Journal of Financial Economics

The effects of policy interventions to limit illegal money lending[☆]

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ARTICLE INFO

Keywords:
Illegal money lending
Loan sharks
Law enforcement
Crime
Structural estimation

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.

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

☆ Toni Whited was the editor for this article. 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] 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.

Received 21 June 2023; Received in revised form 7 June 2024; Accepted 7 June 2024

Available online 15 June 2024

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 enforcement, 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 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

[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/).

[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.

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. (2022), 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. (2022) 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 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., 2022) 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

[4] Apart from our companion paper (Lang et al., 2022), 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.

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. (2022). We provide an overview of the data collection process and summary statistics here, but we refer the reader to Lang et al. (2022) 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 h 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, 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

[5] Our 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 addictive habits prone to repeat borrowing, such as gambling, drugs and alcohol. Furthermore, in parliament 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 medical emergencies or unemployment (Singapore High Court, 2012).

[6] We also found news reports of loan sharks from Chinese syndicates being arrested in Singapore (Chong, 2015), Vietnam (Thang, 2020), Thailand 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

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 syndicates 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 $25\% \times \frac{365}{5\times7} = 208.57\%$.

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 penalties 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 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, vandalism 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 bilateral loan history. We show these event study plots 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.

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.

[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.

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.

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.

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 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 fluctuations in expenses each week. Therefore they often fall short of their loan repayments. The borrowers we 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. (2022) 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 $\gamma_i = 0.382$.

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

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

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

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 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 $\alpha_i = \theta^{\alpha}_r \cdot \boldsymbol{x}^{\alpha}_i$, 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 $\theta^{\alpha} = \left(\theta^{\alpha}_r, \left\{\theta^{\alpha}_i\right\}_{i=1}^{i=\mathcal{I}}\right)$.

Borrower i at time t chooses between a subset of all the lenders active in the market, defined by $C_{it} \subset \{1,\dots,\mathcal{L}\}$, or to not borrow at all. We assume that 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]

3.2.2. Lender choice problem: Loan size and harshness level

If borrower i chooses lender $\ell \in C_{it}$ 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 $k(\ell) \in \mathcal{K} = \{Regular, Harsh, Very\ Harsh\}$ 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:

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

where $\Phi(\cdot)$ 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 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 $\theta^{\eta} = \left(\left\{\theta^{\eta}_h\right\}_{h\in\mathcal{H}}, \left\{\theta^{\eta}_k\right\}_{k\in\mathcal{K}}, \theta^{\eta}_L, \theta^{\eta}_x\right)$.

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:

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

[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 their consideration sets.

Borrowers generate a fixed amount m_{i0t} plus a stochastic component v_{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, 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:

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

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

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

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, $k(\ell)$. 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 $\boldsymbol{\theta}^m = \left(\boldsymbol{\theta}_0^m, \theta_\eta^m, \theta_r^m, \boldsymbol{\theta}_e^m, \{\theta_k^m\}_{k\in\mathcal{K}}\right)$.

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. Second, there is the moral hazard effect which, as we will find, has a negative impact on $m_{i\ell t}\left(h_{i\ell t}\right)$. 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.

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

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 $\widetilde{m}_{i0t}$, $\widetilde{m}_{i\ell t}\left(h_{i\ell t}\right)$ and $\widetilde{\sigma}_i$ as the lender's estimates of m_{i0t}, $m_{i\ell t}\left(h_{i\ell t}\right)$ 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:

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

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

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

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

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

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 $p_{i\ell t}^{\widetilde{m}}\left(L_{i\ell t}, h_{i\ell t}\right)$. 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 $p_{i\ell t}^\eta\left(L_{i\ell t}, h_{i\ell t}\right)$ 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, $p_{\ell t}^e$, and the expected disutility from arrest, $K_{\ell t}$:

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

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

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

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

$$\kappa_{\ell t} = \left(1 + \theta_{k(\ell)}^\kappa\right)\left(\theta_0^\kappa + \theta_{post}^\kappa post_t\right) \tag{14}$$

where $post_t \in \{0, 1\}$ is a post-crackdown indicator. We group these parameters into $\boldsymbol{\theta}^\kappa = \left(\theta_0^\kappa, \theta_{post}^\kappa, \{\theta^\kappa\}_{k\in\mathcal{K}}\right)$, where we normalize $\theta_k^\kappa = 1$ 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 $w \in \{2, \dots, W-1\}$ before the terminal week W as:

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

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 $\left(n_{i\ell tw} - 1\right) r_t L_{i\ell t}$ back to the borrower. They inflict harassment with probability $p^{\eta}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$ 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:

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

where $\widetilde{\varepsilon}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$ 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 $p^{Lh}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$ 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 $\widetilde{\varepsilon}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$. For positive loan sizes, the probability that the lender chooses the combination $\left(L_{i\ell t}, h_{i\ell t}\right)$ is given by

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

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

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 $\left(1 - r_t\right) L_{i\ell t}$. 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 v_{itw} is realized. We further assume borrowers have constant relative risk aversion utility over consumption 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 $\theta^{\chi} = \left\{\theta^{\chi}_{k}\right\}_{k \in \mathcal{K}}$.

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

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

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 $w \in \{2, \dots, W-1\}$ as:

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

[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: $p^{Lh}_{i\ell t}(0, Low) = 1 - \sum_{L_{i\ell t} \in \mathfrak{L}_{it} \setminus \{0\}} \sum_{h_{i\ell t} \in \mathcal{H}} p^{Lh}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$ where we note that $p^{Lh}_{i\ell t}(0, Medium) = p^{Lh}_{i\ell t}(0, High) = 0$.

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 $\left(n_{i\ell tw}-1\right) r_t L_{i\ell t}$ to them and resets the loan. The borrower also is harassed 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 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:

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

3.4.2. Borrower lender choice probabilities

The borrower does not observe the value of the lender's payoff shocks, $\widetilde{\varepsilon}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$. 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 $p^{Lh}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\right)$ 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:

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

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:

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

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 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 will not 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. (2022) 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:

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

We estimate θ in a series of steps. We first jointly estimate all parameters related to the lender's problem, which are given by $\theta^{Lender} =$

$\left(\theta^{\eta}, \theta^{\widetilde{m}}, \theta^{\widetilde{\sigma}}, \theta^{\kappa}, \theta^{\lambda}\right)$. 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, θ^{η}, 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 θ^{η}.

To identify the repayment probability parameters from the lender's perspective, $\theta^{\widetilde{m}}$ and $\theta^{\widetilde{\sigma}}$, 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, θ^{κ}, and the nested logit parameters, θ^{λ}, 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 θ^{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:

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

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

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

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

Harassment likelihood:. The first component in Eq. (28), $\Pr\left(\mathfrak{h}_{i\ell t} \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}, w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\right)$, 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. 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 $h_{i\ell t}$ is given by:

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

The terms C^{w}_{f}, $\hat{\hat{C}}^{w}_{f}$, C^{d}_{f} and $\hat{\hat{C}}^{d}_{f}$ are defined as follows. First, C^{w}_{f} 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, $\hat{\hat{C}}^{w}_{f}$ is the number of ways a loan can have two missed payments in a row when finishing in w weeks with f missed payments. Third, C^{d}_{f} is the number of ways a loan can reach the terminal week with f missed payments. Finally, $\hat{\hat{C}}^{d}_{f}$ is the number of ways a loan can have two missed payments in a row when reaching the terminal week with f missed payments. 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 in Eq. (28), $\Pr\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t} \middle| \theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$, 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 $p^{\widetilde{m}}_{i\ell t}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$, then the probability that the borrower completes the loan in w weeks with f missed payments according to our model is:

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

where C^{w}_{f} is (as in Eq. (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 $\left(w_{i\ell t}, f_{i\ell t}, d_{i\ell t}\right)$ according to the model is then:

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

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 $\Pr\left(L_{i\ell t}\middle|\theta^{Lender}, h_{i\ell t}\right)$ in Eq. (28) is the probability of the observed loan size given the harshness level. This is given by:

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

where

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

in the fourth component. We compute $p_{i\ell t}^{Lh}\left(L_{i\ell t}, h_{i\ell t}\middle|\theta^{Lender}\right)$ via simulation. Given a guess of parameters θ^{Lender}, we compute the $\widetilde{\overline{V}}_{i\ell t}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$ from Eq. (17) for each possible loan size and harshness level by simulating $ns = 10{,}000$ repayment paths using the repayment probability $p_{i\ell t}^{\widetilde{m}}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$ and the harassment probability $p_{i\ell t}^{\eta}\left(\theta^{Lender}, L_{i\ell t}, h_{i\ell t}\right)$. 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, θ^{α}, by estimating Eq. (1) in log form using a linear regression with borrower fixed effects:

$$\log\left(L_{it}^{\star}\right) = \theta_r^{\alpha}\cdot \mathbf{x}_i^{\alpha}\times r_t + \theta_i^{\alpha} + v_{it} \tag{35}$$

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 θ_r^{α}. The differences in how loan demand changes after the crackdown for borrowers of different characteristics identifies the interaction terms in θ_r^{α}.

