The Village Money Market Revealed: Credit Chains and Shadow Banking*

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November 19, 2019

Abstract

This paper takes advantage of unique, high-frequency panel data to document the existence of active, high volume and relatively sophisticated money markets in villages in Thailand, especially among households in villages in relatively poor regions. Formal and informal transactions are shown to be intimately linked, e.g, households borrow informally, often at high interest, to pay off formal sector loans and borrow to relend. As with traditional markets, loan repayment can be deferred through standard restructuring. But there are also more complicated credit refinancing chains involving multiple parties and short/medium maturities. Intensive but creative matching algorithms are utilized on the Townsend Thai survey data to identify loans, transaction partners, and multiple links in the credit refinancing chain. From risk sharing regressions, we find that borrowers, surprisingly, have higher MPC income coefficients than non-borrowers, seemingly smoothing less well. However, this is not because financial access is detrimental, but rather due to the self-selection into debt of more risk-tolerant individuals, who bear fluctuations without great utility loss. Yet, those engaged in credit refinancing chains have the smoothest consumption of all against income shocks, as risk tolerance is dominated by low transaction and verification costs.

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The authors acknowledge helpful comments from Abhijit Banerjee and participants at the MIT Development Lunch. Townsend gratefully acknowledges research support from the University of Thai Chamber of Commerce, the Thailand Research Fund, and the Bank of Thailand, Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD) (grant number R01 HD027638).

1 Introduction

This paper is about shadow banking and money markets. Shadow banking refers to the financial intermediation involved in the facilitation of credit and insurance among non-banks, that is, shadow banks are largely unregulated financial institutions. Yet, despite the higher level of scrutiny of shadow banking institutions in the wake of the financial crisis in the US, the sector has continued to exist and in some cases grow. Much activity remains in collateralized loans and repurchase agreements, high liquidity and high-frequency short-term borrowing and lending of cash and securities among non-bank institutions (mutual funds, hedge funds) and security broker-dealers. This is a prime example of what is meant by the term money market.[1]

Others are beginning to analyze administrative data, taking advantage of the formality of US financial markets. For Cocco, Gomes, and Martins (2009), the main data source is the proprietary Transaction Reporting System audit trail from the MSRB on municipal bond transactions, the 15-year period from February 1998 to December 2012. There are identifiers for the dealer firms intermediating each trade and for customer trades, and the data identify the dealer buying and selling the bonds. Municipal bond dealers intermediate round-trip trades not only by taking the bond into inventory but rather by asking the seller to wait until a matching buyer or buyers are found. In a round-trip transaction, an investor sells bonds to a dealer and then the dealer sells the same bonds to another investor or other dealers. Thus there are intermediation chains, and these can extend up to seven dealers.

The financial crisis also motivated a large and increasing literature on financial contagion, which traces the actual or potential impact of shocks to balance sheets and their potential spread. Oddly though, there are relatively few empirical studies that actually trace out the chain of contagion as it occurs. Most of the empirical literature uses data to calibrate a network model and then run simulations to see what might happen, as opposed to what has actually happened in the past. Das et al (2007) ask why corporate defaults cluster in time and noted that one possible mechanism, among others, is default contagion. We do know from the finance literature that there are impacts of liquidity shocks on bank lending, which can make its way to clients of impacted banks. As one example, Jorion and Zhang (2009) look at US corporate bankruptcies and the impact on the largest claim holders, showing increased distress in years of debtor failure. Likewise, there are other detailed case studies, as on the Lehman default.

Perhaps closest to what we do in this paper is the work on trade credit, though still in advanced country contexts. Jacobson and Schedvin (2015) study the universe of Swedish corporate firms for the period of 2007-2011 using yearly financial statements. Bankruptcy proceedings show the identity of a defaulting firm, its creditors, and their associated losses, and whether in turn any of these creditors also failed. Related is the work of Boissay and Gropp (2013) using French data to document that trade creditors are likely to respond to late trade debtor payments by postponing their own trade credit payments. On average, more than one-fourth of negative liquidity shocks are transmitted along the trade-credit-refinancing chain until it reaches a creditor with either access to external financing or sufficient cash holdings. These credit refinancing chains seem to be an insurance mechanism for allocating liquidity risk.

