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The Whip of Singapore: Can Tough Legal Enforcement Entice Criminal Extortion? *

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Abstract

Using a unique dataset, we study the unlicensed money lending market in Singapore. In this market, borrowers search for loan sharks to borrow from, and loan sharks decide how much money to extort from borrowers. At equilibrium, we observe dispersion over the degree of extortion by different loan sharks. We find that when the authorities increase enforcement efforts specifically targeted at reducing the number of loan sharks in this market, these efforts have, on average, the following effects: The initial interest rate on the loan agreed upon by both the loan sharks and the borrowers increases, the loan amount that the loan shark is willing to lend to the borrower decreases, the amount of money the loan shark extorts from the borrower increases and the loan shark's harassment activities against the borrower remains unchanged.

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1 Introduction

Despite there being many lenders who extort large sums of money from borrowers in unlicensed money lending markets across the globe, including in the United Kingdom, the United States, Vietnam, China, and Singapore, there is very little literature explaining the economics behind how these markets function.[1] Olken and Barron (2009) believed that established pricing theories from industrial organization would be sufficient to explain extortion patterns we observe in the market place.[2] In this paper, we analyze a unique dataset that tracked the borrowing behavior of over a thousand borrowers in the unlicensed money lending market in Singapore for half a decade. Using a completely different setting, we study how a reduction in lenders due to government enforcement efforts affects the lenders' extortion strategies towards borrowers over time in the unlicensed money lending market. Later in this section, we propose a theory different from prevailing explanations about extortion and one that is substantiated by our empirical findings.[3]

Singapore is an ideal country to study how the unlicensed money lending market functions. In 2009, more than half of the overall number of crimes committed in Singapore were related to the unlicensed money lending industry.[4] Thus, it is of great importance for the authorities to understand how this market operates in order to design effective policies to combat crimes related to this market. Using our dataset and information provided by informants, we discovered many interesting facts about this market. First, the unlicensed money lending market in Singapore consists of many relatively homogeneous lenders and many relatively homogeneous borrowers.[5] Borrowers are mainly low income individuals who take out illegal loans to feed their gambling addiction.[6] According to informants, lenders on the other hand, are independent entrepreneurs selected by a few syndicates using approximately the same set of criteria to identify individuals who will likely succeed in this business.[7]

[1]Meikle (2014) states that in the United Kingdom, the Illegal Money Lending Team - a national enforcement team that has powers of arrest and prosecution - has conservatively estimated that there were 310,000 borrowers of illegal loans across Britain who paid around US$1 billion a year to loan sharks (illegal lenders), a figure equivalent to a third of the legal short-term payday loan market. In Singapore, conservative estimates given by market insiders whom we have interviewed put the number of individuals who have borrowed from loan sharks in the years 2000-2010 to be in the hundreds of thousands. In Malaysia, Mustafa (2011) writes that a small operation of 5 individuals running an illegal loan shark business earned SGD20.3 million in 5 years and had more than 1000 customers. She also writes that despite the authorities repeatedly advising borrowers to stop borrowing from these illegal lenders, many borrowers did not heed the advice and still continued to do so.

[2]Their study focuses on how extortion by the North Sumatran authorities changed in response to a reduction in checkpoints across the country.

[3]We define the amount of money extorted by the lender from the borrower as the amount of money the lender obtains by forcing the borrower to pay, without the borrower's consent, using violence and threats in our setting. We provide a detailed discussion of extortion in section 5.3.3.

[4]See Table 1.

[5]In colloquial terms, a lender is known as a loan shark. We will use the term loan shark or lender interchangeably throughout the paper.

[6]Empirically, we found that the borrowers' characteristics do not have any predictive power on both the magnitude of the lender's extortion and harassment levels

[7]We will discuss this further in the conclusion.

However, different lenders choose to extort different amounts of monies from different borrowers. Later in the paper, we will provide a plausible economic explanation for these findings.

Next, understanding how the unlicensed money lending market operates is necessary before we can even begin to understand the possible unintended effects of enforcement policies on this market. In Singapore, borrowers taking out loans from unlicensed money lenders are not criminalized. Most of these borrowers have low incomes and are unable to get loans from legal financial institutions. In this paper, we study enforcement policies that aimed to reduce the number of illegal lenders in this market. The remaining lenders in the market realized that this reduction made it even more difficult for borrowers to get a loan and thus decided to take advantage of the situation by extorting unprecedented large sums of monies from the borrowers. Most borrowers, being desperate for funds, had no choice but to give into extortion and were thus made worse off. The possible further unintended effect of the policy might lead to borrowers becoming criminals to pay off the lenders.

Borrowers whom the first author had helped turned their lives around revealed that it is not wise to take the information from most borrowers in the unlicensed money lending at face value, as the information shared is often far from the truth.[8] According to the borrowers whom the first author had an established relationship with, "Some of these people tend to twist facts either to obtain sympathy and subsequently try to obtain financial help. Others are worried that disclosing real information that could be made public by irresponsible individuals could cause them to be identified and hunted down by these illegal moneylenders." The borrower provided further elaboration by saying "Singapore is a very small place, if I know how much you borrowed, when you borrowed, how many times you borrowed and where you live, I know who the person is. This is because everyone knows everyone in this borrowing and lending community." To overcome all these problems, the first author ensured that whenever possible, documentary proof was obtained when collecting survey information to corroborate what was said. Only enumerators who could be trusted with keeping confidential information were hired to reassure respondents that whatever they revealed would remain private. Furthermore, for over six years, the first author continued to help disadvantaged individuals such as these borrowers while working on related academic topics to build a relationship of trust and a track record in maintaining confidentiality.[9]

Interviews with market insiders reveal the following basic facts about the unlicensed money lending market in Singapore: First, the market is highly decentralized. Different lenders extort different amounts of money from borrowers. Borrowers do not know how much money each lender will extort from them unless they have transacted with a specific lender at least once. By "transacted," we specifically mean that the borrower must go through the entire loan cycle with the lender, as the extortion

[8]The first author spent more than half a decade as a volunteer helping to rehabilitate ex-offenders in Singapore. Many of these individuals were borrowers of the unlicensed money lending market.

[9]See Appendix A for more information how the unlicensed money lending market data was collected. See Leong *et al.* (2016) and Li *et al.* (2017) for examples of the academic work that the first author had done on the underground economy involving the collection of sensitive information that has not led to any problems for the individuals who had provided the information.

process only occurs after the loan has been disbursed.[10]

The following is an illustration of how extortion takes place: If the loan shark decides to lend the borrower money after conducting some simple due diligence, he then proceeds to provide the borrower with only two pieces of information and nothing else. First, he informs the borrower about the length of the repayment period. Second, he informs the borrower how much he should pay during each payment period. No other questions will be entertained by the lender.[11] After the loan has been disbursed, should the borrower fail to make any of the payments on time, the lender would unilaterally impose unreasonable monetary penalties. The borrower could try to negotiate and refuse to pay up. However, the loan shark would then send runners to make physical and verbal threats. Even if the borrower makes all the payments dutifully and on time, the loan shark may still cheat the borrower by claiming that certain payments were not made. Despite any evidence from the borrower proving otherwise, the loan shark would still insist that the borrower is at fault and needs to pay a penalty. If the borrower tries to argue, the loan shark will simply impose more violence and threats. In any given scenario, despite the borrower's initial refusal to accede to the loan shark's request, the borrower usually ends up giving in to the loan shark's unreasonable demands. Thus, we will define the amount of money extorted by the lender from the borrower as the monies the lender gets by forcing the borrower to pay up, without the borrower's consent, by using violence and threats.

Our informants tells us that the rampant unlicensed money lending activities in Singapore have caught the attention of the authorities.[12]. From 2010 to 2015, the authorities carried out a series of enforcement actions on this market which includes but is not limited to the amendment of the "Money Lending Act", installation of CCTVs in public housing areas, community watch groups to patrol neighborhoods etc. For convenience, henceforth, we will denote all these polices as the enforcement effort against the unlicensed money lending market.[13] However, there is no quantitative evidence of whether these compounded policies made an impact on the unlicensed lending market. Taking advantage of the unique dataset we have collected, we aim to explore the answer to this question and also at the same time document the workings of the unlicensed money lending market.

Our data records detailed personal information and behavioral patterns of 1089 borrowers. These borrowers have a total of 10615 loan transactions with their respective lenders over a period of several years. Government policies were implemented

[10] We will provide a detailed discussion about extortion in section 5.3.3.

[11] According to the borrowers we surveyed, the lenders they have met would not answer any other questions pertaining to any aspect of the loan. In a good scenario, if a borrower asked about the penalties for late payments, a polite lender might say that they could negotiate if it came to that. In a bad scenario, the lender would ignore the borrower and ask him to leave now that the deal has been concluded. Ex-lenders we interviewed confirmed that providing no other information pertaining to the loan was standard market practice.

[12] We provide some statistics about the crimes related to this industry in Table 1.

[13] According to the authorities, not all these policies were implemented to decrease unlicensed money lending activities. However, Singaporean police reports have indicated a steady decrease in crimes related to unlicensed money lending activities over the same period. See section 2.2 for a more detailed discussion.

gradually and affected the unlicensed money lending market, but we do not aim to conduct an impact analysis of these enforcement policies, because they were not implemented in the form of a natural experiment. Our purpose is to investigate how market operations and extortion levels have changed during the early stages of implementation of these enforcement policies and after these enforcement policies were completely implemented using the time series data we have. Our dataset comprises two subsets: the first subset contains the loan transactions that occurred during 2011 to 2013, and the second subset captures the majority of the interviewees from the first subset who had recurring loan transactions during 2014 to 2015. In short, we tracked the same group of individuals yearly from 2011 to 2015. Henceforth, we will denote the first data subset as the "pre-enforcement" dataset because this was the time when the policies were in the initial phases of implementation. The second data subset is denoted as the "post-enforcement" dataset because that was when the policies were fully implemented.

Empirically, we find that extortion and harassment activities are commonplace in the unlicensed money lending market, even in the pre-enforcement dataset. Recall that in our setting, at the time of loan disbursement, the only mutually agreed to condition by both parties was that the borrower was supposed to repay both the principal and the interest rate over a pre specified period of time. The borrower did not agree to any other terms. Thus, the amount extorted by a lender from a borrower is the total amount of money a borrower pays to a lender that is above the the initial total repayment(principal plus interest) that the borrower and lender mutually agreed to when the loan was disbursed, and that is obtained by the lender through acts of harassment. Hence, we define the extortion as follows. When the lender has conducted some verbal or physical act of harassment against the borrower to force him to comply, then the amount of money the lender extorts from the borrower is the $[totalpaid - (Principal + Interest)]/Principal$. Harassment refers to the actions the lender undertakes to force the borrower to agree to the unilateral monetary demands of the lender. These acts include phone calls, splashing paint on the walls of the borrower's home, verbally or physically threatening the borrowers' family members or neighbors. In the pre-enforcement dataset, the 6-week interest rate was approximately 20% in the unlicensed money lending market.[14] Different unlicensed lenders extort different amounts of money from borrowers. The distribution of the extortion exhibits two modes in the pre-enforcement data. The left mode distribution depicts a wide dispersion over the range of 0-2 and there is a small but considerable proportion of unlicensed moneylenders who are associated with a high extortion of 2-3. An extortion of 1 means that a borrower was asked to pay S$1000 extra on top of the principal and interest that both borrower and lender previously agreed on when he borrowed S$1000 from the lender. The average amount of time a borrower takes to pay up everything a lender demands is approximately 3.5 months.

We also observe several interesting changes to the terms of the verbal contact that the lender issues to the borrower pre and post enforcement. First, the principal loan amount dropped from an average of S$1670 to S$440, demonstrating that

[14] The maximum effective annual interest rate a licensed money lender can charge is 20%. This cap applies to unsecured loans contracted with individuals earning less than S$30000 per year between 1 June 2012 and 20 September 2015.

the lender is less likely to loan the amount the borrowers requested. The agreed 6-week interest rate increased from an average of 20% to 35%. Both OLS and fixed effects regression show that extortion increased by 0.60 to 0.90 after controlling for both borrowers' characteristics, terms of the loan and repayment outcomes. We also find that the level of harassment acts the loan sharks employed has remained unchanged. We measure the level of harassment using two indicators: the most forceful or harmful harassment act the lender imposed on borrowers (from the borrower's perspective) and the number of different types (frequency) of the harassment activities the loan sharks employed. Based on the ordered-Logit regression results, the drop in harassment was statistically insignificant. We also found that the borrowers' characteristics do not have any predictive power on both the magnitude of the loan shark's extortion and harassment levels.[15]

We develop a simple theoretical search model that is able to provide a plausible explanation as to how homogeneous lenders extort money from the homogeneous borrowers in the unlicensed money lending market. There are many borrowers and lenders in this market. In the model, borrowers search for loan sharks to obtain a loan. After disbursing the loan to a borrower, each lender unilaterally decides how much money to extort from the borrower and the borrower will only know the level of extortion imposed by the loan shark after at least one successful transaction is made with a particular loan shark. The borrower will have no choice but to accede to extortion from the lender out of the fear of being harassed. Each borrower has a choice to stay with the current lender or search for a new one after each transaction is concluded. Due to search frictions that exist in this market, a borrower may not be able to find a new loan shark to take out a loan if he leaves his current lender to search for a new one. The borrower's main consideration is the trade off between staying matched to a loan shark whose level of extortion is already known, and searching for other lenders in the market. For the loan shark, the main consideration is the trade off between the profit he can earn from each transaction (for example, whether or not to extort money from the customer) and the number of transactions he is able to secure with this particular customer. At equilibrium, lenders impose different levels of extortion on different customers and retain different numbers of recurring borrowers. However, they all obtain the same level of profits. Long-run relationships will be formed between some lenders and borrowers in the following sense: if a lender does not extort exorbitant amounts of money from a borrower, the borrower will continue to take out loans from the same lender over long periods of time.

If policy enforcement is enacted to make it more difficult to search for new lenders, more lenders in the market will impose a higher level of extortion on borrowers

[15] In Singapore, borrowers are not criminalized. Furthermore, they are usually introduced to a lender via a friend who has briefed them about the potential dangers of borrowing from these illegal lenders. According to informants, the changes in the loan contracts, extortion and harassment levels pre and post enforcement are largely due to a decrease in the number of lenders in the market because the informants believe that the number of borrowers have remained relatively unchanged. Lenders know that there is a higher risk of being caught and the punishments are more severe. Thus, lenders give out smaller loans and extort more money from borrowers. Borrowers know that it is more difficult to locate lenders and thus are more willing to tolerate increased levels of extortion from lenders.

compared to the pre policy enforcement period. However, lenders will be able to build long run relationships with many borrowers even if they impose this high level of extortion of borrowers. These predictions are qualitatively confirmed by the data.

Our work is related to the literature on the economics of long-run relationships. For example,McMillan and Woodruff (1999), Macchiavello and Morjaria (2015) and Macchiavello and Morjaria (2016) describe how informal relationships based on trust and reputation affect various aspects of trade such as price, quality, volume and trading credits in the absence of formal contract enforcement. Unlike these papers that take the relationships between the two trading parties as given, we study the formation of relationships in the context of a search model.

The remainder of this paper is organized as follows: Section 2 offers a brief overview of the unlicensed money lending market and the enforcement strategies carried out by the authorities in Singapore. We describe the theoretical model in Section 3, followed by an analysis of the model in Section 4. A description of the data takes place in Section 5. Section 6 presents empirical findings. We conclude the study in Section 7.

2 Singapore's Unlicensed Money Lending Market

The unlicensed money lending market in Singapore is challenging to understand; since it is illegal, there are scant official sources on the market. Thus, though we have exhausted all avenues for information, much of our intelligence relies primarily on interviews with several former unlicensed money lenders and over 1,000 borrowers we surveyed.

The unlicensed money lending market in Singapore targets individuals who are desperate for money but who cannot secure loans from the formal financial sector. During the 1990s, Ah-Long San was the most well-known loan shark and was notorious for reviving and reshaping the unlicensed money lending market. Owing to the influential role he played in this industry, "Ah-Long" is now commonly used to refer to a loan shark. Despite the arrest of Ah-Long San, the unlicensed money lending market continued to flourish. In Singapore, conservative estimates given by market insiders whom we have interviewed put the number of individuals who have borrowed from loan sharks in the years 2000-2010 to be in the hundreds of thousands. [16]

The unlicensed money lending market in Singapore comprises two main groups: unlicensed money lenders and borrowers. Each lender in this market is an independent entrepreneur.[17] The loan shark, who is typically male, will usually be located in a coffee shop and accompanied by several individuals. Any potential borrower will go to where the loan shark is located to take out a loan. There is very little competition between the suppliers in this market, as the market is large enough for

[16] According to Kok (2001),unofficial figures released by the Singapore Association of Underground Bankers (Stock Market Plunges With Jailing of Ah Long San 2001), illegal money lending makes up some 9% of the total GDP.

[17] In the conclusion section, we provided an overview about how the lenders obtained funding to start their illegal lending businesses.

everyone to make a profit.[18]

The borrowers in the unlicensed money lending market belong mostly to the middle class income group and below. They borrow money for a plethora of reasons, including gambling, business loans and medical expenses. More than 50% of Singaporeans gamble, and gamblers form the majority of people who borrow from loan sharks.[19] As one interviewee said, "I know of a friend who borrows money because his hawker business needs it. But most of the people I know borrow money because of gambling." Another interviewee claimed, "I am a student of gambling. When the urge arises, I need to borrow from loan sharks to gamble because I never have enough money." Thus, most borrowers are similar because they are not financially well off and are addicted to gambling.

The loan sharks offer a simple product: quick and convenient short-term loans disbursed in small amounts such as SGD500 and repayable over four to six weeks on average. Unlike the formal financial sector, loan sharks usually do not require collateral or financial statements that prove the borrower's ability to repay the loan, and can provide money within 30 minutes. These product features attract people who do not have collateral or strong credit history, but desperately need the money. Owing to the higher implied risk involved, illegal loans charge much higher interest rates than bank loans do. [20]

The typical process of taking out a loan occurs is as follows. The borrower approaches the loan shark for a loan. Before deciding whether to lend the borrower the sum requested, the loan shark does a basic background check which can include making copies of the borrower's identification documents and calling the telephone numbers provided to ensure they are valid.[21]If the loan shark decides to lend the borrower the money after this round of due diligence, then he proceeds to provide the borrower with only two pieces of information. First, he informs the borrower of the number of payment periods, such as six weekly payments or eight biweekly payments for example. Second, he informs the borrower how much he should pay during each payment period.

Should the borrower ask further questions about the terms and conditions of the loan, there are usually only two responses from the loan shark. The loan shark would either say that the terms can be negotiated later on, or warn the borrower not to cause any problems. In essence, the borrower receives no further information from the loan shark.

Given the fact that the majority of borrowers are not financially well off and

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[18]According to Toh (2009), a former loan shark claims that even if four out of ten clients do not pay up, loan sharks can still make money.

[19]According to Tan (2014), 58% of Singapore residents aged 18 and above reported that they have participated in at least one form of gambling activities in 2005. This figure dropped to 47% in 2011. All surveys confirmed that the most popular types of gambling activities are 4D, Toto and Singapore Sweep, and to a lesser extent, social gambling (such as mahjong or card games with friends or relatives).

[20]While the interest rates for legal personal loans range from 5%-10% per year, loan sharks usually impose flat interest rates of 20%-50% per loan (for 6 week term). Note that the interest rates charged by the loan shark stated here only apply to the interest rate that both the borrower and loan shark agreed to verbally when the loan was initially disbursed.

