The Effects of Policy Interventions to Limit Illegal Money Lending *

Kaiwen Leong[1], Huailu Li[2], Nicola Pavanini[3], and Christoph Walsh[4]

[1]Griffith University, Department of Accounting, Finance and Economics, and Nanyang Technological University Economic Growth Center

[2]Fudan University, Department of Economics

[3]Tilburg University, Department of Finance, and CEPR

[4]Tilburg University, Department of Econometrics and Operations Research, and CEPR

January 23, 2024

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 the model to evaluate the effects of interventions aimed at limiting this market. We find that an enforcement crackdown that occurred during our sample period increased lenders' unit cost of harassment and interest rates, while lowering volume of loans, lender profits and borrower welfare. Policies removing borrowers in the middle of the repayment ability distribution, reducing gambling or reducing time discounting are also effective at lowering lender profitability.

Key words: Illegal Money Lending, Loan Sharks, Law Enforcement, Crime, Structural Estimation

JEL Codes: K42, G51

*This research was partially funded by a Singapore Ministry of Education Tier 1 grant (Grant Name: MOE AcRF Tier 1; Grant Number: 2015-T1-002-061). 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 Institutional Review Board (NTU IRB). We thank Sumit Agarwal, Alan Krueger, Kevin Lang, Edward Lazear, Thomas Lemieux, Claudia Robles-Garcia, Jia Panle Barwick and seminar participants at Tilburg, NTU, Purdue, Fudan, the 2022 NBER IO Spring Meeting (Stanford SIEPR), Pavia, Bristol, Mannheim, Nova SBE, NUS, the Barcelona Summer Forum, the Bocconi EEA-ESEM Congress, Helsinki GSE, and CEIBS for their helpful comments and suggestions. The usual caveat applies. Nicola Pavanini gratefully acknowledges financial support from the European Research Council under the Grant Agreement No. 101042069.

1 Introduction

Illegal money lending (IML), often also referred to as usury or loansharking, is the practice of lending money at rates higher than the legally prescribed limit, using illegal harassment methods for loan recollection, and attempting to lock borrowers into never ending debt traps (Kaplan and Matteis, 1968). This is a large scale phenomenon that is widespread across countries[1] and has existed for a very long time. Laws banning individuals from charging excessive interest rates have existed at least as early as the Babylonian Code of Hammurabi from 1800 BC, and were present in the Old Testament and in Roman Law (Blitz and Long, 1965). These bans exist because this market generates severe negative externalities. Lenders are part of criminal organizations that use IML to launder money and conceal profits from other criminal activities, and because borrowers, rejected by any legal creditor, mostly invest IML loans into addictive activities such as gambling, drugs and alcohol (Financial Conduct Authority, 2017; Marinaro, 2017).

On the one hand, due to its detrimental effects on society, law enforcement has exerted considerable effort to eradicate this phenomenon (Savona and Riccardi, 2015). Interventions range from resources to the police force to arrest lenders and other members of the criminal organizations they belong to (Home Office, 2018; DFAT, 2019), to support programs for borrowers via rehabilitation strategies, formal-market alternatives, or financial education.[2] On the other hand, the presence of IML is enhanced by the widespread worldwide adoption of interest rate caps (Maimbo and Henriquez, 2014), which limit access to legal credit for risky borrowers (Temin and Voth, 2008), fostering demand for illegal lending.

Despite the importance of IML historically and worldwide, in the literature there is neither a quantification of the effects of such interventions in this market, nor a clear understanding of the main incentives that drive borrowers and lenders. The reason is that reliable and large scale transaction-level data on the IML market do not exist, because lenders are part of organized criminal groups that operate under the radar of law enforce-

[1] In 2004 around 1% of households in the UK were in debt to an illegal lender (Payne et al., 2020), while in Germany and France the incidence of illegal lending is respectively 2.5 and 3 times higher than in the UK (Ellison et al., 2006). In 2009 in Italy, loansharking raised profits of €15bn (1% of GDP) to organized crime (Schneider, 2013). In 1990 in the US proceeds from loansharking were estimated to be around $14bn, 0.2% of GDP (Levi and Reuter, 2006). Public reports on IML can also be found for various East Asian countries, including China, Vietnam, Malaysia, Thailand, and Singapore.

[2] 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/).

ment, and because borrowers are vulnerable individuals who fear both the consequences of reporting their loan sharks and the stigma of admitting their financial troubles.

In this paper we overcome these challenges with novel data which allow us to estimate a structural model of the IML market to simulate the effects of various policy interventions. We do this using a survey of 11,032 loans granted by loan sharks to 1,090 borrowers, representing the largest dataset of this kind to the best of our knowledge. Our counterfactuals evaluate the effects of three kinds of policy interventions. First, we document that a crackdown on lenders that occurred during our sample period was highly successful at lowering the volume of disbursed loans and the profits of lenders. Second, we show that removing borrowers from this market, either through offering formal market alternatives by relaxing interest rate caps, or via rehabilitation and education programs, also hurts lenders, particularly if they focus on medium-performing borrowers in terms of loan repayment ability. Third, indirect interventions that reduce gambling and drug use, or ones that reduce time discounting through improved financial literacy, are also effective at lowering lender profits, primarily through reduced loan demand.

Our data are from Singapore, which is an interesting context to study IML because of its prevalence during our sample period. According to the Singapore Police Force's 2010 Annual Crime Brief, more than half of the crimes committed in Singapore are related to the IML market. This is because IML is run by transnational criminal organizations involved in various illegal activities and Singapore is an important hub for their operations in Southeast Asia (Emmers, 2003). Furthermore, we collected evidence (documented in Section 2.2) that the transnational crime syndicates operating in Singapore also operate across Southeast Asia and China using the same IML operating model. Singapore is therefore also an interesting context to study the IML market because it has a similar market structure to many other Southeast Asian countries (which have a combined population of over 2 billion people).

Our model and findings also highlight the unique features that make IML different from other formal and informal credit markets with predatory lending practices, such as payday loans, pawnbroking, subprime lending, and informal lending. First, as in several other illegal markets, IML is organized as a non-competitive cartel run by transnational criminal syndicates, which implies that policymakers cannot regulate it and instead aim to eradicate it. 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 limits. These syndicates also set loan terms this way in the other countries where it operates, such as Malaysia and China. Second, being unregulated, lenders in IML engage in severe and illegal harassment methods to recollect payments. Third, loansharking features a particular loan structure with loan reset in case of missed payments, explicitly aimed at debt trapping borrowers. Last, borrowers have very poor creditworthiness, as they are rejected by all sources of formal credit. As we will document, all borrowers in our sample stated they were unable to borrow from the formal sector, including payday lenders and peer-to-peer platforms.[3]

Our structural framework incorporates these specific features of the IML market, as well as aspects that are common in formal credit markets. In our model, borrowers decide how much to borrow and which lender to borrow from. When approached by a borrower, the lender decides whether to give them the loan or not, or to give a smaller loan, and how harsh to be in response to missed payments. The harshness level the lender chooses is the probability of harassing the borrower after a missed payment. They choose the loan size and harshness level based on their estimate of the borrower's ability to repay, which depends on the borrower's characteristics and past loan performance. The harshness level chosen by the lender can also impact the borrower's ability to repay through the threat of harassment. Lenders thus face a trade-off that larger loans provide larger interest payments but are more difficult for borrowers to repay, while higher harshness levels increase repayment ability but are more costly. Borrowers then choose the lender to maximize their expected discounted payoffs, where lenders are heterogeneous in harshness. Borrowers exhibit quasi-hyperbolic discounting and low degrees of risk aversion, and obtain disutility from harassment. Borrower payoffs depend on the expected size of the loan, expected harshness level, the 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 effects of various market interventions.

Our data detail many loan characteristics, such as the requested and granted loan amount, interest rate, number of missed payments, and harassment used by the lender. We also surveyed the characteristics of the borrowers, such as their demographics and addictions. Our borrower panel survey was conducted over 2009-2016. In 2014, the authorities increased the resources targeting the IML market. This crackdown was successful

[3] In Section A.2 in the Online Appendix, we provide additional details on the differences between IML and other credit markets, together with information from interviews we carried out with those involved in those markets.

at causing a large number of lenders to exit the market, often through arrest. The crackdown increased in the cost of lending, which caused the interest rate in the market to increase. The implied annual percentage rate (APR) increased from 261% to 562%. We use our estimated model to compute the effects of this crackdown by simulating what would have happened had it not occurred. We find that the crackdown caused the volume of loans to fall by 48.6%, lender profits by 67.7% and borrower surplus by 12.4%. We also use our model to decompose the effects of the crackdown. Absent the corresponding interest rate increase, the increase in harassment costs would have caused lenders to barely break even, motivating why the cartel increased its rates in response to the crackdown.

We are not able to model the syndicates' interest rate setting due to very limited price variation in our sample and a lack of data on the syndicates' costs and other sources of profits. Nevertheless, to investigate the optimality of their interest rates pre and post crackdown within the context of their loansharking profits from lenders, we conduct a counterfactual to quantify the impact on lenders' profits of changing the common interest rate charged to all borrowers. We find that before the crackdown the syndicates could have made more profits by raising rates, whereas after the crackdown the interest rate we observe in the data was the profit maximizing one. We interpret the suboptimal choice of lower rates in the pre-crackdown period as determined by the incentive to: (i) mitigate the risk of one syndicate deviating from the collusive equilibrium, (ii) deter entry of new syndicates, and (iii) avoid raising too much attention from law enforcement. The higher rates in the post period are instead justified by the substantial increase in harassment costs.

Next, we conduct a counterfactual to compare the crackdown to an alternative policy that involves targeting the borrowers instead. We group borrowers into twenty groups of equal loan demand based on their repayment ability and consider removing each group one at a time. Borrowers could be removed in practice through rehabilitation strategies or education programs that deter them from borrowing, as the majority of loans in our data are taken out for gambling reasons, but also by offering them a formal-market alternative by relaxing the interest rate cap. We find that removing the middle-performing borrowers lowers the profits of lenders 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. This is in contrast to the results found by Agarwal et al. (2015) for the credit card market, who show that consumers at the bottom of the FICO score distribution are the most profitable. The difference with our findings is likely driven by the high monitoring and recollection costs of the riskiest segment of IML borrowers.

Finally, we conduct a set of counterfactuals to evaluate the impact of indirect interventions on lender profitability. We find that policies aiming to reduce gambling, drug use, or heavy time discounting (through improvements in financial literacy) indirectly reduce lender profitability in the IML market. For the median borrower, stopping them from gambling reduces the profits of the lender it chooses by 26%. Although non-gamblers have a higher repayment ability and are less costly to serve, they demand smaller loans which reduces profits. Reducing a borrower's present bias or heavy time discounting also has a large effect on lender profits, with the size of the effect increasing in their initial discounting.

In our counterfactuals we put more emphasis on interventions that reduce lenders' profits, aimed at eradicating IML markets, rather than improving borrowers' surplus within IML. We do so because we believe that the primary goal of policymakers is to eliminate this illegal market, due to its criminal nature and the negative externalities that it generates. In fact, even the kind of policies that target borrowers are aimed at removing them from this market, rather than improving their surplus from borrowing from loansharks.

Our model and findings also shed light on three key unexplored features of formal credit markets. First, while most datasets only report the granted loan amount, we can instead observe and model borrowers' desired loan amount and what lenders eventually decide to grant. This allows us to separately quantify how a policy intervention affects demanded and supplied quantity of credit. Second, while monitoring plays a crucial role in theoretical models of financial intermediation (Diamond, 1984), its empirical importance has not been tested for high-risk consumer credit, and only just recently for large commercial loans (Gustafson et al., 2021). We provide novel evidence with detailed information on lenders' use of a variety of harassment methods, akin to monitoring in formal loans, which are likely to play a key role in high credit risk sectors such as payday loans. Not only we are able to model lenders' optimal choice of harassment probabilities, but can also recover harassment costs and how it incentivizes borrowers' effort in repayment, all features so far unexplored by the literature on formal credit. Last, our second counterfactual quantifies an important trade-off also present in legal credit markets. We show that for lenders the most profitable borrowers are those that do miss some repayments, as this delivers lenders revenues from financial penalties, but that do not miss too many of them, which instead requires lenders to incur substantial monitoring and recollection costs.

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., 2022), 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, 2022), but none of these have direct access to illegal loan contracts.[4] We are the first to develop an equilibrium model of the IML market to quantify the main incentives that drive borrowers and lenders, and to evaluate the effects of law enforcement, leveraging unique and extensive survey data on a large fraction of illegal loan contracts in Singapore.

Our paper uses the same dataset as Lang et al. (forthcoming), whose contributions include describing how they collected data on this financially vulnerable population, developing descriptive facts about this understudied market, and summarizing the effects of the enforcement crackdown on loan outcomes in reduced form. Our contributions relative to their work are as follows. First, we collect additional survey data from borrowers and (former) lenders to better understand the structure of the market they operate in and the relevant incentives and trade-offs they face. Second, we combine this information with the loan-level data also used by Lang et al. (forthcoming) to develop and structurally estimate a model of borrowing and lending in the IML market that captures its specific features. Finally, we use this model to perform the following policy counterfactuals. We quantify the impacts of the enforcement crackdown on loan volume, lender profits and borrower welfare by solving for the counterfactual loan outcomes under no crackdown, as well decomposing the impacts of the harassment cost and interest rate increases. We explore optimal cartel interest rate setting before and after the crackdown. Furthermore, we determine which borrowers are best to target in an intervention aimed at lowering lender profitability, and explore the effects of indirect interventions that reduce gambling, drug

[4] Apart from our companion paper Lang et al. (forthcoming), to our knowledge Soudijn and Zhang (2013) is the only other study with access to any data on illegal loans, describing the ledger of a single lender that was seized from a Dutch casino. We discuss our data relative to theirs in Section A.3 in the Online Appendix.

use or time discounting.

The second contribution we make is to the literature on predatory lending practices. Among formal markets such as pawnbroking (Caskey, 1991) and subprime lending (Adams et al., 2009), the closest lending context to ours is that of payday loans (Stegman, 2007; Morse, 2011; Gathergood et al., 2019; Melzer, 2018). Both IML and payday loans feature small loans with very high interest rates and short maturities, granted to vulnerable borrowers with potential cognitive biases (Bertrand and Morse, 2011). While Melzer (2011) shows that the availability of payday loans in some US states does not alleviate borrowers' economic hardship, we provide a complementary angle, as the lack of payday loans may be compensated by the presence of IML. The literature has also shown that regulating formal predatory lending can increase welfare by limiting repeated borrowing (Allcott et al., 2021) or by prohibiting large penalties for deferred payments (Heidhues and Kőszegi, 2010). These targeted interventions are however not feasible in IML, due to its unregulated and criminal nature.

Our work is also related to the literature studying the effects of debt collection regulations in the formal sector (Fedaseyeu, 2020; Romeo and Sandler, 2021; Fonseca, 2023). The crackdown on lenders making harassment more costly in our setting is akin to a tightening of debt collection laws intending to protect consumers. We contribute to this literature by studying not only the effects of the crackdown on loan outcomes, but also its effect on the lenders' harassment strategies themselves.

A related literature is also that of microfinance (Kaboski and Townsend, 2011, 2012; de Quidt et al., 2018) and informal lending (Aleem, 1990), but these markets present 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 an 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, such as gambling. 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.

Third, our paper also contributes to the growing area of structural models quantifying the effects of market frictions and of policy interventions in financial markets. In recent years several papers have developed equilibrium frameworks of this kind, ranging from business loans (Crawford et al., 2018), mortgages (Allen et al., 2019; Benetton, 2021), consumer credit (Einav et al., 2012), credit cards (Nelson, 2023), 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 coordinate on several loan features, 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 almost always end up repaying the loan. Moreover, we provide a new perspective in the debate on the effects of interest rate caps (Cuesta and Sepúlveda, 2021), quantifying how a relaxation of usury rates can hurt criminal organizations active in IML.

2 Setting and Data

The goal of this paper is to develop and estimate a structural model of the IML market in order to evaluate the effects of different policy counterfactuals on borrowers and lenders. In this section, we describe the market structure, the standard loan contract, and other features of the market that guide us in formulating our structural framework.

2.1 Data Collection

To estimate our structural model, we use the same loan-level panel dataset described in Lang et al. (forthcoming). We provide an overview of the data collection process and summary statistics here, but we refer the reader to Lang et al. (forthcoming) for additional details.

Similar to the strategy used by Blattman et al. (2017), we hired and trained 48 survey enumerators who were previously involved in the unlicensed lending market, as they had a good understanding of the institutional details of our setting. This also had the advantage that they could share their own experiences from borrowing from loan sharks, which made the respondents more comfortable sharing their own experiences. These enumerators initially went to locations where borrowers frequented and asked about the lenders they borrowed from. Based on the approximate total number of lenders known to market participants, we estimate that they 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. We did not interview the full list of borrowers for financial reasons, as borrowers received S$20-40 for participating, where in 2011 US$1 was approximately S$1.20-1.32 at the time. Out of the list of 1,232 borrowers, the enumerators successfully completed interviews with 1,123 respondents over 2011-2013.[5] Respondents were interviewed at least once per year about their latest loan transactions. We gave a financial incentive to borrowers to provide physical evidence of their transactions to ensure low recall error in our sample. These included diaries, repayment schedule notes, text messages from lenders, and ATM withdrawals. Because of the harsh penalties and harassment associated with missing payments, borrowers kept records of their repayment schedules. Interviews were 1-2 hours long and were held in a café chosen by the respondent. Over this period, 57.4% of borrowers reported nine loans and 97.2% reported at least six loans.

After the crackdown on the market in 2014, we held follow-up interviews with each respondent. Due to financial constraints we only held two follow-up interviews, once in 2015 and again in 2016. 1,090 of the original 1,123 were successfully reinterviewed and 95.2% of borrowers reported on two loans over this period. We constrain our sample to the 1,090 borrowers who we successfully reinterviewed over 2015-2016. The main reason for why the remaining 33 borrowers could not be reinterviewed was because we were unable to make contact with them. We believe the high initial take-up rate of 91.1%, together with randomization over the times and locations the enumerators located borrowers, rules out any concerns for sample selection. The full data have information on 11,032 loans taken out by 1,090 borrowers over 2009-2016. For each loan, we observe the borrower's demanded loan size, lender's identity, loan size issued by the lender, interest rate,

[5]Our sample sample does not contain any once-off borrowers. Our evidence suggests, however, that these represent a negligible part of the market. With a 91.1% initial take-up rate, we view our sample of borrowers taking out multiple loans as representative. Table A.1 in the Online Appendix details the reasons borrowers took out loans. The majority of loans were taken out for adictive habits prone to repeat borrowing, such as gambling, drugs and alcohol. Furthermore, in parliamant it was stated that the number of borrowers with a "genuine financial need" is "not very large", as Singapore offers many safety nets for individuals with medican emergencies or unemployment (Singapore High Court, 2012).

repayment time, missed payment penalties, and harassment methods used in the loan. We also observe a large number of borrower characteristics, such as a sociodemographics and addictions.

2.2 The Cartel of Loan Shark Syndicates

To better understand the structure of the market and the lenders' operating model, we carried out interviews with ex-IML lenders from Singapore (4), Malaysia (2) and China (13). From these interviews, we learned that during our sample period the IML market in China and Southeast Asia was controlled by a cartel of on average 10 transnational crime syndicates that were all headquartered in China. These syndicates have branches in each country of operation across the region, which has a combined population of over 2 billion people.[6] Two of the lenders that we interviewed were active in both Singapore and China in the past, and were able to confirm that the syndicate employed the same operating model in each country of operation.

The syndicates recruit lenders via a formal interview process and vetting procedure. The syndicates provide lenders with a start-up loan of approximately S$50,000 (US$36,500) which they can use to lend out to borrowers. The syndicates instruct their lenders to use a standardized loan structure and common interest rate. Two of the ex-lenders we spoke to told us the cartel of syndicates coordinated on this structure and interest rate during our sample period. This is confirmed in our data where we observe that all loans with lenders from different syndicates have the same structure, and almost all loans have the same interest rate at any given time.

The syndicates also provide lenders with a black-market database of borrowers that they can use to screen them. Market insiders have told us this database contains information on 350,000 borrowers. Much of the information about a borrower in this database is from their Singpass account, which is an online portal that allows citizens to view their information related to different government agencies. This includes their formal sector income and basic sociodemographic information, such as age and education. The syndi-

[6]We also found news reports of loan sharks from Chinese syndicates being arrested in Singapore (Chong, 2015), Vietnam (Thang, 2020), Thailand (CTN News, 2021b,a) and Indonesia (Tencent News, 2021), confirming their activity in these countries. Moreover, Curtis et al. (2002) report a large rise in Chinese criminal groups operating throughout the world since the 1990s, including countries in Europe, North and South America and Southeast Asia. They report loansharking to be among the criminal activities that these transnational groups engage in. Thus the validity of our results may also extend beyond Asia to markets where these syndicates are active.

cates also advise lenders on the traits of profitable borrowers. If the borrower is not in their database, lenders will require the borrower to show them the information on their Singpass account.

2.3 Standard Loan Structure

All loans in our sample follow the same payment structure which we incorporate in our structural model. We explain this structure using a S\$1,000 principal as an example. Before the enforcement crackdown in 2014, 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. In this market 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. This implies an annual percentage rate (APR) of $25\% \times \frac{365}{5\times 7} = 208.57\%$.

If a borrower misses a repayment, the lender punishes the borrower in two ways: with harassment and a financial penalty with a loan reset. Harassment can involve anything from threatening text messages, to public shaming and to destruction of personal property.[7] 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 three 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 would then reset the loan and the borrower would be required to 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. The borrower cannot repay early, and thus cannot use the cash returned to them to immediately make some of these repayments. Lenders also do not accept partial repayments. The reason for this is because the financial penalities from the loan reset feature is the main source of lenders' profits.[8]

If a borrower misses a payment two consecutive weeks in a row, they lender will

[7] In Table A.2 in the Online Appendix, we show all the harassment methods and the proportion of loans in our data where each form of harassment method was used.

[8] We asked the ex-lenders we interviewed to contact 32 borrowers in some cities in Guangdong, China and 16 borrowers in Johor, Malaysia and these confirmed that the loan structure that we observe in our setting was identical in all settings. Therefore this loan structure is not specific to Singapore and is used in other markets where the syndicates operate.

Table 1: Summary statistics of loan-level variables.

	N	Mean	Std. Dev.	Min.	Median	Max.
Loan size (in S$)	8836	1288.56	983.28	300	1000	5000
Desired loan size (in S$)	8836	1600.55	1018.65	300	1000	5000
Interest rate (in %)	8836	22.28	6.48	2	20	50
Number of weeks to repay	8836	13.38	5.84	6	12	24
Number of missed payments	8836	3.85	3.91	0	2	23
Number of past loans with lender	8836	4.10	3.43	0	3	19
Worked for lender to repay	8547	0.06	0.24	0	0	1
Harassed at least once in loan	8836	0.54	0.50	0	1	1

The statistics shown are for subsample of data used in estimation.

almost always use a more severe harassment method on the borrower. Because in this case the lender does not have any past payments made by the borrower to punish them financially, the borrower is required to come up with the payment by the end of that week, or face much harsher harassment. This payment is the financial penalty and does not count towards one of the six payments.

To complete a loan, the borrower must make their weekly payment six weeks in a row. In our data, only 14.6% of loans are paid on time within 6 weeks, but 97.5% are eventually repaid. The median and modal loan is repaid after 12 weeks. In cases where the loan lasts up to six months, the lender will make the borrower work for them to pay off the remaining balance. This happens in 8.7% of loans in our data.

Table 1 shows summary statistics of the loan-level variables for the subsample that we use in estimation. The median granted loan size is S$1,000, which is approximately US$800 using the 2011 exchange rate. The desired loan size is the size of the loan the borrower initially asks the lender for. The lender either disperses this loan size or a smaller one, typically a round fraction of the desired loan size.