The same issues arise in emerging market countries, of course. Evidence from matched intermediary-client data has recently suggested that borrowers are unable to smooth bank shocks completely (Khwaja and Mian 2008). But in poor and developing countries, the issue of limited formal sector financial access also looms large. That is, many households and small and medium enterprises (SMEs) have little if any access to formal financial intermediaries. This in itself is a policy issue. But closely related is a measurement issue: In developing countries, there is typically difficulty in measuring any transaction outside of formal financial institutions. That is the focus here.

[1] Non-bank lenders account for an increasing share of mortgages in the US. Another growing segment of the shadow banking industry is peer-to-peer (P2P) lending. There is also a better measurement of financial transactions in these institutions and markets due in part to the reporting requirements stipulated in the Dodd-Frank Act, but large gaps remain in understanding how these markets function (Pozsar 2014).

Relatedly, financial access, or better put, use of formal sector funds, may be greater than it seems at first sight, due to indirect access to formal intermediaries through third parties, e.g., borrowing to lend. Of course, pure informal networks without links to the formal sector are nevertheless also a mode of finance.

This paper takes advantage of unique, high-frequency panel data to document the existence of active, high volume and relatively sophisticated money markets in villages in Thailand. This is especially true among households in villages in relatively poor regions. We see from the survey data not only some borrowing transactions with formal financial institutions (which in principle could be available from administrative data) but also informal transactions among the households and businesses themselves.

The data come from the Townsend Thai survey, which began in September 1998 with an extensive baseline, then resurveying on a monthly basis. Here we use data from 1998 to 2007. For every loan entered into, both preexisting and over time, there is a loan form with detailed questions about the loan (interest, expected repayment, relationship with lender) and a roster to make sure the loan is tracked month by month, over time, from initiation to repayment (if any). If repayment is unobserved, the loan is kept on the roster and questions asked each month. The relatively high monthly frequency allows direct or indirect quantification of repayment, rollover, and refinancing strategies. Intensive but creative matching algorithms are utilized on the data to identify loans, transaction partners, and especially multiple links in credit refinancing chains.

The major findings are the following.

- There is great variety in formal and informal lenders in the village data.
- There is high correlation and a heavy seasonal component between amounts borrowed and amounts repaid.
- This carries over to borrowing from one source to pay off another, which is often statistically significant and nontrivial in magnitude both within and across lenders. Some of this is due to transactions across households and institutions happening at the same time, in the cross section. But a substantial amount is within the same household over time, in the panel.
- Out of the 14,109 loans, 2,422 (17%) are either solely or partly used to repay older loans. The amount borrowed from these 2,422 loans is 62 million baht, representing 19% of the total borrowings. These Repayment loans (as we refer to them subsequently) are especially prevalent in poor provinces, and when borrowed from informal sources these loans have atypically high-interest rates and atypical larger size.
- Half of these Repayment loans are part of Credit Refinancing Chains: transactions involving two or more complementary links. For example, a medium-term loan **A** is due. There is, as noted earlier, borrowing of bridge loan **B** at short-term at high interest in the informal sector to pay off loan **A**, and added here, the proceeds of a new loan **C** allows for repayment of the short-term loan **B**. The two repayment links in this chain are short to long, **B** to **A**, and long to short **C** to **B**. As we will see in Section 3, there also exists more complicated chains involving multiple medium-term lenders.

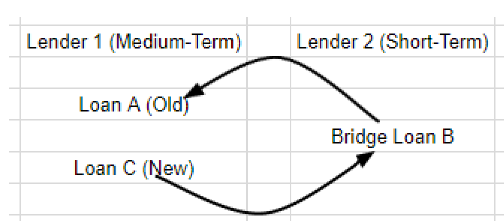

Figure 1: Credit Refinancing Chain

- A priori, we expect that same-lender and credit-refinancing-chains would be mutually exclusive: When loans are from the same lender, simple restructuring can extend the loan without the complications, and thus the chain should not be necessary. But strikingly for the village million baht funds, 55% of all Repayment loans are used to repay another Village Fund loan and are also part of the chains.