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, θ^m and θ^{σ}, 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:

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

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

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

4.4. Estimation of borrower harassment disutility and effort cost

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

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

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 θ^{χ} 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 θ^{χ}, 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 θ^{χ} 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 Eq. (21). Due to the large number of possible paths, combined with

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

	Parameters determine:	Identified though:
θ^{η}	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.
$\theta^{\tilde{m}}, \theta^{\tilde{\sigma}}$	Borrower repayment probabilities from lender's perspective.	Observed number of missed payments and time to repay given observed borrower and loan characteristics.
θ^{κ}	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).
θ^{α}	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.
$\theta^{m}, \theta^{\sigma}$	Borrower repayment probabilities from borrower's perspective	Observed number of missed payments and time to repay given observed borrower and loan characteristics.
$\theta^{\chi}, \theta^{\Psi}$	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 (θ^{χ}) and expected cost of effort (θ^{Ψ}), which vary by lender type, harassment probabilities, and past lending history.

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 relative risk aversion elicited from the surveys for δ_i, β_i, and γ_i, respectively.

With the expression in Eq. (21) calculated for each possible loan size and harshness level the lender could choose, we can compute the expected payoff for a lender using Eq. (22) together with the estimated lender choice probabilities, $p^{Lh}_{i\ell t}\left(L_{i\ell t}, h_{i\ell t}\middle|\hat{\theta}^{Lender}\right)$. 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 Eq. (23). This allows us to compute the likelihood in Eq. (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 θ^{χ} 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 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 coefficients 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

Table 5
Parameter estimation results.

	Cash for repayments (borrower) θ^m, θ^σ		Cash for repayments (lender) $\theta^{\tilde{m}}$, $\theta^{\tilde{\sigma}}$		Lender harassment probability θ^η	
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 $\theta^{\tilde{\sigma}}$)	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 θ^κ		Harassment disutility θ^χ		Effort cost θ^ψ	
Constant	0.437	(1.237)	1.302	(0.047)	1.528	(0.022)
Lender type: Harsh (multiplier for θ^κ)	−0.221	(0.229)	0.248	(0.078)		
Lender type: Very harsh (multiplier for θ^κ)	−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 $\theta^{\tilde{m}}$ and θ^η, 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 characteristics are unobserved by lenders for the first loan. The constant terms in $\theta^{\tilde{\sigma}}$ and θ^σ are normalized to 1.

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.

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 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%.

Table 6 shows the estimates of the borrower loan demand parameters θ^{α}. 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 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 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, 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$3.08 m to S$1.00 m. 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 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 probabilities.

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

[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.

[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.

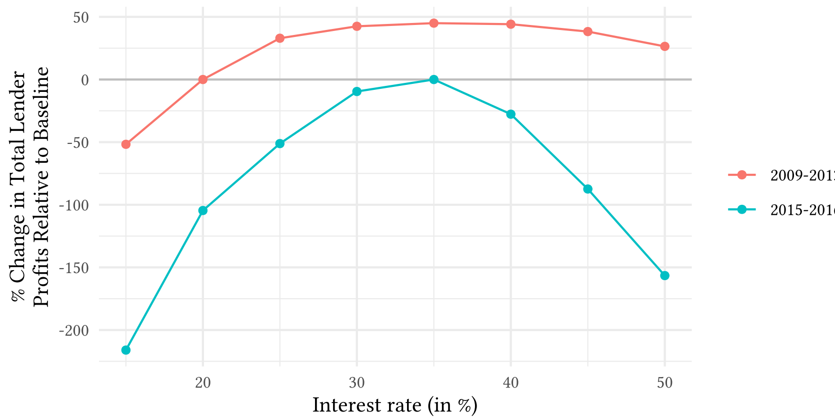

Fig. 1. Percentage change in total lender profits at alternative interest rates before and after the crackdown.