2.4 Enforcement Crackdown

Starting in 2014, there was an increase in enforcement efforts targeting the loan shark market. The police force was expanded with additional funding and law enforcement devoted more efforts to combat the loansharking market. According to the Singapore Police Force Annual reports, the expenditure on manpower increased by 27.3% from 2012-2013 to 2014-2015 while the number of IML-related crimes fell by 37.7% over the same period.

In Singapore, unlicensed lending and harassment methods such as intimidation, van-

TABLE 2: Means of loan-level variables by year.

	2009	2010	2011	2012	2013	2014	2015	2016
Loan size (in S$)	1488.51	1403.75	1456.85	1537.84	1506.85	972.14	425.72	480.43
Desired loan size (in S$)	1701.01	1664.55	1742.50	1838.79	1847.72	1378.89	910.54	966.67
Interest rate (in %)	19.33	19.43	19.44	19.48	19.48	30.33	35.31	38.33
Number of weeks to repay	11.94	12.11	12.06	12.00	13.11	15.81	19.21	19.68
Number of missed payments	2.68	3.01	3.18	3.31	4.15	5.34	7.09	6.85
Number of past loans with lender	4.27	3.57	3.51	3.62	3.19	2.18	7.44	4.75
Worked for lender to repay	0.08	0.05	0.04	0.04	0.04	0.11	0.11	0.12
Harassed at least once in loan	0.50	0.46	0.45	0.43	0.48	0.81	0.89	0.88

The statistics shown are for subsample of data used in estimation.

dalism and stalking are illegal, whereas the act of borrowing itself is not illegal. Thus this crackdown was targeted at lenders and runners (individuals hired by lenders to conduct harassment for them). 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 total number of active lenders in Singapore fell from approximately 1,100 to between 500-1,000 during 2014-2016. In our own sample, we observe 711 unique lenders before the crackdown, and 401 lenders afterwards.

Because the enforcement crackdown increased the risk and cost of conducting harassment, it had several effects on loan contracts. Table 2 shows the means of the loan-level variables by year. The cartel responded by raising the nominal interest rate from 20% to 35%. As a result, borrower loan demand decreased, the total loan volume fell and loan performance worsened. The increase in missed payments led lenders to harass borrowers more. These effects of the crackdown also persist when we control for borrower-lender pair fixed effects and bilaterial loan history. We show these event study plots in in Section A.4 in the Online Appendix.

2.5 Borrowers

Table 3 shows summary statistics for the borrower characteristics for the subsample of borrowers that we use in estimating our structural model. We observe several sociodemographic variables, as well as gang member status and addictions to gambling, drugs, alcohol and visiting sex workers.

The most common reasons borrowers take out loans is for gambling or buying alcohol or drugs.[9] Loan sharks are lenders of last resort, and all borrowers in our sample stated

[9]We show the reasons borrowers take out loans in Table A.1 in the Online Appendix.

Table 3: Summary statistics of borrower characteristics.

	N	Mean	Std. Dev.	Min.	Median	Max.
Age	1057	37.56	7.64	20	38	63
Post-secondary education	1057	0.19	0.39	0	0	1
Female	1057	0.10	0.30	0	0	1
Married	1057	0.49	0.50	0	0	1
Divorced	1057	0.16	0.36	0	0	1
Has children	1057	0.62	0.49	0	1	1
Malaysian	1057	0.14	0.35	0	0	1
Indian	1057	0.11	0.31	0	0	1
Current gang member	1057	0.14	0.35	0	0	1
Previously gang member	1057	0.30	0.46	0	0	1
Number of previous convictions	1057	0.49	1.11	0	0	6
Gambles	1057	0.90	0.29	0	1	1
Drinks alcohol	1057	0.97	0.18	0	1	1
Uses drugs	1057	0.31	0.46	0	0	1
Frequents sex workers	1057	0.69	0.46	0	1	1
Frequently treats friends	1057	0.09	0.29	0	0	1

The statistics shown are for subsample of data used in estimation.

that they would not be borrowing from them if they had access to formal sector loans.

Borrowers undertake limited search when choosing a lender. Borrowers return to the same lenders they have borrowed from in the past 86.1% of the time in our data. The borrowers we interviewed stated that they considered at most one new lender for any loan because on average all lenders would treat a borrower the same way in the first loan. This is because all lenders use the same database on borrowers to estimate their repayment ability. Upon a approaching a lender, borrowers request an amount to borrow. When the interest rate was 20%, the median requested size was S$1,500, but after interest rates increased to 35%, this fell to S$1,000. Lenders then decide whether to lend the requested amount, or to give the borrower a smaller loan. Lenders typically give out round fractions of the desired loan amount, such as one half or two thirds. Lenders gave a smaller loan in 40.4% of cases before the crackdown and 84.9% afterwards.

Borrowers use their own income as the primary source to repay in 84.2% of loans.[10] Many borrowers in our data experience fluctuations in income, as they are mostly self-employed or work for small businesses. They also may experience fluctations in expenses each week. Therefore they often fall short of their loan repayments. The borrowers we

[10]Table A.3 in the Online Appendix shows borrowers' primary source of funds to repay loans.

have interviewed told us they never miss payments when they can afford to, but they may put in additional effort to have cash for repayment under a greater threat of harassment.

In the survey, we asked borrowers questions to estimate their discount factors, present bias and risk aversion.[11] The median borrower has a weekly discount factor of $\delta_i = 0.95$, corresponding to an annual factor of 0.069. 99% of the borrowers exhibit present bias, with the median β_i with $\beta_i \delta_i$ discounting equaling 0.752. This is within the range of estimates found by Allcott et al. (2021) for payday loan borrowers. We also estimate that borrowers have a very low degree of risk aversion. The median estimated coefficient of relative risk aversion is $\gamma_i = 0.382$.

3 Model

3.1 Overview

We now describe our model which captures the features of this market described above, starting with an informal overview before describing it formally.

When approached by a borrower asking for a particular loan size, the lender chooses whether to disburse the loan, or to give a smaller loan size. The lender also chooses how harsh to be with the borrower, which corresponds to a probability of conducting severe harassment after a missed payment. This harassment is costly to the lender, but can increase a borrower's loan repayment efforts because harassment gives them disutility. The lender uses available information they have from past loans and other sources to estimate the borrower's repayment ability, and chooses the loan size and harshness level to maximize their expected payoffs, taking into account the loan resetting property and harassment after missed payments.

When a borrower wants to take out a loan, they decide both how much to borrow and which lender to borrow from. While all lenders charge the same interest rate at any given time, lenders differ from the borrower's perspective because of differing past loan history with each lender. Lenders are also heterogeneous in their expected cost of harassment. Depending on the past loan history and cost of harassment, certain lenders are more likely to give larger loans or be harsher with the borrower. In each week of the loan, borrowers generate cash to make repayments and can increase the amount they have available with costly effort. Borrowers obtain utility from consumption, which is the

[11] We provide details of this in Section A.5 in the Online Appendix.

amount they have left after any loan repayments, and obtain disutility from harassment and effort. Based on the borrower's expectations over possible repayment paths and the loan size and harshness level chosen by each lender, the borrower chooses the lender (or the outside option of no loan) that gives the highest expected present discounted value of payoffs.

3.2 Setup

3.2.1 Borrower Loan Demand and Consideration Set of Lenders

In the market there are $\mathcal{I}$ borrowers and $\mathcal{L}$ lenders. At each time period t, the nominal interest rate r_t is chosen by the network of syndicates and all borrowers and lenders take it as given. At time t, borrower i receives a need to borrow an amount of money. The size of the loan that the borrower demands is given by the following demand function:

$$L^{\star}_{it} = \exp\left(\alpha_i r_t + \theta^{\alpha}_i + \upsilon_{it}\right) \tag{1}$$

The first term, α_i, captures the sensitivity of borrower i's loan demand with respect to the interest rate, r_t. We model this as $\alpha_i = \boldsymbol{\theta}^{\alpha}_r \cdot \boldsymbol{x}^{\alpha}_i$, which is a linear function of borrower characteristics, $\boldsymbol{x}^{\alpha}_i$. The second term, θ^{α}_i, is a borrower fixed effect for loan demand, and the third term, υ_{it}, is a mean-zero normally distributed demand shock. We define the vector of loan demand parameters as $\boldsymbol{\theta}^{\alpha} = \left(\boldsymbol{\theta}^{\alpha}_r, \left\{\theta^{\alpha}_i\right\}_{i=1}^{i=\mathcal{I}}\right)$.

Borrower i at time t chooses between a subset of all the lenders active in the market, defined by $\mathcal{C}_{it} \subset \{1, \ldots, \mathcal{L}\}$, or to not borrow at all. We assume that $\mathcal{C}_{it}$ contains the last three lenders a borrower borrowed from, as well as one new lender they have no history with. For these new lenders, we use the observed network of borrowing and lending. We describe the process of choosing new lenders formally in Section A.6 in the Online Appendix, but intuitively, the process works as follows. If two lenders A and B share a large number of borrowers, they are more likely to operate nearby and be in the same social network. A borrower that has borrowed from lender A is more likely to be referred to lender B by other borrowers, and therefore we add lender B to that borrower's consideration set.[12]

[12]In estimation, we do not observe the last three lenders a borrower borrowed from for the first two lenders they visited in our data. In these cases, we take the first three lenders they borrowed from that we observe in our data. For the 7% of borrowers that do not have a history with three lenders in our data, we add additional new lenders using the network approach so that all borrowers have exactly four lenders in

3.2.2 Lender Choice Problem: Loan Size and Harshness Level

If borrower i chooses lender $\ell \in \mathcal{C}_{it}$ and asks for a loan of size $L^{\star}_{it}$, lender ℓ decides on both the size of the loan to give, $L_{i\ell t}$, and how harsh to be in the loan. Lenders will either disburse the full loan the borrower asks for, no loan, or a round fraction of it. The set of possible loan sizes is given by:

$$\mathfrak{L}_{it} = \left\{ \rho L^{\star}_{it} : \rho \in \left\{ 0, \frac{1}{3}, \frac{1}{2}, \frac{2}{3}, 1 \right\} \right\} \tag{2}$$

The harshness level, $h_{i\ell t}$, corresponds to a probability of harassing the borrower after a missed payment, denoted by $p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$. The lender can choose between three harshness levels: $\mathcal{H} = \{Low, Medium, High\}$. The harassment probability $p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$ also depends on the loan size, the borrower's characteristics and past loan history with the lender. The harshness level $h_{i\ell t}$ chosen by the lender can shift this probability up or down. We also allow for lender heterogeneity in harshness. We denote by $k\left(\ell\right) \in \mathcal{K} = \{Regular, Harsh, Very\ Harsh\}$ as lender ℓ's type. We classify lenders into types based on the observed instances of harassment more severe than verbal threats in the data. Very harsh lenders are the top 10%, while harsh lenders are in the top 20% but not in the top 10%.

We parameterize this probability as a function of the harshness level, loan characteristics and borrower characteristics according to:

$$p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right) = \Phi\left(\sum_{h \in \mathcal{H}} \mathbb{1}\left\{h_{i\ell t} = h\right\} \theta^{\eta}_{h} + \theta^{\eta}_{k(\ell)} + \theta^{\eta}_{L} L_{i\ell t} + \boldsymbol{\theta}^{\eta}_{x} \cdot \boldsymbol{x}^{\eta}_{i\ell t} \right) \tag{3}$$

where $\Phi\left(\cdot\right)$ is the cumulative distribution function of the standard normal distribution and $\boldsymbol{x}^{\eta}_{i\ell t}$ includes borrower characteristics and past loan history (such as the number of past loans and missed payments on the last loan). To account for lenders only observing some borrower characteristics after the first loan, such as addictions, we also include interactions of having a past loan history with these characteristics in $\boldsymbol{x}^{\eta}_{i\ell t}$. In Section A.10 in the Online Appendix we show that our results are not sensitive to this assumption. We obtain very similar results from our counterfactual experiments if we instead assume that lenders know all of these characteristics from the first loan.

We assume that the lender communicates its choice to the borrower and commits

their consideration sets.

to it because they have a reputation to maintain. We make this assumption because our data do not track loans across weeks. We observe if harassment occurs in a loan, but we do not observe the week of the loan where the harassment took place. This probability is the probability with which the lender harasses the borrower every time a borrower misses a payment except in the instance where the borrower has missed two payments in a row. According to standard practice in the market, we assume that the lender conducts severe harassment with probability one in this case. For example, if a borrower misses their payments in weeks 3, 4 and 6, the harassment probability is $p_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$ in weeks 3 and 6 but 1 in week 4. We define the vector of harassment parameters $\boldsymbol{\theta}^{\eta} = \left(\left\{\theta_{h}^{\eta}\right\}_{h\in\mathcal{H}}, \left\{\theta_{k}^{\eta}\right\}_{k\in\mathcal{K}}, \theta_{L}^{\eta}, \boldsymbol{\theta}_{x}^{\eta}\right)$.

3.2.3 Borrower Income Process and Moral Hazard

An important component of the expected payoffs in a loan for both borrowers and lenders is the probability that the borrower makes the weekly payments. This determines how often a loan is reset and how much harassment will take place.

Borrowers generate cash m_{i0tw} each week w, which they can use for consumption and loan repayments. We assume this is generated according to a truncated normal distribution:

$$m_{i0tw} = \max\left\{0, m_{i0t} + \nu_{itw}\right\} \qquad \text{where } \nu_{itw} \sim \mathcal{N}\left(0, \sigma_i^2\right) \tag{4}$$

Borrowers generate a fixed amount m_{i0t} plus a stochastic component ν_{itw}. We model m_{i0t} as $m_{i0t} = \bar{y}_i + \boldsymbol{\theta}_0^m \cdot \boldsymbol{x}_{it}^0$, where $\bar{y}_i$ is the borrower's stated average weekly income and $\boldsymbol{x}_{it}^0$ includes borrower characteristics, such as demographics and addictions. We model the standard deviation of income shocks as $\sigma_i = 1 + \theta^{\sigma} Gambler_i$ to allow the variance of the cash available for repayments to be different for gamblers and non-gamblers.

During the course of a loan, borrowers can increase the amount they have available for loan repayments each week through costly effort. For example, by working additional hours or reducing discretionary consumption. This moral hazard component in borrower repayment may be affected by the lender's harshness choice and other characteristics.

We model the additional fixed amount the borrower generates each week to be a linear function of these variables, similar to Einav et al. (2012) and Einav et al. (2013). More specifically, if borrower i has a loan with lender ℓ using a harshness level $h_{i\ell t}$, they increase the fixed component generated each week from m_{i0t} to $m_{i\ell t}\left(h_{i\ell t}\right)$, resulting in a total amount generated each week of:

$$m_{i\ell tw}\left(h_{i\ell t}\right) = \max\left\{0, m_{i\ell t}\left(h_{i\ell t}\right) + \nu_{itw}\right\} \qquad \text{where } \nu_{itw} \sim \mathcal{N}\left(0, \sigma_i^2\right) \tag{5}$$

We model the fixed component $m_{i\ell t}\left(h_{i\ell t}\right)$ as:

$$m_{i\ell t}\left(h_{i\ell t}\right) = \bar{y}_i + \boldsymbol{\theta}_0^m \cdot \boldsymbol{x}_{it}^0 + \theta_\eta^m p_{i\ell t}^\eta\left(L_{i\ell t}, h_{i\ell t}\right) + \theta_r^m\left(r_t - 0.2\right) + \boldsymbol{\theta}_e^m \cdot \boldsymbol{x}_{i\ell t}^e + \theta_{k(\ell)}^m \tag{6}$$

Each week the borrower generates, $m_{i0t} = \bar{y}_i + \boldsymbol{\theta}_0^m \cdot \boldsymbol{x}_{it}^0$, plus the additional amount due to effort. We do not restrict $m_{i\ell t}\left(h_{i\ell t}\right)$ to be larger than m_{i0t} as higher interest rates could reduce effort.[13] This amount is modeled as a linear function of the harassment probability, $p_{i\ell t}^\eta\left(L_{i\ell t}, h_{i\ell t}\right)$, increases of the interest rate above the baseline 20%, additional covariates, $x_{i\ell t}^e$, and the lender's type, $k\left(\ell\right)$. This includes a flexible functional form for the number of past loans with the lender, the number of missed payments in their last loan, and the borrower's present bias and risk aversion. We define the vector of parameters related to the borrower income process as $\boldsymbol{\theta}^m = \left(\boldsymbol{\theta}_0^m, \theta_\eta^m, \theta_r^m, \theta_e^m, \left\{\theta_k^m\right\}_{k\in\mathcal{K}}\right)$.

Exerting effort is costly for the borrower. We assume a unit cost of effort θ^Ψ and do not allow for negative effort costs. The total effort cost is then

$$\Psi_{i\ell t}\left(h_{i\ell t}\right) = \max\left\{\theta^\Psi\left[m_{i\ell t}\left(h_{i\ell t}\right) - m_{i0t}\right], 0\right\} \tag{7}$$

from increasing the fixed component in the income process from m_{i0t} to $m_{i\ell t}\left(h_{i\ell t}\right)$.

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 payment if $m_{i\ell tw}\left(h_{i\ell t}\right) \geq r_t L_{i\ell t}$, as lenders do not accept partial payments. Although we assume borrowers exhibit moral hazard in their effort of generating cash for repayments, in line with our evidence that we discuss below, we assume borrowers never strategically default on a payment. Thus, they will always make a payment if they can afford it. The probability that the borrower can make a payment in any week is therefore given by:

$$p_{i\ell t}^m\left(L_{i\ell t}, h_{i\ell t}\right) = \Phi\left(\frac{m_{i\ell t}\left(h_{i\ell t}\right) - r_t L_{i\ell t}}{\sigma_i}\right) \tag{8}$$

For a given loan size, an increase in the interest decreases the repayment probability in two ways. First, there is the mechanical effect that the weekly repayment, $r_t L_{i\ell t}$, is larger.

[13] At our estimated parameters, however, $m_{i\ell t}\left(h_{i\ell t}\right) > m_{i0t}$ for 86.2% of observations.

Second, there is the moral hazard effect which, as we will find, has a negative impact on $m_{i\ell t}(h_{i\ell t})$. Thus even if loan demand decreases following an increase in the interest rate that keeps $r_t L_{i\ell t}$ the same, the repayment probability can decrease through the moral hazard effect, which depends on the unit cost of credit.

3.3 Lender's Optimal Choice of Loan Size and Harshness

3.3.1 Lender's Estimate of Repayment Probability

Before a lender has interacted with a borrower, we assume they do not observe their addictions, discounting, risk aversion, gang affiliation or prior convictions. We assume they only learn these characteristics after they have had a loan with the borrower in the past. We define analogous components of the borrower income process $\widetilde{m}_{i0t}$, $\widetilde{m}_{i\ell t}(h_{i\ell t})$ and $\widetilde{\sigma}_i$ as the lender's estimates of m_{i0t}, $m_{i\ell t}(h_{i\ell t})$ and σ_i, respectively, where they only use information available to them at the time. Thus we replace the addiction, gang affiliation and prior conviction variables with interactions of the respective variables with having a past loan history, in addition to an indicator for having no history. For example, we model the lender's estimate of σ_i as:

$$\widetilde{\sigma}_i = 1 + \theta^{\widetilde{\sigma}}_{hist,0}\mathbb{1}\{hist_{i\ell t} = 0\} + \theta^{\widetilde{\sigma}}_{gambler}\mathbb{1}\{hist_{i\ell t} > 0\}\, Gambler_i$$

We combine all parameters relating to the lender's estimate of the borrower income process as $\boldsymbol{\theta}^{\widetilde{m}} = \left(\boldsymbol{\theta}^{\widetilde{m}}_0, \theta^{\widetilde{m}}_\eta, \theta^{\widetilde{m}}_r, \theta^{\widetilde{m}}_e, \left\{\theta^{\widetilde{m}}_{k\in\mathcal{K}}\right\}\right)$ and $\boldsymbol{\theta}^{\widetilde{\sigma}} = \left(\theta^{\widetilde{\sigma}}_{hist,0}, \theta^{\widetilde{\sigma}}_{gambler}\right)$. Given this, the lender's estimate of the borrower's cash available for repayments process is given by:

$$\widetilde{m}_{i\ell tw}(h_{i\ell t}) = \max\{0, \widetilde{m}_{i\ell t}(h_{i\ell t}) + \widetilde{v}_{itw}\} \qquad \text{where } \widetilde{v}_{itw} \sim \mathcal{N}\left(0, \widetilde{\sigma}_i^2\right) \tag{9}$$

The lender's estimate of the borrower's repayment probability is then given by:

$$p^{\widetilde{m}}_{i\ell t}(L_{i\ell t}, h_{i\ell t}) = \Phi\left(\frac{\widetilde{m}_{i\ell t}(h_{i\ell t}) - r_t L_{i\ell t}}{\widetilde{\sigma}_i}\right) \tag{10}$$

3.3.2 Lender's Expected Payoffs from a Loan

We now describe the lenders' expected payoffs from a loan of a given size and harshness level, and then discuss their optimal choice. If the lender originates a loan of size $L_{i\ell t}$ with harshness level $h_{i\ell t}$ to the borrower, in week 1 their payoff from the loan is the cash outflow from disbursing the loan:

$$\widetilde{u}_{i\ell t1}\left(L_{i\ell t}\right) = -\left(1 - r_t\right) L_{i\ell t} \tag{11}$$

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 estimates that the borrower will make the payment with probability $p^{\widetilde{m}}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$. If the borrower makes the payment, the lender receives a cash inflow of $r_t L_{i\ell t}$, but if they miss the payment, the lender conducts harassment with probability $p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$ at an expected cost and disutility, $\kappa_{\ell t}$. This expected cost includes the expected cost of paying runners to conduct harassment, $c_{\ell t}$, the probability of arrest from harassing, $p^{e}_{\ell t}$, and the expected disutility from arrest, $K_{\ell t}$:

$$\kappa_{\ell t} = c_{\ell t} + p^{e}_{\ell t} K_{\ell t} \tag{12}$$

Taken together, the expected payoff in week 2 is given by:

$$\mathbb{E}\left[\widetilde{u}_{i\ell t2}\left(L_{i\ell t}, h_{i\ell t}\right)\right] = p^{\widetilde{m}}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right) r_t L_{i\ell t} - \left[1 - p^{\widetilde{m}}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)\right] p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right) \kappa_{\ell t} \tag{13}$$

We allow the harassment cost to vary after the crackdown, and also to vary by lender type. We parameterize it as:

$$\kappa_{\ell t} = \left(1 + \theta^{\kappa}_{k(\ell)}\right)\left(\theta^{\kappa}_{0} + \theta^{\kappa}_{post} post_t\right) \tag{14}$$

where $post_t \in \{0, 1\}$ is a post-crackdown indicator. We group these parameters into $\boldsymbol{\theta}^{\kappa} = \left(\theta^{\kappa}_{0}, \theta^{\kappa}_{post}, \{\theta^{\kappa}\}_{k \in \mathcal{K}}\right)$, where we normalize $\theta^{\kappa}_{k} = 1$ for regular lenders. In estimation, we do not separately identify the monetary cost of harassment from the expected disutility from arrest. Instead, we estimate the sum of these costs.