[21]In the past, borrowers were required to present a guarantor to the lender when taking now the loan. However after mid 2012, lenders no longer required a guarantor.

the terms of repayment for the loan are exorbitant, it is not surprising that most borrowers will not be able to make some of these installment payments on time. If this happens, the loan shark will unilaterally determine a financial penalty and instruct the borrower to pay up. Later on, should the borrower try to negotiate with the loan shark, the loan shark will cut all conversation short. She would then proceed to send runners to make physical and verbal threats to ensure that the borrower pays up.[22] These runners typically start with sending reminder notes and making calls. If necessary, they then engage in harassment activities such as splashing red paint on the doors where the borrowers live, harassing the borrowers' neighbors and his spouse and children by pressuring them to ask the borrower to repay his debts, vandalizing the vehicles of the borrowers and locking the borrowers' main gate with steel chains and a lock so that they cannot exit, setting the borrower's home on fire etc. For many of the borrowers, the mental strain of dealing with these harassment activities is more than they can bear. These borrowers will do everything within their power to repay these loan sharks as soon as possible.[23] If the borrowers are really unable to make repayments after numerous harassment attempts, loan sharks could force borrowers to commit crimes for the them by laundering money, working for loan sharks to collect repayments and harassing other debtors etc. As a former loan shark claims, "I was charged because I didn't have money to repay my loan. In the end, I had to work for them as a runner. There is no escape. They always get what they want. One way or the other." Through harassment and underhanded tactics, a loan shark will get what they want from a borrower.

In our survey, we asked borrowers whether they accept the financial penalties given that they were at fault for delaying repayments. A vast majority of respondents said no, as they believe that the lenders have already factored in potential late repayments into the high interest rates at the outset. An additional penalty is seen as an unfair double charge. The borrowers also highlighted that even if they agreed to the fine, they generally have no capability to pay it. If a borrower is late on repayments, it is usually because he is completely out of money. He can try to borrow money from everyone he knows, but even then it will not be enough. As summarized by a borrower, "It is ridiculous to agree to something that I knows I cannot do." Acording to an ex loan shark, lenders know that borrowers will strongly oppose any fines. Thus, they have no choice but to force the borrower into compliance by imposing costs so high on the borrowers that they have no other alternative. In most cases, the cost these lenders impose on borrower includes acts of verbal and physical violence.

Even if the borrower makes all the payments dutifully and on time, the loan shark may still cheat the borrower by claiming that certain payments were not made. Despite any evidence from the borrower proving otherwise, the loan shark would still insist that the borrower is at fault and needs to pay a penalty. Sometimes,

[22] The borrower can repeatedly remind the loan shark that the terms are supposedly negotiable. But the loan shark will ignore the borrower and just continue the harassment activities until the borrower caves in.

[23] According to Soh (2012), due to the extraordinarily high interest rates charged, many borrowers may have to use their wages and medical insurance or sell their homes to clear the debts owed to loan sharks.

this penalty involves repaying the entire loan from scratch. For example, suppose a borrower has to go to location X at 1900hrs every Wednesday over six weeks to pay lender Y the weekly installment of the loan. On the Wednesday when the last loan payment is due, the borrower arrives at 1905hrs due to a traffic jam. The borrower has called Y in advance informing him that he will be 5 minutes late due to traffic. When the borrower arrives to make payment, lender Y simply states that the borrower is late is repaying the loan and thus has to start repaying the entire amount, which includes the principal and interest, all over again. Effectively, whatever the borrower has paid off is forfeited. Here is another example. Suppose borrower A has taken out a loan from lender B. However, lender B has instructed borrower A to make the installment payments to debt collector C every Monday at 1700hrs for 6 weeks. On the Monday the final installment is due, debt collector C was not at the designated location. The borrower tried to contact lender B but no one picked up the phone. The next day, lender B can simply claim that A missed a repayment. A can dispute this and try to negotiate with B and even try to provide proof that he tried to contact B. However, B will simply claim that it is A's responsibility to get the money into the hands of either B or C on time. B then unilaterally declares that whatever A has paid will be forfeited and A has to start repaying the principal and interest all over again. If the borrower tries to argue, the loan shark will simply impose more violence and threats.[24] Eventually, though the borrower is not at fault, the borrower usually ends up acceding to the loan shark's unreasonable demands.

Thus, we define the amount of money extorted by a lender as the additional amount that lender is able to force the borrower into paying on top of the initial agreed upon amount. For example, if the lender and borrower agree that the borrower should pay up $1,200 on a $1,000 loan, but the borrower ends up paying $5,000, then effective amount extorted is $3,800. This way of defining amount of money extorted by a lender is apt because the borrower had no knowledge of the terms that would later be unilaterally imposed by the lender.[25] Furthermore, the borrower was forced into submitting to these terms through threats and violence, which highlights the cutthroat nature of this industry.

At this juncture, we would like to point out that only legal licensed money lenders are allowed to charge any form of interest on a loan given out. Thus, any amount that is requested by these loan sharks over and above the principal is illegal.[26]

It is rare to observe any borrower completely defaulting on a loan. Most borrowers need to borrow money in the market repeatedly to satisfy their gambling addiction. Thus, they are very familiar with how the market operates and are aware

[24]It is important to note that loan sharks generally differ in their frequency and intensity in the usage of these underhanded techniques. As an interviewee claims, "There are many different types of loan sharks. Some want to make more money quickly and thus use ruthless methods to get it. For example, even if I pay the installments on time, they will claim I missed some payments and punish me. Others are nicer and do not do these underhanded things as often."

[25]A borrower will try very hard to resist these unreasonable demands from a lender with little success.

[26]On Singapore Statutes Online, Section 3 of Singapore's Moneylender's Act clearly states that "any person, other than an excluded moneylender, who lends a sum of money in consideration of a larger sum being repaid shall be presumed, until the contrary is proved, to be a moneylender."

of the risks they face. Knowing the severe punishment that would be imposed by loan sharks, few borrowers have the courage or intention to default the loans on purpose. Thus, moral hazard on the side of borrowers is negligible in this market. According to the interviewees, the loan sharks seem to know each borrower's greatest pressure points. For example, a borrower told us that his father had a bad heart and was in a bad state of health. Furthermore, the father saw his son as someone who could do no wrong. In the words of this borrower "my father would kill himself if he found out that I have borrowed money from loan sharks." This borrower decided to talk about defaulting on the loan with a particular loan shark with some friends. A few days later, he received a call from a loan shark informing him not to harbour the thought of defaulting, otherwise the loan shark would have no choice but to notify his father about the illegal loan. He was shocked that the loan shark knew that this was the one thing that he could not risk. He said he would do anything to raise the money rather than default and be responsible for "killing" his father. This is the reason why default rates are so low. An ex-offender who was charged for unlicensed money lending says that there are only two types of people who do not pay up: those who are "suicidal" and those who are going someplace where the loan shark cannot reach them like emigrating to another country with their entire families. According to him, these two groups of people consist of a very "tiny" fraction of the entire population of borrowers.

Despite the unreasonable terms and high cost involved, demand for illegal loans in the Singaporean market remains robust. As explained earlier, most borrowers take out loans repeatedly due to a gambling addiction. Often, the loan sharks even run out of capital to lend to potential borrowers.

2.1 Enforcement Activities

In this section, we will discuss the enforcement activities carried out by the Singapore authorities against the underground lending market and the effects of these enforcement efforts. We will focus on the time period from the mid 2000s till the present as this coincides with the timing of our dataset. Prior to 2009, we only found limited information regarding police enforcement on unlicensed money lending activities in public venues. Thus, we spoke to borrowers in the unlicensed money lending market and asked them what was the level of intensity of the enforcement activities carried out by the authorities during this time period. Most of them answered that they felt it was in the low to moderate range.[27] These statements by the borrowers were corroborated by the Law Case PP v. Lee Kim Hock [2011] SGDC 201 which states that reported crime cases relating to the unlicensed money lending market and harassment offences started to climb sharply starting in 2003 and peaked in 2009. A special section on unlicensed money lending market appeared in the Singa-

[27]We would like to point out that just because these borrowers did not observe many enforcement activities does not directly imply there were little or no enforcement efforts undertaken by the authorities. We do not have access to what law enforcement actually did during this period and so we have tried our best to provide some idea of what was going on then. The first author went to two police stations in Singapore wanting to speak to someone to get information about this issue but his request was declined.

pore police annual crime brief only from 2010 onwards. Please see table 1 for some statistics regarding loan shark activities and related arrests in Singapore.

Since then, we found evidence that the Singapore authorities have been making a continuous effort to clamp down on this industry and to discourage individuals from becoming borrowers in this market.[28] We will provide a few examples of such policies. First, in 2010, several amendments were made to the "Moneylenders Act" in order to strengthen the law against illegal money lending activities. According to the Singaporean Ministry of Finance (2013) these changes included an increase to the jail term and fines that can be imposed those giving out illegal loans, and extended the penalty to individuals assisting loan sharks as well. Second, according to the Singapore Police Force (2012) the National Crime Prevention Council (NCPC) set up the X-Ah-Long Hotline (1800-9245664) in August 2010, aiming at receiving UML related information anonymously from the public to better combat this market. Third, according to Coconuts Singapore (2016), effective May 2012, as part of the Community Policing System, the Singapore Police Force installed CCTV cameras in HDB blocks (public housing buildings) and nearby multi-storey parking lots.[29]

Last, according to Kalyani (2012), the Singapore Police Force (SPF) and NCPC launched the inaugural Anti-Unlicensed Moneylending Public Education and Awareness Campaign on 30th November, 2012. According to the Singapore Police Force (2011), as part of the campaign, anti-UML television commercials, unlicensed money lending-themed exhibition, anti-unlicensed money lending webpages, and roadshows were launched. Additionally, the civilian community in Singapore has come forward to cooperate with SPF. For instance, according to the Parliament of Singapore (2013), it has been reported that at the end of 2012, there was a 29% increase in the number of Citizen-on-Patrol members at the pilot areas where CCTVs were installed. So far, according to SPF Annual Crime Report (2015), "the Citizens on Patrol (COP) scheme has steadily grown over the years to over 700 COP groups with more than 14,000 members island-wide." Last, according to the Singapore Police Force (2012), close to 3,800 Neighbourhood Watch Groups have been formed to keep watch over residential neighbourhoods.

There is some evidence showing that these enforcement activities have been effective. There are two types of evidence we will provide. We will first state the relevant summary statistics provided by the authorities about how effective these enforcement policies have been. Later, we will provide comments by local politicans that claims that enforcement efforts have worked well.

According to the Annual Crime Brief (2015), the overall number of unlicensed money lending related harassment cases dropped to a ten-year low in 2015. There were 4,229 cases reported in 2015, a 26.6% fall from 5,763 cases in 2014, and a 76.4% or decrease of 13,654 cases from the peak in 2009. The Brief attributes the success of reducing unclicensed money lending related crime to the multi-pronged approach

[28]See table 20 for details about the different enforcement policies implemented by the authorities over time.

[29]According to the Straits Times (2016), approximately 80% Singapore's resident population live in HDB blocks and by January 2014, cameras were installed in about 1,000 HDB blocks. During 2013 2015, more than 52,000 CCTVs were installed in 8,600 HDB blocks. In 2016, the number of CCTVs expanded to all 10,000 blocks and carparks are now also under the PolCam 1.0 initiative.

of tough enforcement action, community partnerships, public education and strict laws. The Brief in particular claims that the two main contributors of success were the network of Police Cameras (PolCams) in HDB blocks and the community's active participation in the neighborhood watch groups.[30]

In addition, Singaporean politicans also tout the effectiveness of some of these enforcement efforts like the CCTV installation by the authorities by providing ancedotal evidence. We will provide three examples. First, Heng (2016) writes that Ang Mo Kio GRC member of parliament (MP) Gan Thiam Poh said: "I do notice that there are improvements, especially in the cases of loan-shark harassment that used to be quite common." Seond, Heng (2016) writes that Potong Pasir MP Sitoh Yih Pin used to get loan-shark harassment cases at his Meet-the-People Sessions every month, before cameras were installed. Now the MP claims that he has not "got any for quite a while." Last, according to a report from the Parliament of Singapore (2013), Mr. Iswaran, the Second Minister for Home Affairs said that "Police have seen an improvement in the loan shark harassment situation at the blocks where Police Cameras were deployed. This is in the context of an overall decrease in cases of unlicensed money-lending and harassment. The footages received and retrieved from the Police Cameras have also helped solve nine crime cases and provided further leads for investigations in another 61 cases."

Henceforth, we refer to the entire series of government regulation, police actions together with the campaigns implemented from 2010 to date as "enforcement". In the last part of this section, we will provide an overview about how the unlicensed money lending market in Singapore operated pre and post enforcement.

Interviews conducted by the first author and his enumerators find that there were changes in loan terms before and after police enforcement. Before the increase in enforcement, a loan of SGD1,000 would typically mature in six weeks. A guarantor needs to be physically present when the borrower meets the loan shark, and has to verbally agree to repay the loan if the borrower defaults. Once the loan is disbursed, the borrower repays SGD200 each week and the first payment is due on the same day that the loan is made. For example, if the loan is made on January 1, the borrower receives SGD800 dollars on this day, and needs to repay SGD200 on January 8, 15, 22, 29 and February 5.[31] Typically, it is possible to obtain a loan amounting to thousands of dollars.

After the increase in enforcement, a loan of SGD1,000 would typically mature in four weeks. A guarantor is no longer necessary. The borrower needs to repay SGD300 on the same day that the loan is made. Starting from the second week onwards, the borrower then repays SGD150 every three or four days (effectively

[30]The Brief states that "The number of unlicensed money lending harassment cases with property damage reported at 2,152 blocks with PolCams decreased by 1,191 cases in 2015 (-73.7%) to 426 cases, from the pre-PolCams period of 1,617 cases in 2013. Compared to 2014, this represented a decrease of 925 cases (-68.5%), from 1,351 cases." The report notes that the 2,152 blocks refer to the high unlicensed money lending incidence blocks, and not randomly selected blocks. The Brief also highlights the Citizens on Patrol (COP) scheme, which has steadily grown over the years to over 700 COP groups with more than 14,000 members island-wide. These COP groups help augment Police presence by being the 'eyes and ears' for the Police during their patrols.

[31]According to Tan (2009) and Gopal (2012), this market practice is also prevalent in the unlicensed money lending markets of Hong Kong and Malaysia.

twice a week). Hence, there is a significant increase in interest rate post-enforcement. Lastly, the amount of money the loan sharks would be willing to loan to the average borrower decreased significantly to no more than SGD1,000 on average. Interviewees state that after enforcement, it became very difficult to find loan sharks, because the loan sharks were either arrested or in hiding. Even if a borrower managed to find a loan shark, the loan shark would only be willing to lend very small amounts of money. In addition, loan sharks became very cautious, and preferred asking existing customers to refer their friends. For each referral, loan sharks would pay the person a referral fee of SGD50. Lastly, borrowers complained that loan sharks began treating borrowers extremely unreasonably by trying to extort large sums of money from borrowers, including those who have been borrowing from them consistently. According to borrowers, the extortion levels imposed by loan sharks on borrowers post enforcement was unprecedented compared to pre enforcement. For example, the loan sharks began making more frequent claims that they did not receive payments from the borrowers, thus forcing borrowers to restart the entire repayment schedule.

3 Model

In the unlicensed money lending market, there is a continuum of both borrowers with measure μ and a continuum of unlicensed money lenders or loans sharks with measure ρ. We will assume that measures μ and ρ are exogenously determined. Time is discrete and goes to infinity. All agents have the same discount factor β.

In each period, each borrower (henceforth referred to with the pronoun "he") urgently needs a sum of money that he currently does not possess, in order to satisfy his cravings or needs.[32]If the borrower finds a lender to borrow from, the immediate benefit generated from getting the loan is u for the borrower and i for the lender, where we assume $u > 0$ and for simplicity we normalize i to 0.[33]If the borrower fails to locate a lender to borrow money from, we normalize the borrower's payoff in the current period to 0.[34]

If the lender approves the loan, the lender endogenously decides the level of extortion $c \in [0, +\infty)$ she will impose on the borrower.[35] Note that the borrower does not know about the extortion levels c that will be imposed on him prior to

[32]When the first author asked a borrower what is a need so urgent that would justify borrowing money from an unlicensed money lender, a borrower said, "I am a student of gambling. This addiction needs a lot of money. I make peanuts from my day job so of course I need to borrow money in order to do what I love. When I say I need the money, I desperately need it. I cannot wait." Another borrower explained his motivations by sharing, "If we had alternatives, we would not be borrowing from loan sharks. We are desperate."

[33]If we allow i $\geq$ 0, the qualitative results remains unchanged. The proof is available upon request.

[34]In the later section, we show that empirically, more than 90% of all borrowers paid off their debts to the loan sharks they borrowed from. Thus, we did not model unnecessary option of allowing the borrower to default on the loan taken out from loan sharks.

[35]Recall from section 2.1, we define extortion as the additional amount that lenders are able to force the borrower into paying on top of the mutually agreed repayment amount through physical and verbal threats as well as violence.

borrowing from each lender.

Without loss of generality, we will assume that when the lender chooses to extort c from the borrower, this generates a benefit of $m(c)$ for the lender. But, the lender must incur a cost of $k(c)$. This cost incurred by the lender is the cost of carrying out harassment activities against the borrower to ensure that the borrower complies with the extortion request. If the lender wants to extort more from the borrower, she has to ensure that there are more harassment activities imposed on the borrower. [36]

Let us denote $v(c) = m(c) - k(c)$, where $v(c)$ is the net benefit for the lender from imposing a level of extortion c on the borrower to extort money from him. We assume that $v(0) = 0$, $v(c)$ has a maximum point at a unique cost level $\bar{c} > 0$, and strictly increases within the range $[0, \bar{c}]$.[37] The main simplification we make regarding the lenders' behavior is that once a lender decides to impose a level of extortion c on a particular borrower for his first loan transaction, she commits to this harssment level in all future transactions with the same borrower. Alternatively, we may interpret this extortion level c imposed by a lender on the borrower as a reflection of the lender's type, though the type should be seen as endogenously determined.

We will introduce search frictions into the unlicensed money lending market by using the following thought process. At the beginning of any period, each borrower is in one of two possible states of being either unmatched or matched. A borrower is unmatched when he is not borrowing money from any lender. A borrower is matched when he is borrowing money from an existing lender whom he borrowed from in a previous period. If the borrower is unmatched, he is able to find a lender in the market to borrow from with probability $\gamma \in (0, 1)$. If the borrower is matched, his lender from the previous period is available this current period and is able to provide a loan to the borrower with probability $\theta \in (0, 1)$. There is probability $1-\theta$ that this lender is not available in the current period, in which case he also has to go onto the market and search for another lender.[38]At the end of the period, the match between

[36] Here is a testimonial from a borrower: "I have always paid the required installment on the day and time specified by the lender to his runner. One day after I made an installment payment, I received a call from the lender stating that he had not received the required installment payment. I told him that that could not be the case as I had already passed the money to his runner. He said he did not care and told me that because I missed a payment, all previous payments were forfeited and I needed to start repaying the loan from scratch. He told me if I tried to default, he would ensure that I would face severe consequences. For example, the lender constantly reminded me that I have a debt to repay. The lender hired people to put notes in my mailbox to remind me to repay my loans, hired people to write large posts in public locations near where I live, and a whole host of other harassment activities that would continue until the new loan or installment is paid up. The harassment efforts directed against me were too much for me to take. I had no choice but to pay up. "

[37]For example, by introducing standard assumptions that $m(c)$ is concave, $k(c)$ is strictly convex, both are strictly increasing with $m(0) = 0$, $k(0) = 0$, $m'(0) = +\infty$ and $k'(0) = 0$, then $v(c)$ exhibits the features in the assumptions we have made.

[38] Lenders are trying to avoid being arrested by the authorities because what they are doing is an illegal act under Singaporean law. Lenders sometimes go under the radar and temporarily suspend their business if they feel that the authorities are onto them. During this temporary suspension, borrowers would be temporarily unable to reach the lenders, and the measure of available lenders in that period would be less than ρ . However, the qualitative results remain unchanged when this is taken into account. Thus, we will not be modeling this unnecessary complication. Instead, to

a borrower and a lender is exogenously terminated with probability$1-\delta \in (0,1)$.[39] If the match is not exogenously terminated, the borrower must decide whether to stay matched with the current lender. If the borrower decides to stay matched, then the current lender will remain as the lender even in the next period. If the borrower chooses not to stay matched, for tractability reasons, we will assume that he then returns to the lender he was matched with in the previous period.

