is $p_{i\ell t}^5$. For additional clarity, we now discuss particular examples of repayment paths.

Completing the loan in 6 weeks:

A borrower can complete the loan in 6 weeks if they do not miss any payments. This occurs with probability $p_{i\ell t}^5$ because the probability of making the first payment is always 1 as the lender takes this out of the initial loan. There is only one possible path, so $C_0^6 = 1$.

Completing the loan in 7 weeks:
It is not possible to complete a loan in 7 weeks. Missing the first payment is not possible and if the borrower misses the second payment the loan will last at least until week 8. Therefore $C_f^7 = 0$ for all f.
Completing the loan in 8 weeks:
The only way to complete a loan in 8 weeks is to miss one payment in week 2 and make all the subsequent payments. This occurs with probability $p_{i\ell t}^6 (1 - p_{i\ell t})$. As there is only one possible sequence of payments that can arrive at 8 weeks and 1 one missed payment, we have $C_1^8 = 1$.

It is not possible for a borrower to complete a loan in 8 weeks and miss more than 1 payment. If the borrower misses the payment in weeks 2 and 3, the loan will last at least until week 9. If the borrower never misses a payment, the loan will end in week 6. Therefore $C_f^8 = 0$ for all $f \neq 1$.
Completing the loan in 9 weeks:
There are two ways to complete a loan in 9 weeks:

- Miss only week 3 (1 missed payment). This occurs with probability $p_{i\ell t}^7 (1 - p_{i\ell t})$.
- Miss only weeks 2 and 3 (2 missed payments). This occurs with probability $p_{i\ell t}^6 (1 - p_{i\ell t})^2$.

There is only one possible path for each of these possibilites, so $C_1^9 = C_2^9 = 1$ and $C_f^9 = 0$ for all $f \notin \{1, 2\}$.
Completing the loan in 10 weeks with 2 missed payments:
To complete a loan in week 10, the borrower must miss a payment in week 4 and make all the subsequent payments. To complete a loan in 10 weeks with 2 missed payments, there are therefore 2 possibilities: miss weeks 2 and 4 or miss weeks 3 and 4. Therefore $C_2^{10} = 2$ and the probability that this occurs is $2p_{i\ell t}^7 (1 - p_{i\ell t})^2$.
Completing the loan in 13 weeks with 2 missed payments:
It is not possible to complete a loan in 13 weeks with only 1 missed payment. If the borrower misses week 6 and makes all the subsequent payments, the loan is complete by week 12. Therefore $C_1^{13} = 0$. To complete a loan in 13

weeks with 2 missed payments, the borrower must miss the payment in week 7 and make all the following payments. But the other missed payment can occur in any one of weeks 2-6, so there are 5 different combinations. Therefore $C_2^{13} = 5$. The probability of completing the loan in 13 weeks with 2 missed payments is then $5p_{i\ell t}^{10}\left(1-p_{i\ell t}\right)^2$.

A.9 Estimation of the Lender's Estimate of the Borrower's Repayment Probability

To estimate $\boldsymbol{\theta}^{\widetilde{m}}$ we also use the observed number of weeks to repay and the number of missed payments. The lender's estimate of the probability that the borrower completes the loan in w weeks with f failed payments is:

$$C_f^w \left[p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \boldsymbol{\theta}^{\widetilde{m}}\right)\right]^{w-f-1}\left[1-p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \boldsymbol{\theta}^{\widetilde{m}}\right)\right]^f$$

where C_f^w is the number of possible ways a borrower can miss f payments in w weeks under the structure of the loan.

The lender's estimate of the probability that the loan reaches the terminal period unpaid is:

$$1-\sum_{w=1}^{W}\sum_{f=0}^{w} C_f^w \left[p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \boldsymbol{\theta}^{\widetilde{m}}\right)\right]^{w-f-1}\left[1-p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \boldsymbol{\theta}^{\widetilde{m}}\right)\right]^f$$