In the following weeks the lender's payoff depends on the number of consecutive payments the borrower has made up to that point. 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. When a borrower misses a payment in week w, $n_{i\ell tw+1}$ resets to zero. Using this, we can define the lender's expected payoff in each possible case for weeks

$w \in \{2, \ldots, W-1\}$ before the terminal week W as:

$$\widetilde{u}_{i\ell tw}(L_{i\ell t}, h_{i\ell t}) = \begin{cases} r_t L_{i\ell t} & \text{if } n_{i\ell tw} < 6 \text{ and } \widetilde{m}_{i\ell tw}(h_{i\ell t}) \geq r_t L_{i\ell t} \\ -\kappa_{\ell t} + r_t L_{i\ell t} & \text{if } n_{i\ell tw} = 0 \text{ and } \widetilde{m}_{i\ell tw}(h_{i\ell t}) < r_t L_{i\ell t} \\ -(n_{i\ell tw} - 1) r_t L_{i\ell t} - p^{\eta}_{i\ell t}(L_{i\ell t}, h_{i\ell t}) \kappa_{\ell t} & \text{if } n_{i\ell tw} \in \{1, \ldots, 5\} \text{ and } \widetilde{m}_{i\ell tw}(h_{i\ell t}) < r_t L_{i\ell t} \\ 0 & \text{if } n_{i\ell tw} = 6 \end{cases} \tag{15}$$

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 has missed two payments in a row and the lender harasses the borrower with probability one. The borrower is required to come up with the penalty by the end of the week. In the third case, the borrower misses a payment and the lender must return $(n_{i\ell tw} - 1) r_t L_{i\ell t}$ back to the borrower. They inflict harassment with probability $p^{\eta}_{i\ell t}(L_{i\ell t}, h_{i\ell t})$ 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 rarer case that the loan is still unpaid by the terminal week $W = 24$, the lender will make the borrower do work for them to finish paying off the loan. We assume the terminal week is the 24th week because 89.7% of loans are repaid within this timeframe, closely matching the 8.7% rate at which borrowers are made work for the lender when loans are unpaid after many months. We assume that in expectation the value of this work equals the remaining amount due on the loan. We define these payoffs exactly in Section A.7.1 in the Online Appendix.

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

$$\widetilde{V}_{i\ell t}(L_{i\ell t}, h_{i\ell t}) = -(1 - r_t) L_{i\ell t} + \mathbb{E}\left[\sum_{w=2}^{W} \widetilde{\delta}^{w-1} \widetilde{u}_{i\ell tw}(L_{i\ell t}, h_{i\ell t})\right] + \widetilde{\varepsilon}_{i\ell t}(L_{i\ell t}, h_{i\ell t}) \tag{16}$$

where $\widetilde{\varepsilon}_{i\ell t}(L_{i\ell t}, h_{i\ell t})$ is a lender payoff shock specific to the loan size and harshness level that is private information to the lender.

3.3.3 Lender's Choice of Loan Size and Harshness Level

We assume a nested logit structure for the lender's choice problem, where the upper nest is the loan size and the lower nests are the harshness levels. If the lender chooses a loan size of zero, there is no lower nest. For the sake of notation, we assume the lender uses the "Low" harshness level in this case. We denote by $p^{Lh}_{i\ell t}(L_{i\ell t}, h_{i\ell t})$ the nested logit probabilities that the lender chooses loan size $L_{i\ell t} \in \mathfrak{L}_{it}$ and harshness level $h_{i\ell t} \in \mathcal{H}$ before the realizations of the payoff shocks $\widetilde{\varepsilon}_{i\ell t}(L_{i\ell t}, h_{i\ell t})$. For positive loan sizes, the probability that the lender chooses the combination $(L_{i\ell t}, h_{i\ell t})$ is given by

$$p^{Lh}_{i\ell t}(L_{i\ell t}, h_{i\ell t}) = \frac{\exp\left(\widetilde{\widetilde{V}}_{i\ell t}(L_{i\ell t}, h_{i\ell t}) / \lambda_{g_{i\ell t}(L_{i\ell t})}\right)}{\sum_{h'_{i\ell t} \in \mathcal{H}} \exp\left(\widetilde{\widetilde{V}}_{i\ell t}\left(L_{i\ell t}, h'_{i\ell t}\right) / \lambda_{g_{i\ell t}(L_{i\ell t})}\right)} \times \\ \frac{\exp\left(\lambda_{g_{i\ell t}(L_{i\ell t})} \log\left(\sum_{h'_{i\ell t} \in \mathcal{H}} \exp\left(\widetilde{\widetilde{V}}_{i\ell t}\left(L_{i\ell t}, h'_{i\ell t}\right) / \lambda_{g_{i\ell t}(L_{i\ell t})}\right)\right)\right)}{1 + \sum_{L'_{i\ell t} \in \mathfrak{L}_{it} \setminus \{0\}} \exp\left(\lambda_{g_{i\ell t}(L'_{i\ell t})} \log\left(\sum_{h' \in \mathcal{H}} \exp\left(\widetilde{\widetilde{V}}_{i\ell t}\left(L'_{i\ell t}, h'_{i\ell t}\right) / \lambda_{g_{i\ell t}(L'_{i\ell t})}\right)\right)\right)} \tag{17}$$

where $\widetilde{\widetilde{V}}_{i\ell t}(L_{i\ell t}, h_{i\ell t}) = \widetilde{V}_{i\ell t}(L_{i\ell t}, h_{i\ell t}) - \widetilde{\varepsilon}_{i\ell t}(L_{i\ell t}, h_{i\ell t})$ is the choice-specific value without the payoff shock and the function $g_{i\ell t}(L_{i\ell t})$ indexes the elements of $\mathfrak{L}_{it} \setminus \{0\}$.[14] We group the terms $\lambda_{g_{i\ell t}(L_{i\ell t})}$ into $\boldsymbol{\theta}^{\lambda}$.

3.4 Borrower's Optimal Choice of Lender

We now describe the expected payoffs for borrower i from a loan of size $L_{i\ell t}$ and harshness level $h_{i\ell t}$ with lender ℓ at time t. We then discuss the borrower's optimal choice of lender.

3.4.1 Borrower's Expected Payoffs Given Loan Size and Harshness Level

In the first week, the borrower consumes their available cash m_{i0t1} and the disbursed loan $(1 - r_t) L_{i\ell t}$. The borrower does not put in extra effort to raise cash in the first week because the first payment is already taken out of the initial loan size by the lender. We assume the borrower takes out the loan before the weekly cash shock ν_{itw} is realized. We further assume borrowers have constant relative risk aversion utility over consumption

[14] For example, $g_{i\ell t}\left(\frac{1}{3}L^{\star}_{it}\right) = 1$ and $g_{i\ell t}\left(L^{\star}_{it}\right) = 4$. The probability that the lender chooses to give no loan is then: $p^{Lh}_{i\ell t}(0, Low) = 1 - \sum_{L_{i\ell t} \in \mathfrak{L}_{it} \setminus \{0\}} \sum_{h_{i\ell t} \in \mathcal{H}} p^{Lh}_{i\ell t}(L_{i\ell t}, h_{i\ell t})$ where we note that $p^{Lh}_{i\ell t}(0, Medium) = p^{Lh}_{i\ell t}(0, High) = 0$.

each week, where borrower i's coefficient of relative risk aversion is γ_i. The borrower's expected utility in week 1 is then:

$$\mathbb{E}\left[u_{i\ell t1}\left(L_{i\ell t}\right)\right] = \mathbb{E}\left[\frac{\left[m_{i0t1} + \left(1 - r_t\right) L_{i\ell t}\right]^{1-\gamma_i} - 1}{1 - \gamma_i}\right] \tag{18}$$

In week 2, the borrower is able to make the repayment with probability $p^m_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$. If the borrower misses the payment, the borrower will be harassed by the lender with probability $p^\eta_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$, which gives the borrower disutility χ_ℓ. We parameterize this as $\chi_\ell = \theta^\chi_{k(\ell)}$ to allow different lender types to give different harassment disutilities. We denote $\boldsymbol{\theta}^\chi = \left\{\theta^\chi_k\right\}_{k \in \mathcal{K}}$.

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

$$\begin{aligned}
&\mathbb{E}\left[u_{i\ell t2}\left(L_{i\ell t}, h_{i\ell t}\right)\right] = -\Psi_{i\ell t}\left(h_{i\ell t}\right) \\
&+ \left[p^m_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)\right] \mathbb{E}\left[\left.\frac{\left[m_{i\ell t2}\left(h_{i\ell t}\right) - r_t L_{i\ell t}\right]^{1-\gamma_i} - 1}{1 - \gamma_i}\right| m_{i\ell t2}\left(h_{i\ell t}\right) \geq r_t L_{i\ell t}\right] \\
&+ \left[1 - p^m_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)\right]\left(\mathbb{E}\left[\left.\frac{\left[m_{i\ell t2}\left(h_{i\ell t}\right)\right]^{1-\gamma_i} - 1}{1 - \gamma_i}\right| m_{i\ell t2}\left(h_{i\ell t}\right) < r_t L_{i\ell t}\right] - p^\eta_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)\chi_\ell\right)
\end{aligned} \tag{19}$$

Because IML borrowing is legal for borrowers, there is no arrest probability. In the following weeks, the payoff depends on the number of consecutive payments made before week w, $n_{i\ell tw}$. We can define the borrower's expected payoff in each possible case for all weeks $w \in \{2, \ldots, W-1\}$ as:

$$\begin{aligned}
&\mathbb{E}\left[u_{i\ell tw}\left(L_{i\ell t}, h_{i\ell t}\right)\right] = \\
&\begin{cases}
\mathbb{E}\left[\left.\frac{\left[m_{i\ell tw}\left(h_{i\ell t}\right) - r_t L_{i\ell t}\right]^{1-\gamma_i} - 1}{1-\gamma_i}\right| m_{i\ell tw}\left(h_{i\ell t}\right) \geq r_t L_{i\ell t}\right] - \Psi_{i\ell t}\left(h_{i\ell t}\right) & \text{if } n_{i\ell tw} < 6 \text{ and } m_{i\ell tw}\left(h_{i\ell t}\right) \geq r_t L_{i\ell t} \\
-\frac{1}{1-\gamma_i} - \theta^\Psi \mathbb{E}\left[r_t L_{i\ell t} - m_{i\ell tw}\left(h_{i\ell t}\right) \middle| m_{i\ell tw}\left(h_{i\ell t}\right) < r_t L_{i\ell t}\right] & \\
-\chi_\ell - \Psi_{i\ell t}\left(h_{i\ell t}\right) & \text{if } n_{i\ell tw} = 0 \text{ and } m_{i\ell tw}\left(h_{i\ell t}\right) < r_t L_{i\ell t} \\
\mathbb{E}\left[\left.\frac{\left[m_{i\ell tw}\left(h_{i\ell t}\right) + \left(n_{i\ell tw} - 1\right) r_t L_{i\ell t}\right]^{1-\gamma_i} - 1}{1-\gamma_i}\right| m_{i\ell tw}\left(h_{i\ell t}\right) < r_t L_{i\ell t}\right] & \\
\quad -p^\eta_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)\chi_\ell - \Psi_{i\ell t}\left(h_{i\ell t}\right) & \text{if } n_{i\ell tw} \in \{1, \ldots, 5\} \text{ and } m_{i\ell tw}\left(h_{i\ell t}\right) < r_t L_{i\ell t} \\
\mathbb{E}\left[\frac{\left[m_{i0tw}\right]^{1-\gamma_i} - 1}{1-\gamma_i}\right] & \text{if } n_{i\ell tw} = 6
\end{cases}
\end{aligned} \tag{20}$$

In the first case, the borrower is able to make the payment and consumes their remaining income. In the second case, the borrower has missed two payments in a row and is harassed with probability one. They are required to pay the financial penalty by the end of the week and use costly effort to make up for the shortfall. 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. The borrower also is harassed with probability $p^{\eta}_{i\ell t}\,(L_{i\ell t}, h_{i\ell t})$. In the final case, the loan is already fully repaid and the borrower consumes their entire available cash, m_{i0tw}, from that week.

If the loan is unpaid upon reaching the terminal week W, the borrower must work for the lender. This gives the borrower disutility because the lender requires them to complete undesirable tasks. Borrowers we have interviewed stated the expected disutility from this is between 8-10 times the expected disutility from missing a payment, and the expected level of disutility from this depends on the amount outstanding on the loan. We specify the exact terminal week payoffs of the borrower in Section A.7.2 in the Online Appendix in order to match the borrower's responses from the interviews. We note that because the majority of borrowers in our sample discount the future very heavily (the median borrower in our sample values \$1 in one year at 6.5 cents today), the specification of the terminal week payoffs does not have a large impact on the borrowers' expected present discounted payoffs from loans.

Borrowers discount payoffs in future weeks with quasi-hyperbolic discounting. Borrower i discounts expected payoffs w weeks in the future with a discount factor $\beta_i \delta_i^w$. The expected present discounted value of a loan of size $L_{i\ell t}$ and harshness level $h_{i\ell t}$ from lender ℓ is then:

$$v_{i\ell t}\,(L_{i\ell t}, h_{i\ell t}) = \mathbb{E}\left[u_{i\ell t1}\,(L_{i\ell t}) + \sum_{w=2}^{W} \beta_i \delta_i^{w-1} u_{i\ell tw}\,(L_{i\ell t}, h_{i\ell t})\right] \tag{21}$$

3.4.2 Borrower Lender Choice Probabilities

The borrower does not observe the value of the lender's payoff shocks, $\widetilde{\varepsilon}_{i\ell t}\,(L_{i\ell t}, h_{i\ell t})$. Therefore, when a borrower is choosing a lender, they are uncertain about the loan size they will receive and the harshness level that the lender will choose. However, borrowers know the probabilities $p^{Lh}_{i\ell t}\,(L_{i\ell t}, h_{i\ell t})$ of the lender choosing each combination. These probabilities depend on the borrower's past history and performance with the lender, as well as the lender's harshness type, which makes the lenders differentiated from the borrower's perspective. The expected present discounted payoff of choosing lender ℓ is then:

$$V_{i\ell t} = \sum_{L_{i\ell t} \in \mathfrak{L}_{it}} \sum_{h_{i\ell t} \in \mathcal{H}} p_{i\ell t}^{Lh} \left(L_{i\ell t}, h_{i\ell t}\right) v_{i\ell t} \left(L_{i\ell t}, h_{i\ell t}\right) + \varepsilon_{i\ell t} \tag{22}$$

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 consume their weekly available cash, m_{i0tw}, each week. The expected presented discounted value of payoffs from this option is then:

$$V_{i0t} = \mathbb{E}\left[\frac{m_{i0t1}^{1-\gamma_i} - 1}{1-\gamma_i} + \sum_{w=2}^{W} \beta_i \delta_i^{w-1} \frac{m_{i0tw}^{1-\gamma_i} - 1}{1-\gamma_i}\right] + \varepsilon_{i0t} \tag{23}$$

where ε_{i0t} is a Type I extreme value shock to the match value of the outside option.

The borrower chooses the lender or outside option which maximizes their payoff. 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, $\varepsilon_{i\ell t}$ and ε_{i0t}. Before the realization of the match value shock, the probability of choosing lender ℓ is then given by:

$$\Pr\left(V_{i\ell t} > \max_{\ell' \in \{0\} \cup \mathcal{C}_{it} \setminus \{\ell\}} V_{i\ell' t}\right) = \frac{\exp\left(\bar{V}_{i\ell t}\right)}{\sum_{\ell' \in \{0\} \cup \mathcal{C}_{it}} \exp\left(\bar{V}_{i\ell' t}\right)} \tag{24}$$

3.5 Discussion of Modeling Assumptions

In this section we present evidence from our data and interviews we have carried out to justify the modeling assumptions we make above.

3.5.1 The Cartel of Loan Shark Syndicates

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 and loan structure, including the maturity, financial penalties for missed payments, similar harassment methods, and no collateral requirement. Moreover, the syndicates guarantee each of their lenders a monopoly in the geographic area where they operate, aimed at preventing conflicts between lenders that would attract the attention of law enforcement. This form of cartel-like agreements is a typical feature of illicit market products. Allard (2019) writes that "the crime network is also less prone to uncontrolled outbreaks of internecine violence ... The money is so big that long-standing, blood-soaked rivalries among Asian crime groups have been set aside in a united pursuit of gargantuan profits." 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 common practice among lenders. Third, lenders are not cash constrained and their harassment methods ensure that borrowers always repay, so they have little incentive to reject borrowers that approach them. This also limits borrowers' search among lenders, therefore reducing the size of their consideration set and the extent of competition.

Additionally, the IML market does not compete with legal moneylenders in our setting. The formal sector interest rate is capped at 4% per month which implies an APR of 48%, less than one quarter of the pre-crackdown IML APR of 209%. Borrowers with access to the formal sector would have no incentive to borrow from loan sharks, and, as documented above, the borrowers in our sample did not have access to formal-sector loans.

We also do not model lenders choosing the interest rate they charge to borrowers or engaging in any form of price discrimination. The cartel of loan shark syndicates advised lenders on the rate they should charge to all borrowers at any given time. In our data, 88% of loans had a nominal rate of 20% before the crackdown in 2014. After 2015, 89.6% of loans had a nominal rate of 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. Soudijn and Zhang (2013), who document the activities of a Chinese loan shark using a seized ledger from a Dutch casino, also document a lack of price discrimination. Because we only observe two interest-rate regimes in our data, we do not model cartel interest-rate setting in our baseline model. However, we explore optimal cartel interest-rate setting before and after the crackdown in Section 6.1.2.

3.5.2 Lenders

Our model assumes that lenders are not cash constrained and choose how much to lend to a borrower, instead of which borrowers to lend to. Actively-trading lenders make large profits as there is very little default, high interest rates, and high revenue from missed payment penalties. 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 from the syndicate 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.

Our model further assumes that lenders have no fixed costs of lending to a particular borrower. For each individual loan, we consider the lender's fixed costs as sunk. While there are very few loans for less than S$300 in our sample, lenders are still willing to give out small loans. There are a small number of S$100 loans in our sample, and we also tried to take out a loan for S$150 ourselves and were able to do so. This is evidence that lenders do not have an economically significant fixed cost per loan.

3.5.3 Borrowers

Our model assumes that borrowers choose between three past lenders and one new lender when they want to take out a loan. We assume borrowers undertake limited search for new lenders because all the borrowers in our dataset stated that they considered less than or equal to one new lender for all transactions. This assumption is consistent with the high persistence in borrowers' choice of lenders that we observe in our data, where only 15% of loans were taken with a new lender. While this persistence suggests that modeling the first choice of lender, similarly to Crawford et al. (2018), is important, the nature of our data prevents us to do so. First, we do not observe the first lender chosen by our borrowers, as all of them were already in the IML market before the start of our survey. Second, even if we were to focus on instances where existing borrowers switch to a new lender, having only 15% of the observations would raise issues of statistical power for our estimation, and of sample selection for our estimation and counterfactuals.

Our model assumes that borrowers ask lenders for the amount they desire and do not inflate it because they think a lender will only give them half of what they ask for. The borrowers we have interviewed stated they had little incentive to ask for a larger amount, mainly for two reasons. First, lenders ultimately decide whether to lend at each loan size and asking for a larger amount won't alter their decision. Second, if the lender gave them an amount larger than what they desired, they would have greater difficulty repaying it.

During a loan, borrowers typically use their own income to make repayments. Table A.3 in the Online Appendix shows the primary source of funds borrowers used to repay loans in our survey. In 84.2% of loans they used their own income as the primary source, whereas borrowing from colleagues and friends (4.2%), family (2.3%) or another loan shark (1.6%) to be able to repay is much less common. In our model, for reasons such as the threat of harassment, they expend effort to have additional cash available for repayments.

Because it is less common, we do not model borrowers choosing to borrow from friends, family or other lenders to repay existing loans. Borrowers sometimes use a part of new loans to help repay part of their existing loans, but it is generally not the primary reason they take out a loan. Table A.1 in the Online Appendix shows that 34.3% of borrowers stated that they used part of the loan to repay an existing lender, but this was the primary reason for only 9.1% of loans. Table 2 in Lang et al. (forthcoming) also reports borrowers using other loans to help repay existing loans. However, they report an aggregation of all sources used to repay and not the primary source, which is why all sources taken together add up to much more than 100%. The reason borrowers do not take out loans with the primary purpose of repaying existing loans is because lenders 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. In our model we therefore assume that borrowers cannot take out another loan to repay an existing one.

We assume borrowers always make a repayment when they can afford to. Because of the threat of harassment, together with the fact that lenders almost always get the loans repaid eventually, borrowers exert effort to make repayments and almost always make a repayment when they can 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. Our model estimates show that the median borrower would need to be compensated with at least S$2,599.91 to accept lenders' harassment. Even with the model's average harassment probability of 21.9%, and ignoring that the loan will reset, the median borrower is still better off making the weekly repayment of S$200 at the median loan size. Therefore, in our model we assume that borrowers will always make a loan repayment when they have enough cash available to do so. The borrowers we have interviewed also stated that borrowers do not report lenders to the authorities when they cannot repay. This is because lenders would seek revenge on the borrower which would be much more severe than the harassment from a missed payment. Reporting a lender would also exclude the borrower from future loans, as this information would be shared between lenders.

Our model assumes that borrowers do not save money across weeks. All borrowers in our sample stated they have zero savings that they can withdraw. They said that if they had savings, they would not be borrowing 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.

Due to the large fraction of impatient and 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 larger loan they could get in the future from the same lender if they were to perform well on the current loan. Because the median borrower values the payoff of a loan in one year at only 6.5% of the same loan today, we argue that the dynamic strategic incentives for borrowers are minimal. According to our model estimates, the average borrower would obtain a higher surplus of S$0.69 per week during a loan from having missed one fewer payment with all of their past lenders when deciding to take out a loan. This low return, together with the high rate of discounting and present bias, implies that incorporating dynamic incentives in borrower effort and lender choice would likely have negligible effects on borrower behavior. Therefore we argue it would not impact our main results.

Finally, our modeling of the borrower's choice of lender is a complex dynamic problem. We use this formulation which takes into account the specific loan structure in our setting for the following reasons. First, the borrowers in our sample are very experienced and understand the structure of loans. In our surveys we asked borrowers mathematical questions about the loan structure and only 2 of the 1,090 borrowers answered questions incorrectly. This is evidence that the borrowers are not cognitively impaired. This is similar to a result found by Carvalho et al. (2016), who find that among low-income households, financial strain does not impede cognitive function, nor worsens the quality of decision-making. Furthermore, 93% of the borrowers in our sample stated that they have talked to others to obtain advice about borrowing. Therefore we argue that on average borrowers are able to compute the expected payoffs from a lender. Second, although we model the choice of lender as a rational problem, the extremely low discount factors and high degree of present bias in most borrowers lead borrowers to weight the initial utility of receiving the loan much higher than the following repayments and harassment. Thus our framework is able to rationalize decisions that are not dynamically consistent. Third, in order to analyze the effects of law enforcement interventions, we want to be able to decompose how changes in interest payments and harassment contribute to welfare changes within the structure of loans in the market.

4 Estimation

The full vector of parameters to be estimated is given by:

$$\boldsymbol{\theta} = \left(\boldsymbol{\theta}^{\eta}, \boldsymbol{\theta}^{\widetilde{m}}, \boldsymbol{\theta}^{\widetilde{\sigma}}, \boldsymbol{\theta}^{\kappa}, \boldsymbol{\theta}^{\lambda}, \boldsymbol{\theta}^{\alpha}, \boldsymbol{\theta}^{m}, \boldsymbol{\theta}^{\sigma}, \boldsymbol{\theta}^{\chi}, \theta^{\Psi}\right) \tag{25}$$

We estimate $\boldsymbol{\theta}$ in a series of steps. We first jointly estimate all parameters related to the lender's problem, which are given by $\boldsymbol{\theta}^{Lender} = \left(\boldsymbol{\theta}^{\eta}, \boldsymbol{\theta}^{\widetilde{m}}, \boldsymbol{\theta}^{\widetilde{\sigma}}, \boldsymbol{\theta}^{\kappa}, \boldsymbol{\theta}^{\lambda}\right)$. We then estimate the remaining parameters related to the borrowers in three further steps. We describe each of these steps in turn.