Let us illustrate this with an example. Suppose the borrower was matched with lender A in period t. In period $t+1$, lender A is unavailable. Thus, the borrower searches for a new lender and finds lender B to borrow from. At the end of period $t+1$, if the borrower decides not to continue borrowing from lender B, he will then go back to lender A. If he was unmatched in the current period t, he goes back to the market to search for a new lender. This entire process is repeated in the exact same way during the next period. [40]

4 Analysis

First and foremost, we consider the borrower's decision-making problem. Let $F(c)$ denote any distribution of extortion levels imposed by lenders on borrowers in the market. It follows directly from our assumptions that lenders will not impose an extortion level strictly higher than $\bar{c}$. Therefore, the support of the distribution F, $supp(F)$, is a subset of $[0, \bar{c}]$. Since a borrower can be either unmatched or matched, we let V_0 and $V(c)$ be the borrower's respective value functions in these states, where c in $V(c)$ indicates the extortion level imposed by the borrower's regular lender. We define a borrower's regular lender as follows:

Definition 1. *Regular Lender - At the end of any period, if a borrower decides to stay matched with a lender, then from the next period onwards, we will define this lender as the regular lender whom the borrower takes loans from.*

For simplicity, we assume that $u > \bar{c}$. This implies that even when all lenders in the market impose an extortion level of $\bar{c}$, borrowers still prefer to borrow from a lender rather than not borrow at all. This assumption is consistent with interview responses from borrowers who state that they are desperate enough to borrow money at any cost in order to satisfy their needs or cravings.

The value functions are given by

capture this situation, we use the probabilities γ to represent how readily available lenders are to new customers that are unmatched and θ to represent the availability of a lender to a matched borrower.

[39]Lenders may get arrested or choose to exit the market permanently because of the fear of being arrested. For example, an interviewee told an intermediary that "Loan sharks come and go all the time. Sometimes, you talk to person A at location X and the next week at the same location, person B tells you he is here to "replace" A because A has been arrested." These events automatically cause the exogenous termination of matches between these lenders and their respective borrowers. Thus, for simplicity, we assume that at the end of each period, a fraction $1-\delta$ of lenders in the market is exogenously replaced by new entrants.

[40]Note that our search model is a variant of Burdett and Mortensen (1998). Galenianos *et al.* (2012) also uses a similar variant of the former to capture some basic stylized facts they observed in the illegal drug markets in America.

$$V_0 = \gamma(u + \int_0^{\bar{c}} (-c + \delta\beta max\{V_0, V(c)\})dF(c) + (1-\delta)\beta V_0) + (1-\gamma)\beta V_0$$

and

$$V(c) = \theta(u - c + \delta\beta V(c)) + (1-\theta)[\gamma(u + \int_0^{\bar{c}} (-c' + \delta\beta max\{V(c), V(c')\})dF(c')) + (1-\gamma)\delta\beta V(c)] + (1-\delta)$$

Consider the value function V_0. When the borrower is unmatched with any lender, the probability of him finding a lender is γ. Since the lender is randomly matched in this case, the extortion level c imposed by this lender is drawn from the distribution F. At the end of the period, if the match is not exogenously terminated, the borrower has to decide whether to stay matched with this lender or become unmatched again, which is captured by the discounted value $\delta\beta max\{V_0, V(c)\}$; if the match is exogenously terminated, the borrower's discounted utility is $(1-\delta)\beta V_0$. With probability $1-\gamma$ the borrower fails to find a lender,he enjoys no utility in the current period and has discounted utility of βV_0.

Alternatively, consider the value function $V(c)$ so the borrower is matched with a lender who imposes an extortion level of c. With probability θ the lender is available in the current period and given that the borrower can get a loan without searching for another lender in the market, it is optimal for the borrower to stay matched with this lender at the end of the period. With probability $1-\theta$ the lender from the previous period is unavailable in the current period, the borrower has no choice but to return to the market in order to search for another lender. In the case that he finds a new lender, he enjoys the benefit of taking out the loan but also incurs a cost in the form of extortion from the lender. At the same time, he has to decide whether or not to stay matched with the new lender or to return to the regular lender in future periods. In the case that he cannot find a lender, he enjoys no utility in the current period and his only remaining option is to return to the previous lender. At the end of the period, the match is exogenously terminated with probability $1-\delta$.

As V_0 is constant while $V(c)$ strictly decreases in its argument, there is a unique cutoff value, which is positive and denoted as c^*, satisfying $V(c^*) = V_0$. Explicitly, c^* is given by

$$c^* = (1-\gamma)u + \gamma \int_0^{\bar{c}} cdF(c) - \theta\gamma\delta\beta \int_0^{c^*} \frac{F(c)}{1-\delta\beta + (1-\theta)\gamma\delta\beta F(c)} dc$$

Thus, a borrower's matching strategy can be fully described as follows: if the borrower is in an unmatched state, he will stay matched with a new lender if and only if this lender imposes an extortion level lower than the cutoff value c^*; if the borrower is in the matched state, he will stay matched with a new lender if and only if this lender imposes a lower extortion level than his previous lender.

A lender's problem is to maximize her steady state level of profits by optimally choosing to impose an extortion level c. For tractability, we will assume that the lender cannot discriminate against borrowers by imposing different levels of extortion on different borrowers. The lender's steady state profits are given by

$$\pi(c) = v(c)t(c)$$

, where $t(c)$ is the steady state measure of borrowers who trade with the lender in each period.

A market equilibrium is characterized by a cutoff value c^* and a distribution F such that: (1) given distribution F, borrowers follow the matching strategy with the cutoff value c^*; (2) given the borrowers' matching strategy, lenders' profits satisfy $\pi(c) = \bar{\pi}$ for $c \in supp(F)$ and $\pi(c) \leq \bar{\pi}$ for $c \notin supp(F)$.

Let $p(c)$ denote the mass of probability that a lender imposes the extortion level c. Let $\underline{c}^*$ and $\bar{c}^*$ be cutoff values of extortion levels c, where $0 < \underline{c}^* < \bar{c}^* < \bar{c}$ and the characterization of these values are shown in appendix. The main result of the model is as follows.

Proposition 2. *Equilibrium of this model exists and is unique. Specifically, there are cutoff values, $\underline{\gamma}$ and $\bar{\gamma}$, such that:*

(a) Equilibrium Regime I occurs when $\gamma > \bar{\gamma}$, where c^* are F determined by

$$\underline{c}^* \leq c^* < \bar{c}^* \quad and \quad \left\{ \begin{array}{c} supp(F) = [\underline{c}, c^*] \cup \{\bar{c}\} \\ p(\bar{c}) = 1 - F(c^*) > 0 \\ F(c) = \frac{1}{(1-\theta)\gamma\delta}(\sqrt{\frac{\theta\delta(1-\delta)v(c)}{v(\bar{c})-v(c)}} - 1 + \delta) \quad if \quad c \in [\underline{c}, c^*] \end{array} \right\}$$

(b) Equilibrium Regime II occurs when $\underline{\gamma} < \gamma \leq \bar{\gamma}$, where c^* are F are determined by

$$\bar{c}^* \leq c^* < \bar{c} \quad and \quad \left\{ \begin{array}{c} supp(F) = [\underline{c}, c^*] \\ p(\bar{c}) = 0 \\ F(c) = \frac{1}{(1-\theta)\gamma\delta}(\sqrt{\frac{\theta\delta(1-\delta)v(c)}{(1+\frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta]^2})v(c^*)-v(c)}} - 1 + \delta) \quad if \quad c \in [\underline{c}, c^*] \end{array} \right\}$$

(c) Equilibrium Regime III occurs when $\gamma \leq \underline{\gamma}$, where c^* are F are determined by

$$c^* = \bar{c} \quad and \quad \left\{ \begin{array}{c} supp(F) = [\underline{c}, \bar{c}] \\ p(\bar{c}) = 0 \\ F(c) = \frac{1}{(1-\theta)\gamma\delta}(\sqrt{\frac{\theta\delta(1-\delta)v(c)}{(1+\frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta]^2})v(\bar{c})-v(c)}} - 1 + \delta) \quad if \quad c \in [\underline{c}, \bar{c}] \end{array} \right\}$$

Finally, $\underline{c}$ is determined by

$$v(\underline{c}) = \left\{ \begin{array}{cc} \frac{(1-\delta)v(\bar{c})}{1-\delta+\delta\theta} & in\ case\ (a) \\ \frac{(1-\delta)}{1-\delta+\delta\theta}(1 + \frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta]^2})v(c^*) & in\ case\ (b)\ and\ (c) \end{array} \right\}$$

At market equilibrium, lenders impose different extortion levels on borrowers. Intuitively, if all lenders impose the same extortion levels at equilibrium, then a lender who deviates to impose a slightly lower extortion level would be able to retain all his current customers as well as acquire any other customers she meets for the first time when the borrower searches the market. Thus, the lender attracts a discrete increase in the measure of customers from this deviation. Meanwhile, the loss of profit per customer from the deviation is negligible. As a result, it is profitable for the lender to impose this lower extortion level. Thus, at equilibrium, the market must exhibit a dispersion of extortion levels.

Interestingly, when search friction is relatively insignificant such that $\gamma > \bar{\gamma}$ borrowers can easily find new lenders in the market, a positive proportion of lenders impose the highest extortion level $\bar{c}$ and no borrowers elect to stay matched with them. The intuition is that if the borrowers can find new lenders in the market without much friction, they would be less motivated to maintain long-term borrowing relationships with the lenders unless the lenders impose low levels of extortion; that is, $c \leq c^*$ with $c^* < \bar{c}^*$. Since lenders anticipate the borrowers' reluctance to stay matched and also know that the probability of meeting new borrowers is high, some lenders find that it is optimal to extort money from the borrowers. We define extortion as follows:

Definition 3. *Extortion - We say that a lender extorts money from a borrower if the lender chooses to maximize her profits in the current period and disregards the effect this action has on her future payoffs. In other words, the lender does not care about staying matched with this borrower.*[41]

When it is more difficult for the borrowers to find lenders in the market, say $\gamma \leq \bar{\gamma}$, borrowers are more inclined to stay matched with the lenders they have met. Consequently, even if lenders impose a higher level of extortion on borrowers (represented by a higher cutoff value of extortion level, $c^* \in [\bar{c}^*, \bar{c}]$), borrowers will still be willing to stay matched with these lenders. Compared to extorting the borrowers for money by imposing the highest extortion level $\bar{c}$, imposing a lower extortion level $c \leq c^*$ would not cause a significant loss in profit per customer for the lender, but would significantly increase the number of customers overall. As a result, in this case, the market exhibits no extortion. In the appendix we show that c^* decreases in γ. In addition, if $\gamma \leq \underline{\gamma}$, then $c^* = \bar{c}$, so even by setting the highest extortion level $\bar{c}$,lenders will still be able to stay matched with borrowers.

At equilibrium, the lenders' behavior exhibits a variety of patterns. Some lenders impose lower extortion levels and become regular lenders to a large group of borrowers, while some lenders impose higher extortion levels and become regular lenders to a smaller group of borrowers. Last, some lenders will choose to impose very high extortion levels such that they will not be regular lenders to any borrowers.

We will do some comparative statistics on Equilibrium Regime I. Notice that in Equilibrium Regime I, $\underline{c}$ is independent of γ, while $F(c)$ and c^* are both strictly decreasing in γ. As a result, if police enforcement causes a decrease in γ, a larger fraction of lenders choose to stay matched with borrowers, and the average extortion levels imposed by lenders becomes lower. Intuitively, if it is very difficult to find new lenders in the market such that borrowers are less likely to find new lenders in the market, borrowers would be more willing to stay matched with lenders even though the extortion levels imposed by lenders are not favorable. Consequently,

[41] As explained in earlier sections, in reality, the amount the lender extorts from the borrower is equivalent to the additional amount of money she forces the borrower to pay via harassment activities and that is on top of the amount both parties had agreed to when the loan was initially disbursed. To be clear, at the time of agreement, the borrower would have no idea what the level of extortion imposed would be be, as extortion only takes place after the loan has been disbursed.

more lenders choose to make profits by staying matched with borrowers instead of from one-off or short-term extortion. However, conditional on the borrowers being matched to lenders, the average extortion levels imposed by lenders becomes higher when γ decreases.

Corollary 4. *In Equilibrium Regime I, the cutoff value c^* strictly decreases in θ.*

In Equilibrium Regime I, when matched borrowers are able to stay with their regular lenders with a higher probability θ, the borrowers do not need to search for new lenders in the market as frequently as compared to when θ is small in value. However, this implies that their chances of meeting lenders who might impose a lower extortion level is also reduced. As a result, borrowers become more picky in choosing lenders to stay matched with; that is, c^* decreases in θ. Thus, if enforcement policies make it difficult for borrowers to stay matched with their regular lenders, lenders will decide to impose relatively higher extortion levels as borrowers will still decide to stay matched with them despite this increase in extortion levels.

5 Data Description

The extensive qualitative and quantitative information we have obtained is the result of the first author's prolonged and tireless effort over half a decade. The description of the data collection process is detailed in Appendix A. Our data is holistic, covering the personal characteristics of each borrower, detailed information of each loan transaction, as well as the personal characteristics of each lender or loan shark.

There are two parts to the information we have collected. Let us first describe the first part of our survey. Prior to this paper, very few studies had been done on profiling the borrowers in the unlicensed lending market even though these borrowers are likely to be very different from borrowers in the formal market. Since understanding the market participants is crucial to the formulation of any effective policy, this was a gap that we sought to fill. Thus, the first part of the survey was specifically designed to analyze the characteristics of the borrowers. For example, we asked questions that include but are not limited to the following: Which types of individuals are most likely to become borrowers? What drives them to borrow from loan sharks? What kind of borrowing experiences have they had in the unlicensed lending market?

Next, in the second part of the survey, we asked the borrower to answer a set of detailed questions regarding each loan transaction. These questions include the loan amount initially sought by the borrower, the principal amount granted, interest rate, date of transaction, length of repayment, reason for choosing a particular loan shark, reason for requiring the loan and collateral. We also tracked what happened after the loan was drawn down, and collected information on whether the borrower repaid the loan on time, the total amount that the borrower ended up paying, how long it took for the borrower to repay the loan, how the borrower found funds to repay the loan, the harassment imposed by the loan shark if the borrower failed to repay on time and the type of work that the borrower was asked to do in the case of default.[42]

The entire dataset consists of information from 1,090 unique borrowers and their borrowing activities between 2009 and 2016. Each borrower made between 9 to 11 unique loan transactions with various loan sharks, which adds up to a total of 11,218 loan transactions. Since borrowing transactions do not occur on a monthly basis for most of the borrowers, we managed to obtain a complete time series of borrowing incidences across time for each borrower. Note that borrowers may sometimes repeatedly borrow from one loan shark, and hence provide information on more than one transaction with one loan shark. The vast majority or 95% of overall loan transactions were made with unlicensed money lenders, while the remaining loan transactions were concluded with licensed money lenders. For the purpose of this analysis, we only take into account the 10,615 loan transactions conducted with unlicensed money lenders.

In addition, the dataset comprises two subsets that were collected during two distinct time periods. The first set of data was collected in 2011 and 2013, and contains 8,878 (83%) transactions that occurred in the unlicensed money lending market between 2009 and 2013. The second set was collected in 2015 and 2016, and consists of 1,737 (17%) transactions that occurred in the unlicensed money lending market between 2014 and 2016. There are 1090 borrowers in the first set. Out of these 1090 borrowers, 855 borrowers were interviewed again in the second set. In other words, there is an overlap of 855 borrowers between the two sets.

5.1 Borrowers

The sample of borrowers is diverse (see Table 2). The ethnic composition of the borrowers is similar to the Singaporean population composition: 75% of borrowers are Chinese, 14% are Malay and 11% are Indian. 90% or most of the borrowers are men. The majority of the borrowers do not have college degrees, but around 80% have at least completed secondary school. A significant proportion of borrowers has participated in or participates in illegal activities. Around 45% of borrowers are or used to be gang members and 20% have prior convictions. Most of the borrowers currently have or have had stable jobs. 92% of the borrowers have a full time job; two thirds of those with a full time job stayed in their current job for at least 1 year, and 60% of them were never fired by their employers.

Most of the borrowers fall in the lower end of the income distribution. According to the Ministry of Manpower (2016), the median monthly income of full time employed residents in Singapore was S$3,949 in 2015. In our sample, however, about 75% of the borrowers make less than S$3,000 a month. We observe that a negligible number of borrowers have no job and no fixed source of income in our sample, which implies that loan sharks do conduct a certain level of screening before lending to prospective customers. The borrowers in this market have distinctive traits. Most of them indicated they have bad habits that potentially led them to have financial problems (see Table 3). We find that the overwhelming majority of borrowers are habitual gamblers, with at least 60% of them identifying as regular or heavy

[42] We only asked what the lender requested the borrower to do. We do not know if the borrower carried out the lender's requests.

gamblers. Another common trait is alcoholism - nearly half of the borrowers are alcoholic. Many of them also have the habit of patronizing sex workers and frequently treating friends to free meals or entertainment related activities such as nights out at karaoke outlets. 20% of borrowers are drug abusers. The borrowers' responses to risk and time preferences reveal that they are very impatient individuals.

The borrowers in our sample have relatively long borrowing histories. Over two thirds of the borrowers have at least 3 years of borrowing experience with loan sharks at the time of the interview. Most of them borrow at least 2-5 times from loan sharks, family or friends in any given year (see Table 4). While the borrowers do take loans from family or friends, the most popular source of loans is still the illegal money lender (see Table 5). Only 11% of borrowers indicated banks and other licensed financial institutions as one of their funding sources but they all failed to obtain the loan they wanted and eventually turned to loan sharks for funds.

These underground borrowers have very low ability to repay their loans. Regardless of the source of borrowing, according to (see Table 4), one third of borrowers claim to face difficulties in making the loan repayment on time, while the remainder regularly or very frequently fail to make timely payments. At the time of each interview, which was arranged at random, over 90% of borrowers in the sample have short-term debt. These statistics are consistent with the findings from our qualitative interviews. It seems that once an individual borrows money from a loan shark, most of them inevitably become recurrent borrowers in the unlicensed market and become perpetual debtors.

5.2 Loan Transactions

The principal amount of each loan transaction ranges from as low as S$30 to as high as S$50,000 with a mean value of S$1468. Note, however, that the average loan amount the borrowers initially requested from the loan shark is S$1790, but this may not always be approved. Loan sharks conduct some level of due diligence before deciding on the approved loan amount. We found that in general, the loan shark tended to approve the requested loan amount in only half of the cases. The loan sharks lent less than the amount the borrowers asked in 46% of all transactions.

In the illegal money lending market, loans are typically quoted at 6-week tenors, with installments due on a weekly basis. The mean interest rate is 22%, with insignificant standard deviation. The loan sharks do not compete in terms of interest rate, as the profit they generate mainly comes from late payments and their method of unilaterally forcing the borrower to repay loans that have already been settled. Unsurprisingly, we observe that the borrowers never make full repayments according to the agreed interest and payment frequency within the promised time period in 86% of all loan transactions. The loan sharks do have a provision for bad debts, but this provision is small, as bad debt is uncommon. Only a handful of borrowers had no intention of repaying the loans from the outset, as they knew they would be jailed soon. In total, there are 180 loan cases involving 86 borrowers, whereby the borrower either only repaid the loan partially or did not repay the loan at all. On average, it takes 3.4 months for the borrower to settle the loan. For over 35% of all transactions, this repayment time period stretches for over 4 months.[43]. Unlike in the formal sector, the loan sharks are happy when borrowers fail to repay on time, as they make handsome profits from late fees. Often, the loan sharks even deliberately create such scenarios. For example, a borrower indicated in the survey that the loan shark insisted that the borrower had only made three installments, when in fact the borrower had made five. Despite the loan sharks' unreasonable methods, they have been effective in reinforcing repayment using harassment strategies. We find that 92% of all loans were eventually repaid in full.