The probability of observing $(w_{i\ell t}, f_{i\ell t}, d_{i\ell t})$ according to these probabilities is then:

$$\begin{aligned} L_{2i\ell t}\left(\boldsymbol{\theta}^{\widetilde{m}}\right) = &\left(1-d_{i\ell t}\right) C_{f_{i\ell t}}^{w_{i\ell t}}\left[p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \boldsymbol{\theta}^{\widetilde{m}}\right)\right]^{w_{i\ell t}-f_{i\ell t}-1}\left[1-p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \boldsymbol{\theta}^{\widetilde{m}}\right)\right]^{f_{it}} \\ &+ d_{i\ell t}\left(1-\sum_{w=1}^{W}\sum_{f=0}^{w} C_f^w\left[p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \boldsymbol{\theta}^{\widetilde{m}}\right)\right]^{w-f-1}\left[1-p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, \boldsymbol{\theta}^{\widetilde{m}}\right)\right]^f\right) \end{aligned}$$

We estimate this with maximum likelihood:

$$\widehat{\boldsymbol{\theta}}^{\widetilde{m}} = \arg\max_{\boldsymbol{\theta}^{\widetilde{m}}} \sum_{i=1}^{I}\sum_{t\in\mathcal{T}_i} \log\left(L_{2i\ell t}\left(\boldsymbol{\theta}\right)\right)$$

A.10 Loan Size Probabilities

The probability that the lender will give the borrower their full desired loan size is:

$$p^L_{i\ell t}\left(L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right) = \frac{\exp\left(\widetilde{V}_{i\ell t}\left(L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right)}{1+\exp\left(\widetilde{V}_{i\ell t}\left(L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right)}$$

The probability that the lender will reject $L^\star_{it}$, but accept $\frac{2}{3}L^\star_{it}$ is given by:

$$p^L_{i\ell t}\left(\frac{2}{3}L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right) = \left[1-p^L_{i\ell t}\left(L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right]\frac{\exp\left(\widetilde{V}_{i\ell t}\left(\frac{2}{3}L_{i\ell t}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right)}{1+\exp\left(\widetilde{V}_{i\ell t}\left(\frac{2}{3}L_{i\ell t}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right)}$$

The probability that the lender will reject both $L^\star_{it}$ and $\frac{2}{3}L^\star_{it}$ but accept $\frac{1}{2}L^\star_{it}$ is given by:

$$\begin{aligned} p^L_{i\ell t}\left(\frac{1}{2}L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right) = &\left[1-p^L_{i\ell t}\left(L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right] \\ &\times\left[1-p^L_{i\ell t}\left(\frac{2}{3}L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right] \\ &\times\frac{\exp\left(\widetilde{V}_{i\ell t}\left(\frac{2}{3}L_{i\ell t}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right)}{1+\exp\left(\widetilde{V}_{i\ell t}\left(\frac{1}{2}L_{i\ell t}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right)} \end{aligned}$$

The probability that the lender will reject all of $L^\star_{it}$, $\frac{2}{3}L^\star_{it}$ and $\frac{1}{2}L^\star_{it}$, but accept $\frac{1}{3}L^\star_{it}$ is given by:

$$\begin{aligned} p^L_{i\ell t}\left(\frac{1}{3}L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right) = &\left[1-p^L_{i\ell t}\left(L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right] \\ &\times\left[1-p^L_{i\ell t}\left(\frac{2}{3}L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right] \\ &\times\left[1-p^L_{i\ell t}\left(\frac{1}{2}L^\star_{it}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right] \\ &\times\frac{\exp\left(\widetilde{V}_{i\ell t}\left(\frac{2}{3}L_{i\ell t}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right)}{1+\exp\left(\widetilde{V}_{i\ell t}\left(\frac{1}{3}L_{i\ell t}, \boldsymbol{\theta}^\kappa, \widehat{\boldsymbol{\theta}}^{\widetilde{m}}, \widehat{\boldsymbol{\theta}}^\eta\right)\right)} \end{aligned}$$

We note that if the loan in the data is not one of the fractions $\frac{1}{3}$, $\frac{1}{2}$, or $\frac{2}{3}$ of the desired loan size, we replace the closest fraction with the actual fraction in the data. For example, supppose the borrower initially asked for S$1,500 and the loan size was actually S$1,200. In this case we would have $L_{i\ell t} = \frac{4}{5}L^{\star}_{it}$. We assume that the borrower first asks for S$1,500, then S$1,200 (80% instead of two-thirds). If rejected they would ask for S$750 (one half) and then finally S$500 (one third).