4.1 Estimation of Lender Parameters

To identify the harassment probability parameters, $\boldsymbol{\theta}^{\eta}$, we use observed harassment events in our data given the observed number of missed payments. We denote by $\mathfrak{h}_{i\ell t} \in \{0, 1\}$ whether severe harassment was used in a loan. In our data, we observe if harassment was used at the loan level, but we observe neither the exact number of times harassment was used nor its timing. 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 were used for different missed payments, or if they were both used at the same time in response to a single missed payment. We also do not observe how many times a single form of harassment was used in a loan. Therefore we only use if harassment was used at least once to identify $\boldsymbol{\theta}^{\eta}$.

To identify the repayment probability parameters from the lender's perspective, $\boldsymbol{\theta}^{\widetilde{m}}$ and $\boldsymbol{\theta}^{\widetilde{\sigma}}$, we use the observed total number of weeks to repay, $w_{i\ell t}$, the total number of missed payments, $f_{i\ell t}$, and whether the borrower reached the terminal week, $d_{i\ell t} \in \{0, 1\}$. This is because we do not observe the specific weeks in which missed payments occurred in our data.

Finally, to identify the lender harassment cost parameters, $\boldsymbol{\theta}^{\kappa}$, and the nested logit parameters, $\boldsymbol{\theta}^{\lambda}$, we use variation in the observed loan sizes in the data. A higher harassment cost leads lenders to be more likely to choose smaller loans for a given repayment ability and harshness level, as they will need to harass borrowers more often to ensure they repay.

We now discuss the likelihood function that we use to jointly estimate the parameters $\boldsymbol{\theta}^{Lender}$. We do not observe the harshness level, $h_{i\ell t}$, chosen by the lender (we only observe if harassment occurs). Therefore we integrate it out of our likelihood:

$$\Pr\left(\mathfrak{h}_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}, L_{i\ell t} \middle| \theta^{Lender}\right) = \sum_{h_{i\ell t} \in \mathcal{H}} \Pr\left(\mathfrak{h}_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}, L_{i\ell t} \middle| \theta^{Lender}, h_{i\ell t}\right) \times \Pr\left(h_{i\ell t} \middle| \theta^{Lender}\right) \tag{26}$$

The first term in the sum can be re-written as:

$$\Pr\left(\mathfrak{h}_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}, L_{i\ell t} \middle| \theta^{Lender}, h_{i\ell t}\right) = \Pr\left(\mathfrak{h}_{i\ell t} \middle| \theta^{Lender}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}, L_{i\ell t}, h_{i\ell t}\right) \times \Pr\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t} \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right) \times \Pr\left(L_{i\ell t} \middle| \theta^{Lender}, h_{i\ell t}\right) \tag{27}$$

Combining equations (26) and (27), the contribution of loan (i, ℓ, t) to the likelihood can be written as:

$$\Pr\left(\mathfrak{h}_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}, L_{i\ell t} \middle| \theta^{Lender}\right) = \sum_{h_{i\ell t} \in \mathcal{H}} \underbrace{\Pr\left(\mathfrak{h}_{i\ell t} \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\right)}_{\text{Harassment Likelihood}} \times \underbrace{\Pr\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t} \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)}_{\text{Loan Performance Likelihood}} \times \underbrace{\Pr\left(L_{i\ell t} \middle| \theta^{Lender}, h_{i\ell t}\right)}_{\text{Loan Size Likelihood}} \underbrace{\Pr\left(h_{i\ell t} \middle| \theta^{Lender}\right)}_{\text{Harashness Level Probabilities}} \tag{28}$$

In the following subsections we describe the functional form of each component of the likelihood contribution.

Harassment Likelihood: The first component $\Pr\left(\mathfrak{h}_{i\ell t} \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\right)$ in equation (28) is the likelihood of whether harassment was used at least once or not given the harassment probability (which depends on the loan size and harshness level), the time to repay and number of missed payments. In our model, if a borrower misses one payment, the lender will harass the borrower with probability $p^{\eta}_{i\ell t}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$. If the borrower misses two payments in two consecutive weeks, the lender will harass the borrower with probability one after the second missed payment. For example, a loan with missed payments in weeks 2 and 3 has harassment in week 2 with probability $p^{\eta}_{i\ell t}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$ and in week 3 with probability 1. On the contrary, a loan with missed payments in weeks 2 and 4 has harassment with probability $p^{\eta}_{i\ell t}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$ in both weeks.

We use the number of missed payments combined with the number of possible ways a loan can have two consecutive missed payments given the time taken to repay to estimate the harassment probability. We denote by $\Pr\left(\mathfrak{h}_{i\ell t} = 1 \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\right)$ the probability of harassment occurring at least once given $w_{i\ell t}$, $f_{i\ell t}$, $d_{i\ell t}$, $L_{i\ell t}$ and $h_{i\ell t}$. This is given by:

$$\begin{aligned} &\Pr\left(\mathfrak{h}_{i\ell t} = 1 \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\right) = \\ &(1 - d_{i\ell t})\left(\frac{\widehat{\widehat{C}}_{f_{i\ell t}}^{w_{i\ell t}} + \left(C_{f_{i\ell t}}^{w_{i\ell t}} - \widehat{\widehat{C}}_{f_{i\ell t}}^{w_{i\ell t}}\right)\left(1 - \left[1 - p_{i\ell t}^{\eta}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)\right]^{f_{i\ell t}}\right)}{C_{f_{i\ell t}}^{w_{i\ell t}}}\right) \\ &+ d_{i\ell t}\left(\frac{\widehat{\widehat{C}}_{f_{i\ell t}}^{d} + \left(C_{f_{i\ell t}}^{d} - \widehat{\widehat{C}}_{f_{i\ell t}}^{d}\right)\left(1 - \left[1 - p_{i\ell t}^{\eta}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)\right]^{f_{i\ell t}}\right)}{C_{f_{i\ell t}}^{d}}\right) \end{aligned} \tag{29}$$

The terms C_f^w, $\widehat{\widehat{C}}_f^w$, C_f^d and $\widehat{\widehat{C}}_f^d$ are defined as follows. First, C_f^w is the number of ways (possible paths of missing and making payments) through which a loan can finish in w weeks with f missed payments. Second, $\widehat{\widehat{C}}_f^w$ is the number of ways a loan can have two missed payments in a row when finishing in w weeks with f missed payments. Third, C_f^d is the number of ways a loan can reach the terminal week with f missed payments. Finally, $\widehat{\widehat{C}}_f^d$ is the number of ways a loan can have two missed payments in a row when reaching the terminal week with f missed payments. We provide example cases of this formula in Section A.8 in the Online Appendix.

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

$$\begin{aligned} \Pr\left(\mathfrak{h}_{i\ell t} \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\right) =& \mathfrak{h}_{i\ell t} \Pr\left(\mathfrak{h}_{i\ell t} = 1 \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\right) + \\ & (1 - \mathfrak{h}_{i\ell t})\left[1 - \Pr\left(\mathfrak{h}_{i\ell t} = 0 \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\right)\right] \end{aligned} \tag{30}$$

Loan Performance Likelihood: The second component $\Pr\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t} \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$ in equation (28) is the probability of the observed total number of weeks to repay and the total number of missed payments given the loan size and harshness level. If the probability of making a payment in any given week is $p_{i\ell t}^{\widetilde{m}}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$, then the probability that the borrower completes the loan in w weeks with f missed payments according to our model is:

$$C_f^w \left[p_{i\ell t}^{\widetilde{m}}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)\right]^{w-f-1}\left[1-p_{i\ell t}^{\widetilde{m}}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)\right]^f \tag{31}$$

where C_f^w is (as in equation (29)) the number of possible ways a borrower can miss f payments in w weeks under the structure of the loan.

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

$$\begin{aligned}
&\Pr\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\,\middle|\,\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right) = \\
&\quad (1-d_{i\ell t})\, C_{f_{i\ell t}}^{w_{i\ell t}}\left[p_{i\ell t}^{\widetilde{m}}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)\right]^{w_{i\ell t}-f_{i\ell t}-1}\left[1-p_{i\ell t}^{\widetilde{m}}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)\right]^{f_{i\ell t}} \\
&\quad + d_{i\ell t}\left(1-\sum_{w=1}^{W}\sum_{f=0}^{w} C_f^w\left[p_{i\ell t}^{\widetilde{m}}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)\right]^{w-f-1}\left[1-p_{i\ell t}^{\widetilde{m}}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)\right]^{f}\right)
\end{aligned} \tag{32}$$

The final term in parentheses is the probability that the loan reaches the terminal period unpaid.

Loan Size Likelihood and Harshness Level Probabilities: The third component $\Pr\left(L_{i\ell t}\,\middle|\,\boldsymbol{\theta}^{Lender}, h_{i\ell t}\right)$ in equation (28) is the probability of the observed loan size given the harshness level. This is given by:

$$\Pr\left(L_{i\ell t}\,\middle|\,\boldsymbol{\theta}^{Lender}, h_{i\ell t}\right) = \frac{p_{i\ell t}^{Lh}\left(L_{i\ell t}, h_{i\ell t}\,\middle|\,\boldsymbol{\theta}^{Lender}\right)}{\Pr\left(h_{i\ell t}\,\middle|\,\boldsymbol{\theta}^{Lender}\right)} \tag{33}$$

where

$$\Pr\left(h_{i\ell t}\,\middle|\,\boldsymbol{\theta}^{Lender}\right) = \sum_{L_{i\ell t}\in\mathfrak{L}_{it}} p_{i\ell t}^{Lh}\left(L_{i\ell t}, h_{i\ell t}\,\middle|\,\boldsymbol{\theta}^{Lender}\right) \tag{34}$$

in the fourth component. We compute $p_{i\ell t}^{Lh}\left(L_{i\ell t}, h_{i\ell t}\,\middle|\,\boldsymbol{\theta}^{Lender}\right)$ via simulation. Given a guess of parameters $\boldsymbol{\theta}^{Lender}$, we compute the $\widetilde{\widetilde{V}}_{i\ell t}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$ from equation (17) for each possible loan size and harshness level by simulating ns =10,000 repayment paths using the repayment probability $p_{i\ell t}^{\widetilde{m}}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$ and the harassment probability $p_{i\ell t}^{\eta}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$. If the fraction of the actual loan size to the desired loan size is not one of the fractions $\frac{1}{3}$, $\frac{1}{2}$, $\frac{2}{3}$, or 1, we replace the ρ in $\mathfrak{L}_{it}$ closest to that in the data with the actual fraction in the data. To do this, we assume the lender's weekly discount factor is $\widetilde{\delta} = 0.999$, corresponding to an annual discount factor of 0.95. This is a common annual discount factor used in empirical settings, such as in Holmes (2011) and Collard-Wexler (2013). We have also elicited the discount factor from two ex-lenders and found them to be consistent with this assumption.

4.2 Estimation of Borrower Loan Demand Parameters

We estimate the borrower loan demand parameters, $\boldsymbol{\theta}^{\alpha}$, by estimating equation (1) in log form using a linear regression with borrower fixed effects:

$$\log\left(L_{it}^{\star}\right) = \boldsymbol{\theta}_r^{\alpha} \cdot \boldsymbol{x}_i^{\alpha} \times r_t + \boldsymbol{\theta}_i^{\alpha} + \upsilon_{it} \tag{35}$$

Because the crackdown increased the costs of lending, the cartel of syndicates responded by increasing the nominal interest rate from 20% to 35%. All other loan characteristics, such as the maturity, loan reset structure, and lack of a collateral requirement remained unchanged. Because the change in the interest rates were due to the crackdown's effect on the cost of harassment and not due to changes in demand, the variation in the interest rate over time with variation in the loan sizes demanded on the intensive margin identifies the level term $\boldsymbol{\theta}_r^{\alpha}$. The differences in how loan demand changes after the crackdown for borrowers of different characteristics identifies the interaction terms in $\boldsymbol{\theta}_r^{\alpha}$.

Although the crackdown only affected the interest rate in loan contracts, the borrower's consideration sets of lenders changed after the crackdown as some lenders were arrested or exited. We argue that this did not have a significant impact on borrowers' price sensitivity. Below, we document that the borrowers have price elasticity of -0.817. If we instead estimate this elasticity using only the 74% subsample of borrowers who did not borrow from a new lender after the crackdown (i.e. those borrowers whose normal lenders were still in the market after the crackdown), we obtain a very similar (and statistically indistinguishable) elasticity of -0.823. Furthermore, in our counterfactual where we undo the effects of the crackdown, we find only minimal effects if we reinstate borrowers' pre-crackdown consideration sets after the crackdown.

4.3 Estimation of Borrower Repayment Parameters

To estimate the borrower repayment parameters, $\boldsymbol{\theta}^m$ and $\boldsymbol{\theta}^\sigma$, we use variation in the observed total weeks to repay and the number of missed payments, similar to the second component of the lender likelihood. As the repayment probability depends on the harshness level, which is unobserved, we integrate it out using the estimated lender parameters. The contribution of a loan to this likelihood is given by:

$$\begin{aligned}&\Pr\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\left|L_{i\ell t}, \widehat{\boldsymbol{\theta}}^{Lender}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma\right.\right) = \\ &\sum_{h_{i\ell t}\in\mathcal{H}} \Pr\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\left|\widehat{\boldsymbol{\theta}}^{Lender}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma, L_{i\ell t}, h_{i\ell t}\right.\right) \times \Pr\left(h_{i\ell t}\left|\widehat{\boldsymbol{\theta}}^{Lender}\right.\right)\end{aligned} \tag{36}$$

The expression for $\Pr\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\left|\widehat{\boldsymbol{\theta}}^{Lender}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma, L_{i\ell t}, h_{i\ell t}\right.\right)$ is analogous to equation (32) where we use the estimated lender parameters for the harassment probabilities:

$$\begin{aligned}&\Pr\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\left|\widehat{\boldsymbol{\theta}}^{Lender}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma, L_{i\ell t}, h_{i\ell t}\right.\right) = \\ &\quad (1-d_{i\ell t})\, C^{w_{i\ell t}}_{f_{i\ell t}} \left[p^m_{i\ell t}\left(\widehat{\boldsymbol{\theta}}^{Lender}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma, L_{i\ell t}, h_{i\ell t}\right)\right]^{w_{i\ell t}-f_{i\ell t}-1} \left[1-p^m_{i\ell t}\left(\widehat{\boldsymbol{\theta}}^{Lender}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma, L_{i\ell t}, h_{i\ell t}\right)\right]^{f_{i\ell t}} \\ &\quad + d_{i\ell t}\left(1-\sum_{w=1}^{W}\sum_{f=0}^{w} C^w_f \left[p^m_{i\ell t}\left(\widehat{\boldsymbol{\theta}}^{Lender}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma, L_{i\ell t}, h_{i\ell t}\right)\right]^{w-f-1} \left[1-p^m_{i\ell t}\left(\widehat{\boldsymbol{\theta}}^{Lender}, \boldsymbol{\theta}^m, \boldsymbol{\theta}^\sigma, L_{i\ell t}, h_{i\ell t}\right)\right]^{f}\right)\end{aligned} \tag{37}$$

4.4 Estimation of Borrower Harassment Disutility and Effort Cost

We estimate the harassment disutility parameters, $\boldsymbol{\theta}^\chi$, and effort cost, θ^Ψ, via simulated maximum likelihood using the observed choices of lenders by borrowers, taking the estimated values of $\widehat{\boldsymbol{\theta}}^{Lender}$, $\widehat{\boldsymbol{\theta}}^m$ and $\widehat{\boldsymbol{\theta}}^\sigma$ as given. The contribution of a loan to the likelihood is given by:

$$\Pr\left(V_{i\ell t} > \max_{\ell'\in\{0\}\cup\mathcal{C}_{it}\setminus\{\ell\}} V_{i\ell' t}\left|\boldsymbol{\theta}^\chi, \theta^\Psi, \widehat{\boldsymbol{\theta}}^{Lender}, \widehat{\boldsymbol{\theta}}^m, \widehat{\boldsymbol{\theta}}^\sigma\right.\right) = \frac{\exp\left(\bar{V}_{i\ell t}\left(\boldsymbol{\theta}^\chi, \theta^\Psi, \widehat{\boldsymbol{\theta}}^{Lender}, \widehat{\boldsymbol{\theta}}^m, \widehat{\boldsymbol{\theta}}^\sigma\right)\right)}{\sum_{\ell'\in\{0\}\cup\mathcal{C}_{it}} \exp\left(\bar{V}_{i\ell' t}\left(\boldsymbol{\theta}^\chi, \theta^\Psi, \widehat{\boldsymbol{\theta}}^{Lender}, \widehat{\boldsymbol{\theta}}^m, \widehat{\boldsymbol{\theta}}^\sigma\right)\right)} \tag{38}$$

Because borrowers have different loan histories with different lenders, lenders differ in how likely they are to choose certain harshness levels and loan sizes. Lenders are also heterogeneous through their type $k \in \{Regular, Harsh, Very\ Harsh\}$. We identify $\boldsymbol{\theta}^\chi$ and θ^Ψ through the borrower's trade-offs between the loan size they expect to receive, and the expected penalties and harassment from missing payments from the lender. Variation in harassment probabilities across lenders identifies $\boldsymbol{\theta}^{\chi}$, while variation in loan histories affecting effort levels identifies θ^{Ψ}.

In order to compute the expected payoff from choosing a lender for a trial value of $\boldsymbol{\theta}^{\chi}$ and θ^{Ψ}, we first need to compute the expected payoff of a lender for a given loan size and harshness level, $v_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$, as in equation (21). 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 first calculate the expected payoff $\mathbb{E}\left[u_{i\ell tw}\left(L_{i\ell t}, h_{i\ell t}\right)\right]$ 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. We provide the exact expressions for these approximations in Section A.9 in the Online Appendix. We then simulate ns =10,000 repayment paths for each possible loan using the borrower's repayment probabilities. We use the discount factors, present bias and coefficients of relevative risk aversion elicited from the surveys for δ_i, β_i, and γ_i, respectively.

With the expression in equation (21) calculated for each possible loan size and harshness level the lender could choose, we can compute the expected payoff for a lender using equation (22) together with the estimated lender choice probabilities, $p_{i\ell t}^{Lh}\left(L_{i\ell t}, h_{i\ell t}\middle|\widehat{\boldsymbol{\theta}}^{Lender}\right)$. We compute this for every lender in each borrower's consideration set. In addition, we compute the value of the outside option for each borrower using equation (23). This allows us to compute the likelihood in equation (38).

Similar to the approach of estimating dynamic entry models (Ryan, 2012; Collard-Wexler, 2013), we also include potential loan instances for each borrower where they chose the outside option of no loan when estimating $\boldsymbol{\theta}^{\chi}$ and θ^{Ψ}. We construct these potential loans 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 outside option being chosen approximately 39.9% of the time. We have also tested the sensitivity of our estimates to changing the number of potential loans. We did this by increasing the number of potential loans by 10% and reestimating our parameters. Only the borrower harassment disutility and effort cost are affected by this change. These

Table 4: Summary of the variation in the data that identify our parameters.

	Parameters determine:	**Identified though:**
$\boldsymbol{\theta}^{\eta}$	Lender's probability of severe harassment after a missed payment.	Observed harassment events the data, given the observed number of missed payments, time to repay, and borrower and loan characteristics.
$\boldsymbol{\theta}^{\widetilde{m}}, \boldsymbol{\theta}^{\widetilde{\sigma}}$	Borrower repayment probabilities from lender's perspective.	Observed number of missed payments and time to repay given observed borrower and loan characteristics.
$\boldsymbol{\theta}^{\kappa}$	Lender's cost of harassment.	Observed loan sizes, where lenders trade off the expected revenue from a loan of a given size with the expected cost of harassment at that loan size (determined by the harassment cost, repayment probability and harassment probability at that loan size).
$\boldsymbol{\theta}^{\alpha}$	Borrower loan demand parameters.	Observed borrower loan demand sizes, where the change in the interest rate from the enforcement event (supply-side shock) identifies the price elasticity.
$\boldsymbol{\theta}^{m}, \boldsymbol{\theta}^{\sigma}$	Borrower repayment probabilities from borrower's perspective	Observed number of missed payments and time to repay given observed borrower and loan characteristics.
$\boldsymbol{\theta}^{\chi}, \theta^{\Psi}$	Borrower harassment disutility and effort cost	Observed choices of lenders by borrowers, where borrowers trade off the expected loan size with the expected disutility of harassment ($\boldsymbol{\theta}^{\chi}$) and expected cost of effort (θ^{Ψ}), which vary by lender type, harassment probabilities, and past lending history.

increase slightly in magnitude (between 1-18%) compared to our baseline model.

Finally, we summarize the identification arguments for all the parameters discussed above in Table 4.

5 Estimation Results

Table 5 shows our parameter estimates. The first two columns in the upper part of the table shows the estimates of the borrower repayment probability parameters. The first shows those from the borrower's perspective, whereas the second shows those from the lender's perspective. The difference between these columns is that the lender does not observe certain borrower characteristics in the first loan, such as their addictions, prior convictions, or gang membership status. Instead, these characteristics are interacted with having a loan history with the borrower. Based on our modeling approach, these coeffi-

Table 5: Parameter Estimation Results.

	Cash for repayments (borrower) $\boldsymbol{\theta}^{m}$, $\boldsymbol{\theta}^{\sigma}$		Cash for repayments (lender) $\boldsymbol{\theta}^{\widetilde{m}}$, $\boldsymbol{\theta}^{\widetilde{\sigma}}$		Lender harassment probability $\boldsymbol{\theta}^{\eta}$	
Constant	1.022	(0.124)	1.071	(0.240)		
Lender type: Harsh	0.027	(0.027)	−0.019	(0.018)	0.383	(1.820)
Lender type: Very harsh	0.103	(0.071)	0.013	(0.029)	1.552	(5.481)
Harassment probability	0.257	(0.032)	0.384	(0.203)		
Prevailing interest rate	−2.395	(0.182)	−2.208	(1.044)		
No lending history	−0.770	(0.046)	0.320	(0.418)	−0.085	(0.117)
Number of previous loans	0.024	(0.008)	0.002	(0.004)	−0.084	(0.131)
Number of previous loans squared	−0.003	(0.001)	−0.001	(0.000)	0.004	(0.007)
Number of missed payments in last loan	−0.087	(0.004)	−0.054	(0.045)	−0.190	(0.074)
Asked for loan under the influence of alcohol	−0.024	(0.015)	0.001	(0.008)	−0.448	(0.491)
Age	0.007	(0.002)	0.004	(0.003)	−0.047	(0.033)
Has post-secondary education	−0.070	(0.030)	−0.064	(0.021)	−0.939	(1.452)
Female	0.099	(0.040)	0.074	(0.070)	−0.569	(1.477)
Married (rel. to single)	0.018	(0.043)	0.025	(0.015)	−1.115	(1.152)
Divorced (rel. to single)	0.046	(0.044)	0.038	(0.061)	−0.211	(0.480)
Has children	−0.060	(0.042)	−0.039	(0.010)	0.006	(0.016)
Malaysian (rel. to Singaporean Chinese)	0.059	(0.033)	0.060	(0.053)	−0.009	(0.168)
Indian (rel. to Singaporean Chinese)	−0.023	(0.040)	0.006	(0.009)	−0.331	(0.359)
Currently a gang member	0.097	(0.036)	0.054	(0.115)	−0.947	(0.509)
Previously a gang member	0.037	(0.027)	0.045	(0.090)	−0.092	(0.225)
Number of previous convictions	−0.023	(0.012)	−0.005	(0.008)	−0.081	(0.126)
Drinks alcohol	−0.056	(0.052)	−0.071	(0.025)	−0.625	(0.273)
Uses drugs	−0.005	(0.030)	0.011	(0.005)	0.073	(0.102)
Frequents sex workers	0.057	(0.029)	0.011	(0.005)	0.289	(0.256)
Frequently treats friends	−0.142	(0.038)	−0.161	(0.350)	−0.268	(0.571)
Borrower's discounting, $\beta_i \times \delta_i$	0.174	(0.070)	0.094	(0.042)	−0.028	(0.060)
Borrower's risk aversion, γ_i	0.090	(0.061)	0.023	(0.023)	−0.454	(0.413)
Gambles (in θ^{σ} and $\theta^{\widetilde{\sigma}}$)	0.528	(0.042)	0.409	(0.420)	1.871	(1.366)
Loan size					1.368	(1.161)
Low harshness level intercept					−5.832	(4.662)
Medium harshness level intercept					−2.287	(4.564)
High harshness level intercept					1.442	(1.919)
	Harassment cost $\boldsymbol{\theta}^{\kappa}$		Harassment disutility $\boldsymbol{\theta}^{\chi}$		Effort cost $\boldsymbol{\theta}^{\psi}$	
Constant	0.437	(1.237)	1.302	(0.047)	1.528	(0.022)
Lender type: Harsh (multiplier for $\boldsymbol{\theta}^{\kappa}$)	−0.221	(0.229)	0.248	(0.078)		
Lender type: Very harsh (multiplier for $\boldsymbol{\theta}^{\kappa}$)	−0.119	(0.754)	1.616	(0.481)		
Post crackdown	1.050	(0.557)				

Robust standard errors clustered at the borrower level are shown in parentheses. For $\boldsymbol{\theta}^{\widetilde{m}}$ and $\boldsymbol{\theta}^{\eta}$, gang affiliation, prior convictions, addictions, discounting and risk aversion are interacted with a dummy for having a past loan history with the lender, as these characterstics are unobserved by lenders for the first loan. The constant terms in $\boldsymbol{\theta}^{\widetilde{\sigma}}$ and $\boldsymbol{\theta}^{\sigma}$ are normalized to 1.

cients can be interpreted in S$ terms when multiplied by 1,000. The estimates show that borrowers increase the cash they have available when faced with a higher harassment probability, showing the effectiveness of higher harshness for lenders. When the interest rate increased after the crackdown, borrowers put in less effort into repayment.