- Another type of chain arises from loans which are borrowed to lend to someone else. These we refer to as Borrow-to-Relend loans. Lending is measured much less frequently in the data than borrowing, and households may be under-reporting their own informal lending activity. But 2.5% of all loans are borrowed to be relent, and this can reach 19% of loans from the BAAC in one of the wealthier provinces. Money for lending can also come from own-savings. As a percent of total lending, 40% is own-savings and 30% is borrowed from others. These latter linked transactions are again found via a matching algorithm.

- When a borrower down the credit refinancing chain is late in repaying, what happens to the upstream lender who had borrowed money in the first place? For some, the delays propagate, and both are late. This happens 19/28 times. However, in the remaining cases, the lender at an intermediate link in the chain still repays the original loan, effectively providing loan-repayment insurance to others. Interesting and even more striking, when the downstream loan is repaid early, the original loan is also repaid early, a positive propagation back though the chain. This happens most of the time (19/23).

- From risk sharing regressions, of consumption onto income, we find that borrowers have higher marginal propensity to consume (MPC) out of income than non-borrowers. However, this is not because financial access is detrimental, but instead due to self-selection into borrowing of risk-tolerant individuals, which we document. Additionally, those engaged in credit refinancing chains have the smoothest consumption of all against income shocks as they benefit from low transaction and verification costs, despite high risk tolerance. We take advantage of data and preexisting work to separate risk aversion from these transaction costs.

2 Data

In this section, we describe the data used in the study and present some summary statistics. We feature loan duration and rate amount.

2.1 Townsend Thai Data

The Townsend Thai project covers a broad range of surveys conducted over the past two decades in Thailand. The project website describes the project in detail.[2] This paper uses the monthly version of the household survey from the project, commonly known as the Townsend Thai Monthly Household Survey.

This long-term panel tracks household response to policy changes. Of importance to this paper is the Thai Village Fund Program, which during the year 2001 transferred one million baht ($30,000) each to nearly 80,000 villages in Thailand (Kaboski and Townsend 2011, 2012). These funds were used to start village banks. The aggregated sum of the transfers is a sizable 1.5 percent of GDP. The Program provides access to basic financial products, including pledged saving accounts, to rural Thai villagers. One may refer to this as quasi-formal finance.

The Townsend Thai project began as a cross-sectional survey in 1997. The project chose two of Thailand's regions: the relatively rich central region (with two provinces, Chachoengsao and Lopburi), and the relatively poor northeastern region (with two provinces, Si Sa Ket and Buri Ram). For the monthly survey, beginning in 1998, only one subdistrict for each province, each with 4 villages, was selected. There are on average 45 households per village. One goal was to capture networks within the community.

[2] http://townsend-thai.mit.edu/.

2.2 Loan Duration, Rate, Amount

The paper focuses on the borrowing and repayment of loans by households in the monthly sample. The team conducted a baseline survey of these families over the summer of 1998, asking each household to count the outstanding loans it owes; for each loan, the team filled out a detailed form (15F). The team also asked about loans lent out by the household and filled out the form for that (16F). Starting from September 1998, the Thai team revisited each household monthly to document any changes in their lives. These changes include new loans, for which the 15F or 16F form is filled out. Additionally, the team records any changes to existing credit or lack thereof in the monthly 15M or 16M form.

The data analyzed here comprises 96 months and includes the crucial year of 2001 when the Thai government implemented the Village Fund program nationwide. In total, the team collected information on a total of 16,283 loans borrowed by 694 households. We will analyze loans that originated within the eight-year period from January 1999 to December 2007.[3]

In the main text below, we consider the loans borrowed by the 694 households. We will later summarize the 2,021 loans lent by households in Section 3.3.

We calculate Amount Borrowed (loan size), Loan Purpose, Lender, Expected Duration, and Interest Rate using data from form15F.[4] We retrieved repayment from form 15M. The household reports any loan repayment the family made since the surveyor's last visit. We shall first provide a brief overview of loan characteristics.