A.11 Lender Network Matrix

We construct a yearly network matrix where element (ℓ, ℓ') is the number of different borrowers lenders ℓ and ℓ' both lent to in that year. We do this year-by-year to account for the fact that lenders enter and exit, as some are arrested. We will use a simple example to explain how we use this matrix. Suppose borrower 1 borrowed from lenders A, B and C, borrower 2 borrowed from lenders B, C, and D, and borrower 3 borrowed from lenders C, D and E. The network matrix would be:

$$\begin{pmatrix} 1 & 1 & 1 & \mathbf{0} & \mathbf{0} \\ 1 & 2 & 2 & \mathbf{1} & \mathbf{0} \\ 1 & 2 & 3 & \mathbf{2} & \mathbf{1} \\ 0 & 1 & 2 & 2 & 1 \\ 0 & 0 & 1 & 1 & 1 \end{pmatrix}$$

For borrower 1, we look at the lenders that are close to borrower 1's lenders that borrower 1 did not borrow from. We do this by looking at the submatrix of rows of the lenders that 1 did borrow from and the columns of lenders that 1 did not borrow from. This is shown in bold. We then take the lender with the maximum value in the matrix, which is lender D in this case.

More generally, to find the additional lender for borrower i, we take the submatrix of rows corresponding to borrower i's lenders and the columns corresponding to all other lenders. The additional lender is then the lender associated with the maximum value of this submatrix. In the event of ties, we

draw a lender randomly from the largest values. In the event that we need to draw more than one new lender for a borrower (because they only borrowed from 1-2 lenders in the data), we take the largest values from the submatrix until we have the desired number of lenders.

A.12 Expected Weekly Payoff Calculations

We use Gauss-Hermite quadrature with H weights w_h and nodes z_h to numerically evaluate the conditional and unconditional expectations in the borrower's payoff functions. We use $H = 200$ in estimation.

A.12.1 Expected Payoff in the First Week

The expected payoff in week 1 before the realization of $\nu_{i\ell t1}$ is given by:

$$
\begin{aligned}
&\mathbb{E}\left[\frac{\left(m_{i\ell t1}+\left(1-r_t\right)L_{i\ell t}\right)^{1-\gamma_i}-1}{1-\gamma_i}\right] \\
=&\Phi\left(-\frac{m_{i\ell t}}{\sigma_i}\right)\frac{\left[\left(1-r_t\right)L_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}+ \\
&\int_{-m_{i\ell t}/\sigma_i}^{\infty}\frac{\left(m_{i\ell t}+\sigma_i\nu_{i\ell t1}+\left(1-r_t\right)L_{i\ell t}\right)^{1-\gamma_i}-1}{1-\gamma_i}\frac{e^{-\nu_{i\ell t1}^2/2}}{\sqrt{2\pi}}d\nu_{i\ell t1} \\
\approx&\Phi\left(-\frac{m_{i\ell t}}{\sigma_i}\right)\frac{\left[\left(1-r_t\right)L_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}+ \\
&\sum_{h=1}^{H}\frac{w_h}{\sqrt{\pi}}\mathbb{1}\left\{m_{i\ell t}+\sqrt{2}\sigma_i z_h>0\right\}\frac{\left[m_{i\ell t}+\sqrt{2}\sigma_i z_h+\left(1-r_t\right)L_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}
\end{aligned}
$$

The probability that $m_{i\ell t1} = 0$ is $\Phi\left(-\frac{m_{i\ell t}}{\sigma_i}\right)$ so the first term is this probability multiplied by the expected payoff conditional on $m_{i\ell t1} = 0$. The second term is the probability that $m_{i\ell t1} > 0$ multiplied by the expected payoff conditional on $m_{i\ell t1} > 0$.