Borrowers who have previously been in prison and who treat friends regularly have lower repayment ability, while more patient borrowers and borrowers involved in a gang have higher repayment ability, because they may have access to more money-making opportunities. We also estimate that gamblers have a higher variance in income, compared to non-gamblers. The harshness level intercepts in the harassment probability parameter estimates capture heterogeneity across harshness levels, although imprecisely estimated. The average harassment probabilities for each harshness level are 0.3%, 5.6% and 59.9%.

The harassment cost is estimated to be S$437 before the crackdown for regular lenders, and increasing to S$1,487 afterwards. This cost includes both the actual cost of harassment, such as fees paid to runners, and the expected disutility from possible arrest. Harsh lenders have a 22.1% lower harassment cost, while very harsh lenders have a 11.9% lower cost. These lower costs explain why they employ more severe forms harassment more frequently. The harassment disutility and effort costs do not have a direct dollar interpretation, but a back-of-the-envelope calculation shows that the median borrower would need to be compensated at least S$2,599.91 to be willing to accept certain harassment from a regular lender in a period. This is significant as the modal borrower earns between S$2,000-3,000 per month. Harassment from harsh and very harsh lenders gives borrowers more disutility, because these are more likely to employ more severe forms of harassment. For the harshest lenders, the same back-of-the-envelope calculation shows that the borrower would need to be compensated S$5,301.48 to be willing to accept certain harassment. These numbers may appear very large in comparison to the median loan size of S$1,000. However, unless the borrower misses several payments in a row, harassment only occurs when both a payment is missed and the lender uses severe harassment. In any given week, this occurs with probability 3.8% for the average borrower. Harassment also only occurs in the future, which borrowers discount very heavily. According to our model estimates, the median borrower be willing to pay S$107.48 each week throughout the course of a loan to eliminate the disutility from harassment, but still retaining the loan resetting property.

Table 6 shows the estimates of the borrower loan demand parameters $\boldsymbol{\theta}^{\alpha}$. These estimates show that borrower loan demand is decreasing in the interest rate, but gamblers have a lower price sensitivity. In a regression of log loan demand on log interest rate with borrower fixed effects, the price elasticity of loan demand is -0.817. In Table A.4 in the Online Appendix we show how well our model is able to match our data. The expected loan outcomes at the estimated parameters match the average number of weeks, number

TABLE 6: Borrower Demand Estimates

	Log Loan Asked	
Interest rate	−5.818	(0.906)
Interest rate × Age	−0.039	(0.015)
Interest rate × Post-secondary education	0.075	(0.242)
Interest rate × Female	2.059	(0.326)
Interest rate × Married (rel. to single)	0.112	(0.426)
Interest rate × Divorced (rel. to single)	0.047	(0.449)
Interest rate × Has children	−0.205	(0.428)
Interest rate × Malaysian (rel. to Singaporean Chinese)	0.766	(0.285)
Interest rate × Indian (rel. to Singaporean Chinese)	0.740	(0.321)
Interest rate × Drinks alcohol	0.696	(0.512)
Interest rate × Uses drugs	0.345	(0.213)
Interest rate × Frequents sex workers	0.028	(0.237)
Interest rate × Gambles	2.907	(0.382)
Borrower fixed effects	Yes	
Number of observations	10269	

Robust standard errors in parentheses clustered at the borrower level.

of missed payments, proportion of loans with harassment, and loan sizes reasonably well on aggregate.

6 Policy Interventions in the IML Market

6.1 Cracking Down on Lenders

6.1.1 Decomposing the Effects of the Crackdown on Loan Outcomes

We use our model estimates to decompose the effects of the crackdown on lender profits, borrower payoffs and the total value of disbursed loans. Our sample period spans 2009-2016 and the crackdown occurred in 2014. We run a counterfactual simulation where we assume the crackdown did not occur and compare payoffs and loan sizes in the 2014-2016 period to the baseline scenario where the crackdown does occur. We then run further counterfactuals to decompose the effects of the crackdown.

The crackdown affected three elements in our model. First, the crackdown increased the lenders' cost of harassment, $\kappa_{\ell t}$. In the no-crackdown counterfactual, we assume this cost would have remained at the pre-crackdown level. Second, in response to the increased costs, the cartel raised the nominal interest rate, r_t, from 20% to 35%. Because the original 20% rate was stable throughout our pre-crackdown data from 2009-2013, in the

TABLE 7: Decomposing the effects of the crackdown.

	No Crackdown (*Level*) (1)	Crackdown (Baseline) (*Level*) (2)	Overall (*% Difference*) (3)	Only $\kappa_{\ell t}$ Increases (*% Difference*) (4)	Only r_t Increases (*% Difference*) (5)
Total lender profits (in S$m)	3.08	1.00	−67.66	−94.16	+36.16
Total loan volume (in S$m)	2.63	1.35	−48.64	−4.82	−46.44
Average harassment probability chosen	0.17	0.08	−51.10	−32.31	−26.82
Total interest revenue (in S$m)	6.99	6.66	−4.75	−4.36	−0.95
Total harassment costs (in S$m)	1.28	4.31	+235.88	+212.06	+3.03
Average borrower surplus (in S$000)	0.51	0.45	−12.38	+2.06	−13.55
Average number of missed payments	4.58	6.00	+30.78	+1.04	+27.76
Average number of times harassed	1.93	2.52	+31.02	−6.78	+32.59

Column (3) shows the baseline (total) effects of the crackdown. Column (4) shows the effects of the crackdown if only the harassment cost, $\kappa_{\ell t}$, increased. Column (5) shows the effects of only the nominal interest rate, r_t, increasing from 20% to 35%.

no-crackdown scenario we assume it would have remained at 20%.[15] We use the borrower loan demand function to compute the adjusted loan demand to this interest rate. Third, the crackdown caused lenders to be arrested and exit the market, which impacted the borrowers' consideration sets of lenders, $\mathcal{C}_{it}$. In the no-crackdown counterfactual, we assume exited and arrested lenders stayed in the market and add them back to the borrowers' consideration sets. In Section A.4 in the Online Appendix, we also provide further evidence that rule out alternative explanations for the change in harassment costs, interest rate and lender exit in 2014. To decompose the effects of the crackdown, we show the impact of changing the harassment cost, $\kappa_{\ell t}$, and the interest rate, r_t, in isolation and compare their effects to the no-counterfactual scenario.

The results of this counterfactual experiment are summarized in Table 7. The crackdown caused a large decrease in total lender profits from S$3.08m to S$1.00m. This was accompanied by a large decrease in the volume of disbursed loans of 48.6%. Although the interest rate increased after the crackdown, the reduction in loan sizes meant that total interest revenue fell by only 4.75%. The decrease in profits therefore is mostly driven by the increase in harassment costs, which increased by 235.9%. This increase is mainly due to the large increase in the unit cost of harassment, but lenders also harassed borrowers 31% more often despite on average choosing a lower harassment probabilities in the event of a missed payment. This is because borrowers missed 31% more payments, as they put in

[15] We obtained details of 23 loans taken out by borrowers in Malaysia over 2012-2015 from a charity that helps IML borrowers. The same cartel of syndicates operates in this market and used the same 6-week loan structure with a 20% nominal interest rate throughout this entire period, providing further evidence that the cartel would have maintained the 20% rate in the absence of the crackdown.

less effort in repaying with the higher interest rate. This result is consistent with Table 2, which shows that lenders conducted harassment more frequently after the crackdown in 2014. Although not reported in the table, lenders with a harsh type reduced their average harassment probability from 20.6% to 11.4%, and very harsh lender types from 28.2% to 16.4%.

Borrowers were also negatively affected by the crackdown, where we find a 12.4% decrease in surplus. To compute borrower welfare under each scenario, we first convert borrower surplus to dollar values by calculating a certainty equivalent amount for each borrower. We do this by calculating 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. We follow the standard in the literature (e.g. Heidhues and Kőszegi (2010)) and measure borrower welfare using week-zero preferences at their stated discount factors. If we instead assume a more standard 0.95 annual discount factor with no quasi-hyperbolic discounting, borrower surplus decreases by 8.9% instead of 12.4%. Borrower surplus decreases because borrowers receive smaller loans, yet have to make weekly interest payments similar in size to pre-crackdown amounts because of the interest rate increase. Because of the interest rate increase and lower harassment probabilities, borrowers put in less effort to make repayments, resulting in more missed payments. This increase in missed payments ultimately results in more harassment, despite lenders choosing lower harassment probabilitiies.

Columns (4)-(5) of Table 7 decompose the effects of the crackdown.[16] Column (4) shows that if only the harassment cost increased without an accompanying interest rate increase, then lending would have become almost unprofitable. Because of the higher cost of harassment, lenders choose a lower harassment probability which improves borrower welfare. Column (5) shows that if the cartel raised its interest rate to 35% without a crackdown, it could have raised its joint profitability. We explore cartel optimal interest rate setting in the next subsection. In Table A.5 in the Online Appendix we show evidence of heterogeneous effects of the crackdown. We find that gamblers, drug-users and drinkers were especially affected by the crackdown, but gang members were less affected.

Our model only includes the payoffs of borrowers and lenders and does not include the welfare of the borrowers' friends and families, which may also be affected by the loans through harassment. This is an example of the negative externalities that IML generates.

[16] The change in the composition of borrower consideration sets in the crackdown does not have a meaningful impact on loan outcomes. We therefore omit this part of the decomposition from the table.

Because the crackdown caused borrowers to miss more payments and be harassed more often, the estimated decrease in borrower welfare from the crackdown is arguably a lower bound. As shown in Table A.2 in the Online Appendix we observe if the harassment events were on the borrower only or on family, friends, colleagues or neighbors of the borrower. In Table A.6 in the Online Appendix, we regress the instances of harassment events affecting external parties on a post-crackdown dummy. In the richest specification with borrower-lender pair fixed effects and controlling for past loan history, we observe an increase in 5.7 percentage points over baseline of 27.2% in the likelihood of harassment on external parties. Through these externalities, this is evidence that the crackdown had even larger negative welfare impacts than we measure. Overall, however, 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 lenders. Although we do not have precise estimates of the cost of this crackdown, the 27.3% increase in manpower indicates that the costs were significant.

6.1.2 Effects of the Crackdown on Cartel Interest-Rate Setting

In our no-crackdown counterfactual above, we assumed that the cartel would continue to advise lenders to charge a 20% nominal interest rate on loans and did not allow the cartel to endogenously optimize their rate. Figure 1 shows the results of a counterfactual experiment where we simulate loans at alternative interest rates set by the cartel and compute the relative changes in joint profitability for lenders. In the pre-crackdown period of 2009-2013, the interest rate charged by lenders was 20%. We compute the expected total profits for all lenders if the cartel had instead set the interest rate differently. We present results for all interest rates between 15% and 55% at 5 percentage point intervals. We adjust loan demand, borrower effort, lender choices, and the endogenously chosen loan sizes and harshness levels accordingly for each interest rate.[17]

At 20%, the percentage change relative to the baseline is zero because 20% is the baseline rate observed during this time period. We find that if the cartel lowered the interest rate to below 20%, total lender profits would have fallen. However, the lenders as a whole would have benefited from a higher interest rate. An interest rate of 35% would have maximized lender profits before the crackdown. Above 35%, lender profits begin to fall because

[17]We do not endogenize the cartel choosing the interest rate in our baseline model because we do not have sufficient variation in our data to do so. We only observe two main interest-rate regimes, the pre-crackdown rate of 20% and the post-crackdown rate of 35%. Instead, as in Asker et al. (2021), we take the cartel's optimal choices as given.

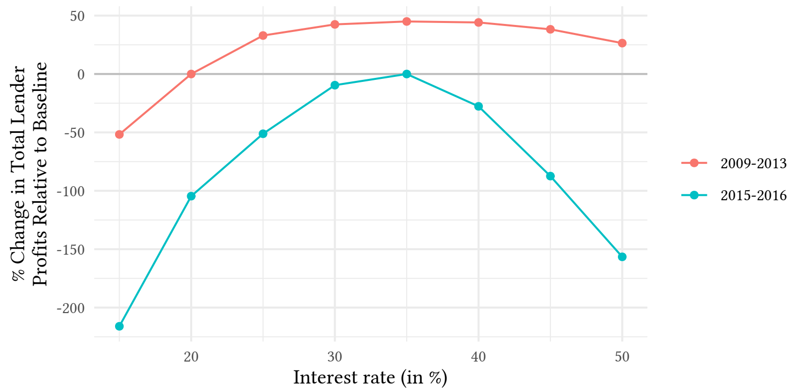


FIGURE 1: Percentage change in total lender profits at alternative interest rates before and after the crackdown.

at this higher rate, loan demand is smaller and borrower effort is reduced substantially.

There are several reasons why we did not observe the cartel advising lenders to use the profit-maximizing rate of 35% in our data during the pre-crackdown period. First, because of the number of different syndicates operating in the market, they may not have been able to sustain the higher rate of 35%. At 35%, the incentive for one syndicate to deviate to a lower rate would have been too large. Second, if the syndicates made such large profits, it would have encouraged other entrants into the market. The syndicates may have kept the interest rate lower to deter further entry into the market. Third, if the syndicates were making even larger profits the authorities may have cracked down on the market sooner. They may have chosen the lower rate to stay off the radar of law enforcement.

After the crackdown, the baseline interest rate was 35%. We omit 2014 from this analysis because during this year the interest rate rose in 5 percentage point increments before stabilizing at 35%. Over the 2015-2016 period, our model predicts that 35% was the optimal rate. Because of the increase in costs and reduced profitability, it became easier for the cartel to sustain the optimal rate. Furthermore, with reduced profitability, the cartel also had less incentive to deter future entrants.

6.1.3 Effects of Crackdown Intensity

We also use our model to simulate the impacts of varying the intensity of the crackdown. We do this by considering different values of the post-crackdown lender unit cost of harassment, θ^{κ}_{post}. We consider values from 90% smaller to 90% larger, in 10 percentage-point increments. For each new value of θ^{κ}_{post}, we also find the optimal cartel interest rate in

5 percentage-point increments. At the alternative unit costs of harassments we consider, 35% is always the optimal cartel rate. We then simulate loan outcomes using each different value of θ^{κ}_{post} and compare loan outcomes to the counterfactual case of no-crackdown in the 2015-16 period. We show the results in Figure A.1 in the Online Appendix. At higher intensity levels, loan sizes are smaller and lenders use harassment less frequently because it is more costly. Because the harassment probability effect dominates the loan size effect, borrowers are slightly less worse off with more intense crackdowns compared to less intense ones. The most intense version we consider leads to a decrease in borrower surplus of 11.2%, whereas the least intense leads to a decrease of 15.7%.

6.2 Targeting Borrowers

As an alternative market intervention, we consider the effect of removing different types of borrowers on lender profits. These borrowers could be removed in practice by either offering them formal-market alternatives, providing rehabilitation for their gambling, drug or alcohol use, or educating them on the perils of borrowing from loan sharks. We have spent over 100 hours interviewing 4 of the 5 major charities that help IML borrowers in Singapore.[18] From our interviews with these organizations in Singapore, we gathered supporting evidence that these organizations, due to their limited resources and lack of staff, can only support a very small fraction of the borrowers that approach them, and often focus on those with the lowest repayment ability that are harassed more frequently.[19] In this counterfactual, we aim to provide guidance to these charities on how helping different types of borrowers can have a differential impact on lenders' profits. The charities – some of which that were founded by former police officers – share the same aim as law enforcement in eradicating this market, and lowering lender profitability can help achieve this goal.

We sort borrowers by their average loan repayment probability and group them into twenty groups, such that the sum of the desired loan size within each group is approximately equal. Thus each group, or "vintile", has a similar size in terms of loan demand but differs in their repayment ability. We consider the effect of removing each of these groups in turn on lender profits. We implicitly assume that removing only 5% of borrowers has

[18] A report conducted by the Singaporean Ministry of Law that lists these organizations and their roles can be found here: https://www.mlaw.gov.sg/files/news/press-releases/2015/05/Rep.pdf.

[19] The charities were typically staffed with only 3-4 volunteers. Over the six months that we spent working with these charities we observed that many borrowers that came to seek help did not receive any because the charities were unable to meet the demand.

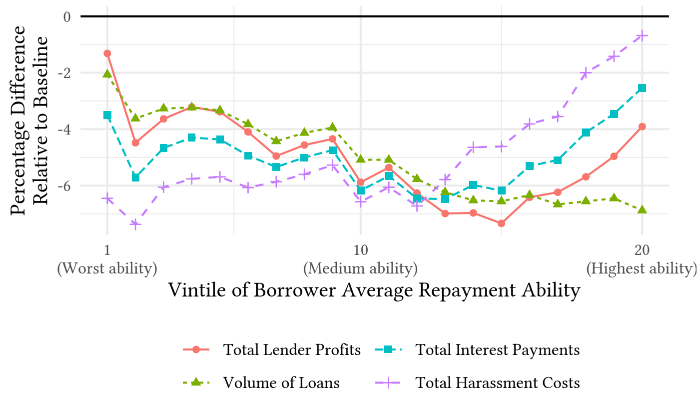


FIGURE 2: Effects of targeting borrowers on lender outcomes.

no effect on the market interest rate or harassment schedule of lenders.

The results of this counterfactual experiment are shown in Figure 2.[20] We find that removing the worst borrowers (vintile 1) is the least effective at lowering lender profits. This is because these borrowers are more costly for lenders to serve as they miss many payments, leading to high harassment costs. Lenders often only give these borrowers smaller loan sizes relative to what they request, such that they are better able to repay them. Removing borrowers from the middle of the distribution, especially near the 75th percentile, hurts lenders the most. These borrowers are the most profitable for the lender because they still miss several payments, leading to greater payment penalty revenue for the lender, while at the same time they do not miss too many payments such that they need to be harassed very frequently. Removing the borrowers with the highest repayment ability (vintile 20) lowers the volume of loans the most, but does not impact the lenders' profits as much as those in the middle of the distribution. 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.

This counterfactual can also be interpreted as the result of a change in usury rates. A relaxation of interest rate caps would in fact allow formal intermediaries to offer credit to high-risk borrowers at high interest rates. We can then think of a progressive increase in usury rates as causing the inclusion into formal credit of IML borrowers starting from the

[20]The fluctuations in outcomes across vintiles are due to not being able to split borrowers in twenty groups with exactly the same loan demand. If we use a coarser grouping, such as 10 groups, we obtain a similar-shaped figure but with less noise.

highest vintile of repayment ability and moving down cumulatively. If the objective of policy makers is to raise interest rate caps to harm profits of loan sharks, our results can quantify how these profit losses would increase by offering increasingly risky borrowers a formal alternative.

The characteristics of borrowers that represent the best and worst borrowers can be seen in the parameter estimates in Table 5. We also show the average borrower characteristics for the most and least profitable vintiles in Table A.7 in the Online Appendix. The most profitable borrowers are on average more likely to be in a gang, have fewer convictions, be less likely to gamble and use drugs. Therefore enforcement efforts targeting gang members, such as drug pushers, also can have a large knock-on effect on the lenders in the loan shark market. Potential IML borrowers and their repayment ability could also be identified by collaborating with the licensed payday lending sector. The members of the Credit Association of Singapore (CAS) try to refer borrowers rejected from formal credit to charitable organizations to prevent them from going to IML market. In Section A.2.2 in the Online Appendix we discuss interviews with have carried out with the CAS.

We also ran a related counterfactual experiment where we target borrowers having a particular characteristic. We did this for gamblers, drug users, prior convicts and gang members. These borrowers could be identified, for example, through conviction records or through rehab centers. We did this by randomly drawing borrowers having that characteristic until we have removed 5% of the total loan demand. We repeated this 1,000 times and calculated the mean decrease in lender profits from these draws. In each case the total effect on lender profits was similar, between 4.4-5.2%. This is because of the large degree of overlap between borrowers with such characteristics.

6.3 Effects of Indirect Interventions

We now consider the impact of indirect interventions on lender profitability, such as reducing gambling or drug use, or improving financial literacy. The charities we have interviewed organize support groups to help people out of their addictions and improve their financial choices. These charities also try to help borrowers learn "the value of money", which can be interpreted as helping borrowers improve their financial literacy and reduce their heavy time discounting. We show an example flyer for a support group aiming to reduce gambling and improve financial literacy in Figure A.2 in the Online Appendix. Singapore's National Council for Problem Gambling also allows individuals to apply for

Table 8: Effects of indirect interventions on lender profits.

	Median Impact on	
Intervention	Lender Profits	Borrower Surplus
Stop a borrower gambling	−26.16	23.09%
Stop a borrower using drugs	−13.62	7.68%
Remove a borrower's present bias (setting borrower's β_i to 1)	−46.09	6.66%
Set a borrower's β_i to 1 and δ_i to 0.999 (0.95 annual discount factor)	−57.07	13.45%

self-exclusion from gambling for at least one year, providing them with a commitment device to reduce their gambling.[21] Self-exclusion excludes them from casinos, jackpot machine rooms and online gambling on Singapore Pools, a state-owned lottery company.

To perform this counterfactual, we consider removing a single borrower's addiction to either gambling or drugs, or reducing the extent of their time discounting. We then compute the impact of this change on the lender's profits it chooses to borrow from, as well as on the borrower's own surplus. We do this separately for each borrower and report the median impacts. When we alter one of the borrowers' characteristics, we adjust the borrower's repayment ability, and allow all endogenous choices to change. That is, the borrower's loan demand and lender choice, and the lender's choice of loan size and harshness level. Borrower loan demand depends on these characteristics through the price sensitivity and the fixed effects, θ_i^{α}. We compute a counterfactual borrower fixed effect by regressing the estimated fixed effects on the characteristic, and using this regression to compute a counterfactual borrower fixed effect with an altered characteristic.