The borrowers' behavioral patterns towards taking out loans from these loan sharks can be inferred from the survey questionnaire regarding their loan transactions. Borrowers borrow from loan sharks for various reasons, table 7 shows that a surprisingly low number of people borrow to fulfill actual needs. Half of the time, borrowers borrow to gamble or to purchase drugs or alcohol. The second most mentioned reason is that the borrowers needed the money to repay other debts. That could include the debt owed to another loan shark or friends, gambling debt or credit card debt. We also observe borrowers claiming that they borrow in order to support an extravagant lifestyle that is beyond their means. In 15% of all borrowing transactions, the stated borrowing reason is for entertainment purposes or footing the bill for friends for different activities. Borrowers did borrow to pay for rent, children's education, hospital fees and daily bills, but need-based borrowing transactions are rare. These borrowers who turn to loan sharks for money to pay off expenses are typically those who have spent money gambling and drinking. The borrowers' behavioral habits have a huge impact on their decision to borrow from the loan sharks. Half of the borrowing incidences take place because the borrowers gamble. In 34% and 9% of the incidences, borrowers borrow from loan sharks to purchase alcohol and drugs, respectively (see table 9).

Owing to the loan sharks' notorious reputation for extortion, borrowers do exercise caution when selecting a lender to borrow from. To minimize the uncertainty relating to the loan terms and harassment the loan sharks may impose, borrowers choose loan sharks based on referrals from trusted friends in more than half of the transactions. Borrowers also consider whether the loan shark can meet their borrowing needs. 47% of loan transactions happen not because the loan shark has a good reputation, but because the loan shark is willing to loan the initial amount requested by the borrower. Other considerations frequently mentioned by the borrower are longer repayment terms, the borrower's previous borrowing interactions with the loan shark and the loan shark's flexibility in accepting collateral. In about 10% of all borrowing incidences, borrowers pick loan sharks based on whether they believe these lenders will use physical violence to ensure timely repayments such as by harassing their families. Interestingly, the loan sharks who were perceived to be nicer did indeed end up imposing lower degrees of harassment. Although the loan sharks can use illegal means to enforce repayments, this form of enforcement does come at a cost. Therefore, loans sharks were observed to implement preventive measures to minimize the cost such enforcement. For example, loan sharks demanded that the borrowers surrender their identification documents in every loan transaction. In 70% of transactions, loan sharks also asked for the guarantor's identification

[43]Here we exclude the 448 cases where the repayment duration is not indicated in the survey.

documents. In this market, it is common for borrowers to become guarantors for each other. As a consequence, the loans issued for these borrowing transactions were S$600 higher and interest rates were 6% lower. In relatively fewer cases (16% of transactions), the loan sharks asked for the borrowers' SingPass. This request occurs mostly when the loan sharks have no confidence in the borrower's ability to service the loan. In these cases, the average loan size is S$458 which is about S$1000 less than transactions where the SingPass was not required. Moreover, the loan sharks also imposed a 34% interest rate on those loans, which is 14% higher than the cases where the SingPass was not required.

Borrowers are usually not individuals who borrow for temporary financial relief. Rather, they are a group of individuals who are saddled with debt and are financially insolvent. Borrowers finance repayments by using their income and by borrowing from other sources equally frequently, which was observed in 80% of all loans. In about 14% of transactions, borrowers service loans by selling valuable items or by using proceeds from gambling. In only a handful (5%) of transactions, borrowers were asked by the loan sharks to work for them in order to repay the loans. According to these borrowers, working for loan sharks means that the borrower can either help the loan sharks to collect debt repayments, or help them to promote loans to others.[44] Borrowers can also receive debt forgiveness by helping the loan sharks launder money through the provision of the borrowers' personal identification documents, bank account or ATM card.

5.3 Loan Sharks

5.3.1 Identification of Loan Sharks

Since the borrowers typically have limited information about the loan sharks, the characteristics we obtained about loan sharks is also limited. For each loan shark, we only have the following information: nickname, age range, and business size. Business size is measured in terms of the lending capacity of the loan shark. The bigger the loan or the more loans the loan shark is capable of issuing, the bigger the loan shark's business size.

Correctly identifying the loan sharks is crucial for our empirical exercises. For robustness, we create three distinct identifications of loan sharks. In the first classification (denoted as C1), we use the lender's information such as the lender's name, age range and size to identify the same lenders. In total, we identified 2033 loan sharks. In the second classification (denoted as C2), we use the area where the borrowers reside and the lender's name. Here, we implicitly assume that if there are two loan sharks who have the same name and transact with borrowers from the same district, then they are identical loan sharks. There are 3578 loan sharks identified. The rationale behind this assumption is that loan sharks are normally active in a fixed location near the borrower's home. It would be rare for a loan shark to be active in several lending locations, because it is too costly to compete for influence an another area where other loan sharks reside and establish a foothold there.

[44]Under the "Moneylender" Act, debtors who become runners for loan sharks are not exempted from the law, as the Act has clearly stated that being involved in illegal lending is a crime and subject to fines and imprisonment if caught.

Both C1 and C2 suffer from drawbacks. The shortcoming of C1 is that the size of the lender may grow or shrink across time and result in a scattered time series. A potential aspect that C2 may overlook is that some borrowers borrow from the lenders located where they apply for the loans, instead of from lenders located near the borrowers' residence. For example, the location could be where the borrowers gamble, and not where they reside. To compensate for the drawbacks of C1 and C2, we create a third classification (denoted as C3) identifying the loan sharks using matches based on loan shark name and borrower ID. For example, if Borrower 1 has two loan transactions with a loan shark under the same name, say "Ace", then we consider these two "Ace" lenders to be the same loan shark. This is the most restrictive classification by which we identified 5354 loan sharks.

In all three classifications, we used the loan shark's name as one of the identification criteria. This is the most plausible way because it is uncommon for the loan shark to keep changing names in this business. A fixed name makes the loan shark more easily identifiable and is essential for reputation building. A loan shark may only elect to change his/her name to gain a fresh start if he/she decides to exit from the business.

5.3.2 Loan Sharks' Harassment

Loan sharks are notorious for using tough methods to reinforce repayments and for unilaterally imposing exorbitant interest rates. In this subsection, we focus the discussion on the degree to which loan sharks use harassment to ensure debt repayment and how they use extortion to extract extra profit.

Harassment is often imposed on borrowers who fail to repay on time or to repay in full. It could also occur when the loan shark wants to impose and collect proceeds from unilateral and unreasonable interest rate hikes. The loan sharks almost never harass the borrower in person. Instead, the loan sharks hire student dropouts and debtors who were unable to repay their loans to conduct harassment activities. In our survey, we asked: "Which of the following harassment activities has the loan shark done to you when you failed to repay in full and on time?" According to the survey, there are about 20 various ways that the loan shark can harass the borrowers, ranging from verbal threats to harassing the borrower's family. Harassment activities could include physical attacks, which were more prevalent in the past than they are now. Loan sharks also decide the form and frequency of punishments taking into account the goal they need to achieve and the level of police enforcement. Phone calls and verbal threats are the most common methods used to harass the borrower into repaying the loans (see table 13). When the reminder calls fail to work, loan sharks will employ more aggressive strategies, such as visiting the borrower's home and knocking on the door (18% of the time), vandalizing the walls or splashing paint (10% of the time). In a few occasions, the loan shark also harassed the borrower's neighbour or family members to expedite repayment.

For easy comparison and analysis, we created 3 indicators to measure the loan sharks' degree of harassment. The first indicator (denoted as T1) focuses only on the most severe form of harassment that a loan shark has inflicted on the borrower. T1 is a discrete scoring measure; the higher the score, the more severe the harassment activity. T1 is coded as zero if no harassment was carried out on a borrower in relation to a particular loan. T1 ranges from 1 to 5.[45] The second indicator (denoted as T2) aims to capture the frequency of the punishment without considering the actual magnitude of the punishment. If a borrower indicates in the survey that the loan shark had harassed him via the phone and splashed paint on his house to obtain loan repayments, then T2 is recorded as 2. Notice that the loan shark may have called the borrower many times to threaten the borrower, but this measure does not record the frequency of the activity. Hence, a borrower who receives a reminder call is counted as 1 regardless of the number of the phone calls he actually received. The third indicator (denoted as T3) captures both the magnitude and frequency of the punishment. We assign a score to each punishment the borrower experienced, and the scoring is defined in the same way as in T1. Then, we add up the scores of all the harassment activities the borrower faced in order to create T3.

As expected, the use of harassment is highly correlated with the borrower's repayment behavior. The loan sharks did not use any form of harassment in 20% of the total loan contracts (see table 13). Among the loan transactions where the borrowers paid the loan shark in full on time, 92% of them did not suffer from any form of harassment from the loan sharks and the remainder did not receive harassment beyond reminder calls or verbal threats. Moreover, while there are a few loan sharks who do conduct an unusually high degree of harassment activities (i.e only 2.5% of loans have toughness rating above 4), most of the loan sharks use more or less similar strategies to ensure debt repayment. These three measures (T1,T2 and T3), particularly the first two, are positively correlated. That means loan sharks elevate harassment levels gradually and the longer the borrowers delay repayment, the higher the frequency and severity of harassment they receive. Depending on the loan terms and other market factors, a loan shark may exert different levels of harassment activities on different borrowers, or even on the same borrower but in relation to different loan transactions. We examine this phenomenon in detail in the later section of the paper.

5.3.3 Loan Sharks' Extortion

Let us provide some information about the regulations on interest rates in the legal money lending market. This will allow the reader to have an understanding about the difference in interest rates charge in both the leader and illegal markets respectively. The annual lending interest rate to private individuals in the formal financial institutions was only 5.4% during 2006-2014 in Singapore (Trading Economics, n.d.).

[45] T1 is coded as 1 if punishment remains only at the verbal level: Verbal threats, phone harassment/reminder calls, demand letter/send note/threatening message; T1 is coded as 2 when borrowers experience the following: Shout at you in your neighborhood, Stalk and shout at you, Harass you in your workplace, Visiting home, Visiting workplace; T1 is coded as 3 when the most severe punishment inflicts direct harm on the borrowers such as Splashing Paint/Kerosene in your building, Knocking doors/gate, Throwing flowerpots, Vandalizing wall, Graffiti, Chain door/gate/block key holes/put superglue in key holes, Scratch & splash paint on car; T1 is coded as 4 if the punishment is further elevated to individuals apart from the borrower: Harass family members/friends, Harass neighbors. T5 is coded as 5 if punishment involves physical attack/torture, Use or threaten to use the identification documents that had previously been surrendered to the loan sharks for criminal activities.

That is equivalent to a 6-week interest rate of 0.68%. According to the registry of moneylenders published by the Ministry of Law, the maximum effective annual interest rate an authorized money lender can charge a borrower with an annual income less than S$30,000 is 13% for secured loans and 20% for unsecured loans contracted between 1 June 2012 and 30 September 2015. This cap does not apply to individuals with an annual income above S$30,000. Effective 1 October 2015, the Ministry of Law readjusted this interest rate cap requirement. Irrespective of an individual's annual income and whether the loan is secured or not, the maximum interest rate the moneylenders can charge is 4% per month, which is equivalent to 6% per 6 weeks. In the event a borrower fails to repay the loan on time, the maximum late interest rate a moneylender can charge is 4% per month for each month the loan is due. Similar restrictions are further imposed on the moneylenders on the fees they can charge after 1 October 2015. In stark contrast, the agreed 6-week interest rate in the unlicensed money lending money was high at 20% even before enforcement policies by the authorities were enacted.

We create a variable called *Extortion* that aims to capture the exorbitant rent extracted by lenders in the unlicensed money lending market. Since the beginning of the paper, we have defined the amount of money extorted by the lender from the borrower as the amount of money the lender obtains by forcing the borrower to pay, without the borrower's consent, using violence and threats in our setting. Recall that the only condition of the loan that both the lender and borrower mutually agreed to was the interest rate that should be paid on the principal of the loan amount. The agreed interest rate is almost identical across all loan contracts and is universal knowledge to the participants of this market. Lenders provide no information on late fees charges and possible penalties that they may impose on borrowers at the outset. Thus, a natural measure of extortion is the amount of money extracted by using harassment to force the borrower into compliance with the lender's unreasonable demand, $(totalamounttheborrowerpaid - principalofloan(1+interestrate))/pricipalofloan$. Henceforth, throughout the remainder of the paper, we will refer to this number simply as extortion.

Notice that it follows from our definition of extortion that if the lender did not harass the borrower, then the measure extortion is 0. Among the 2023 loan transactions where no acts of harassments were used by lenders on the borrowers, the mean extortion is very close to zero at 0.10 over the average repayment period of 6 weeks. One third of the transactions from this no harassment sample showed that borrowers willingly agreed to pay the lender an extra 0.2 to 0.8 times of the total mutually agreed repayment amount. For example, the borrower might have been late in paying an installment and the lender asked for a late penalty which the borrower agreed to pay without the lending having to resort to any verbal or physical threats. Twenty percent of the no harassment sample involve transactions where the total amount repaid is less than loan amount. This type of transactions typically involve borrowers who borrow with no intention to pay (i.e they are migrating overseas or going to jail). The remaining half of this no harassment sample contains largely transactions where the borrower successfully renegotiated the loan terms with the lender (without the lender having to resort to harassment to force the borrower into agreeing to these terms) which results in small discounts on the repayment.

Collectively, these pieces of evidence implies that transactions where lenders did not harass borrowers typically involve transactions that did not result in lenders violating the mutual agreement when the loan was disbursed. In other words, the lenders did not extort money from the borrowers.

For the loan transactions where some level of harassment was imposed on the borrowers by the lenders, the mean extortion is 1.04. If we exclude borrowers who borrow with no intention to repay, the mean extortion is 1.52 In 10% of the loans, the extortion is higher than 2.75. In fact, lenders target borrowers and use harassment to extort money from borrowers who are late in repaying their installments. Both harassment level and magnitude of extortion are very close to zero for 1539 loan transactions where borrowers paid in full on time. However, harassment level and magnitude of extortion are both much higher for the group of borrowers who did not repay in full on time when compared to the group who repaid in full on time.

This definition of extortion covers all the different scenarios that may arise in the unlicensed money lending market as described by the borrowers we interviewed. First, if the borrower makes timely payments according to the agreed interest rate and dates, this formula captures the extortion the lender unilaterally imposes on the borrowers through acts of harassment. Second, suppose a borrower is unable to make repayments on time. Thereafter, the lender will unilaterally force a penalty onto the borrower without his consent via acts of harassment. Using harassment, the lender may also unilaterally change the terms of the loan before or even after the borrowers settle the payments demanded by the loan shark.

6 Empirical Analysis

As documented in the subsection 2.1, government agencies have taken a series of serious actions to clamp down on illegal money lending activities especially since 2012. This set of policies, though not all particularly targeted at the unlicensed money lending industry, had pronounced impact on this market. According to table 1, loan shark harassment cases reported dropped by 72% between 2010 and 2015, but the number of people arrested for involvement in loan sharking activities increased by an absolute figure of 500 annually from 2009 to 2011 and plateaued at around 2000 until year 2013. The drop in the harassment cases is closely followed by a decrease in the unlicensed money lending market related cases, since the majority of the reported unlicensed money lending market cases are harassment related. The significant decrease in unlicensed money lending market related cases suggests that the illegal lending market has become less active with potentially fewer participants from both the supply and demand side. It is important to note that according to Singaporean law, the borrowers are not subject to legal penalties when they borrow from the loan sharks, as long as they do not work for the loan sharks as runners.

Most of the people who borrow from the loan sharks are those who are in financial trouble and who do not possess alternative funding sources.[46] With the increased

[46] The authorities have run many informative campaigns warning the public of the dangers of borrowing from unlicensed moneylenders. However, almost all of the one thousand borrowers we interviewed with the exception of three told us that these activities will not do much to change

legal penalties and greater risk of arrest, it is likely that the unlicensed money lending market market shrunk mainly due to loan sharks withdrawing from the market, rather than from a decreased number of borrowers.

The series of enforcement activities against the unlicensed money lending market was initiated in 2010 and was gradually implemented over the years. Combined, the various measures created spillover effects that targeted unlicensed money lending activities. Based on police reports, we observed a fall in the number of harassment activities and an increase in the number of lenders arrested. However, these reports do not show how enforcement activities affected the market equilibrium. For example, how did the relational contracts between a borrower and lender change? Taking advantage of our unique dataset, we aim to shed light on the connection between policy and the unlicensed money lending market market. We do note that a policy environment that using a mixture of measures inevitably poses challenges for researchers in terms of isolating a clear cause and effect connection. While we are not equipped to overcome this challenge, we will focus on documenting how the unlicensed money lending market operations have been altered (if at all) using the data we have collected during and after major enforcement activities have been implemented. For easy reference, we loosely define the sample collected during the enforcement years as pre-enforcement (namely, before enforcement was implemented) and the second sample as post-enforcement. We will use these terms hereafter in the paper.

In terms of analysis, we assess the enforcement impact from three dimensions: First, we study how the terms (loan size, interest rate) in the loan contracts have evolved in response to tighter police monitoring and stricter laws. Second, we investigate how extortion in this market has changed post-enforcement. In other words, how did the loan sharks react to enforcement in terms of adjusting their extortion strategies, such as the imposition of late fee or unilateral term renewal, as well as harassment levels?

6.1 Market Operation Pre and Post Enforcement

The basic contract terms changed significantly post-enforcement (see table 15). To hedge against default risk in a post-enforcement environment, the loan sharks became more cautious in setting the loan terms. They were more reluctant to loan the amount the borrowers were seeking. In pre-enforcement, the loan sharks agreed to lend the loan amount equal or more than the amount the borrowers were seeking in 62% of transactions. But, in post-enforcement, this figure was drastically reduced to only 16% of transactions. The average loan size also shrank from S$1670 in the pre-enforcement period to S$439 in the post-enforcement period. Moreover, this post-enforcement change in behavioral pattern is consistent across the loan sharks. Figure 1 shows that loan sharks were more flexible in issuing different loan amounts in the pre-enforcement sample. But, post-enforcement, the loan sharks became less flexible and would only issue loan sizes within a small fixed range. Furthermore, the loan sharks imposed a much higher interest rate during the post-enforcement

their behavior as they already knew of this information from their friends prior to borrowing.

period. The agreed 6-week interest rate was raised to 35%, which was 20% higher than during the pre-enforcement period.

A snapshot of the outcome summary statistics reveals more interesting phenomena. Borrowers appeared to be less fearful of loan shark's threats post-enforcement. Almost 100% of borrowers did not fully settle the loan within the promised time frame post-enforcement, while only 83% of them failed to do so in the pre-enforcement sample. This could be potentially due to the protective measures the authorities have implemented for the borrowers (such as a hotline to report loan sharks and tighter monitoring of loan sharks). Post enforcement, we observe a 7% increase in the borrowers who cleared the entire loan repayment. In 6.42% of the loans from the pre-enforcement sample, the total amount the borrowers paid was less or equal to the principal loan amount, and this percentage was reduced to 0.17% in the post-enforcement sample. Based on ground research, we believe this is the consequence of the loan sharks' strategic response to tighter enforcement. Market insiders revealed that the loan sharks became more selective in choosing the types of borrowers to deal with, bearing in mind the higher operational risks in the post-enforcement environment. They made loans to fewer customers and chose only the borrowers whom they were familiar with. Familiarity was measured in terms of the information they possessed about the borrower, including the borrower's family, personal history and employment background. Loan sharks also utilize the borrowers' greatest weaknesses (i.e made threats to inform the borrower's wife about the loans, knowing well that the wife may divorce the borrower if she found out about the illegal debt) to more effectively enforce loan repayment. We would also like to highlight that all the above mentioned differences pre and post-enforcement are statistically significant using a simple t-test.