A.12.2 Expected Payoff from Making a Payment

The borrower can make a payment only if $m_{i\ell tw} \geq r_t L_{i\ell t}$ which can also be written as $\nu_{i\ell tw} \geq \left(r_t L_{i\ell t} - \mu_{i\ell t}\right)/\sigma_i$. The expected payoff from making a payment conditional on being able to make the payment is:

$$\begin{aligned}
&\mathbb{E}\left[\left.\frac{\left(m_{i\ell tw} - r_t L_{i\ell t}\right)^{1-\gamma_i} - 1}{1-\gamma_i}\right| m_{i\ell tw} \geq r_t L_{i\ell t}\right] \\
&= \left[\Phi\left(\frac{m_{i\ell t} - r_t L_{i\ell t}}{\sigma_i}\right)\right]^{-1} \int_{\frac{r_t L_{i\ell t} - m_{i\ell t}}{\sigma_i}}^{\infty} \frac{\left(m_{i\ell t} + \sigma_i \nu_{i\ell tw} - r_t L_{i\ell t}\right)^{1-\gamma_i} - 1}{1-\gamma_i} \frac{e^{-\nu_{i\ell tw}^2/2}}{\sqrt{2\pi}} d\nu_{i\ell tw} \\
&\approx \left[\Phi\left(\frac{m_{i\ell t} - r_t L_{i\ell t}}{\sigma_i}\right)\right]^{-1} \sum_{h=1}^{H} \frac{w_h}{\sqrt{\pi}} \mathbb{1}\left\{m_{i\ell t} + \sqrt{2}\sigma_i z_h \geq r_t L_{i\ell t}\right\} \frac{\left[m_{i\ell t} + \sqrt{2}\sigma_i z_h - r_t L_{i\ell t}\right]^{1-\gamma_i} - 1}{1-\gamma_i}
\end{aligned}$$

A.12.3 Expected Payoff from Not Making a Payment

The borrower is unable to make the payment when $m_{i\ell tw} < r_t L_{i\ell t}$, which can also be written as $\nu_{i\ell tw} < \left(r_t L_{i\ell t} - m_{i\ell t}\right)/\sigma_i$. The expected payoff conditional on not being able to make the payment is:

$$\begin{aligned}
&\mathbb{E}\left[\left.\frac{\left[m_{i\ell tw} + \left(n_{i\ell tw} - 1\right)\mathbb{1}\left\{n_{i\ell tw} > 0\right\} r_t L_{i\ell t}\right]^{1-\gamma_i} - 1}{1-\gamma_i}\right| m_{i\ell tw} < r_t L_{i\ell t}\right] \\
&- \mathbb{1}\left\{n_{i\ell tw} > 0\right\} p_{i\ell t}^{\eta} \chi_{\ell t} - \mathbb{1}\left\{n_{i\ell tw} = 0\right\} \chi_{\ell t}
\end{aligned}$$

The term inside the expectation is can be written in two parts: when $m_{i\ell tw} = 0$ and when $m_{i\ell tw} \in (0, r_t L_{i\ell t})$. The probability that $m_{i\ell tw} = 0$ conditional on $m_{i\ell tw} < r_t L_{i\ell t}$ is $\frac{\Phi(-m_{i\ell t}/\sigma_i)}{\Phi((r_t L_{i\ell t} - m_{i\ell t})/\sigma_i)}$. Given this, the term inside the expectation

is:

$$\frac{\Phi\left(\frac{-m_{i\ell t}}{\sigma_i}\right)}{\Phi\left(\frac{r_t L_{i\ell t}-m_{i\ell t}}{\sigma_i}\right)}\frac{\left[\left(n_{i\ell tw}-1\right)\mathbb{1}\left\{n_{i\ell tw}>0\right\}r_t L_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}+$$

$$\frac{1}{\Phi\left(\frac{r_t L_{i\ell t}-m_{i\ell t}}{\sigma_i}\right)}\int_{-\frac{m_{i\ell t}}{\sigma_i}}^{\frac{r_t L_{i\ell t}-m_{i\ell t}}{\sigma_i}}\frac{\left[m_{i\ell t}+\sigma_i\nu_{i\ell tw}+\left(n_{i\ell tw}-1\right)\mathbb{1}\left\{n_{i\ell tw}>0\right\}r_t L_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}\frac{e^{-\nu_{i\ell tw}^2/2}}{\sqrt{2\pi}}d\nu_{i\ell tw}$$