The results from this counterfactual are shown in Table 8. The results show that reducing gambling and drug use among borrowers lowers lender profitability and increases borrower surplus. Although removing these traits among borrowers improves their repayment ability and requires less costly harassment to serve, they demand smaller loans from lenders which ultimately means they become less profitable. A similar effect occurs when we make borrowers more forward-looking. Removing a borrower's present bias, which means setting their $\beta_i = 1$, reduces the median lender's profits by 46.1%. If additionally we make borrowers discount the future with a 0.95 annual discount factor, the median lender's profits fall by 57.1%. Again, this is because more forward-looking borrowers put in more effort to make repayments, but also demand smaller loans. The reduction in profits is largely driven by this smaller loan demand. Changing borrower discounting also improves borrowers' payoffs, when evaluated using an annual discount

[21] https://www.ncpg.org.sg/services/self-exclusions-and-visit-limits/apply-self-exclusion/for-individuals

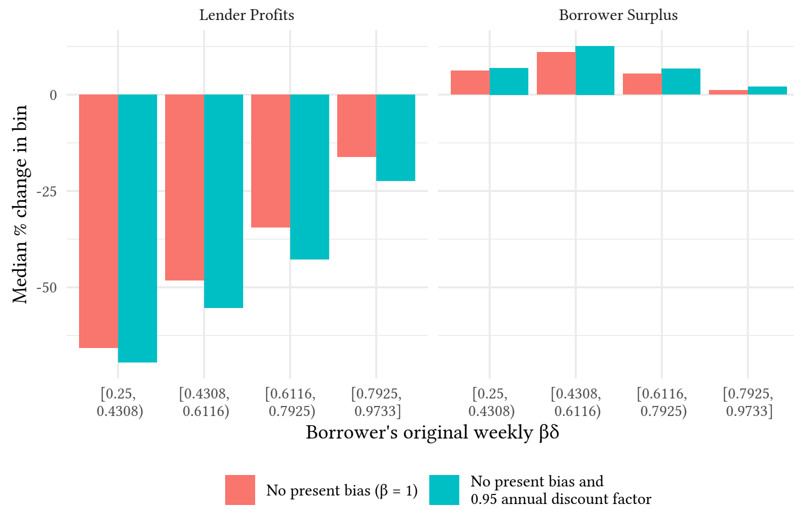


FIGURE 3: Heterogeneous effects of discounting interventions.

factor of 0.95 without present bias.

The effect sizes of these interventions also depend on the initial discounting of the borrower. In Figure 3 we show how much the median lender profits change in six equally-sized bins of the borrower's $\beta_i\delta_i$. When borrowers are very impatient, with weekly $\beta_i\delta_i \in [0.25, 0.3705]$, the effect is largest at over 60% in both cases. The effect for more patient borrowers, with weekly $\beta_i\delta_i \in [0.8527, 0.9733]$, is smallest, but still cause a decrease in lender profits of over 10%.

7 Conclusion

Illegal money lending is prevalent across the world, yet due to a lack of high-quality data, 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 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 lenders and borrowers in the market, as well as lowering the total volume of loans disbursed. Removing borrowers from the market, either through offering formal market alternatives, rehabilitation or education programs, also hurts lenders, particularly if they focus on medium-performing borrowers in terms of loan repayment time. Indirect interventions that reduce gambling addictions or improve financial literacy and lower borrower discounting are also effective at reducing lender profitability.

References

Adams, W., L. Einav, and J. Levin (2009): "Liquidity Constraints and Imperfect Information in Subprime Lending," *American Economic Review*, 99, 49–84.

Adda, J., B. McConnell, and I. Rasul (2014): "Crime and the Depenalization of Cannabis Possession: Evidence from a Policing Experiment," *Journal of Political Economy*, 122, 1130–1202.

Agarwal, S., S. Chomsisengphet, N. Mahoney, and J. Stroebel (2015): "Regulating Consumer Financial Products: Evidence from Credit Cards," *The Quarterly Journal of Economics*, 130, 111–164.

Aleem, I. (1990): "Imperfect Information, Screening, and the Costs of Informal Lending: A Study of a Rural Credit Market in Pakistan," *World Bank Economic Review*, 4, 329–349.

Allard, T. (2019): "The Hunt for Asia's El Chapo," *Reuters*.

Allcott, H., J. Kim, D. Taubinsky, and J. Zinman (2021): "Are High-Interest Loans Predatory? Theory and Evidence from Payday Lending," *The Review of Economic Studies*.

Allen, J., R. Clark, and J.-F. Houde (2019): "Search Frictions and Market Power in Negotiated Price Markets," *Journal of Political Economy*, 127.

Asker, J., A. Collard-Wexler, and J. De Loecker (2021): "The Welfare Impact of Market Power: The OPEC Cartel," Working Paper.

Becker, G. S., K. M. Murphy, and M. Grossman (2006): "The Market for Illegal Goods: The Case of Drugs," *Journal of Political Economy*, 114, 38–60.

Benetton, M. (2021): "Leverage Regulation and Market Structure: An Empirical Model of the U.K. Mortgage Market," Forthcoming at *Journal of Finance*.

Bertrand, M. and A. Morse (2011): "Information Disclosure, Cognitive Biases, and Payday Borrowing," *Journal of Finance*, LXVI, 1865–1893.

Blattman, C., J. C. Jamison, and M. Sheridan (2017): "Reducing Crime and Violence: Experimental Evidence from Cognitive Behavioral Therapy in Liberia," *American Economic Review*, 107, 1165–1206.

Blitz, R. C. and M. F. Long (1965): "The Economics of Usury Regulation," *Journal of Political Economy*, 73, 608–619.

Carvalho, L. S., S. Meier, and S. W. Wang (2016): "Poverty and Economic Decision-Making: Evidence from Changes in Financial Resources at Payday," *American economic review*, 106, 260–284.

Caskey, J. P. (1991): "Pawnbroking in America: The Economics of a Forgotten Credit Market," *Journal of Money, Credit and Banking*, 23, 85–99.

Chong, E. (2015): "China-based Loanshark Jailed 4 Years and Fined $600K for Unlicensed Moneylending," *The Straits Times*.

Collard-Wexler, A. (2013): "Demand Fluctuations in the Ready-Mix Concrete Industry," *Econometrica*, 81, 1003–1037.

Crawford, G. S., N. Pavanini, and F. Schivardi (2018): "Asymmetric Information and Imperfect Competition in Lending Markets," *American Economic Review*, 108, 1659–1701.

CTN News (2021a): "Crime Thai Police Take Down Huge Chinese Illegal Online Lending Network," *Chiang Rai Times*.

——— (2021b): "Thailand's Immigration Police Take Down Foreign Loan Shark Gang," *Chiang Rai Times*.

Cuesta, J. I. and A. Sepúlveda (2021): "Price Regulation in Credit Markets: A Trade-off between Consumer Protection and Credit Access," Working Paper.

Curtis, G. E., S. L. Elan, R. A. Hudson, and N. A. Kollars (2002): "Transnational Activities of Chinese Crime Organizations," *Trends in Organized Crime*, 7, 19–57.

de Quidt, J., T. Fetzer, and M. Ghatak (2018): "Market Structure and Borrower Welfare in Microfinance," *Economic Journal*, 128, 1019–1046.

DFAT (2019): "DFAT Country Information Report Malaysia," Australian Government Department of Foreign Affairs and Trade.

Diamond, D. W. (1984): "Financial Intermediation and Delegated Monitoring," *Review of Economic Studies*, 51, 393–414.

Egan, M., A. Hortaçsu, and G. Matvos (2017): "Deposit Competition and Financial Fragility: Evidence from the U.S. Banking Sector," *American Economic Review*, 107, 169–216.

Einav, L., A. Finkelstein, S. P. Ryan, P. Schrimpf, and M. R. Cullen (2013): "Selection on Moral Hazard in Health Insurance," *American Economic Review*, 103, 178–219.

Einav, L., M. Jenkins, and J. Levin (2012): "Contract pricing in consumer credit markets," *Econometrica*, 80, 1387–1432.

ELLISON, A., S. COLLARD, AND R. FORSTER (2006): "Illegal Lending in the UK," Research Report URN 06/1883 published by the UK Department of Trade and Industry.

EMMERS, R. (2003): "The Threat of Transnational Crime in Southeast Asia: Drug Trafficking, Human Smuggling and Trafficking and Sea Piracy," *Revista UNISCI*, 1–11.

FEDASEYEU, V. (2020): "Debt Collection Agencies and the Supply of Consumer Credit," *Journal of Financial Economics*, 138, 193–221.

FINANCIAL CONDUCT AUTHORITY (2017): "Shining a Light on Illegal Money Lending: Consumer Experiences of Unauthorised Lending in the UK," Report.

FONSECA, J. (2023): "Less Mainstream Credit, More Payday Borrowing? Evidence from Debt Collection Restrictions," *The Journal of Finance*, 78, 63–103.

GALENIANOS, M. AND A. GAVAZZA (2017): "A Structural Model of the Retail Market for Illicit Drugs," *American Economic Review*, 107, 858–896.

GALENIANOS, M., R. L. PACULA, AND N. PERSICO (2012): "A Search-Theoretic Model of the Retail Market for Illicit Drugs," *Review of Economic Studies*, 79, 1239–1269.

GATHERGOOD, J., B. GUTTMAN-KENNEY, AND S. HUNT (2019): "How Do Payday Loans Affect Borrowers? Evidence from the U.K. Market," *Review of Financial Studies*, 32, 496–523.

GUSTAFSON, M. T., I. T. IVANOV, AND R. R. MEISENZAHL (2021): "Bank Monitoring: Evidence from Syndicated Loans," *Journal of Financial Economics*, 139, 452–477.

HEIDHUES, P. AND B. KŐSZEGI (2010): "Exploiting Naivete about Self-Control in the Credit Market," *American Economic Review*, 100, 2279–2303.

HOLMES, T. J. (2011): "The Diffusion of Wal-Mart and Economies of Density," *Econometrica*, 79, 253–302.

HOME OFFICE (2018): "Country Policy and Information Note: Fear of Illegal Moneylenders, Vietnam," Vietnam: Country Policy and Information Notes.

JACOBI, L. AND M. SOVINSKY (2016): "Marijuana on Main Street? Estimating Demand in Markets with Limited Access," *American Economic Review*, 106, 2009–2045.

KABOSKI, J. P. AND R. M. TOWNSEND (2011): "A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative," *Econometrica*, 79, 1357–1406.

——— (2012): "The Impact of Credit on Village Economies," *American Economic Journal: Applied Economics*, 4, 98–133.

KAPLAN, L. J. AND S. MATTEIS (1968): "The Economics of Loansharking," *American Journal of Economics and Sociology*, 27, 239–52.

Koijen, R. S. J. and M. Yogo (2016): "Shadow Insurance," *Econometrica*, 84, 1265–1287.

Lang, K., K. Leong, H. Li, and H. Xu (forthcoming): "Borrowing in an Illegal Market: Contracting with Loan Sharks," *Review of Economics and Statistics.*

Leong, K., H. Li, M. Rysman, and C. Walsh (2022): "Law Enforcement and Bargaining over Illicit Drug Prices: Structural Evidence from a Gang's Ledger," *Journal of the European Economic Association*, 20, 1198–1230.

Levi, M. and P. Reuter (2006): "Money Laundering," *Crime and Justice*, 34, 289–375.

Limodio, N. (2022): "Terrorism Financing, Recruitment, and Attacks," *Econometrica*, 90, 1711–1742.

Maimbo, S. M. and C. A. Henriquez (2014): "Interest Rate Caps Around the World: Still Popular, But a Blunt Instrument," *Policy Research Working Paper 7070, World Bank Group, Washington, DC.*

Marinaro, I. C. (2017): "Loan-Sharking in a Time of Crisis: Lessons from Rome's Illegal Credit Market," *Trends in Organized Crime*, 20, 196–215.

Melzer, B. T. (2011): "The Real Costs of Credit Access: Evidence from the Payday Lending Market," *Quarterly Journal of Economics*, 126, 517–555.

——— (2018): "Spillovers from Costly Credit," *Review of Financial Studies*, 31, 3568–3594.

Morse, A. (2011): "Payday Lenders: Heroes or Villains?" *Journal of Financial Economics*, 102, 28–44.

Nelson, S. T. (2023): "Private Information and Price Regulation in the US Credit Card Market," Working Paper.

Payne, B., C. Murray, D. Morrow, and J. Byrne (2020): "Illegal Money Lending and Debt Project," Research Report of Findings - Ulster University.

Romeo, C. and R. Sandler (2021): "The Effect of Debt Collection Laws on Access to Credit," *Journal of Public Economics*, 195, 104320.

Ryan, S. P. (2012): "The Costs of Environmental Regulation in a Concentrated Industry," *Econometrica*, 80, 1019–1061.

Savona, E. U. and M. Riccardi (2015): "From Illegal Markets to Legitimate Businesses: The Portfolio of Organized Crime in Europe," Report for the European Commission - Directorate-General Home Affairs.

Schneider, F. (2013): "The Financial Flows of Transnational Crime and Tax Fraud in OECD Countries: What Do We (Not) Know?" *Public Finance Review*, 41, 677–707.

Soudijn, M. R. and S. X. Zhang (2013): "Taking Loan Sharking into Account: A Case Study of Chinese Vest-Pocket Lenders in Holland," *Trends in Organized Crime*, 16, 13–30.

Stegman, M. A. (2007): "Payday Lending," *Journal of Economic Perspectives*, 21, 169–190.

Temin, P. and H.-J. Voth (2008): "Interest Rate Restrictions in a Natural Experiment: Loan Allocation and the Change in the Usury Laws in 1714," *Economic Journal*, 118, 743–58.

Tencent News (2021): "Indonesian Police Arrested a Large Number of Illegal Loan and Violent Collection Personnel," *Tencent News*.

Thang, Q. (2020): "Chinese Loan Sharks Caught Charging Monthly Interest of 90 Percent," *VN Express*.

Online Appendix to:

The Effects of Policy Interventions to Limit Illegal Money Lending

A.1 Additional Figures and Tables

TABLE A.1: Uses for loans and primary reasons for taking out loans.

	Uses for loan (Proportion) (1)	Primary reason for loan (Proportion) (2)
Gambling or buying lottery tickets	0.551	0.264
Buying alcohol or drugs	0.479	0.381
Paying lender	0.343	0.091
Paying bills	0.213	0.052
Treating friends	0.144	0.006
Paying gambling debt	0.132	0.035
Sex worker, girlfriend, or KTV	0.130	0.009
Business needs	0.049	0.038
Paying credit card debt	0.047	0.013
Paying rent	0.046	0.039
Paying company creditor	0.034	0.012
Children's education	0.029	0.020
Holidays or special celebrations	0.021	0.004
Paying other debt	0.019	0.006
Paying hospital fees	0.012	0.009
Bank loan installment	0.012	0.004
Loan sharing with friends in need	0.008	0.004
Others	0.006	0.003
Child medical fee	0.005	0.001
Supporting family	0.004	0.003
Guarantor for others	0.004	0.001
Pay debts for others	0.004	0.002
Vehicle	0.002	0.001
Marriage	0.001	0.001
Renovations	0.001	0.001
Lawyer fees	0.001	0.000
Helping Friend to Borrow	0.000	0.000

Column 1 shows the proportion of loans that were used for each category. Because multiple responses were possible for each loan, the sum of proportions can exceed one. Column 2 shows the primary reason for taking out the loan.

Table A.2: Harassment methods used by loan sharks.

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

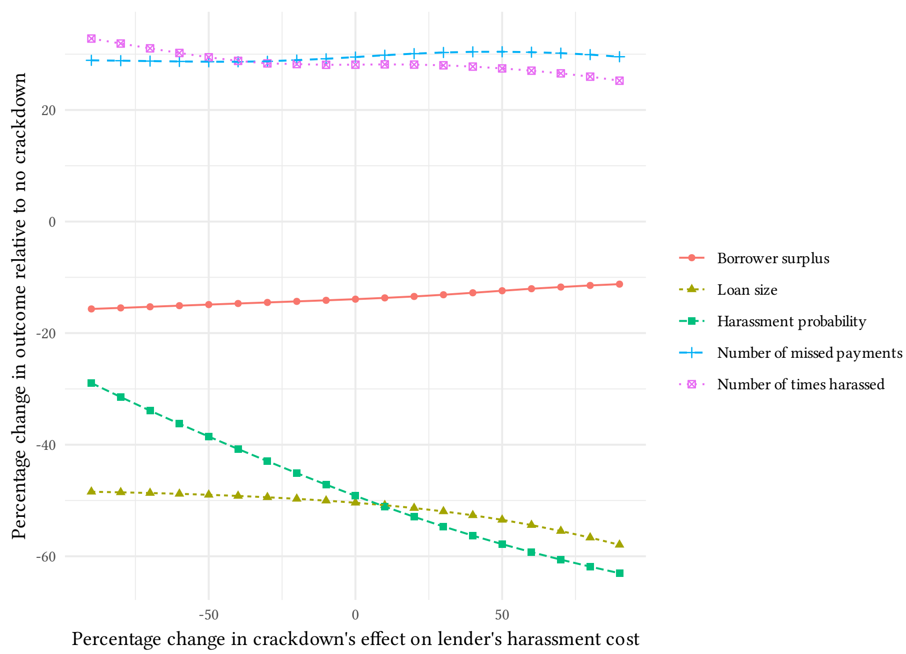
Proportion of loans involving different harassment methods used by loan sharks in our data. Lenders often used multiple harassment methods in the same loan hence the sum of proportions exceeds one. We note that none of the borrowers in our sample reported any use of body attacks or torture. When discussing the loansharking market, Seidl (1970) notes that "actual violence is minimized" and "fear and anxiety about it are used instead to motivate delinquent borrowers." He also notes that violence may be counterproductive as it may bring increased scrutiny by law enforcement and make repayment more difficult for borrowers.

Table A.3: Primary sources of funds used to repay loans.

Source	Number of loans	Proportion of Loans
Use own income/funds	9293	0.842
Borrow from boss, colleagues or friends	466	0.042
Use gambling winnings	346	0.031
Borrow from family	259	0.023
Did not repay	240	0.022
Borrow from another lender	179	0.016
Sell or pawn possessions	58	0.005
Lender arrested	44	0.004
Other	142	0.013

Table A.4: Expected outcomes at parameter estimates versus observed outcomes in the data.

	Data	Model
Average number of weeks	13.38	15.71
Average number of missed payments	3.85	4.51
Proportion of loans with harassment	0.54	0.57
Average loan size	1.29	1.30



Each point on the horizontal axis represents a counterfactual experiment where we consider the impact of a different increase in the lender's unit cost of harassment from the crackdown (θ^{κ}_{post}) from the estimated value of 1.050. For each alternative harassment cost we find the optimal cartel interest rate. In each case it remains to be 35%. The reported outcomes are shown relative to the no-crackdown situation for all loans in 2015-2016.

Figure A.1: The impacts of alternative increases in the lender's unit cost of harassment from the crackdown.

Table A.5: Heterogeneous effects of the crackdown.

	Borrower Surplus	
Post-crackdown × Age	−0.001	(0.001)
Post-crackdown × Post-secondary education	−0.006	(0.021)
Post-crackdown × Female	0.019	(0.029)
Post-crackdown × Married (rel. to single)	0.011	(0.033)
Post-crackdown × Divorced (rel. to single)	−0.012	(0.034)
Post-crackdown × Has children	0.013	(0.032)
Post-crackdown × Malaysian (rel. to Singaporean Chinese)	−0.018	(0.024)
Post-crackdown × Indian (rel. to Singaporean Chinese)	0.002	(0.024)
Post-crackdown × Current gang member	0.066	(0.026)
Post-crackdown × Previously gang member	0.020	(0.018)
Post-crackdown × Number of previous convictions	−0.005	(0.008)
Post-crackdown × Drinks alcohol	−0.157	(0.042)
Post-crackdown × Uses drugs	−0.041	(0.019)
Post-crackdown × Frequents sex workers	0.033	(0.019)
Post-crackdown × Gambles	−0.039	(0.027)
Post-crackdown × Frequently treats friends	0.008	(0.026)
Post-crackdown × Borrower discounting	−0.067	(0.052)
Post-crackdown × Borrower risk aversion	−0.025	(0.038)
Borrower fixed effects	Yes	
Period fixed effects	Yes	

Standard errors in parenthesis clustered at the borrower level. The dependent variable is borrower surplus of the loan measured in S$000.

Table A.6: The effect of the crackdown on harassment affecting external parties.

Dependent variable:	Indicator for harassment affecting an external party			
	(1)	(2)	(3)	(4)
Post crackdown	0.083	0.144	0.159	0.057
	(0.013)	(0.014)	(0.015)	(0.024)
Past loan history controls	Yes	Yes	Yes	Yes
Borrower fixed effects	No	Yes	Yes	No
Lender fixed effects	No	No	Yes	No
Borrower-lender pair fixed effects	No	No	No	Yes
Mean of dependent variable	0.272	0.272	0.272	0.272

Columns (1)-(4) show estimates from a regression of an indicator for harassment affecting an external party (e.g. harassment on family, friends, neighbors, work colleagues, or graffiti or paint splashing on the borrower's home) on a post-crackdown dummy, fixed effects for the number of past loans and the number of missed payments in their previous loan. Columns (1)-(4) differ by the inclusion of borrower, lender and borrower-lender pair fixed effects. Standard errors are clustered at the borrower level.

TABLE A.7: Characteristics of the most and least profitable borrowers.

	Vintile 15 (Most profitable)	Vintile 1 (Least profitable)
Age	38.63	32.53
Post-secondary education	0.29	0.21
Female	0.04	0.08
Married	0.57	0.45
Divorced	0.17	0.18
Has kids	0.70	0.57
Malay	0.04	0.19
Indian	0.04	0.20
Number of convictions	0.27	1.08
Currently gang member	0.13	0.10
Previously gang member	0.29	0.34
Uses drugs	0.19	0.43
Drinks alcohol	0.96	0.97
Gambles	0.94	1.00
Frequents sex workers	0.85	0.60
Frequently treats friends	0.11	0.03
Borrower discounting ($\beta_i \times \delta_i$)	0.73	0.72
Borrower risk aversion (γ_i)	0.36	0.32

The table shows the means for each borrower characteristic for borrowers in vintile 15 (most profitable) and 1 (least profitable) according to Figure 2.

FIGURE A.2: Example Support Group of a Charity in Singapore.

A.2 IML versus Other Credit Markets

Although the illegal money lending (IML) market shares features with some formal and other informal credit markets, we argue that there remain substantial differences. In this section we provide additional evidence to support this claim.

A.2.1 Core Features Differentiating IML

We begin by outlining four core characteristics of IML. First, because loans fall outside the scope of financial regulators, loans have very high interest rates that exceed the legal maximum. Second, its customers are low-ability borrowers who do not have access to credit from the formal sector and often use the money for gambling, drugs and alcohol. Third, lenders operate with or under organized criminal groups, often coordinating on the loan structure, and use severe forms of harassment to encourage repayment that are not possible in legal credit markets. Fourth, it is phenomenon primarily found in urban areas of developed countries.[22] We expand on these points below.

Loan Structure Loan sharks, payday lenders, microfinance institutions and informal moneylenders all typically charge high interest rates. These loans also often have short maturities. Unlike payday lending, however, interest rates often exceed the legal maximum in IML. Allcott et al. (2021) find that all loans issued by a large payday lender in Indiana had interest rates at the legal maximum. In our setting, lenders charge interest rates at least four times the legal maximum. The resetting structure of loans in our setting has the purpose of debt trapping borrowers. In contrast, Karlan et al. (2019) finds no evidence that moneylenders in India and the Philippines debt-trap borrowers.