6.2 Extortion Pre and Post Enforcement

Our key objective is to uncover how police enforcement has shaped the level of extortion imposed in the unlicensed money lending market. We begin by presenting the distribution of extortion in the pre and post enforcement sample.[47] The left plot in figure 3 reveals a few interesting facts in the pre-enforcement period: The distribution of the extortion has two modes. The extortion on the left mode distribution has wide dispersion covering the range of 0-2 with peak at 0.5. There is a small but considerable proportion of loan sharks who exhibit extreme severity in their imposition of extortion. The right mode distribution is associated with these contracts with extortion ranges from 2 to 3. Post-enforcement, the extortion in the unlicensed money lending market became even more exaggerated. Not only did the agreed interest rate jump to 35%, the distribution of the extortion further shifted to the right with a higher mean of 2.4 and with an even greater dispersion (a standard deviation of 1.5).

Notice that there are 573 (5.4%) loan transactions where the borrowers underpay, which means the total amount the borrower paid is less or equal to the principal loan amount. According to the qualitative remarks the borrowers provided for these transactions, we learn that underpaying occurs either because the borrowers bor-

[47] Refer to the previous section for our definition of extortion.

rowed with no intention to pay (i.e. They were going to jail or planning to run away by migrating overseas) or because they were able to obtain police protection. Since the key interest of the paper is to study how the lender extorts money from the borrower, we also exclude these transactions in all regression analysis.

Table 16 outlines the determinants of extortion and how the extortion has changed in response to overall police enforcement efforts. In column (1), we only used pre and post enforcement indicators as the explanatory variables. These variables explain 32% of the variation of extortion in our sample. This regression captures the raw difference of extortion in the pre and post enforcement period, which amounts to a magnitude of 1.7. In column (2), we purge the effects of basic loan terms and the borrower's repayment performance by controlling them and found the difference in extortion between the pre and post enforcement periods reduces to a current value of one unit. In column (3), we further control for the harassment levels exerted by the loan sharks. The harassment levels exerted by the loan sharks does not change the coefficient on the indicator variable *enforcement*, but suggests that the relationship between extortion and harassment is complementary, rather than substitutive. This result is somewhat expected because harassment activities facilitate a higher likelihood of more timely repayments. In column (4), we examine how the borrower's individual characteristics influence the extortion the loan sharks inflicted on the borrowers and find that the borrowers' personal characteristics have almost no impact on extortion levels. However, we do find that extortion is also well explained by reasons driving borrowers to seek illegal loans. The types of collateral used for the loans and the types of financial sources the borrowers used to repay the loans have weaker correlations with the extortion. In column (6), we eliminate the high level of extortion due to the borrowers' repayment behavior and personal characteristics by controlling for all the mentioned variables and found that the loan shark's extortion level increased by a magnitude of 0.6 post-enforcement. In fact, the source of repayment, funding source, collateral and reason for borrowing have very limited influence on how much the lender will choose to extort. Hence, the coefficient of 0.89 from column (3) is a better estimate of change in extortion pre and post enforcement.

In table 17, we further explore this question using the loan shark's fixed effects. Notice that we have used three different ways to identify the loan sharks and column (1)-(3) correspond to the classification of C1, C2 and C3, respectively. The estimation results are largely consistent under these various classifications. Unsurprisingly, we observe that the loan sharks elevated extortion levels post-enforcement by a magnitude of 0.60. The tighter enforcement environment greatly increases the loan sharks' cost of operating in the illegal money lending market. The loan sharks respond to enforcement by issuing only small loans and demanding a higher return. This translates into the lender extorting more money from the borrower.

Nevertheless, we did not observe a significant drop in harassment levels in the post-enforcement period. Table 18 displays the output of ordered logit regression using the toughness measures we have created. The dependent variable in the first three columns is the loan shark's toughness level. "Toughness" is defined by the most severe harassment activity imposed by the loan shark, and the dependent variable in the last three columns is the loan shark's toughness level as defined by the total number of all the different types of harassment activities inflicted on the borrower. Both columns (1) and (4) show basic loan terms (loan size and agreed interest rate) and the borrower's individual characteristics; collectively, these have very minimal impact on the loan sharks' harassment levels. The more crucial factors are whether the borrowers fully settled the loan on time and the repayment duration. Those loans which were not paid in full on time were associated with harsher and more frequent harassment. The longer the borrowers take to repay the loan, the more harassment they suffer. Borrowers tended to select loan sharks who were perceived to be more benevolent and often used referrals from trusted friends to identify such loan sharks. The loan sharks who were perceived to be more benevolent were did not turn out to be less forceful in enforcing repayment. In fact, loan sharks who were flexible with collateral ended up inflicting more harassment to reinforce the loan. However, loan sharks tend to be more strict with borrowers who borrow to fund bad habits (i.e gambling). These borrowers are more likely to be repeat borrowers in the market and perpetual debtors. Since they have lower ability to service loans, the loan sharks have to employer tougher reinforcement to ensure repayment. Overall, we find that enforcement by the authorities did not have significant impact on the loan sharks' harassment activities. In terms of both severity and frequency of harassment measures, we observed no significant change on harassment decrease between the pre and post enforcement periods.

Last not the least, it is worth exploring how the terms of the loan contract and outcomes changed in response to enforcement, even though we do not intend to discuss the effectiveness of the each enforcement policy. In table 19, we present how the loan size, agreed interest rate, extortion and harassment levels varied over the years as enforcement is gradually implemented. The general trend is as follows: the granted loan size stayed constant during 2009-2010 and increased by 6% in years 2011-2013. A drop of 4% occurred in 2014. We only have 151 loan transactions in 2016, hence the estimation may be less accurate and reliable. An inverse trend is observed for the agreed 6-week interest rate. Broadly speaking, the agreed interest rate does not change much from 2009 to 2013. However, a jump occurred in 2014 and further spiked in 2015 until relative stabilization in 2016. In terms of the loan shark's extortion level, this metric also exhibits a gradual increasing trend with a spike in 2014 and further jump in 2015 until it plateaued in 2016. As far as the loan shark's harassment level is concerned, harassment began to decrease beginning in 2011 and continued to decrease on a yearly basis thereafter until 2014. This applies to both harassment by severity and frequency. The interesting observation is the level of harassment by severity in 2015 and 2016 does no differ much when compared to that of 2009. Whereas for harassment frequency, the degree is still lower than 2009 level by 0.20 during 2014-2016, but this difference is not significant.

We conclude that the set of enforcement efforts impacted the unlicensed money lending market both in terms of the loan contract and the amounts extorted by the loan sharks. The harassment activities of loan sharks decreased and then increased again. According to market insiders, during the time of enforcement, the lenders reduced both the frequency and severity of harassment methods used because they were worried that they may become easy targets of the authorities' enforcement policies if they continued with what they were doing as they believed that the authorities formulate policies specifically targeted at what they knew existing lenders would do. Eventually, most lenders found a way to avoid detection by the authorities and lowered the risk of carrying our acts of harassments against the borrowers. According to our informants, many lenders relocated overseas and made use of technology (via the phone for example) to screen borrowers and give out loans. Lenders also hired proxies (who will never met these lenders in person) to carry out high levels of harassments against borrowers on their behalf. Since these lenders had already reduced the risk of being arrested due to harassment activities, they had no issue with continuing business as usual.

7 Conclusion

Our paper analyzes a unique dataset that tracks the behavior of borrowers in the Singaporean unlicensed money lending market over several years. In this market, borrowers search for loan sharks to borrow from, and loan sharks decide how much money to extort from borrowers. At equilibrium, we observe dispersion over the degree of extortion by different loan sharks. We find that increasing enforcement efforts by the authorities, on average, have the following effects: The initial interest rate attached to the loan agreed upon by both the lender and the borrowers increases, the loan amount that the lender is willing to give out to the borrower decreases, the amount of money the lender extorts from the borrower increases and harassment activities by the lenders directed against the borrower fall in terms of both severity and frequency.

Studying the unlicensed money lending market in Singapore has far-reaching implications from a policy-making perspective. Even more pertinently, these findings could very likely be applicable to other countries as well. For example, our study on how and why Singaporean enforcement efforts have been effective in clamping down on this illegal market could lead to similar efforts being replicated in other countries as well. Owing to a lack of data about unlicensed money lending markets in other Asian countries, we rely on testimonials from former unlicensed moneylenders that the first author's intermediaries know well. According to these informants, several large syndicates with headquarters in China are operating in the unlicensed money lending market not just in Singapore but also in many other Asian countries. If the intelligence given is indeed true, then our findings can be generalizable to other countries. In essence, these organizations are like illegal venture capital firms. They begin by recruiting individuals with high potential of being successful lenders or "entrepreneurs." The syndicates then provide the startup capital and necessary advice - for example, how to determine appropriate penalties for loan defaulters, how to advertise their business - needed for individuals to become an independent unlicensed moneylenders in return for monetary compensation. These transnational syndicates do not take equity in each lender's business in return for the support provided. Each lender is completely responsible for his or her own business and makes all decisions independent from the syndicate. Rather, the syndicates make a profit by expecting the lenders to repay the capital with interest. These transnational syndicates fund a large number of lenders in the Singapore market.

For example, the similarities between the Chinese and Singaporean unlicensed money lending markets are numerous. Zhang (2016) states that similar to Singapore, China has an unlicensed money lending market that is sustained by many independent unlicensed money lenders. Furthermore, according to ChinTell Limited (2016), Chinese loan sharks often attract borrowers who are unable to obtain loans from the formal lending sector. Additionally, based on findings by Zhang and Li (2016), China's unlicensed money lenders also do not state all the terms and conditions of the loans upfront. Both countries' syndicates adopt similar strategies to harass debtors and to pressure debtors into repaying their loans. Mediacorp News Group (2016) has highlighted that in China, examples of these harassment tactics include phone calls, text messages and demanding payment at the borrowers' homes. Zhang (2016) also confirmed that as documented in the Singaporean market, Chinese borrowers may also be forced to become runners for loan sharks in the event of default.

Singapore and Malaysia's unlicensed money lending markets also share many similarities. According to The Star Online (2015) media reports, similar to Singapore's unlicensed lending markets, there are many independent unlicensed money lenders operating in the Malaysia's unlicensed lending market. Abdullah and Hanafi of the Consumer Association of Penang reported that Malaysia's loan sharks also attract habitual gamblers who are unable to obtain credit from legal sources to fund their gambling habits. As negotiations are usually conducted via phone or social media platforms, illegal loan agreements in Malaysia usually involve verbal contracts instead of formal written contracts. In the case of default, Malaysian loan sharks will also take similar actions to harass the debtors into repaying their loans. Benjamin (2016) cited an example which involved locking the gates of the borrowers' house and leaving threatening notes. Furthermore, Ho (2009) observed that as in Singapore, borrowers may be forced to settle loan payments by becoming runners for the unlicensed money lenders.

Vietnam's UML market also shares similar features with Singapore's UML market. TN News (2010) reported that similar to Singapore's UML market, Vietnam's UML market is supported by independent unlicensed money lenders. According to Tuoi Tre News (2016), at the initial stage of loan negotiations, both countries' unlicensed money lenders will request for borrower's particulars and conduct background checks before making loan decisions. Similar to Singapore's unlicensed money lenders, TN News (2010) states that there are some unlicensed moneylenders in Vietnam who would allow borrowers to clear their debts instead of trapping them in a cycle of unaffordable loans (TN News, 2010). In the case of default, both Vietnam and Singapore's unlicensed money lenders will employ violence and threats to force borrowers into repaying their debts. For instance, Thanh Nien News (2014) states that unlicensed money lenders in Vietnam may engage in actions such as hurling jars of wet paint over the wall or furniture, harassing borrowers' neighbors and locking the borrowers' door from the outside using a strong lock.

It is clear that many countries have unlicensed money lending markets that are similar to Singapore's.[48]Moving forward, there is still much to be done in order to

[48]We have hired 8 students in total located in Singapore and China. They spent 10 hours a week for nine months scouring libraries, searching online written and video documents to search

fully capitalize on the insights we have gleaned from the unlicensed money lending market. How does legalizing online gambling affect the borrowers in unlicensed money lending markets? Recently, the Singapore government is considering legalizing certain forms of online gambling such as betting on horse races, lottery tickets etc. Since a large fraction of borrowers are gamblers, would the introduction of this new technology increase the borrowers' demand for loans from the unlicensed money lending markets? According to informants, an increasing number of unlicensed moneylenders are using online peer-to-peer lending platforms to acquire new customers. Unlike in the past where borrowers needed referrals from people who are already in the unlicensed money lending market to gain access to lenders, the advent of technology means that potential borrowers can now easily search for a lender online. How does the emergence of these new online markets affect the unlicensed money lending market? Lastly, what are the strategies used by lenders in this market to avoid detection and enforcement by the authorities? When a lender is arrested, does he share with other lenders what he had done to attract the attention of the authorities and why he failed to avoid detection? To our knowledge, there is no quantitative data available yet to answer these questions.

for evidence about how the unlicensed money lending market functions in these countries. As there is a great deal of incorrect information, we do subject any information submitted by the students to a verification process that includes cross-checking with market insiders. What we have included in the paper is the most credible information the students have found. In addition to academic research, the first author himself has also asked his enumerators to check if they can arrange for meetings with loan shark borrowers in other countries. None of his enumerators were unable to convince borrowers in other countries to agree to share information because the enumerators did not have a strong enough relationship with foreign borrowers. The foreign borrowers also had not had contact with the first author, and were unfamiliar with academic studies. As a last resort, the first author listed the information these students have found about other countries and asking his enumerators to check with their overseas informants in those respective countries to see if they were valid. It was only after validation did we include this information in the writeup. While the evidence here may seem lacking, it the best we can do given our lack of contacts in the unlicensed money lending markets in other countries.

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Table 1: **Statistics of loan shark activities in Singapore (2009-2014)**

Year	Overall crime cases	Overall UML and harassment cases reported	Loan shark harassment cases reported	Persons involved in loan sharking activities of any nature arrested
2009	33186	18649	-	965
2010	33152	16834	15525	1508
2011	31508	13342	11776	1981
2012	31015	10,840	8989	1915
2013	29984	8,306	7052	1953
2014	-	-	5763	>1203
2015	-	-	4229	-

[1] Source 1: Annual Crime Brief (2010-2015) by Singapore Police Force. Notice that each report indicates the statistics for the year of report and the previous year. When inconsistency is observed across the report, we take the statistics from the latest report.
[2] Source 2: Parliament of Singapore, "Illegal Money Lending Cases", April 14 2014
[3] Source 3: Tan Shin Bin (2014)
[4] The 4th column refers to harassment specific cases, which are part of the overall cases in the 3rd column.

Table 2: **Borrower's Characteristics**

	Col %
Highest Education Level	
Illiterate	2.8
Elementary School	20.1
Junior School	36.6
Polytechnic	14.7
Junior College	2.5
Diploma or Certificate	19.4
Bachelor	3.9
Ethnicity	
Chinese	74.5
Malay	14.1
Indian	11.1
Other	0.3
A Gang Member or Not	
Yes	14.1
No	56.6
Used to be	29.3
Years in Gang	
Less than 1 year	4.1
1 to 3 years	10.7
3 to 5 years	20.7
5 years or more	64.6
Have been Convicted	
Yes	20.9
No	79.1
Working Status	
Jobless	1.4
Part time	7.0
Full time	91.6
Duration Within a Job	
Less than 3 months	0.1
3 months to 6 months	3.0
6 months to 1 year	17.4
1 year to 3 years	48.3
More than 3 years	31.1
How often Fired	
Never	59.8
Occasionally	35.6
Regularly	4.6
Monthly Income	
Less than S$500	0.1
S$500-S$1000	2.5
S$1000-S$2000	35.4
S$2000-S$3000	36.8
S$3000-S$5000	19.8
More than S$5000	5.2
No fixed income	0.2
Percentage of Monthly Income Saving or Investing for Future Use	
Less than 10%	63.8
10%-20%	29.8
20%-30%	5.8
More than 30%	0.6
Percentage of Monthly Income Spent on Lavish Affairs	
Less than 10%	0.5
10%-20%	3.2
20%-40%	39.2
More than 40%	57.2
Total	100.0

Table 3: **Borrower's Behavior Characteristics**

	Col %
Frequency of Drinking	
Never	3.6
Occasionally	16.6
Regularly	40.4
Very Frequently	39.3
Frequency of Drug Abusing	
Never	69.6
Occasionally	12.4
Regularly	10.3
Very Frequently	7.7
Frequency of Gambling	
Never	9.7
Occasionally	27.6
Regularly	28.9
Very Frequently	33.8
Frequency of Purchasing Lotteries	
Never	7.0
Occasionally	26.0
Regularly	26.6
Very Frequently	40.5
Frequency of Patronizing Sex Workers	
Never	31.3
Occasionally	33.9
Regularly	30.1
Very Frequently	4.7
Frequency of Treating Friends for Meals or Entertainment	
Never	2.1
Occasionally	42.6
Regularly	46.1
Very Frequently	9.3
Total	100.0

Table 4: **Borrower's Borrowing Behaviors**

	Col %
How long since First Borrowed Money	
Less than 1 year	0.3
1 to 3 years	13.2
3 to 5 years	41.6
5 to 10 years	38.3
More than 10 years	6.6
Frequency of Borrowing Money from Loan Shark on average each year	
1 time or less	1.3
2 to 3 times	41.7
4 to 5 times	41.7
6 times or more	15.3
Frequency of Failing to Repay on time to Loan Shark	
Never	0.6
Occasionlly	29.2
Regularly	54.9
Very Frequently	15.4
Frequency of Borrowing Money from friends/colleagues/family members/relatives on	
1 time or less	2.5
2 to 3 times	31.3
4 to 5 times	38.1
6 times or more	28.2
Frequency of Failing to Repay on time to friends/colleagues/family members/related	
Never	7.2
Occasionally	33.3
Regularly	48.5
Very Frequently	11.0
Total Debt as of today	
No debt	7.3
Less than 1000S$	4.3
1000 to 3000S$	13.4
3000 to 5000S$	19.5
5000 to 10000S$	28.3
10000S$ or more	27.2
Immediate Loan due today	
Within 1 week	50.4
1 week to 1 month	37.2
1 month to 3 months	12.0
More than 3 months	0.4
Total	100.0

Table 5: Borrower's Borrowing Source

	Col%
Loan Sharks	81.47
Friends and colleagues	53.94
Family members/relatives	53.94
Banks or other institutions	10.55
Pawn shops	8.17
Company or Boss	0.55
Others	0.09

Table 6: Loan statistics

Variable	**Mean**	**Std. Dev.**	**N**
Loan Amount	1468	1576	10615
Loan Size Initially Sought	1790	1640	10404
Total Amount of Paid	2449	2061	10562
Agreed 6 weeks Interest Rate	0.22	0.07	10615
Extortion	0.86	1.2	10615
Repay Month	3.40	1.82	10100
			Col %
Finally Repay or Not			
Yes			92.2
Yes,but partially			6.8
No			0.96
Repay in-full on time or Not			
Yes			14.5
No			85.5
Total			100.0

[1] Statistics in this table excludes the loans with authorized money lender.
[2] Calculation for statistics for Repay Month excludes the 448 cases where borrowers did not provide repay period.