$$\approx\frac{\Phi\left(\frac{-m_{i\ell t}}{\sigma_i}\right)}{\Phi\left(\frac{r_t L_{i\ell t}-m_{i\ell t}}{\sigma_i}\right)}\frac{\left[\left(n_{i\ell tw}-1\right)\mathbb{1}\left\{n_{i\ell tw}>0\right\}r_t L_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}+$$

$$\left[\Phi\left(\frac{r_t L_{i\ell t}-m_{i\ell t}}{\sigma_i}\right)\right]^{-1}\sum_{h=1}^{H}\frac{w_h}{\sqrt{\pi}}\mathbb{1}\left\{m_{i\ell t}+\sqrt{2}\sigma_i z_h>0\right\}\mathbb{1}\left\{m_{i\ell t}+\sqrt{2}\sigma_i z_h<r_t L_{i\ell t}\right\}\times$$

$$\frac{\left[m_{i\ell t}+\sqrt{2}\sigma_i z_h+\left(n_{i\ell tw}-1\right)\mathbb{1}\left\{n_{i\ell tw}>0\right\}r_t L_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}$$

A.12.4 Expected Payoff from a Completed Loan

The expected payoff when the loan is complete is the unconditional expectation $\mathbb{E}\left[\frac{m_{i\ell tw}^{1-\gamma_i}-1}{1-\gamma_i}\right]$. This can be approximated by:

$$\mathbb{E}\left[\frac{m_{i\ell tw}^{1-\gamma_i}-1}{1-\gamma_i}\right]=\int_{-m_{i\ell t}/\sigma_i}^{\infty}\frac{\left(m_{i\ell t}+\sigma_i\nu_{i\ell tw}\right)^{1-\gamma_i}-1}{1-\gamma_i}\frac{e^{-\nu_{i\ell tw}^2/2}}{\sqrt{2\pi}}d\nu_{i\ell tw}$$

$$\approx\sum_{h=1}^{H}\frac{w_h}{\sqrt{\pi}}\mathbb{1}\left\{m_{i\ell t}+\sqrt{2}\sigma_i z_h>0\right\}\frac{\left[m_{i\ell t}+\sqrt{2}\sigma_i z_h\right]^{1-\gamma_i}-1}{1-\gamma_i}$$

A.13 Model Fit

Table A.8 shows how well our model can fit our data. We simulate loan outcomes at the estimated model parameters and compare them to the average outcomes in the data. We can see that the model matches the number of weeks, missed payments, proportion of loans with harassment and the average loan size reasonably well on aggregate.

	Data	Model
Average number of weeks	13.42	14.05
Average number of missed payments	3.87	3.46
Proportion of loans with harassment	0.54	0.47
Average loan size	1.29	1.37

TABLE A.8: Simulated outcomes with parameter estimates versus observed outcomes in the data.

A.14 Decomposition of the Enforcement Crackdown

	Earlier Crackdown	Only Interest Rate Increases	Use $Post_t$=1 Parameters Only	Earlier Lender Exit
Total lender surplus (in S$m)	+7.69%	+50.70%	−14.34%	−1.74%
Low harshness Lender surplus (in S$m)	+68.52%	+50.81%	−10.24%	−5.71%
Medium harshness lender surplus (in S$m)	−42.52%	+46.55%	−1.21%	+6.01%
High harshness lender surplus (in S$m)	−17.72%	+54.74%	−32.70%	−4.61%
Total interest payments (in S$m)	+66.10%	+115.81%	+19.67%	−0.84%
Total harassment costs (in S$m)	+140.81%	+13.56%	+81.93%	−2.10%
Average loan size (in S$000)	−38.80%	+8.59%	−5.36%	−0.24%
Average borrower surplus (in S$000)	−67.43%	−21.42%	−60.63%	−2.03%
Average amount paid (in S$000)	+19.56%	+101.39%	+8.69%	+0.26%
Average number of weeks	+28.21%	+12.03%	+25.30%	+1.18%
Average number of missed payments	+78.59%	+28.83%	+68.66%	+3.04%
Average number of times harassed	+106.63%	+39.28%	+98.67%	+1.04%

TABLE A.9: Welfare effects if the crackdown occurred at the begining of the sample period.