The main difference between IML and other fringe markets is arguably the manner in which lenders respond to missed payments. Lenders in IML often use severe harassment methods in response to missed payments such as damaging a borrower's property or harassing their friends or family members. These methods are outside the scope of legal lenders. Dobbie and Skiba (2013) state that payday loans "have the unique feature that delinquencies are not reported to traditional credit rating agencies, and default comes with few penalties outside of calls from debt collection agencies." The primary penalty for default in other markets is not being able to borrow again from a lender. This was adopted by some lenders in Kaboski and Townsend (2011) as well as by the Nigerian digital lender in Björkegren et al. (2022). Thus the threat of exclusion is what encourages repayment in these markets, whereas the threat of harassment is what encourages repayment in IML. Furthermore, in our setting, lenders will also make borrowers do work for them to finish paying off loans that they cannot repay, virtually guaranteeing that all loans will be repaid.

Borrower Characteristics and Loan Uses The borrowers in our setting have very low creditworthiness. None of the borrowers in our survey had access to loans in the formal sector. Thus they represent a different sector of the population compared to payday lending or the credit card markets. They also represent a large portion of the population, as the

[22] Seidl (1970) defines IML similarly. He defines loansharking by the following characteristics. "[First,] cash is lent at very high interest rates – generally 20 to 100 times higher than rates charged by legitimate lending institutions. [Second,] the borrower-lender agreement rests on the borrower's willingness to pledge the physical well-being of him and his family as collateral against a loan. The corollary of the borrower's willingness is the lender's willingness to accept such collateral, with its obvious implications for what he *may* have to do to collect. [Third,] the borrower believes the lender has connections with ruthless criminal organizations. That fact and his expected need for future loans induce him to repay."

black market database of IML borrowers in Singapore includes information on approximately 350,000 individuals.[23] Payday loans are also often used to pay rent or bills (Morgan et al., 2012), whereas we find that IML loans are mostly taken out for gambling, drugs or alcohol. This also differs from typically loans from microfinance instutitions, which are often for agricultural uses or household investment reasons (Kaboski and Townsend, 2011).

Market Structure The loan sharks in our setting operate under a cartel of transnational crime syndicates that set common loan terms such as the interest rate and loan duration. In contrast, the payday lending, microfinance and informal lending markets are typically competitive. Allcott et al. (2021) states that "payday lending has the hallmarks of a competitive market", as entry barriers and profit margins are low. Using a data from a survey of 14 moneylenders in rural Pakistan, Aleem (1990) describes the informal lending market as monopolistically competitive, driven by asymmetric information between borrowers and lenders. Finally, McIntosh et al. (2005) finds competitive effects of entrants on an incumbent lender in the Ugandan microfinance market.

A.2.2 Information from Interviews with Market Participants in Other Credit Markets

To verify the claim that IML is substantially different to other credit markets, we carried out interviews with market participants in licensed money lending (payday lending), Fintech/Peer-to-Peer lending, microcredit and informal lending. We discuss these interviews below.

Licensed Money Lending (Payday Lending) We interviewed two members of the Credit Association of Singapore (CAS).[24] Over a five-year period, the lenders of this association serve more than 70,000 unique borrowers in Singapore. According to our respon-

[23] During our sample period, the population of Singapore was approximately 5 million. Although the size of this database is likely a lower bound on the number of borrowers, this indicates that they make up approximately 5-10% of the population. The size of the illicit drugs market can also be used to gauge the size of the IML market, as loansharking is used as a means to launder drug money and make it more difficult to trace (Jorgic, 2020; UNODC, 2018). Over 100 metric tons of methamphetamine were seized in Southeast Asia in 2018, compared to only 68 tons in the US (NETI, 2019; UNODC, 2020). Singapore is also an important transit point for illegal drugs that is used by many transnational gangs in Southeast Asia (Emmers, 2003). Therefore the size of the drug market and amount of cash needed to be laundered is likely very large.

[24] This association represents more than 90% of all licensed moneylenders in Singapore. The less than 10% of licensed lenders that are not members are part time lenders with a handful of customers or lenders who are inactive most of the time.

dents, licensed moneylenders mainly serve two types of customers. Either customers that have taken out the maximum possible from a bank but need more cash, or customers do not meet the bank requirements to take out a loan. CAS told us that their members will not lend to anyone who shows signs of having borrowed or is going to borrow from the IML market.

Generally, it is very difficult for borrowers to borrow money from any licensed moneylender in Singapore. A borrower is required to show the lender their credit statement, bank account transactions, and all other related financial documents. There is a legal cap on how much a borrower can take out from a licensed lender. A licensed lender has the right to reject the borrower even though the borrower meets the minimum requirements to take out a loan set by the government. A lender can use the bank accounts, credit rating statements or their own information-gathering sources to check if the borrower is likely to be involved in IML or not. In many cases, the borrowers themselves will tell the lender about their intention to take out a loan from the IML market if they fail to secure a loan from the licensed lender. If a lenders feels that the borrower is part of IML, they will reject the loan immediately. To verify this sentiment, we spoke to an separate licensed lender. This lender told us that he rejects approximately half of all the borrowers that apply for a loan. About half of the rejected borrowers end up in the IML market. Furthermore, another lender told us that one of the authorities advised them to focus on lending to the wealthier segments of the Singapore population. He said most lenders have closely followed this piece of advice.

Generally, CAS members will try to refer borrowers with the intention of borrowing from the IML market or those who are currently borrowing from IML to charities that will attempt help these borrowers.[25] According to one of the CAS respondent's own personal experience, borrowers that are rejected by the legal money lending market (either legal lenders do not want to give them anymore loans or they are rejected outright) are those who end up in the IML market.

Fintech/Peer-to-Peer (P2P) Platforms In Singapore, all Fintech/P2P lending platforms are regulated by either the Ministry of law or the Monetary Authority of Singapore. To protect borowers, there are regulations set by these agencies about who is eligible for a loan. Similar to taking out a loan from any formal sector lenders, there is an application process which uses an individual's credit rating or company history to determine interest

[25] These charities that help these borrowers include Blessed Grace, Adullam, Arise2care and Silver lining.

rates and whether an individual is eligible for a loan.[26] We spoke to one of the owners of a lending platform in Singapore. We were told that the documentation needed to take out a loan from this website was the same as those required by licensed moneylenders. Consistent with what our borrowers have told us, none of them qualify for P2P loans. Generally, eligible borrowers of P2P loans need to earn more than S$35,000 per year and have a good credit history.

Microcredit and Informal Lending To verify that the IML market is different to the microcredit and informal lending markets, we spoke to market participants from these markets which include lenders, borrowers, government officers and charities working with borrowers in two of the world's largest developing economies – China and India – to obtain their views and to provide some suggestive evidence about the differences between IML and these markets. We asked market participants in both countries the following questions: (1) Who are these professional moneylenders and are they part of organized crime syndicates? (2) What is the definition of professional moneylenders? (3) Can you describe the marketplace in which professional moneylenders operate? (4) Do professional moneylenders behave in similar ways in different areas within a country? We first discuss our findings in India and then discuss our findings for China.

India: We collected information from approximately 20 street vendors in India. These correspond to the types of borrowers from professional moneylenders in Karlan et al. (2019). We also interviewed a senior management officer of one of India's largest microcredit firms and one ex-government officer.[27] The answers to all the above questions are similar across all respondents. Borrowers claim that professional moneylenders are normal individuals and business owners who are not part of any organized crime group. The government of India views microcredit firms and these individual lenders and business that charge high interest rates as "professional moneylenders". These lenders are an important group of people that will help India achieve its financial inclusion program goals, i.e. to help the poor gain access to credit. As such, even though some of these businesses are unlicensed, they are tolerated and are not the target of enforcement activities.[28]

[26] SingSaver in Singapore - https://www.singsaver.com.sg/blog/pros-and-cons-of-peer-to-peer-lending

[27] We have obtained permission from the relevant parties to be able to provide photographs of these meetings with mosaiced faces. These are available upon request.

[28] Market insiders did tell us, however, that in the run-up to elections, there are sometimes politically motivated small-scale enforcement activities carried about against some professional moneylenders that are harsh with borrowers during debt collection. They believed that political candidates want to demonstrate their concern for the electorate with these acts.

The professional moneylending market is heterogeneous even within a particular area in India. The loan structures used by microcredit firms in India are heterogeneous, but only within the ranges of the directive by the Reserve Bank of India. For individuals and small unlicensed businesses, they are heterogeneous as they follow their own defined rules around interest charges, penalties, repayment methodology, and other terms. The professional moneylender market is also competitive. They compete with one another in interest rates and other dimensions. There are also some market frictions. For example, in some of the areas in India that respondents were from, the government will require some larger microcredit firms to set lower interest rates so that everyone else will follow suit.

China: We asked individuals from a religious organization that helps provide credit counseling to borrowers in 35 rural villages in different parts of China to collect information from 20 borrowers of professional moneylenders from 10 different villages (2 borrowers per village).[29] From these interviews we learned that professional moneylenders are usually people that they know. For example, people who have made their fortune in the cities and have moved back home and started a lending business. None of these lenders are part of an organized criminal syndicate. Informal lending is also heterogeneous across villages. In some villages, borrowers are required to continuously give gifts in kind to the lender to establish trust with the lender before they will give them a loan. This process could take a number of months and it was not possible to bypass this requirement. In other places, it is possible to obtain a loan via a referral that both the lender and borrower knows. There is no standard structure to the loans and depends on the lender and borrower. In some villages, you can choose to keep paying fixed interest rates in perpetuity on the loan until you decide to pay off the loan in full. In other places, you will have to pay the interest and principal back by a fixed time period.

We also interviewed one ex-prison officer and an ex-police officer in China. They are not aware of any enforcement activities that are carried out against the lenders mentioned in this subsection, i.e. professional moneylenders in villages. To the best of their knowledge, they said that the government is only actively targeting organized criminal lending syndicates nationwide.[30]

[29]We have been asked by the organization not to provide their information in any public forum. We are able to provide more information upon request subject to non-disclosure agreements.

[30]We also spoke to a smaller number of market participants in the professional moneylending market in Malaysia and Indonesia. According to them, the professional moneylending market is similar to China in the sense that it is relatively heterogeneous across different parts within the same country.

A.3 Features in Our Data Compared to Soudijn and Zhang (2013)

In this section we briefly describe the main similarities and differences with our data and the data described by Soudijn and Zhang (2013). Their dataset is an accounting ledger of a single loan shark that was seized in a police raid on a Dutch casino in 1997, whereas our dataset comes from a survey of 1,090 borrowers borrowing from loan sharks in Singapore over 2009 to 2016. They observe 497 distinct loans whereas we observe 11,032.

There are a number of features in their setting which are similar to ours. The lender in their dataset charges all borrowers the exact same interest rate, regardless if they are a new customer or differ in repayment ability. This is exactly the same as in our setting, albeit with a different interest rate. They also do not have any interest rate compounding. They report very low default rates, where only 4 loans defaulted and 5 loans were reported missing. Thus their default rate is approximately 2%, similar to our setting. They also note that a small number of loans were cleared by paying via other means, which they interpret as doing jobs for the lender. This also occurs in our setting for borrowers that struggle to repay. The borrowers in their sample are also borrowing for gambling reasons, which is also the most common reason in our setting.

From their ledger it is unclear what types of harassment methods were used by the lender, but they do note that some fees were paid to individuals for debt collection. This corresponds to the runners in our setting. They also know that several lenders operated in the casino where the ledger was seized, and speculate that the lenders cooperated. This corresponds to our setting in that lenders used the same interest rate and loan terms at any given time, which were set by the transnational syndicates operating in the country.

There are also some features in their setting that differ from ours. The basic loan structure differs in that interest is charged at 10% per week on the original principal and the principal plus interest must be paid to close the loan in the last payment. In our case, borrowers in the pre-crackdown period pay 20% of the original principal per week for six weeks, but do not have to pay the original principal back at the end to close the loan. This is incorporated in the repayment schedule. The APR in their setting is 521%, whereas in our setting it is 261% before the crackdown and 562% afterwards. In their setting, early repayment is possible but in our setting borrowers cannot repay earlier. In fact, in their setting borrowers receive a discount when repaying earlier: if they repay the loan principal on the same day it is issued, they are only charged 5% interest. Missing a payment in their setting does not result in a reset loan, unlike ours. Instead, the loan continues until the principal plus interest is repaid. Finally, borrowers repay much faster in their setting compared to ours. The median time to repay was 1 week and the longest time to repay was 17 weeks. In our setting, the median time to repay was 12 weeks. This shorter time to repay is likely because early repayment in our setting is not possible.

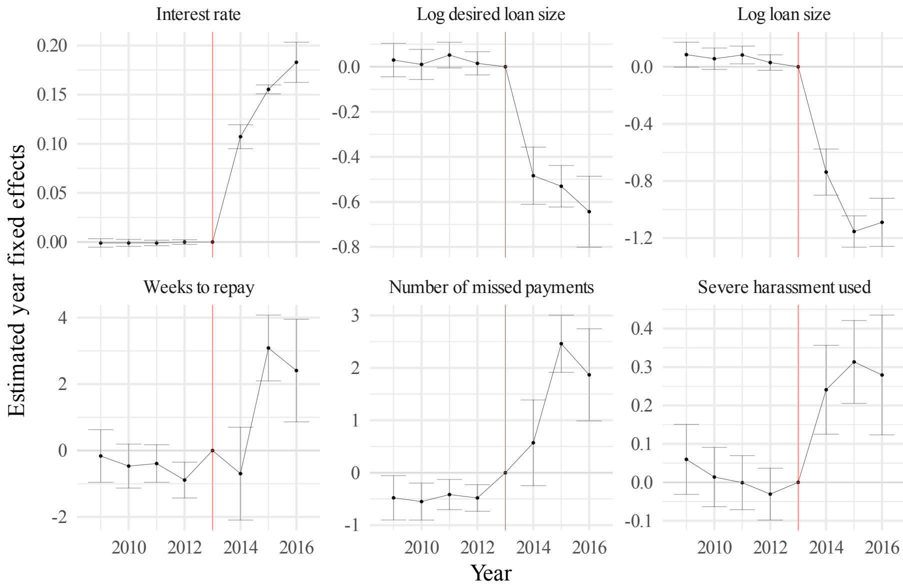
A.4 Enforcement Crackdown

The enforcement crackdown had several effects on loan contracts, such as the interest rate, loan demand, actual loans disbursed, loan performance and harassment. We describe these effects by running regressions of the form:

$$y_{i\ell t} = year_{i\ell t} + hist_{i\ell t} + lag\_num\_missed_{i\ell t} + a_{i\ell} + e_{i\ell t} \tag{39}$$

where $y_{i\ell t}$ is a loan outcome or characteristic for a loan taken out by borrower i with lender ℓ at time t, $year_{i\ell t}$ are fixed effects for the year the loan was taken out, $hist_{i\ell t}$ are fixed effects for the number of past loans the borrower has taken out with the lender, $lag\_num\_missed_{i\ell t}$ are fixed effects for the number of payments the borrower missed in their last loan with the lender, and $a_{i\ell}$ are borrower-lender pair fixed effects. The estimates of the year fixed effects for each variable are shown in Figure A.3. The graphs show that the pre-crackdown period of 2009-2013 was relatively stable. Only the number of missed payments in a loan shows a significant difference between 2009-2012 and 2013. However this difference is very small when compared to the large increase after 2014. Starting in 2014, there was a large increase in the interest rate, which decreased the desired loan size and actual loan sizes. Borrowers took longer to repay and missed more payments, which ultimately meant that severe harassment was used more often in loans.

These regressions lack a suitable control group. However, we provide arguments that rule out possible alternative explanations for the changes we observe in the market in 2014-2016. First, the changes are unlikely to be due to changing macroeconomic conditions. There was no recession during our sample period and GDP growth remained stable over the entire period of 2012-2016. We also tested for a structural break in 2014 using a simple trend regression and did not find any evidence for a structural break. Therefore, it is unlikely that the increase in the interest rate charged by lenders is due to a higher cost of capital. Furthermore, it is unlikely that borrowers faced major changes in income that would require them to change their borrowing habits during this time. We also note that although GDP growth in Singapore fell briefly following the 2007-2008 global financial crisis, annual GDP growth was never negative during this period. Because our sample



Estimates of the year fixed effects in regressions of loan outcome variables on year fixed effects (with 2013 as the base year), fixed effects for the number of past loans, fixed effects for the number of missed payments in their previous loan, and borrower-lender pair fixed effects. Severe harassment used is an indicator for if any harassment method (excluding reminder phone calls or messages) was used throughout the course of the loan. Standard errors are clustered at the borrower level. Error bars represent a 95% confidence interval.

FIGURE A.3: Event study graphs of the crackdown.

period begins after GDP growth had recovered, our estimates are unlikely to be impacted by this financial crisis.

Second, it is unlikely that the transnational syndicates that fund the lenders reduced funding due to changes in capital controls. Singapore dismantled its capital controls in the 1970s. Furthermore, the majority of lending operations in Singapore did not require funds from abroad as lenders were highly profitable as there is very little borrower default.

Third, it is unlikely that the borrowers' addictions intensified in 2014, which increased risk for lenders, causing them to charge higher interest rates. This is because we do not observe any decrease in eventual repayment after the crackdown. Furthermore, the net gambling revenue at the Marina Bay Sands and Resorts World Sentosa, the two largest gambling locations in Singapore, did not increase after 2014. In fact, the average gambling revenue over 2011-2013 was approximately 4 billion USD per year, and fell to on average 3.5 billion USD per year from 2014-2016 (Noble, 2018). There was also a small drop in the national gambling participation rate from 47% in 2011 to 44% in 2014 (National Council on

Problem Gambling, 2017). This, combined with the fact that over 95% of the borrowers in our sample continued to borrow after the crackdown means it also unlikely that adverse selection in the market worsened after the crackdown.

Fourth, it is unlikely that the crackdown saw the beginning of (or an increase in) protection money paid to corrupt police offers. It is challenging to obtain direct evidence on corrupt activities related to IML. However, Transparency International (2020) reports that Singapore was always consistently ranked one of the least corrupt countries in the world in the past decade. The 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 focuses on IML, the number of corruption cases related to IML 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.

Fifth, there were no significant changes in regulation in the formal credit sector that would change the demand for loans in the IML market. The only significant policy change over our period of study (2009-2016) was the 2008 Moneylenders Act. This policy change regulated the loan sizes, required income levels, and interest rates in the legal money lending sector (Singapore Ministry of Law, 2009). Because the policy was enforced already at the beginning of our sample period (2009), it is unlikely that it was driving the changes that we observe in 2014.

Finally, we also obtained details of 23 loans taken out by borrowers in Malaysia over 2012-2015 from a charity that helps IML borrowers. Malaysia is the closest country to Singapore, separated only by a 1km-wide causeway. The same cartel of syndicates also control the IML market there. Each of these 23 loans had the same structure as the pre-crackdown period in Singapore with a 6-week maturity and 20% nominal interest rate. This is further evidence that the change in the interest rate in Singapore in 2014 was due to the crackdown and not changes in the cartel's business strategy.

A.5 Borrower Discounting and Risk Aversion

A.5.1 Discount Factors and Present Bias

In our model we assume borrowers discount payoffs in future weeks with quasi-hyperbolic discounting. Borrower i discounts a payoff w weeks into the future with $\beta_i \delta_i^w$. In our surveys we asked borrowers two question to elicit their discount factors and present bias. We use these responses to calculate each borrower's β_i and δ_i as follows.

In the first question, we asked borrowers what they would need to receive in ten months to be equivalent to receiving S\$800 in nine months. The median borrower said S\$980. Let X_i^δ be the amount stated by borrower i for this question.

We assume that this the X_i^δ that solves $\beta_i \delta_i^{\left(\frac{9}{12}\times\frac{365.25}{7}\right)} 800 = \beta_i \delta_i^{\left(\frac{10}{12}\times\frac{365.25}{7}\right)} X_i^\delta$. Thus the δ_i for borrower i is:

$$\delta_i = \left(\frac{800}{X_i^\delta}\right)^{12\times\frac{7}{365.25}} \tag{40}$$

In the second question, we asked borrowers what they would need to receive in one month to be equivalent to receiving S\$500 now. The median borrower said S\$700. 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 (40) and solving for β_i yields:

$$\beta_i = \left(\frac{500}{X_i^\beta}\right) \frac{1}{\delta_i^{\left(\frac{1}{12}\times\frac{365.25}{7}\right)}} = \left(\frac{500}{X_i^\beta}\right)\left(\frac{800}{X_i^\delta}\right) \tag{41}$$

The average borrower in our sample is slightly more impatient compared to the average borrower in Meier and Sprenger (2010) who surveyed individuals at tax assistance sites in Boston, MA during the 2006 tax season. In their survey they elicit the monthly discount factor between months 0 and 1 and between months 6 and 7 for each respondent. When they average these two discount factors and average these over respondents, they find an average monthly discount factor of 0.84. If we compute a similar average with our data (using months 9 and 10 instead of months 6 and 7), we find an average monthly discount factor of 0.77. In contrast to Meier and Sprenger (2010), however, the borrowers in our sample are much more likely to be present biased, with 99% in our sample and only 36% in theirs. The average of the borrowers' present focus parameters, β_i is 0.762. This falls within the range of $[0.74, 0.83]$ found by Allcott et al. (2021).

Table A.8: Number of borrowers with each possible coefficient of relative risk aversion.

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

A.5.2 Borrowers' Coefficients of Relative Risk Aversion

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. 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 use these responses to calculate each borrower's coefficient of relative risk aversion as follows. The borrower's utility function is $u_i(c) = \left(c^{1-\gamma_i} - 1\right)/(1-\gamma_i)$, 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:

$$\frac{\bar{c}^{1-\gamma_{\bar{c}}} - 1}{1-\gamma_{\bar{c}}} = 0.5 \times \frac{1^{1-\gamma_{\bar{c}}} - 1}{1-\gamma_{\bar{c}}} + \frac{1}{2} \times \frac{0^{1-\gamma_{\bar{c}}} - 1}{1-\gamma_{\bar{c}}} \tag{42}$$

Canceling terms and solving for $\gamma_{\bar{c}}$ yields: $\gamma_{\bar{c}} = 1 + \frac{\log(2)}{\log(\bar{c})}$. These indifference points are $\gamma_{\bar{c}} \in \{0.424, 0.340, 0.244\}$ for $\bar{c} \in \{0.3, 0.35, 0.4\}$.

Based on the survey responses, we assign 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 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.8. The majority of borrowers would take the gamble over the certain S$300, but would take the certain S$400 over the gamble. The range of risk aversion estimates are in line with those found by Chetty (2006), who finds a mean value of 0.71 with values ranging from 0.15 to 1.78. We also find that gamblers are significantly less risk averse compared to non-gamblers, with an 18.2% lower average γ_i coefficient compared to non-gamblers. The fact that gamblers can be measured to be risk averse (although with a low coefficient of risk aversion) can be rationalized by the utility from gambling itself (Conlisk, 1993).

A.6 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 $\mathcal{C}_{it}$, 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. We assume this because all the borrowers in our dataset stated that they considered less than than or equal to one new lender for all transactions. If the borrower does not have history with other lenders, we add additional new lenders so that all borrowers have exactly five options in their consideration sets. Because borrowers do not have access to formal sector loans, these types of loans are not part of their consideration set.

For the new lenders in the borrower's consideration set, we do not draw lender's randomly but instead use the lending network to choose a lender close to the borrower's own lenders. The idea behind this approach is if i's lenders also frequently lend to borrower i', then i's additional lender should be one of i''s lenders that i has not borrowed from before. This is because this lender is more likely to operate nearby and be in the same social network.

To do this, 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 of five lenders and three borrowers 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 borrower 1 did borrow from and the columns of lenders that borrower 1 did not borrow from. This is shown in bold. We then take the lender with the maximum value in this submatrix, 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 borrowed from fewer than three lenders in the data), we take the largest values from the submatrix until we have the desired number of lenders (again drawing randomly in the event of ties).

A.7 Terminal Week Payoffs

If the loan is still unpaid by the terminal week W, the lender will make the borrower do work for them to finish paying off the loan. In this section we describe the exact specification for the lender's and borrower's payoffs in this case.