Table 7: Loans: Why Need to Borrow Money

	Col%
Gambling or buying lotteries	55.85
Buy alcohol or drugs	48.21
Pay loan shark/debt	34.38
Pay gambling debt	13.65
Pay credit card debt	4.78
Pay debts for friends/family	0.42
Pay other debt	1.91
Bank loan installment	1.14
Pay bills	20.81
Paying rents	3.88
Children education	2.96
Paying hospital fees	1.26
Child medical fee	0.48
Supporting family	0.46
Treating friends	14.71
Entertainment and women	13.30
Business needs	4.57
Pay Investment loss	3.20
For special celebration	2.03
Loan sharing for friends	0.81
Guarantor for friends/family	0.45
For vehicle	0.24
For marriage	0.13
Renovation of house	0.08
Lawyer fee	0.07
Others	0.61

Table 8: **Loans: Why Need to Borrow Money (Summary)**

	Col %
Borrow Money for Real Needs	
No	68.4
Yes	31.6
Borrow Money for Marriage/Vehicle/Renovation	
No	99.5
Yes	0.5
Borrow Money to Sustain Bad Habit	
No	17.1
Yes	82.9
Borrow Money to Pay various Debts	
No	49.3
Yes	50.7
Borrow Money to Help Others	
No	98.5
Yes	1.5
Total	100.0

Table 9: Loans: Under What Condition Your Borrow

	Col%
Under gambling	50.56
Under normal conditions	40.56
After drinking	34.13
Under threat	14.02
Under drug	8.86

Table 10: Loans: Collateral Loan Shark Demanded

	Col%
Personal ID	98.95
Friends ID	70.16
Singpass	16.34
Friends or Relatives contact number	3.84
Family members' ID	1.57
Others	1.56
No collateral	0.91
Proof of income	0.13

Table 11: Loans: How Borrowers Repay

	Col%
Using income	85.45
Borrow from another Loan Shark	46.82
Borrow from company/friends	27.38
Borrow from family and relatives	26.84
Gambling winnings	14.35
Get cash from Pawn shop	7.30
Sell valuable items	5.47
Can't afford to repay	2.81
Allowance or family repay	2.53
Work for loan shark	2.15
Borrower run away or in prison	1.71
Others	0.93
Profit from business or Bonus	0.84
Negotiate for discount	0.73
Loan shark caught by police	0.73
Sell illegal drugs/cigarettes	0.72
Don't wanna pay	0.67
Do more work/take more jobs	0.62
Insurance	0.53
Investment gain	0.49
Get bank loan	0.43
Withdraw FD due	0.34
Loan Shark unreasonable	0.17
BF/GF/Friend help pay	0.12
Did not pay at all	0.07
Friend pay for himself	0.04
Clear early	0.04
Working for another Loan Shark	0.00

Table 12: **Loans: How Borrowers Repay (Summary)**

	Col %
Repay using Income	
No	14.3
Yes	85.7
Repay by Investment Gain and Family Help	
No	96.6
Yes	3.4
Repay by Borrowing	
No	28.0
Yes	72.0
Repay by Sell or Pawn Valuable Items	
No	87.3
Yes	12.7
Repay by Gambling Winnings	
No	85.7
Yes	14.3
Repay by Working for Loan Shark	
No	97.1
Yes	2.9
Total	100.0

Table 15: **Contract Terms Pre and Post Enforcement**

	Enforcement	
	Pre	**Post**
Finally Repay or Not		
Yes	91.0	98.2
Yes,but partially	8.4	1.8
No	0.6	0.0
Repay in-full on time or Not		
Yes	17.2	0.7
No	82.8	99.3
Total	100.0	100.0
	Mean	
Loan	1670	439
Loan Amount Sought or More	62%	16%
Agreed 6 weeks Interest Rate	19%	35%
Extortion	0.56	2.39
Toughness (By Most Forceful)	1.19	1.70
Toughness (By Frequency)	1.53	2.24
Borrower Disappeared or Ran Away	2.1%	0.05%

Table 13: Loans: Ways Loan Shark of Enforce the Repayment

	Col%
Phone harassment/reminder call	50.47
Verbal threat	43.23
Demand letter	26.71
Nothing	19.75
Knock doors	17.73
Scribble wall	6.77
Splash Paint/Kerosene	5.80
Graffiti	3.08
Harass neighbors	2.35
Harass family and friends	2.02
Use or threat to misuse ID	1.87
Visiting workplace	1.65
Shout at you in neighborhood	1.63
Throw flowerpot	0.72
Chain gate/block key holes	0.35
Harass you in your workplace	0.33
Visiting home	0.21
Stalking you and shout at you	0.07
Scratch & splash paint on car	0.03
Legal action	0.00
Body attack/torture	0.00
Toughness of Ah-long (Most Forceful)	
0	19.8
1	56.7
2	2.3
3	18.7
4	1.9
5	0.5
Toughness of Ah-long (Frequency)	
0	20.0
1	24.3
2	30.5
3	21.4
4	3.4
5	0.2
6	0.1
7	0.0
Toughness of Ah-long (Aggregate Points)	
0	20.0
1	23.8
2	22.4
3	5.0
4	7.4
5	9.8
6	1.8
7	3.5
8	1.8
9	1.3
>=10	3.1

Table 14: Loans: Ways Working for Loan Shark

	Col%
Nothing	92.15
Help him to lender the loan	3.29
Money laundry	3.20
Help to collect/enforce the debt	1.57
Use ID to buy cell phone	0.08
Others	0.04
Pimping	0.00
Sell drugs	0.00

Table 16: **Determinants of Extortion**

	(1) Extortion	(2) Extortion	(3) Extortion	(4) Extortion	(5) Extortion	(6) Extortion
Enforcement (Base=Pre-Sample)						
Post Sample	1.755***	0.892***	0.890***			0.590***
	(0.026)	(0.030)	(0.030)			(0.047)
Log Loan Amount		-0.202***	-0.206***			-0.312***
		(0.012)	(0.012)			(0.015)
Log Interest Rate (6 weeks)		0.078*	0.059			0.042
		(0.047)	(0.047)			(0.049)
Did not Repay in Full on Time		-0.005	-0.041*			-0.013
		(0.021)	(0.022)			(0.023)
Repay Month		0.399***	0.392***			0.380***
		(0.004)	(0.005)			(0.005)
Loan Amount Asked or More		-0.056***	-0.058***			-0.029*
		(0.015)	(0.015)			(0.015)
Loan Shark's Toughness (Most Forceful Harassment)			0.042***			0.047***
			(0.008)			(0.008)
Borrow for Real Needs					0.132***	0.053***
					(0.021)	(0.015)
Borrow For House Enhancement					-0.047	0.125
					(0.130)	(0.093)
Borrow to Feed Bad Habit					0.162***	0.006
					(0.028)	(0.021)
Borrow to Pay Debt					0.283***	0.039***
					(0.020)	(0.014)
Borrow to Help Other					-0.014	-0.003
					(0.080)	(0.056)
Collateral: Friend Family's ID					-0.029	-0.060***
					(0.024)	(0.017)
Collateral: Income Proof					-0.044	0.024
					(0.255)	(0.193)
Collateral: Singpass					1.449***	0.200***
					(0.028)	(0.044)
Repay with Income					0.185***	-0.025
					(0.029)	(0.021)
Repay with Other Gain					0.773***	0.038
					(0.051)	(0.037)
Repay by Borrowing					0.581***	0.023
					(0.023)	(0.018)
Repay by Selling Valuable Items					0.385***	0.039*
					(0.028)	(0.020)
Repay with Gambling Wins					0.159***	0.033
					(0.029)	(0.021)
Repay by Working for Loan Sharks					0.616***	0.104**
					(0.060)	(0.046)
Constant	0.643***	0.990***	1.029***	1.580***	-0.306***	2.215***
	(0.011)	(0.088)	(0.088)	(0.243)	(0.046)	(0.174)
Borrower's Characteristics	No	No	No	Yes	No	Yes
Dummy for Repay Month Missing	No	Yes	Yes	No	No	Yes
N	10042	9908	9894	10026	10042	9878
R^2	0.317	0.704	0.705	0.053	0.396	0.712

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: **Determinants of Extortion (Loan Shark's Fixed Effects)**

	(1) Extortion	(2) Extortion	(3) Extortion
Enforcement (Base=Pre-Sample)			
Post Sample	0.627***	0.684***	0.601***
	(0.059)	(0.049)	(0.061)
Log Loan Amount	-0.255***	-0.237***	-0.331***
	(0.016)	(0.014)	(0.020)
Log Interest Rate (6 weeks)	0.080	0.085	0.222***
	(0.062)	(0.053)	(0.066)
Did not Repay in Full on Time	-0.034	-0.033*	-0.053***
	(0.026)	(0.020)	(0.019)
Repay Month	0.382***	0.363***	0.370***
	(0.007)	(0.006)	(0.008)
Loan Amount Asked or More	-0.041**	-0.052***	-0.033**
	(0.017)	(0.013)	(0.014)
Loan Shark's Toughness (Most Forceful Harassment)	0.049***	0.047***	0.059***
	(0.009)	(0.007)	(0.008)
Borrow for Real Needs	0.040**	0.046***	0.032**
	(0.018)	(0.014)	(0.014)
Borrow For House Enhancement	0.136	0.100	0.194**
	(0.108)	(0.088)	(0.086)
Borrow to Feed Bad Habit	-0.042*	-0.015	0.022
	(0.024)	(0.020)	(0.022)
Borrow to Pay Debt	0.036**	0.028**	0.032***
	(0.017)	(0.013)	(0.012)
Borrow to Help Other	-0.060	-0.003	0.024
	(0.070)	(0.060)	(0.062)
Collateral: Friend Family's ID	-0.045**	-0.025	-0.010
	(0.020)	(0.015)	(0.016)
Collateral: Income Proof	-0.025	-0.095	0.136
	(0.227)	(0.175)	(0.206)
Collateral: Singpass	0.219***	0.197***	0.104**
	(0.054)	(0.045)	(0.052)
Repay with Income	-0.036	0.000	0.010
	(0.025)	(0.018)	(0.019)
Repay with Other Gain	0.011	0.074**	0.057
	(0.044)	(0.036)	(0.039)
Repay by Borrowing	-0.009	-0.000	0.015
	(0.021)	(0.016)	(0.016)
Repay by Selling Valuable Items	0.018	0.065***	0.091***
	(0.023)	(0.018)	(0.018)
Repay with Gambling Wins	0.018	0.048***	0.082***
	(0.023)	(0.018)	(0.018)
Repay by Working for Loan Sharks	0.051	0.139***	0.189***
	(0.055)	(0.045)	(0.046)
Dummy for Repay Month Missing	Yes	Yes	Yes
N	9889	9889	9889
R^2 Within	0.664	0.792	0.832
R^2 Between	0.799	0.597	0.622
R^2 Overall	0.706	0.706	0.700

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: **Loan Shark's Toughness (Ordered Logit)**

	(1) Tough 1)	(2) Tough 1	(3) Tough 1	(4) Tough 2	(5) Tough2	(6) Tough2
Post Enforcement Sample	1.045***	-0.0525	-0.226	0.983***	-0.0442	-0.170
	(11.59)	(-0.51)	(-1.32)	(11.76)	(-0.50)	(-1.18)
Log Loan Amount	0.598***	0.364***	0.423***	0.394***	0.355***	0.359***
	(14.27)	(8.26)	(9.01)	(10.20)	(9.14)	(8.67)
Log Interest Rate (6 weeks)	1.052***	1.522***	1.374***	0.976***	1.364***	1.116***
	(7.46)	(8.94)	(6.78)	(7.48)	(9.33)	(6.32)
Did not Repay in Full on Time		4.206***	4.212***		3.712***	3.722***
		(39.76)	(39.58)		(35.29)	(35.27)
Repay Month		0.369***	0.391***		0.783***	0.790***
		(26.22)	(25.46)		(50.56)	(48.16)
Borrow from Shark b/c He seemed Kind			0.178*			0.233***
			(2.22)			(3.39)
Borrow from Shark b/c Referred by Friend			0.0916			0.0982*
			(1.69)			(2.06)
Borrow from Shark b/c He offers Best Rate			0.190*			-0.0200
			(1.98)			(-0.24)
Borrow from Shark b/c He Easy on Collaterals			0.0160			0.182**
			(0.21)			(2.70)
Borrow from Shark b/c He Allows Delay			-0.114			-0.0458
			(-1.45)			(-0.69)
Borrow from Shark b/c He has Good Terms			-0.215***			-0.0173
			(-3.39)			(-0.32)
Borrow for Real Needs			-0.0616			-0.0539
			(-1.17)			(-1.16)
Borrow For House Enhancement			0.246			0.0466
			(0.70)			(0.16)
Borrow to Feed Bad Habit			0.183**			0.137*
			(2.61)			(2.23)
Borrow to Pay Debt			-0.149**			0.0207
			(-2.96)			(0.47)
Borrow to Help Other			0.213			0.204
			(1.09)			(1.17)
Collateral: Friend Family's ID			-0.0245			0.240***
			(-0.33)			(3.62)
Collateral: Income Proof			1.015			0.530
			(1.60)			(0.83)
Collateral: Singpass			0.346*			0.454***
			(2.22)			(3.39)
Cut1	1.553**	7.281***	8.107***	0.140	7.648***	8.541***
	(3.06)	(20.88)	(18.45)	(0.30)	(24.30)	(21.54)
Cut2	4.309***	11.21***	12.05***	1.383**	9.880***	10.78***
	(8.45)	(31.48)	(26.98)	(2.98)	(30.74)	(26.82)
Cut3	4.450***	11.38***	12.22***	2.820***	12.14***	13.05***
	(8.73)	(31.94)	(27.36)	(6.07)	(37.40)	(32.19)
Cut4	6.863***	14.08***	14.93***	5.059***	15.36***	16.27***
	(13.37)	(38.68)	(32.93)	(10.83)	(45.92)	(39.28)
Cut5	8.415***	15.67***	16.52***	7.395***	17.53***	18.44***
	(15.97)	(39.99)	(34.71)	(15.05)	(46.59)	(41.09)
Cut6				8.495***	18.59***	19.50***
				(15.70)	(41.45)	(38.16)
Cut7				9.675***	19.60***	20.51***
				(14.17)	(32.65)	(31.64)
Borrower's Characteristics	Yes	No	No	Yes	No	No
Dummy for Repay Month Missing	No	Yes	Yes	No	Yes	Yes
Observations	10557	10119	10119	10594	10152	10152

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[1] The dependent variable in Column (1)-(3) is the toughness of the loan shark using the most forceful harassment they employed; The column (4)-(6) is the frequency of toughness of the loan shark employed.

Table 19: **The Graduate Impact of Enforcement on UML Market**

	(1) Log Loan Amount	(2) Log Interest Rate (6 weeks)	(3) Extortion	(4) Tough 1	(5) Tough 2
Enforcement (Base=2009)					
2010	-0.023	-0.002	0.001	-0.226**	-0.201**
	(0.015)	(0.005)	(0.023)	(-2.73)	(-2.79)
2011	0.044***	0.005	0.034	-0.185*	-0.302***
	(0.016)	(0.005)	(0.024)	(-2.13)	(-4.00)
2012	0.065***	0.009	0.053*	-0.568***	-0.461***
	(0.019)	(0.006)	(0.028)	(-5.40)	(-5.12)
2013	0.060***	0.010	0.042	-0.557***	-0.462***
	(0.022)	(0.007)	(0.033)	(-4.57)	(-4.38)
2014	-0.102***	0.255***	0.529***	-0.335	-0.204
	(0.039)	(0.011)	(0.059)	(-1.60)	(-1.18)
2015	-0.075*	0.397***	0.658***	-0.0115	-0.207
	(0.039)	(0.011)	(0.058)	(-0.05)	(-1.13)
2016	0.026	0.459***	0.686***	0.153	-0.218
	(0.052)	(0.015)	(0.077)	(0.59)	(-0.91)
Log Interest Rate (6 weeks)	-1.293***		0.044	1.168***	0.977***
	(0.032)		(0.052)	(5.43)	(5.22)
Loan Amount Asked or More	0.294***	-0.008**	-0.025	-0.025	-0.025
	(0.010)	(0.003)	(0.016)	(0.016)	(0.016)
Borrow for Real Needs	0.037***	-0.023***	0.050***		
	(0.011)	(0.003)	(0.016)		
Borrow For House Enhancement	0.313***	-0.067***	0.115		
	(0.066)	(0.020)	(0.100)		
Borrow to Feed Bad Habit	0.025*	0.054***	-0.001		
	(0.015)	(0.004)	(0.022)		
Borrow to Pay Debt	0.086***	0.003	0.040***		
	(0.010)	(0.003)	(0.015)		
Borrow to Help Other	0.064	0.030**	-0.009		
	(0.042)	(0.013)	(0.063)		
Collateral: Friend Family's ID	-0.003	-0.012***	-0.061***	0.0640	0.297***
	(0.012)	(0.004)	(0.018)	(0.81)	(4.27)
Collateral: Income Proof	-0.072	0.017	0.055	0.611	0.389
	(0.122)	(0.037)	(0.196)	(0.91)	(0.56)
Collateral: Singpass	-0.129***	0.073***	0.160***	0.0864	0.296
	(0.033)	(0.010)	(0.050)	(0.48)	(1.89)
Log Loan Amount		-0.116***	-0.311***	-0.311***	-0.311***
		(0.003)	(0.016)	(0.016)	(0.016)
Did not Repay Full on Time			-0.014	3.944***	3.469***
			(0.024)	(36.09)	(31.84)
Repay Month			0.381***	0.515***	0.943***
			(0.006)	(29.68)	(48.88)
Loan Shark's Toughness (Most Forceful Harassment)			0.051***		
			(0.008)		
Repay with Income			-0.032		
			(0.022)		
Repay with Other Gain			0.040		
			(0.041)		
Repay by Borrowing			0.018		
			(0.020)		
Repay by Selling Valuable Items			0.039*		
			(0.021)		
Repay with Gambling Wins			0.033		
			(0.022)		
Repay by Working for Loan Sharks			0.093*		
			(0.048)		
Constant	4.959***	-0.808***	1.785***	1.785***	1.785***
	(0.113)	(0.036)	(0.187)	(0.187)	(0.187)
Borrower's Characteristics	Yes	Yes	Yes		
Dummy for Repay Month Missing	No	No	Yes		
Why Borrow From This Loan Shark	No	No	No	Yes	Yes
Why Need to Borrow Money	No	No	No	Yes	Yes
Collateral	No	No	No	Yes	Yes
N	9298	9298	9156	9156	9156
R^2	0.682	0.784	0.707	0.707	0.707
Likelihood				-7250	-9043

[1] Borrower's personal characteristics are controlled in all regressions. Due to space limitation, the coefficients are omitted.
[2] The dependent variable in column (2) is the ln agreed interest rate for 6 weeks.
[3] The column (4) presents the toughness of the loan shark using the most forceful harassment they employed; The column (5) presents the frequency of toughness of the loan shark employed.