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. 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. Fig. 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 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

[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.

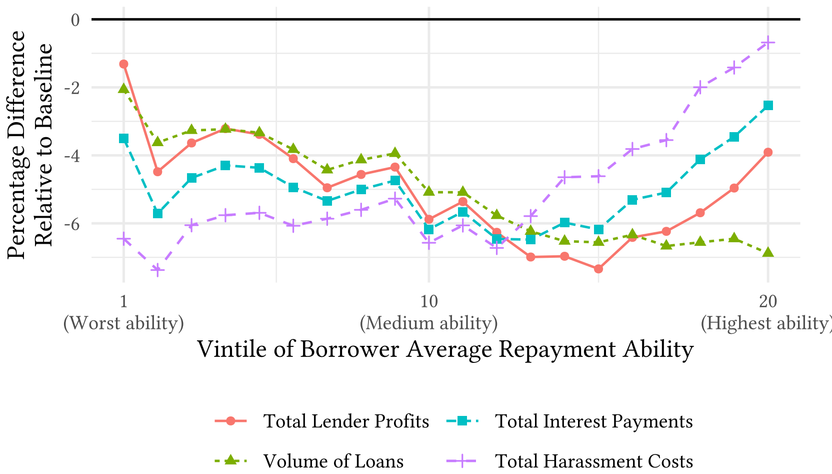

Fig. 2. Effects of targeting borrowers on lender outcomes.

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

The results of this counterfactual experiment are shown in Fig. 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 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

[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.

[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.

Table 8
Effects of indirect interventions on lender profits.

Intervention	Median Impact on	
	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%

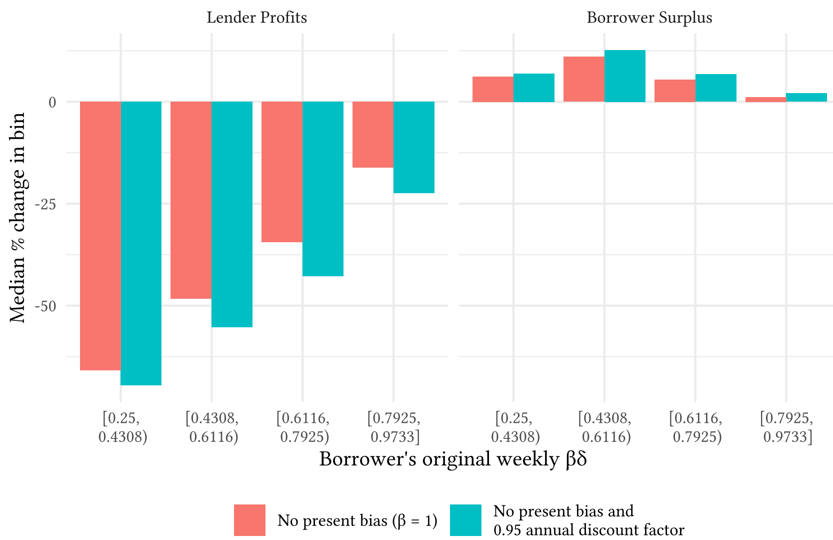

Fig. 3. Heterogeneous effects of discounting interventions.

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 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 factor of 0.95 without present bias.

The effect sizes of these interventions also depend on the initial discounting of the borrower. In Fig. 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

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

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.

CRediT authorship contribution statement

Kaiwen Leong: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Huailu Li:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Nicola Pavanini:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Christoph Walsh:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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). Authors declare that they have not received other significant financial support, in the form of consultant fees, grants, retainers, and the like, or in-kind support, from parties with financial, political, or ideological stakes in the effect of anything we study in this paper. Authors do not serve in any paid or unpaid position with an organization whose positions, goals, or financial interests relate to this research. And no party other than the authors had the right to review it before submission. Authors received the ethics approval from Nanyang Technological University's IRB.

Data availability

Leong, Kaiwen; Li, Huailu; Pavanini, Nicola; Walsh, Christoph (2024), "FINEC-D-23-00516_Leong-Li-Pavanini-Walsh_The-Effects-of-Policy-Interventions-to-Limit-Illegal-Money-Lending", Mendeley Data, V2, (Reference data) (Mendeley Data).

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