- **Loan Size:** Available on almost all loans except special cases with recall issues.
- **Duration:** We know the expected repayment date for the 97.7% of loans that are not open-ended. We have actual repayment dates for the 90% of loans that are completely repaid. This larger residual is natural for loans that are due in future months not yet surveyed. Additionally, households do not always repay on time. We find that 20.5% of loans were overdue at some point. We use the expected repayment date when actual repayment date is not available.
- **Interest Rate:** Households do not share a uniform concept of interest rates, making comparison difficult. We annualized the interest rate to make it comparable. But, the charge usually includes a fixed cost fee, so low duration loans have very high APRs.[5] There are some loans without interest rate data, mainly because of the use of land which serves as payment instead of an interest charge, or there is unspecified interest value on open-ended loans. Overall, the interest rate figure is available for 94% of the loans.
- **Purpose:** The distribution of loans by purpose and over time is the main interest of this paper. We shall give special consideration to the subset of loans that are used for repayment of other loans.

[3]Data from loans outside this range still play a part in how they interact with loans within the selected range.

[4]These are detailed in Table A.1.

[5]For example, 5% interest on a monthly loan will have 60% APR. The household is unlikely actually to face a rate that high if it borrowed a year-long loan.

(Amount Borrowed) % of Column	Buri Ram	Chachoengsao	Lopburi	Si Sa Ket	Total
Agricultural Cooperative	0.0	19.1	0.7	0.9	5.8
Commercial Bank	0.9	8.1	2.1	0.2	3.3
PCG	2.2	0.0	0.1	0.5	0.5
Village Fund	19.9	13.8	16.2	48.2	21.6
BAAC	30.0	32.4	42.8	20.2	33.6
Other Institution	21.8	16.7	13.7	19.9	17.1
Institution Total	**74.7**	**90.0**	**75.6**	**89.8**	**81.9**
Kin Relationship	9.4	8.1	3.0	3.7	5.8
Non-Kin Relationship	12.1	1.3	20.2	5.4	10.8
No Relationship	3.8	0.6	1.2	1.1	1.5
Informal Total	**25.3**	**10.0**	**24.4**	**10.2**	**18.1**

Table 1: Distribution of Loan Amount across Lender and Province

Table 1 shows the total amount borrowed on the selected loans totaling 337 million Baht, and we tabulate it across lender and province. Households borrowed 82% of this sum from institutions while the remaining 18% come from informal sources. The BAAC and Village Fund are the primary institutional lenders. We do not find this surprising, given both institutions' mandate to operate in rural areas. Commercial banks claim it is difficult to compete for small loans against government-subsidized rates. BAAC accounts for 34% compared to 22% of the Village Fund. BAAC dominates Village Fund in all provinces except Si Sa Ket. Commercial bank loans are rare but do show up at 3.3% due to their large loan size.[6] Agricultural Cooperative is significant in Chachoengsao but barely present elsewhere. The Production Credit Group (PCG) is a precursor to Village Fund; the government promoted it in villages but did not provide funding, hence the lack of lending from this institution. The category 'Other Institutions' groups all institutional lenders that the survey does not code, such as credit unions and companies selling goods on finance. Altogether they have a significant share at 17%.

We classify informal lenders by the relationship between the borrower and the lender. In most cases, the borrower knows the lender, with only 1.5% of the loans borrowed from someone without a previous relationship. Households obtained 6% from kin and another 11% from a person with a non-kin relationship (e.g., neighbor). The percentage of informal sources varies across provinces, from 10% in Chachoengsao to 25% in Buri Ram. For more on heterogeneity and changes over time see Section A.3 in the Online Appendix.

(Median) Duration and Rate weighted by Amount	**Whole Set**			**Subset with Purpose==Repay**		
	Duration (Month)	Rate (%)	Amount (Baht)	Duration (Month)	Rate (%)	Amount (Baht)
Agricultural Cooperative	7	8.0	40,000	6	9.5	27,500
Commercial Bank	12	5.5	50,000	8	9.6	20,000
PCG	12	12.0	3,000	11	12.0	5,000
Village Fund	12	6.0	15,000	12	6.0	18,000
BAAC	12	8.0	30,000	12	9.0	28,000
Other Institution	12	6.0	3,000	60	9.0	11,000
Institution Total	**12**	**7.0**	**13,000**	**12**	**7.0**	**20,000**
Kin Relationship	10	0.0	5,000	12	10.0	13,000
Non-Kin Relationship	1	0.0	5,000	0	24.0	11,000
No Relationship	6	1.9	5,000	1	24.0	10,000
Informal Total	**1**	**0.0**	**5,000**	**1**	**10.0**	**11,000**
Total	**12**	**6.8**	**10,000**	**12**	**7.0**	**17,000**