Table 20: **Brief Time Line of All Kinds of Government Policies**

Time	Event
2009	Bukit Panjang (HDB carparks) installed. (Sim, 2013)
Feb 11, 2010	Commencement of Moneylenders Act Amendment. (Ministry of Finance Singapore, 2013)
Aug 2010	National Crime Prevention Council's 1800-X-Ah-Long (1800-9-24-5664) Hotline. (Singapore Police Force, 2012)
Before Jun 2011	Bukit Batok, Jurong West Chua Chu Kang, Woodlands, Marsiling Bukit Panjang. (Safe Trolley, n.d.a)
2012	Through collaborations with the grassroots community, close to 3,800 Neighbourhood Watch Groups have been formed to keep watch over residential neighbourboods. (Singapore Police Force, 2012)
Before Apr 20th 2012	Jalan Bukit Merah installed. (Safe Trolley, n.d.b)
May 2012	Started install CCTV
Before Aug 2012	Jalan Kayu installed CCTV. (Asian One, 2012)
Sep-Nov 2012	Bukit Panjang, Pasir Ris, West Coast, Hong Kah and Sembawang. (Gdy2shoez, 2012)
30 Nov, 2012 (Kalyani, 2012)	SPF and the National Crime Prevention Council (NCPC) launched the inaugural Anti-Unlicensed Moneylending Public Education and Awareness Campaign
	Launched Anti-UML television commercial
	UML-themed exhibition was showcased
	More roadshows including talks conducted at Secondary Schools and localised Community Safety and Security Programmes (CSSP) will be conducted around Singapore.
	Anti-UML webpage
End of 2012	Community cooperation – 29% increase in the number of Citizens-on-Patrol members at the pilot areas. (Parliament of Singapore, 2013)
	The Citizens on Patrol (COP) scheme has steadily grown over the years to over 700 COP groups with more than 14,000 members island-wide. (Singapore Police Force, 2015)
2013	Another 6 NPCs
Mar 2013	Bedok, Toa Payoh and Sengkang. (Sim, 2013)
Nov 2014	SPF and the National Crime Prevention Council (NCPC) rolled out the 2nd nationwide Anti-Unlicensed Moneylending (AUML) Public Education and Awareness Campaign. (Singapore Police Force, 2014)
Jan 2015	Sengkang. (Admin, 2015)
30 Jan, 2015	Body-Worn Cameras (BWC) – Frontline Police officers from the Bukit Merah West NPC. (Singapore Police Force, 2014)
By Jun 2015 (Singapore Police Force, 2014)	Body-Worn Cameras (BWC): Ang Mo Kio North NPC, Ang Mo Kio Police Division Bedok South NPC, Bedok Police Division Bukit Merah East NPC, Central Police Division Jurong West NPC, Jurong Police Division Toa Payoh NPC, Tanglin Police Division
Jul 2015	Sengkang – A HDB flat in Sengkang area installed. (Admin, 2015)
Mar 2016	Over 52,000 police cameras has been installed in 8,600 blocks. (Heng, 2016)
2016	All 10,000 blocks and carparks under the PolCam 1.0 initiative, which was first rolled out in April 2012, are now equipped with the cameras. (The Straits Times, 2016; Safe Trolley, n.d.a)

Figure 1: Distribution of Loan

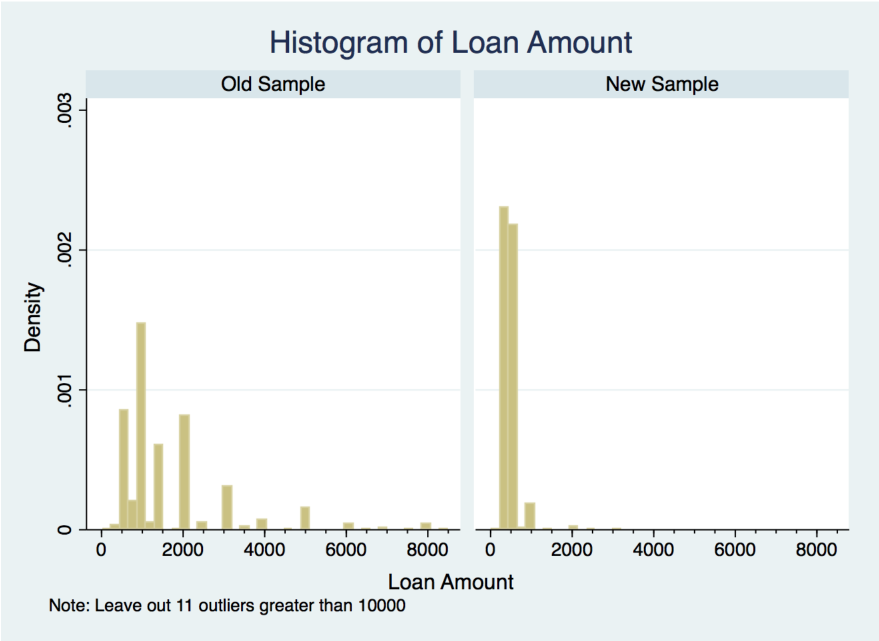


Figure 2: Distribution of Actual Rate Group

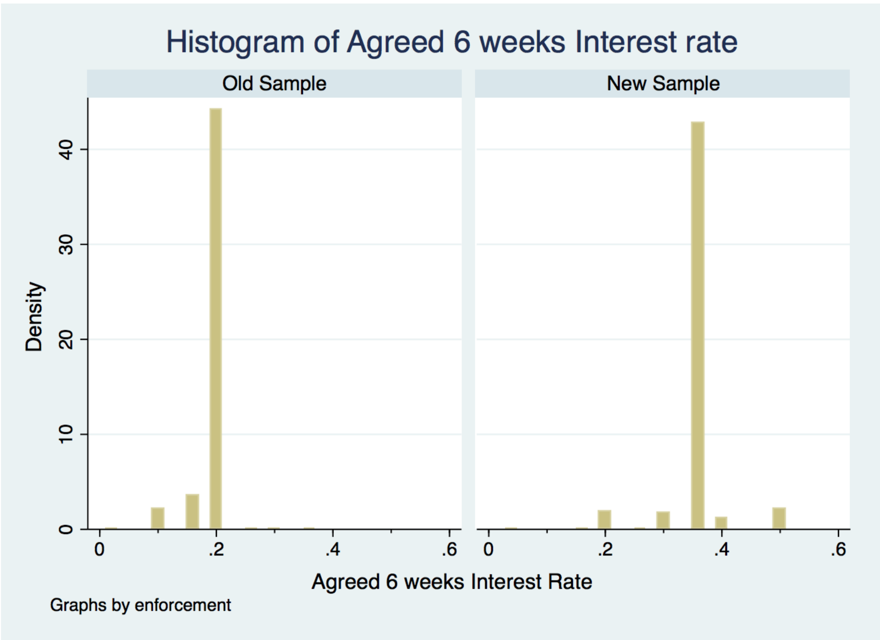


Figure 3: Distribution of Extortion

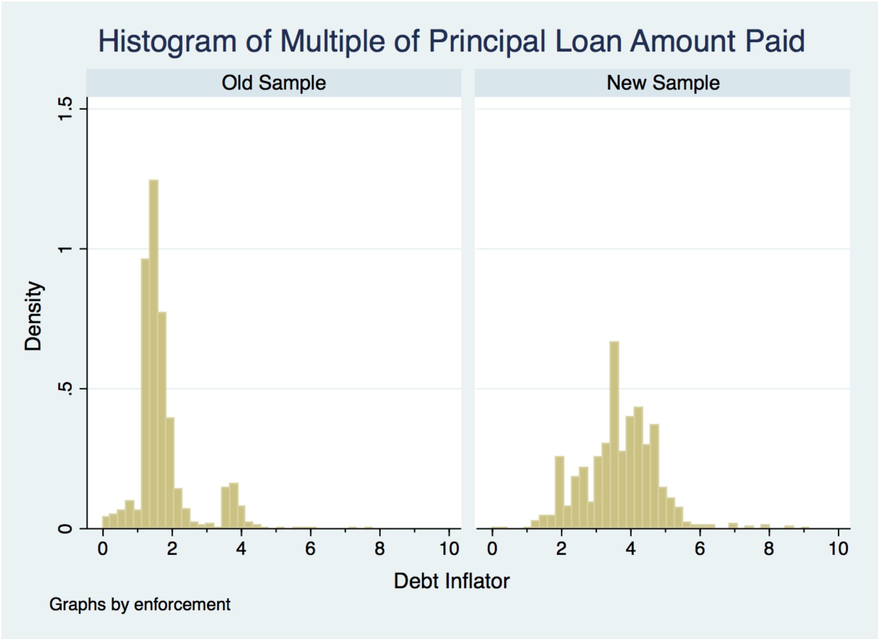


Figure 4: Distribution of Loan Shark Toughness (Most Forceful Harassment)

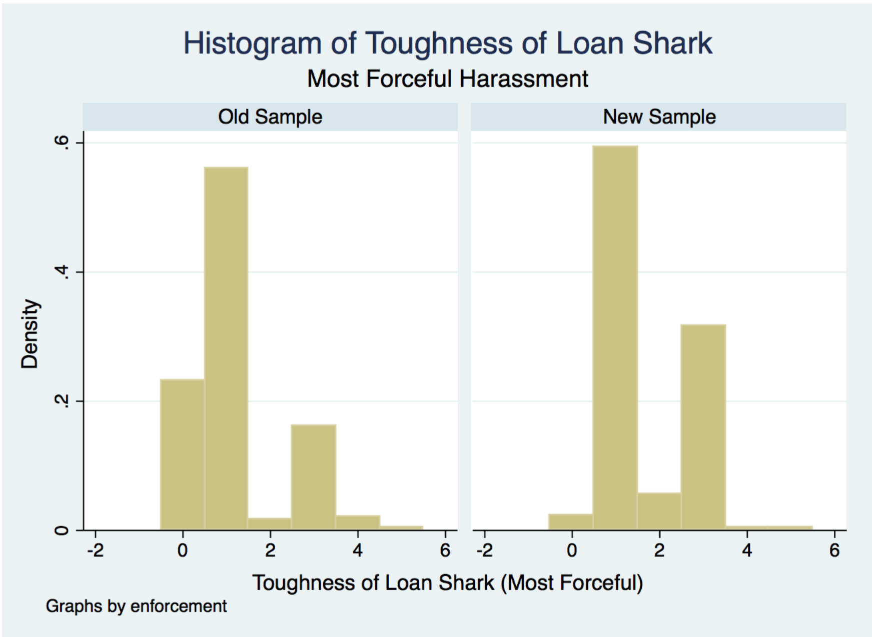


Figure 5: Distribution of Loan Shark Toughness (Frequency of Harassment)

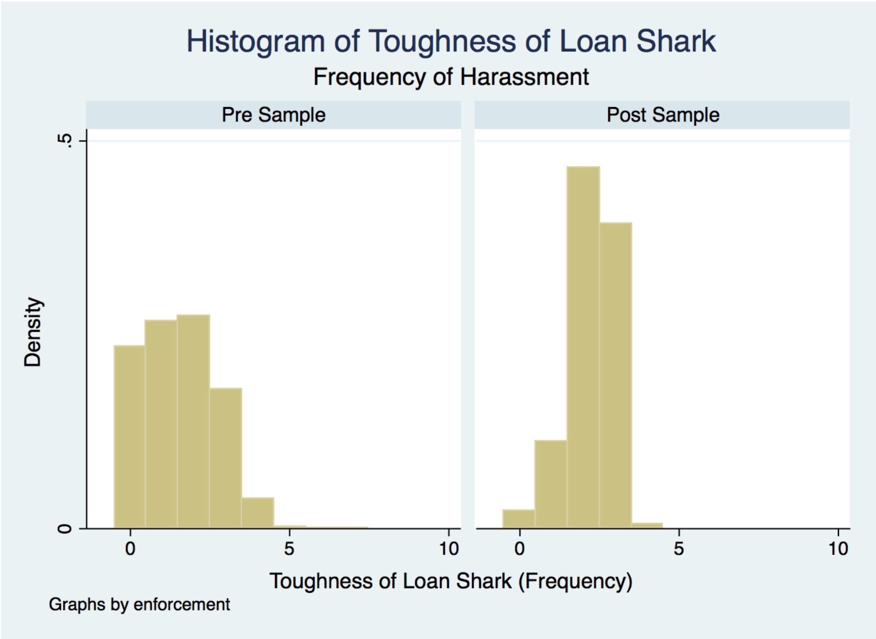
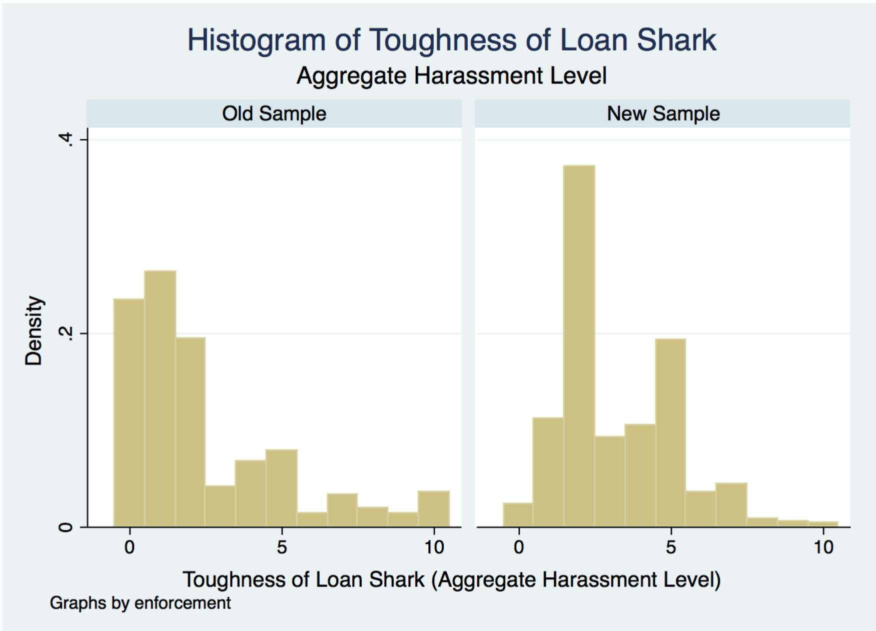


Figure 6: Distribution of Loan Shark Toughness (Aggregate Harassment Level)



Appendix A: Data Collection

Our dataset comprises two parts. The first part contains transaction data from the UML market between 2009 and 2013. This proprietary data was sourced over 2011-2013 through the social enterprise Princeton Mind, which the first author had founded during his tenure as an unpaid social worker[49]

After the first author joined academia, the first author and his team wanted to expand this dataset to study the effects of police enforcement on the unlicensed money lending market. Thus, they began work on a second dataset that traces the same group of borrowers in 2015 and covers transaction data from 2014 to 2016. This second dataset was also collected by the first author and the same group of enumerators who had helped with the first dataset.

The first author mapped the universe of borrowers in the unlicensed money lending (UML) market in all of Singapore to develop a sample frame. The mapping methodology first identified the locations where borrowers frequented and then estimated the population size of the borrowers at each of these sites. [50] In order to increase the demographic representativeness of the sample, the first author created an initial group of interviewees that was as diverse as possible. He exhausted all avenues to interview different types of borrowers that exist in this market. For example, he tried to ensure that the first group of borrowers were of different ethnicities, marital statuses, employment statuses, incomes and had different purposes when taking out a loan from unlicensed money lenders. To do this, the first author enlisted the assistance of 48 enumerators who were from backgrounds that were as diverse as possible, such as ex-offenders, small business owners, low income individuals, female and male gamblers and former unlicensed money lenders. In doing so, the first author leveraged on the diverse backgrounds of the enumerators to gain access to different networks, and in turn, different types of market participants in order to form the initial respondent pool. Next, information about each site was obtained via interviews with informants and thereafter, he implemented the snowball method. This is the only feasible method the first author could come up with for developing a sample frame for a widely-dispersed borrower population that is very difficult to reach. Each site was identified with the help of informants (i.e, borrowers, ex-lenders, gamblers, referrals by government agencies etc) and then a snowball method was implemented. In other words, as new locations were discovered, people at current locations there were asked about their knowledge of borrowers in other locations.

This method could be biased in favor of areas frequented by most borrowers and may overlook locations where there are only very few borrowers. Such locations include locations where only “part time” unlicensed money lenders located. These are individuals who perform unlicensed money lending on a smaller scale and for

[49]Princeton Mind’s mission was to identify issues plaguing disadvantaged individuals such as ex-offenders and low-income individuals, and to subsequently create programs to address these issues. Achieving this goal involved first and foremost collecting vast information relating to the disadvantaged individuals concerned. After analyzing the information collected, Princeton Mind presented their findings and recommendations to relevant government agencies.

[50]For example, these sites included locations such as gambling establishments and coffee shops where borrowers go to swap stories.

short periods of time before exiting the market. According to our informants, their customers consists mainly of one-off individuals looking to borrow very small sums of money. We are not concerned about this bias because according to all market participants that we spoke to, non-hardcore borrowers constitute a "very tiny fraction" of total borrowers.

The refusal rate for participating in our study is very low and stands at approximately 10%. There are three reasons for the low refusal rate. First, the individuals interviewed, especially the borrowers, were desperate for the remuneration of 20 to 40 Singapore dollars received for each interview. Second, prior to the commencement of any interview, all respondents were properly notified of the research study's purpose and our commitment to maintaining the confidentiality of their personal information. For example, we asked all respondents upfront if we could get their permission to release the information provided by them to other researchers and organizations wanting to study their behavior. We made it clear that if they refused, then we would not release the information. 100% of borrowers requested that the information they provided not be released to anyone. If they felt that there was significant risk of information leakage, they would not agree to participate in the interviews. Third, the most important reason for our success in collecting the data was because interviews were conducted with the recommendation or physical presence of someone whom the respondent trusted. For example, borrowers would more readily consent to interviews if these interviews were upon the recommendation of a friend whom they frequently gambled with or if there was someone whom they considered "reputable" in their circles willing to vouch for us. These individuals shared examples of the types of different types of confidential data that the first author had collected about individuals in the prostitution and drug industry and explained to the respondents that none of the disaggregate data that had been collected was disclosed to anyone in accordance with what the previous respondents had requested. These examples were useful in assuring the borrowers that we had a good track record in protecting the information that was entrusted to us.

While we believe that the respondents provided accurate information, to further ensure the veracity of the information that was shared with us, we gave extra monetary compensation of 10 Singapore dollars if the interviewees could provide physical evidence of the claims that they made in the survey. Examples of physical evidence include diaries, repayment schedules and phone messages with the loan shark. The borrowers were generally willing to share this information, with over 50 percent providing proof of their claims.[51]Asking for physical evidence helped minimize the risk of recall errors.

After some time, the respondents who participated in the first interview and who saw that nothing they revealed to us was leaked, they were not resistant to accommodate further interviews. They welcomed the interviews because they could earn, as they put it, "fast and easy money" that they needed for debt repayments. To date, with the assistance of 48 enumerators, our dataset contains information

[51]When talking to the respondent/borrower, we also requested to talk to witnesses who knew of the borrowers' loans. We asked each borrower to provide a referral to one witness if possible. This was to ensure that we found evidence to corroborate what the borrower was saying.

from over 1,000 borrowers. We tracked this same group of individuals over several years. To the best of our knowledge, after talking to our informants, there is no data available about the population of borrowers prior to our study. Thus, we are unable to compare what we have done with anyone else.

Appendix B: Proofs

Proof of Proposition 1.
Let a denote the proportion of borrowers who are unmatched in the steady state. In the steady state, in each period, the measure of borrowers who change from the unmatched state to the matched state is $\mu a\gamma\delta F(c^*)$, while the measure of borrowers who change from the matched state to the unmatched state is $\mu(1-a)(1-\delta)$. In the steady state, these two measures equal each other, which implies that

$$\mu a\gamma\delta F(c^*) = \mu(1-a)(1-\delta) \quad \Rightarrow \quad a = \frac{1-\delta}{1-\delta+\gamma\delta F(c^*)}$$

From the perspective of the lenders, their money-lending transactions in each period are undertaken with two groups of borrowers: a group of borrowers who are new to the market and a group of borrowers who are their regular customers. The total measure of borrowers who are new to the lenders is

$$\mu a\gamma + \mu(1-a)(1-\theta)\gamma = \mu\gamma\frac{1-\delta+(1-\theta)\gamma\delta F(c^*)}{1-\delta+\gamma\delta F(c^*)}$$

which consists of the unmatched borrowers as well as the matched borrowers whose regular lenders are temporarily unavailable.
Let b_N denote the measure of borrowers who are new to each lender in the period, then

$$b_N = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta)\gamma\delta F(c^*)}{1-\delta+\gamma\delta F(c^*)}$$

Notice that if a lender imposes an extortion level c on the borrowers , where $c > c^*$, then b_N is the only measure of transactions that this lender has in each period.
Let $b_R(c)$ denote the measure of transactions that a lender who imposes an extortion level c will encounter with her regular borrowers, then

$$b_R(c) = \theta R(c)$$

where $R(c)$ is the measure of borrowers who are matched with her. Clearly, if $c > c^*$, then $R(c) = 0$ since no borrower will stay matched with this lender. Therefore we only need to consider the measure $R(c)$ with $c \leq c^*$. Let $G(c)$ denote the distribution of extortion levels that borrowers face in steady state conditional on being matched with lenders. Thus, at the beginning of each period, the measure of the group of borrowers who are matched with lenders imposing extortion levels in the interval $[c, c^*]$ is $\mu(1-a)(1-G(c))$. During this period, the measure of borrowers who enter this group is $\mu a\gamma\delta(F(c^*)-F(c))$. On the other hand, during this period the measure of borrowers who exit this group is

$\mu(1-a)(1-G(c))[1-\delta+\gamma\delta(1-\theta)F(c)]$, including borrowers whose matches with their regular lenders are exogenously terminated and borrowers who choose to stay matched with new lenders who impose extortion levels in the interval $[0, c)$. In the steady state, these two measures equal each other, which implies that

$$\mu a\gamma\delta(F(c^*)-F(c)) = \mu(1-a)(1-G(c))[1-\delta+\gamma\delta(1-\theta)F(c)]$$

therefore

$$G(c) = 1 - \frac{(1-\delta)(F(c^*)-F(c))}{F(c^*)(1-\delta+(1-\theta)\gamma\delta F(c^*))}$$

for $c \in [0, c^*]$.
Conditional on being matched, the measure of borrowers who receive extortion in the interval $[c-\epsilon, c]$ is $\mu(1-a)(G(c)-G(c-\epsilon))$, on the other hand, the measure of lenders who impose extortion in this interval is $\rho(F(c)-F(c-\epsilon))$. In the steady state, $R(c)$ is determined by

$$R(c) = \lim_{\epsilon\to 0} \frac{\mu(1-a)(G(c)-G(c-\epsilon))}{\rho(F(c)-F(c-\epsilon))} = \frac{\mu(1-a)G'(c)}{\rho F'(c)}$$

After applying algebra, we obtain

$$R(c) = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta)\gamma\delta F(c^*)}{1-\delta+\gamma\delta F(c^*)}\frac{\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta F(c)]^2}$$

In conclusion, in the steady state, the measure of transactions a lender has in a period is given by

$$b(c) = \left\{ \begin{array}{cc} b_N = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta)\gamma\delta F(c^*)}{1-\delta+\gamma\delta F(c^*)} & if \quad c > c^* \\ b_N + b_R(c) = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta)\gamma\delta F(c^*)}{1-\delta+\gamma\delta F(c^*)}(1+\frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta F(c)]^2}) & if \quad c \leq c^* \end{array} \right\}$$

Now we characterize the distribution F at market equilibrium. The work is based on several claims.