A.7.1 Terminal Week Payoffs for the Lender

We assume reaching the terminal week 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. The expected payoff to the lender in the terminal week in each possible case is given by:

$$\widetilde{u}_{i\ell tW}\left(L_{i\ell t}, h_{i\ell t}\right) = \begin{cases} \left(6 - n_{i\ell tW}\right) r_t L_{i\ell t} & \text{if } n_{i\ell tW} \in \{0, \ldots, 5\} \text{ and } \widetilde{m}_{i\ell tW}\left(h_{i\ell t}\right) \geq r_t L_{i\ell t} \\ 7 r_t L_{i\ell t} - \kappa_{\ell t} & \text{if } n_{i\ell tW} = 0 \text{ and } \widetilde{m}_{i\ell tW}\left(h_{i\ell t}\right) < r_t L_{i\ell t} \\ \left(7 - n_{i\ell tW}\right) r_t L_{i\ell t} - p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right) \kappa_{\ell t} & \text{if } n_{i\ell tW} \in \{1, \ldots, 5\} \text{ and } \widetilde{m}_{i\ell tW}\left(h_{i\ell t}\right) < r_t L_{i\ell t} \\ 0 & \text{if } n_{i\ell tW} = 6 \end{cases} \tag{43}$$

In the first case, the borrower manages to make a payment in the last week. If this is the last payment, they do not work for the lender. This would happen if $n_{i\ell tW} = 5$ going into the last week. Otherwise they work for the lender to a value of $\left(5 - n_{i\ell tW}\right) r_t L_{i\ell t}$ in expectation. In the second case, the borrower has not made any payments towards the loan and must work to repay the loan in full, plus an additional payment as a penalty. 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, plus an additional payment $r_t L_{i\ell t}$ as a penalty. Because of the missed payment, the lender additionally harasses the borrower with probability $p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$. In the final case, the loan is already fully paid by week W.

A.7.2 Terminal Week Payoffs for the Borrower

Borrowers we have interviewed stated that the expected disutility from working for a lender to finish repaying a loan 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:

$$\left[8 + 2\left(\frac{5 - \mathbb{1}\left\{m_{i\ell tW}\left(h_{i\ell t}\right) \geq r_t L_{i\ell t}\right\} - n_{i\ell tW}}{5}\right)\right] p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right) \chi_{\ell} \tag{44}$$

If the borrower has not made any payments towards the loan, the expected disutility is $10 p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right) \chi_{\ell}$. If they only have one outstanding payment, the disutility is $8 p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right) \chi_{\ell}$.

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

$$u_{i\ell tW}\left(L_{i\ell t},h_{i\ell t}\right)=$$

$$\begin{cases}\mathbb{E}\left[\frac{\left[m_{i\ell tW}\left(h_{i\ell t}\right)-r_tL_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}\middle|m_{i\ell tW}\left(h_{i\ell t}\right)\geq r_tL_{i\ell t}\right]-\Psi_{i\ell t}\left(h_{i\ell t}\right) & \text{if } n_{i\ell tW}=5 \text{ and } m_{i\ell tW}\left(h_{i\ell t}\right)\geq r_tL_{i\ell t}\\ \mathbb{E}\left[\frac{\left[m_{i\ell tW}\left(h_{i\ell t}\right)\right]^{1-\gamma_i}-1}{1-\gamma_i}\middle|m_{i\ell tW}\left(h_{i\ell t}\right)<r_tL_{i\ell t}\right] & \\ -\left(10p^{\eta}_{i\ell t}\left(L_{i\ell t},h_{i\ell t}\right)+1\right)\chi_\ell-\Psi_{i\ell t}\left(h_{i\ell t}\right) & \text{if } n_{i\ell tW}=0 \text{ and } m_{i\ell tW}\left(h_{i\ell t}\right)<r_tL_{i\ell t}\\ \mathbb{E}\left[\frac{\left[m_{i\ell tW}\left(h_{i\ell t}\right)\right]^{1-\gamma_i}-1}{1-\gamma_i}\middle|m_{i\ell tW}\left(h_{i\ell t}\right)<r_tL_{i\ell t}\right] & \\ -\left(9+2\left(\frac{5-n_{i\ell tW}}{5}\right)\right)p^{\eta}_{i\ell t}\left(L_{i\ell t},h_{i\ell t}\right)\chi_\ell-\Psi_{i\ell t}\left(h_{i\ell t}\right) & \text{if } n_{i\ell tW}\in\{1,\ldots,5\} \text{ and } m_{i\ell tW}\left(h_{i\ell t}\right)<r_tL_{i\ell t}\\ \mathbb{E}\left[\frac{\left[m_{i\ell tW}\left(h_{i\ell t}\right)-r_tL_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}\middle|m_{i\ell tW}\left(h_{i\ell t}\right)\geq r_tL_{i\ell t}\right] & \\ -\left(8+2\left(\frac{4-n_{i\ell tW}}{5}\right)\right)p^{\eta}_{i\ell t}\left(L_{i\ell t},h_{i\ell t}\right)\chi_\ell-\Psi_{i\ell t}\left(h_{i\ell t}\right) & \text{if } n_{i\ell tW}\in\{0,\ldots,4\} \text{ and } m_{i\ell tW}\left(h_{i\ell t}\right)\geq r_tL_{i\ell t}\\ \mathbb{E}\left[\frac{m_{i0tW}^{1-\gamma_i}-1}{1-\gamma_i}\right] & \text{if } n_{i\ell tW}=6\end{cases} \tag{45}$$

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 χ_ℓ from two missed payments in a row and an expected disutility of $10p^{\eta}_{i\ell t}\left(L_{i\ell t},h_{i\ell t}\right)\chi_\ell$ 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 $p^{\eta}_{i\ell t}\left(L_{i\ell t},h_{i\ell t}\right)\chi_\ell$ 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 Harassment Likelihood Examples

In this section we provide some simple examples of how equation (29) works. In the simplest case, suppose a borrower finishes a loan with no missed payments ($f_{i\ell t}=0$). Then the harassment probability is zero. This is because $\widehat{\widehat{C}}^{w}_0=0$: 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 $p^{\eta}_{i\ell t}\left(\theta^{Lender},L_{i\ell t},h_{i\ell t}\right)$. This is because $\widehat{\widehat{C}}^{w}_1=0$ 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:

$$\frac{\left(1 + \left(1 - \left[1 - p_{i\ell t}^{\eta}\left(\boldsymbol{\theta}^{Lender}, L_{i\ell t}, h_{i\ell t}\right)\right]^2\right)\right)}{2}$$

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.

A.9 Gauss-Hermite Quadrature Approximations of Borrower Payoffs

We use Gauss-Hermite quadrature with $H = 200$ weights w_h and nodes z_h to numerically evaluate the conditional and unconditional expectations in the borrower's payoff functions. For ease of notation, we omit the $h_{i\ell t}$ argument in $m_{i\ell t}\left(h_{i\ell t}\right)$ in this subsection and write it simply as $m_{i\ell t}$ (and similarly for $m_{i\ell tw}$).

Expected Payoff in the First Week:

The expected payoff in week 1 before the realization of ν_{it1} is the expected utility from consuming the income, m_{i0t1}, plus the cash from the loan, $\left(1 - r_t\right) L_{i\ell t}$. This expected payoff and its approximation are given by:

$$\begin{aligned}
&\mathbb{E}\left[\frac{\left(m_{i0t1} + \left(1 - r_t\right) L_{i\ell t}\right)^{1-\gamma_i} - 1}{1 - \gamma_i}\right] \\
&= \Phi\left(-\frac{m_{i0t}}{\sigma_i}\right) \frac{\left[\left(1 - r_t\right) L_{i\ell t}\right]^{1-\gamma_i} - 1}{1 - \gamma_i} + \int_{-m_{i0t}/\sigma_i}^{\infty} \frac{\left(m_{i0t} + \sigma_i \nu_{it1} + \left(1 - r_t\right) L_{i\ell t}\right)^{1-\gamma_i} - 1}{1 - \gamma_i} \frac{e^{-\nu_{it1}^2/2}}{\sqrt{2\pi}} d\nu_{it1} \\
&\approx \Phi\left(-\frac{m_{i\ell t}}{\sigma_i}\right) \frac{\left[\left(1 - r_t\right) L_{i\ell t}\right]^{1-\gamma_i} - 1}{1 - \gamma_i} + \sum_{h=1}^{H} \frac{w_h}{\sqrt{\pi}} \mathbb{1}\left\{m_{i\ell t} + \sqrt{2}\sigma_i z_h > 0\right\} \frac{\left[m_{i\ell t} + \sqrt{2}\sigma_i z_h + \left(1 - r_t\right) L_{i\ell t}\right]^{1-\gamma_i} - 1}{1 - \gamma_i}
\end{aligned}$$

The probability that $m_{i0t1} = 0$ is $\Phi\left(-\frac{m_{i0t}}{\sigma_i}\right)$ 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 $m_{i\ell t1} > 0$.

Expected Payoff from Making a Payment:

In weeks 2 to W, if a borrower makes their payment they consume their remaining cash

$m_{i\ell tw} - r_t L_{i\ell t}$ and experience disutility from effort. A borrower can make a payment only if $m_{i\ell tw} \geq r_t L_{i\ell t}$ which can also be written as $v_{itw} \geq (r_t L_{i\ell t} - m_{i\ell t}) / \sigma_i$. The expected payoff conditional on being able to make the payment is then approximated by.:

$$\underbrace{\mathbb{E}\left[\frac{(m_{i\ell tw} - r_t L_{i\ell t})^{1-\gamma_i} - 1}{1-\gamma_i}\middle| m_{i\ell tw} \geq r_t L_{i\ell t}\right]}_{\text{Expected payoff from consuming } m_{i\ell tw} - r_t L_{i\ell t} \text{ after payment}} - \underbrace{\Psi_{i\ell t}(h_{i\ell t})}_{\text{Disutility from effort}}$$

$$= \left[\Phi\left(\frac{m_{i\ell t} - r_t L_{i\ell t}}{\sigma_i}\right)\right]^{-1} \int_{\frac{r_t L_{i\ell t} - m_{i\ell t}}{\sigma_i}}^{\infty} \frac{(m_{i\ell t} + \sigma_i v_{itw} - r_t L_{i\ell t})^{1-\gamma_i} - 1}{1-\gamma_i} \frac{e^{-v_{itw}^2/2}}{\sqrt{2\pi}} dv_{itw} - \Psi_{i\ell t}(h_{i\ell t})$$

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

Expected Payoff from Not Making a Payment:

The borrower is unable to make the payment when $m_{i\ell tw} < r_t L_{i\ell t}$. If a borrower misses a payment when they have made the previous week's payment ($n_{i\ell tw} > 0$), they consume their income and any transfers from the lender. They also receive disutility from any harassment and effort costs. The expected payoff conditional on not being able to make the payment is then given by:

$$\underbrace{\mathbb{E}\left[\frac{\left[m_{i\ell tw} + (n_{i\ell tw} - 1) r_t L_{i\ell t}\right]^{1-\gamma_i} - 1}{1-\gamma_i}\middle| m_{i\ell tw} < r_t L_{i\ell t}\right]}_{\text{Expected payoff from consuming cash } m_{i\ell tw} \text{ plus any transfers after missing a payment}}$$

$$- \underbrace{p_{i\ell t}^{\eta} \chi_\ell}_{\text{Expected disutility from harassment which occurs with probability } p_{i\ell t}^{\eta}} - \underbrace{\Psi_{i\ell t}(h_{i\ell t})}_{\text{Disutility from effort}}$$

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 can be approximated by:

$$\mathbb{E}\left[\frac{\left[m_{i\ell tw}+(n_{i\ell tw}-1)\,r_t L_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}\middle| m_{i\ell tw}<r_t L_{i\ell t}\right]$$

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

$$\frac{1}{\Phi\left(\frac{r_t L_{i\ell t}-m_{i\ell t}}{\sigma_i}\right)}\int_{-\frac{m_{i\ell t}}{\sigma_i}}^{\frac{r_t L_{i\ell t}-m_{i\ell t}}{\sigma_i}}\frac{\left[m_{i\ell t}+\sigma_i v_{itw}+(n_{i\ell tw}-1)\,r_t L_{i\ell t}\right]^{1-\gamma_i}-1}{1-\gamma_i}\times\frac{e^{-v_{itw}^2/2}}{\sqrt{2\pi}}dv_{itw}$$

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

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

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

If the borrower has missed a second payment in a row ($n_{i\ell tw}=0$), then the lender will harass the borrower with probability 1. The borrower is then required to come up with the payment shortfall by the end of the week to avoid even more severe harassment. The expected payoff in this case does not require any approximation and is given by:

$$-\frac{1}{1-\gamma_i}-\underbrace{\theta^{\Psi}\left[r_t L_{i\ell t}-m_{i\ell t}+\sigma_i\frac{\phi\left(\frac{r_t L_{i\ell t}-m_{i\ell t}}{\sigma_i}\right)}{\Phi\left(\frac{r_t L_{i\ell t}-m_{i\ell t}}{\sigma_i}\right)}\right]}_{\text{Disutility from effort in making up the shortfall}}-\underbrace{\left(\chi_\ell+\Psi_{i\ell t}\left(h_{i\ell t}\right)\right)}_{\text{Disutility from harassment and baseline effort}}$$

Expected Payoff from a Completed Loan:

The expected payoff when the loan is complete is the unconditional expectation of $\frac{m_{i0tw}^{1-\gamma_i}-1}{1-\gamma_i}$. We approximate this using:

$$\mathbb{E}\left[\frac{m_{i0tw}^{1-\gamma_i}-1}{1-\gamma_i}\right]=\int_{-m_{i0t}/\sigma_i}^{\infty}\frac{(m_{i0t}+\sigma_i v_{itw})^{1-\gamma_i}-1}{1-\gamma_i}\frac{e^{-v_{itw}^2/2}}{\sqrt{2\pi}}dv_{itw}$$

$$\approx\sum_{h=1}^{H}\frac{w_h}{\sqrt{\pi}}\mathbb{1}\left\{m_{i0t}+\sqrt{2}\sigma_i z_h>0\right\}\frac{\left[m_{i0t}+\sqrt{2}\sigma_i z_h\right]^{1-\gamma_i}-1}{1-\gamma_i}$$

A.10 Removing Lenders' Information Asymmetry

In our baseline model we assume that lenders do not know the borrowers' addictions in the first loan and only learn these after having interacted with a borrower throughout the loan. In this section we re-estimate our structural model assuming these characteristics are known to the lender for all loans. Using the parameter estimates from this assumption, we repeat all the counterfactual experiments from 6. These are shown in Tables A.9 and A.10 and Figures A.4 to A.6. In each case, the results are qualitatively the same and in most cases very similar to the baseline model.

TABLE A.9: Decomposing the effects of the crackdown under no lender information asymmetry.

	No Crackdown (*Level*) (1)	Crackdown (Baseline) (*Level*) (2)	Overall (*% Difference*) (3)	Only $\kappa_{\ell t}$ Increases (*% Difference*) (4)	Only r_t Increases (*% Difference*) (5)
Total lender profits (in S$m)	3.83	1.21	−68.48	−95.70	+33.26
Total loan volume (in S$m)	2.60	1.36	−47.84	−5.18	−45.63
Average harassment probability chosen	0.19	0.08	−59.12	−32.98	−35.69
Total interest revenue (in S$m)	6.87	6.73	−2.04	−4.05	+1.45
Total harassment costs (in S$m)	0.44	4.17	+846.92	+800.30	+2.85
Average borrower surplus (in S$000)	0.50	0.45	−10.29	+3.64	−12.61
Average number of missed payments	4.49	6.11	+36.00	+3.58	+30.21
Average number of times harassed	1.96	2.64	+34.35	−4.65	+30.75

Column (3) shows the baseline (total) effects of the crackdown. Column (4) shows the effects of the crackdown if only the harassment cost, $\kappa_{\ell t}$, increased. Column (5) shows the effects of only the nominal interest rate, r_t, increasing from 20% to 35%.

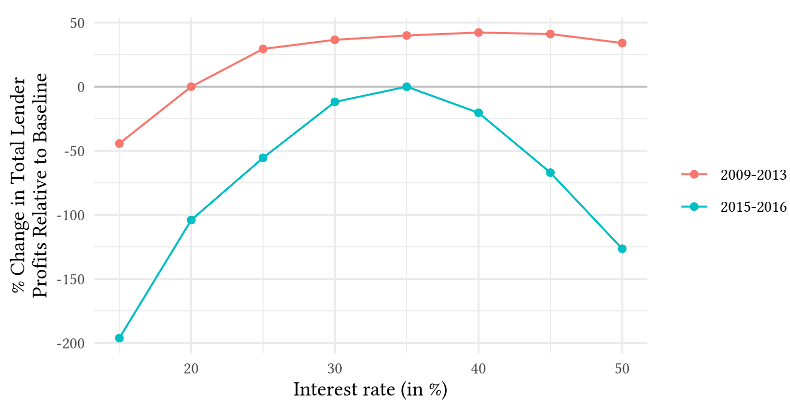


FIGURE A.4: Percentage change in total lender profits at alternative interest rates before and after the crackdown under no lender information asymmetry.

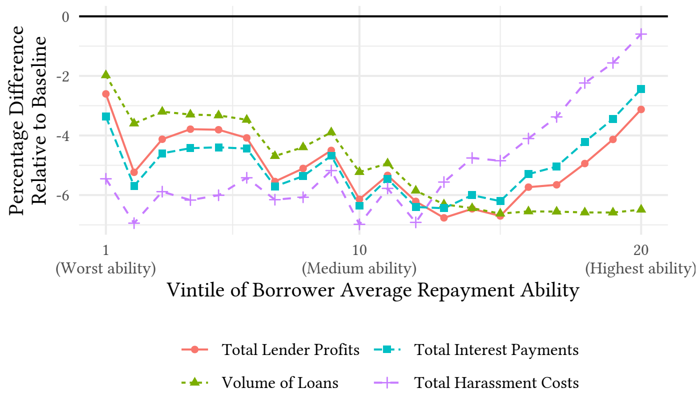


FIGURE A.5: Effects of targeting borrowers on lender outcomes under no lender information asymmetry.

TABLE A.10: Effects of indirect interventions on lender profits under no lender information asymmetry.

Intervention	Median Impact on Lender Profits	Median Impact on Borrower Surplus
Stop a borrower gambling	−33.84	25.51%
Stop a borrower using drugs	−12.46	8.20%
Remove a borrower's present bias (setting borrower's β_i to 1)	−40.79	7.89%
Set a borrower's β_i to 1 and δ_i to 0.999 (0.95 annual discount factor)	−54.13	15.27%

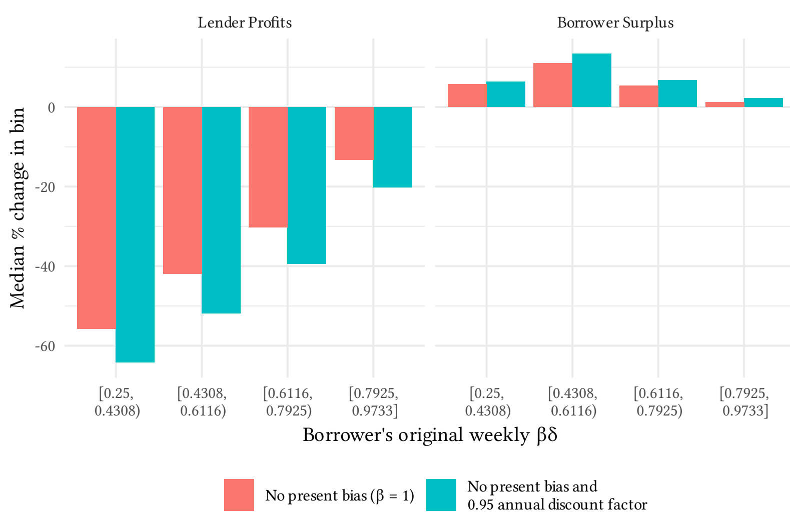


FIGURE A.6: Heterogeneous effects of discounting interventions under no lender information asymmetry.

References

Aleem, I. (1990): "Imperfect Information, Screening, and the Costs of Informal Lending: a Study of a Rural Credit Market in Pakistan," *The World Bank Economic Review*, 4, 329–349.

Allcott, H., J. Kim, D. Taubinsky, and J. Zinman (2021): "Are High-Interest Loans Predatory? Theory and Evidence from Payday Lending," *The Review of Economic Studies*.

Björkegren, D., J. Blumenstock, O. Folajimi-Senjobi, J. Mauro, and S. R. Nair (2022): "Instant Loans Can Lift Subjective Well-Being: A Randomized Evaluation of Digital Credit in Nigeria," *arXiv preprint arXiv:2202.13540*.

Chetty, R. (2006): "A New Method of Estimating Risk Aversion," *American Economic Review*, 96, 1821–1834.

Conlisk, J. (1993): "The Utility of Gambling," *Journal of Risk and Uncertainty*, 6, 255–275.

Corrupt Practices Investigation Bureau (2017): "Corruption in Singapore at Low Levels," https://www.cpib.gov.sg/press-room/press-releases/corruption-singapore-low-levels.

Dobbie, W. and P. M. Skiba (2013): "Information Asymmetries in Consumer Credit Markets: Evidence from Payday Lending," *American Economic Journal: Applied Economics*, 5, 256–82.

Emmers, R. (2003): "The Threat of Transnational Crime in Southeast Asia: Drug Trafficking, Human Smuggling and Trafficking and Sea Piracy," *Revista UNISCI*, 1–11.

Gallup (2020): "Global Law and Order Report," https://www.gallup.com.

Jorgic, D. (2020): "Special Report: Burner Phones and Banking Apps: Meet the Chinese "Brokers" Laundering Mexican Drug Money," *Reuters*.

Kaboski, J. P. and R. M. Townsend (2011): "A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative," *Econometrica*, 79, 1357–1406.

Karlan, D., S. Mullainathan, and B. N. Roth (2019): "Debt Traps? Market Vendors and Moneylender Debt in India and the Philippines," *American Economic Review: Insights*, 1, 27–42.

McIntosh, C., A. De Janvry, and E. Sadoulet (2005): "How Rising Competition Among Microfinance Institutions Affects Incumbent Lenders," *The Economic Journal*, 115, 987–1004.

Meier, S. and C. Sprenger (2010): "Present-Biased Preferences and Credit Card Borrowing," *American Economic Journal: Applied Economics*, 2, 193–210.

Morgan, D. P., M. R. Strain, and I. Seblani (2012): "How Payday Credit Access Affects Overdrafts and Other Outcomes," *Journal of Money, Credit and Banking*, 44, 519–531.

National Council on Problem Gambling (2017): "Report Of Survey On Participation In Gambling Activities Among Singapore Residents," Singapore.

NETI (2019): "Emerging Threats Report 2019: Status and Factors Affecting the United States," National Emerging Threats Initiative.

Noble, L. W. (2018): "Chart of the Day: Gaming Revenue in Singapore Slipped in H1 after 2017 Growth," *Singapore Business Review*.

Seidl, J. M. (1970): "Let's Compete With Loan Sharks." *Harvard Business Review*, 48, 69 – 77.

Singapore High Court (2012): "Ong Chee Eng v Public Prosecutor [2012] SGHC 115," https://www.singaporelawwatch.sg.

Singapore Ministry of Law (2009): "Implementation of the New Moneylenders Act and Rules," Press release.

Soudijn, M. R. and S. X. Zhang (2013): "Taking Loan Sharking into Account: A Case Study of Chinese Vest-Pocket Lenders in Holland," *Trends in Organized Crime*, 16, 13–30.

Transparency International (2020): "Corruption Perceptions Index," https://www.transparency.org.

UNODC (2018): "Infiltration of Organized Crime in Business and Government: Loan-sharking," *United Nations Office on Drugs and Crime*.

——— (2020): "Synthetic Drugs in East and Southeast Asia," *United Nations Office on Drugs and Crime*.