Claim 5. *There is a value $\underline{c} > 0$ such that any equilibrium extortion level c imposed by lenders satisfies $c \geq \underline{c}$.*

To observe this, notice that

$$\pi(0) = v(0)b(0) = 0 < \pi(\bar{c}) = v(\bar{c})b_N$$

That is, setting an extortion level $c = 0$ only generates profit 0 to a lender, which is strictly dominated by setting an extortion level $\bar{c}$. Therefore there must be a value $\underline{c} > 0$ such that any extortion level imposed at equilibrium is larger than it. Together with the value $\bar{c}$, we conclude that $supp(F) \subseteq [\underline{c}, \bar{c}]$.

Claim 6. *No extortion level c in the interval $(c^*, \bar{c})$ is imposed by lenders.*

To observe this, notice that $b(c) = b(\bar{c}) = b_N$ for any $c \in (c^*, \bar{c})$, which implies that

$$\pi(c) = v(c)b_N < \pi(\bar{c}) = v(\bar{c})b_N$$

Therefore setting an extortion level $c \in (c^*, \bar{c})$ is strictly dominated by setting an extortion level $\bar{c}$.

Claim 7. $F(c^*) > 0$.

Suppose not, and $F(c^*) = 0$. Hence, no borrower chooses to stay matched with any lender at equilibrium. At this equilibrium, all lenders must impose the same extortion level $\bar{c}$ on the borrowers. However, in this case, if a lender deviates to set an extortion level $\bar{c} - \epsilon$, which is arbitrarily close to $\bar{c}$, she should be able to retain all the borrowers she meets as regular customers. The deviation increases this lender's measure of transactions in each period by a discrete amount, while reducing her profit in each transaction by only an arbitrarily small amount. Therefore the deviation is strictly profitable for the lender. A contradiction.

Claim 8. *Distribution F has no mass point in the interval $[\underline{c}, c^*]$.*

Suppose not, so there is a positive measure of lenders who set an extortion level $c \in [\underline{c}, c^*]$. Similar to the argument shown in the previous claim, we can show that a lender who sets an exortion level $c - \epsilon$ rather than c will obtain a discrete increase in terms of transactions in each period, while her loss in each transaction is negligible. Therefore there is no mass point in the interval $[\underline{c}, c^*]$.

Claim 9. *Distribution F is continuous on the interval $[\underline{c}, c^*]$.*

Suppose not, so there exist extortion levels c_1 and c_2 at the equilibrium such that $F(c_1) = F(c_2)$, where $\underline{c} \leq c_1 < c_2 \leq c^*$. This implies that $b(c_1) = b(c_2)$, and in addition

$$\pi(c_1) = v(c_1)b(c_1) < \pi(c_2) = v(c_2)b(c_2)$$

Therefore setting an extortion level c_1 is strictly dominated by setting An extortion level c_2, which contradicts with that c_1 is set by some lenders in the equilibrium. The previous claims indicate that if distribution F has a mass point, it can only have this mass point at the extortion level $\bar{c}$. Let $p(\bar{c})$ denote the mass of probability that lenders impose extortion level $\bar{c}$.

Claim 10. *If $c^* = \bar{c}$, then $p(\bar{c}) = 0$. If $c^* < \bar{c}$, then $F(c^*) = 1 - p(\bar{c})$.*

To understand the first part, notice that if $c^* = \bar{c}$ but $p(\bar{c}) > 0$, it would contradict the claim that distribution F has no mass point in the interval $[\underline{c}, c^*]$. To understand the second part, notice that the claim that no extortion level c in the interval $(c^*, \bar{c})$ is imposed by lenders, hence $F(c^*) = 1 - p(\bar{c})$.
Let $\bar{c}^*$ and $\underline{c}^*$be values determined by

$$v(\underline{c}^*) = \frac{(1-\delta)v(\bar{c})}{1-\delta+\delta\theta} \quad \textit{and} \quad v(\bar{c}^*) = \frac{(1-\delta+(1-\theta)\gamma\delta)^2 v(\bar{c})}{(1-\delta+(1-\theta)\gamma\delta)^2+\theta\delta(1-\delta)}$$

It can be verified that $0 < \underline{c}^* < \bar{c}^* < \bar{c}$.

Claim 11. *At equilibrium, for any $c^* \in [0, \bar{c}]$, probability $p(\bar{c})$ has the property such that: (1) $p(\bar{c}) = 1$ if $c^* \leq \underline{c}^*$; (2) $p(\bar{c}) = 0$ if $c^* \geq \bar{c}^*$; and (3) $p(\bar{c}) \in (0, 1)$ if $c^* \in (\underline{c}^*, \bar{c}^*)$.*

Consider part (1) first and suppose the opposite, so $c^* \leq \underline{c}^*$ but $p(\bar{c}) < 1$. At this equilibrium, the lender who imposes the lowest equilibrium extortion level $\underline{c}$, where $\underline{c} < c^* \leq \underline{c}^*$, should have payoff satisfying $\pi(\underline{c}) \geq \pi(\bar{c})$. However, notice that with $F(\underline{c}) = 0$,

$$\pi(\underline{c}) = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta)\gamma\delta F(c^*)}{1-\delta+\gamma\delta F(c^*)}\frac{\theta\delta+1-\delta}{1-\delta}v(\underline{c}) < \pi(\bar{c}) = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta)\gamma\delta F(c^*)}{1-\delta+\gamma\delta F(c^*)}v(\bar{c})$$

which contradicts the requirement that $\pi(\underline{c}) \geq \pi(\bar{c})$. Therefore if $c^* \leq \underline{c}^*$, then $p(\bar{c}) = 1$.

Consider part (2) and suppose the opposite, so $c^* \geq \bar{c}^*$ but $p(\bar{c}) > 0$. Notice the claim that if $c^* = \bar{c}$, then $p(\bar{c}) = 0$. Thus we only need to consider the case that $\bar{c} > c^* \geq \bar{c}^*$ but $p(\bar{c}) > 0$, which implies that $\pi(\bar{c}) \geq \pi(c^*)$ at equilibrium. However, notice that with $F(c^*) < 1$,

$$\pi(c^*) = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta)\gamma\delta F(c^*)}{1-\delta+\gamma\delta F(c^*)}(1+\frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta F(c^*)]^2})v(c^*) > \pi(\bar{c}) = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta}{1-\delta+\gamma\delta}$$

which contradicts the requirement that $\pi(\bar{c}) \geq \pi(c^*)$. Therefore if $c^* \geq \bar{c}^*$ then $p(\bar{c}) = 0$.

Consider part (3). First suppose that $c^* > \underline{c}^*$ but $p(\bar{c}) = 1$, which implies that $\pi(\bar{c}) \geq \pi(c^*)$ at equilibrium. However, notice that with $F(c^*) = 0$,

$$\pi(c^*) = \frac{\mu\gamma}{\rho}\frac{1-\delta+\delta\theta}{1-\delta}v(c^*) > \pi(\bar{c}) = \frac{\mu\gamma}{\rho}v(\bar{c})$$

so it is strictly profitable for some lenders to impose c^* rather than $\bar{c}$. A contradiction.

Now suppose that $c^* < \bar{c}^*$ but $p(\bar{c}) = 0$, which implies that $\pi(\bar{c}) \leq \pi(c^*)$ at equilibrium. However, notice that with $F(c^*) = 1$,

$$\pi(c^*) = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta)\gamma\delta}{1-\delta+\gamma\delta}(1+\frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta]^2})v(c^*) < \pi(\bar{c}) = \frac{\mu\gamma}{\rho}\frac{1-\delta+(1-\theta)\gamma\delta}{1-\delta+\gamma\delta}v(\bar{c})$$

so it is strictly profitable for some lenders to impose $\bar{c}$ rather than c^*. A contradiction.

With the results shown above, we can now fully characterize the distribution F as a function of c^*.

Claim 12. *Distribution F is given as follows: (1) If $c^* \leq \underline{c}^*$, then*

$$\left\{\begin{array}{lll} F(c) = 0 & if & c < \bar{c} \\ p(\bar{c}) = 1 & if & c = \bar{c} \end{array}\right\}$$

(2) If $c^* \in (\underline{c}^*, \bar{c}^*)$, then

$$\left\{\begin{array}{ccc} F(c) = \frac{1}{(1-\theta)\gamma\delta}(\sqrt{\frac{\theta\delta(1-\delta)v(c)}{v(\bar{c})-v(c)}} - 1 + \delta) & if & c \in [\underline{c}, c^*] \\ F(c) = F(c^*) & if & c \in (c^*, \bar{c}) \\ p(\bar{c}) = 1 - F(c^*) & if & c = \bar{c} \end{array}\right\}$$

with $\underline{c}$ determined by

$$v(\underline{c}) = \frac{(1-\delta)v(\bar{c})}{1-\delta+\delta\theta}$$

(3) If $c^* \geq \bar{c}^*$, then

$$\left\{ \begin{array}{lll} F(c) = \frac{1}{(1-\theta)\gamma\delta}(\sqrt{\frac{\theta\delta(1-\delta)v(c)}{(1+\frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta]^2})v(c^*)-v(c)}}-1+\delta) & if & c \in [\underline{c}, c^*] \\ F(c) = 1 & if & c \in (c^*, \bar{c}] \\ p(\bar{c}) = 0 & if & c = \bar{c} \end{array} \right\}$$

with $\underline{c}$ determined by

$$v(\underline{c}) = \frac{(1-\delta)}{1-\delta+\delta\theta}(1+\frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta]^2})v(c^*)$$

Notice that part (1) has been derived before. For part (2), notice that we have the equilibrium condition

$$\pi(\bar{c}) = v(\bar{c})b_N = \pi(c) = v(c)(b_N + b_R(c))$$

for $c \in [\underline{c}, c^*]$. Plug in b_N and $b_R(c)$ and after some algebra, we obtain:

$$F(c) = \frac{1}{(1-\theta)\gamma\delta}(\sqrt{\frac{\theta\delta(1-\delta)v(c)}{v(\bar{c})-v(c)}}-1+\delta)$$

for $c \in [\underline{c}, c^*]$. Moreover, $F(\underline{c}) = 0$ implies that $\underline{c}$ is determined by

$$v(\underline{c}) = \frac{(1-\delta)v(\bar{c})}{1-\delta+\delta\theta}$$

which satisfies $\underline{c} \in (0, \bar{c})$.
For part (3), since $p(\bar{c}) = 0$ if $c^* \geq \bar{c}^*$, the previous analysis shows that distribution F is continuous and has no mass point in the interval $[\underline{c}, c^*]$. With $F(c^*) = 1$, notice that we have the equilibrium condition

$$\pi(c^*) = v(c^*)(b_N + b_R(c^*)) = \pi(c) = v(c)(b_N + b_R(c))$$

for $c \in [\underline{c}, c^*]$. Plug in b_N and $b_R(c)$ and after some algebra, we obtain

$$F(c) = \frac{1}{(1-\theta)\gamma\delta}(\sqrt{\frac{\theta\delta(1-\delta)v(c)}{(1+\frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta]^2})v(c^*)-v(c)}}-1+\delta)$$

for $c \in [\underline{c}, c^*]$. In addition, $F(\underline{c}) = 0$ implies that $\underline{c}$ determined by

$$v(\underline{c}) = \frac{(1-\delta)}{1-\delta+\delta\theta}(1+\frac{\theta\delta(1-\delta)}{[1-\delta+(1-\theta)\gamma\delta]^2})v(c^*)$$

Now we proceed to show the existence and uniqueness of equilibrium. Let function $H(c^*)$ be denoted as

$$H(c^*) = c^* - (1-\gamma)u - \gamma\int_0^{\bar{c}} cdF(c) + \theta\gamma\delta\beta\int_0^{c^*} \frac{F(c)}{1-\delta\beta+(1-\theta)\gamma\delta\beta F(c)}dc$$

Integration by parts, $H(c^*)$ can also be expressed as

$$H(c^*) = c^* - (1-\gamma)u - \gamma\bar{c} + \gamma(\bar{c} - c^*)p(\bar{c}) + \int_0^{c^*} (\gamma F(c) + \frac{\theta\gamma\delta\beta F(c)}{1-\delta\beta+(1-\theta)\gamma\delta\beta F(c)})dc$$

Notice that if $H(c^*) = 0$, then the cutoff value c^* and the corresponding distribution $F(c)$ consist of an equilibrium. If $H(c^*) < 0$ for any $c^* \in [0, \bar{c}]$, then $c^* = \bar{c}$ and the associated distribution $F(c)$ consists of an equilibrium.

Claim 13. *$H(c^*)$ is continuous and is strictly increasing on the interval $[0, \bar{c}]$.*

Continuity of $H(c^*)$ can be established by verifying that $H(c^*)$ is continuous on the cutoff values $\underline{c}^*$ and $\bar{c}^*$.
If $c^* \leq \underline{c}^*$, then $p(\bar{c}) = 1$, and so $H(c^*) = (1-\gamma)(c^* - u)$, which strictly increases in c^*. If $c^* \in (\underline{c}^*, \bar{c}^*)$, then notice that $p(\bar{c})$ strictly decreases in c^* while $F(c)$ on $c \in [0, c^*)$ is independent of c^*, so the aggregated effect also shows that $H(c^*)$ strictly increases in c^*. Finally, if $c^* \geq \bar{c}^*$, by plugging the distribution $F(c)$ into $H(c^*)$ and after applying some algebra, it can be verified that $H(c^*)$ strictly increases in c^*.
Therefore, the equilibrium is unique. We summarize these results using the following descriptive steps.

Claim 14. *There is a unique profile c^* and F that consists of an equilibrium. Moreover, the equilibrium satisfies that:*

$$\left\{ \begin{array}{ccc} H(\bar{c}) \leq 0 & \Rightarrow & c^* = \bar{c} \quad \textit{and} \quad p(\bar{c}) = 0 \\ H(\bar{c}^*) \leq 0 < H(\bar{c}) & \Rightarrow & \bar{c}^* \leq c^* < \bar{c} \quad \textit{and} \quad p(\bar{c}) = 0 \\ H(\bar{c}^*) > 0 & \Rightarrow & \underline{c}^* \leq c^* < \bar{c}^* \quad \textit{and} \quad p(\bar{c}) > 0 \end{array} \right\}$$

Lastly, we show the existence of different equilibrium regimes when the probability γ changes.

Claim 15. *There exists cutoff values $\underline{\gamma}$ and $\bar{\gamma}$, where $0 < \underline{\gamma} < \bar{\gamma} < 1$, such that*

$$\left\{ \begin{array}{ccc} \gamma \leq \underline{\gamma} & \Rightarrow & H(\bar{c}) \leq 0 \\ \underline{\gamma} < \gamma \leq \bar{\gamma} & \Rightarrow & H(\bar{c}^*) \leq 0 < H(\bar{c}) \\ \gamma > \bar{\gamma} & \Rightarrow & H(\bar{c}^*) > 0 \end{array} \right\}$$

To observe this, let $H(c^*;\gamma)$ be the function $H(c^*)$ with the additional argument γ. We first show that $H(c^*;\gamma)$ strictly increases in γ for $\gamma \in (0,1)$. If $c^* \leq \underline{c}^*$, then $p(\bar{c}) = 1$, and so $H(c^*) = (1-\gamma)(c^* - u)$, which strictly increases in γ. If $c^* \in (\underline{c}^*, \bar{c}^*)$, then $\gamma F(c)$ in the integral of $H(c^*;\gamma)$ is independent of γ, while the remaining terms of $H(c^*;\gamma)$ strictly increases in γ. Finally, if $c^* \geq \bar{c}^*$, then the term in the integral of $H(c^*;\gamma)$ and the remaining terms of $H(c^*;\gamma)$ strictly increase in γ.
Denote $\underline{\gamma}$ and $\bar{\gamma}$ as

$$H(\bar{c}^*;\bar{\gamma}) = 0 \quad \textit{and} \quad H(\bar{c};\underline{\gamma}) = 0$$

Since $\bar{c}^* < \bar{c}$, we have $\bar{\gamma} > \underline{\gamma}$. Thus, we can see that

$$\left\{ \begin{array}{ccc} \gamma \leq \underline{\gamma} & \Rightarrow & H(\bar{c};\gamma) \leq 0 \\ \underline{\gamma} < \gamma \leq \bar{\gamma} & \Rightarrow & H(\bar{c}^*;\gamma) \leq 0 < H(\bar{c};\gamma) \\ \gamma > \bar{\gamma} & \Rightarrow & H(\bar{c}^*;\gamma) > 0 \end{array} \right\}$$

Finally, notice that if $\gamma \to 1$,

$$H(\bar{c}^*;\gamma) > H(\underline{c}^*;\gamma) \to 0$$

therefore $\bar{\gamma} < 1$. On the other hand, if $\gamma \to 0$,

$$H(\bar{c};\gamma) \to \bar{c} - u < 0$$

therefore $\underline{\gamma} > 0$.

Proof of Corollary 2.

Suppose that $c^* \in (\underline{c}^*, \bar{c}^*)$, so the market equilibrium is in Equilibrium Regime I. Fixing c^*, notice that if θ increases, then $\underline{c}$ strictly decreases, $F(c)$ strictly increases for any $c \in [\underline{c}, c^*]$, and therefore $\int_0^{\bar{c}} cdF(c)$ in $H(c^*)$ strictly decreases. On the other hand, denote

$$x(\theta) = \frac{\theta\gamma\delta\beta F(c)}{[1-\delta\beta+(1-\theta)\gamma\delta\beta F(c)]} \quad and \quad y = \sqrt{\frac{\delta(1-\delta)v(c)}{v(\bar{c})-v(c)}}$$

so $x(\theta)$ is the term in the integral of $H(c^*)$. Fixing c^*, we can verify that

$$\frac{dx(\theta)}{d\theta} = \frac{(y\sqrt{\theta}-1+\delta)(1-\beta+\frac{\beta y(1+\theta)\sqrt{\theta}}{2}) + \frac{y(1-\theta)\sqrt{\theta}}{2}(1-\beta+\beta y\sqrt{\theta})}{[(1-\theta)(1-\beta+\beta y\sqrt{\theta})]^2} > 0$$

so $x(\theta)$ strictly increases in θ. Overall, $H(c^*)$ strictly increases in θ. Therefore, for $H(c^*) = 0$, c^* strictly decreases in θ in Equilibrium Regime I.