Table 2: Loan's Duration, Interest Rate, and Amount Across Lender and Purpose

Table 2 shows the median value of the loan duration, interest rate, and loan size for the entire sample of loans, in contrast to Repayment Loans to the right. We weight the median values for

[6] Chachoengsao's figure is high due to a single 10 million baht loan.

duration and interest rates by the amount borrowed. The most striking difference is that informal repayment loans have an interest rate that is even higher than for institutional loans. There is high demand for these loans.[7] The duration for borrow-to-repay loans is longer if borrowed informally from kin.

To understand the nature the village money market, we investigate the average size of the loan, as well as total borrowing. We look at the differences across provinces, and the distribution across lender and loan purpose. Loan size ranges from 63 baht to 7 million baht, with a mean of 24 thousand baht, a standard deviation of 88 thousand baht and median of 10 thousand baht. The box plot in the Online Appendix (Figure A.1) shows the amount borrowed, by province. The statistics presented in the following sections will weight each loan according to its size.

2.3 Repayment

Households are borrowing new loans for repayment of older loans. These older loans are likely borrowed in the same month the prior year. We investigate these Repayment loans. While most loans have a single purpose, some have multiple purposes. For these, we split the loan across the purposes into equal amounts. We combine any category with less than 5% into the Other category. Consumption as a purpose has the highest share at 34%. Meanwhile, household uses 16% of loans for repayment of older loans. The pie graph in the online appendix (Figure A.3) shows the distribution of amount borrowed across self-reported purposes.

Here are some key patterns of these Repayment loans:[8]

- Households literally receive cash from the Repayment loan and use it to repay another loan. This process usually involves creating a credit refinancing chain around a short-term Bridge loan which allows households to avoid a liquidity constraint.
- But there is also formal loan restructuring. We realize that this is a peculiar way to record such activity, but is due to a limitation in survey design. In these cases, money does not actually exchange hands, but the records are simply updated at the financial institutions.
- These Repayment loans are usually used to defer repayment on consumption loans. Investment loans are present (8.9%) in the sample, but usually have multi-year duration from the onset and do not require deferment.

Table A.2 in the Online Appendix shows the prevalence of Repayment loan across lender and province, and we report the salient facts here. Village Fund and BAAC are the institutional sources with high percentages of repayment loans. This is especially so in the poor provinces of Buri Ram and Si Sa Ket. The percentage of Repayment loan for Village Fund is negligible in the rich provinces of Chachoengsao and Lopburi. The BAAC figures are also lower but remain significant. Repayment loans involving Commercial Banks are associated with formal restructuring, which is not very common in the rural economy. The large 50% figure for Si Sa Ket is an outlier because we observe only two loans in the sample. Informal sources have a higher percentage of repayment loans than institutional sources. This is especially true for loans borrowed from Kin. Loans borrowed from Non-Kin (e.g., high interest) are only high in the poor provinces. The proportion of Repayment loans also varies with time. The figure for Village Fund has been growing over time since its inception in 2001. The proportion of Repayment loans for BAAC and Informal Sources were initially declining. But after the introduction of Village Fund, the figures started to recover. We will see that Village Fund plays a complementary role to both the BAAC and the Informal Lenders in the credit refinancing chain.

[7] Using Repayment Loan is an indicator of liquidity constraint.

[8] Repayment is not a coded choice in the survey. Instead, we use specific keywords to identify them from the free response answer.

3 Matching Loans

In this section we describe how Target and Repayment loans are found in the data and then discuss their duration.

3.1 Algorithms for Matching

Out of 14,109 loans, there are 2,422 repayment loans whose purpose is solely or at least partly to repay an older loan. We want to match these Repayment loans to the Target loans that they repay. This approach will allow us to exclude households whose borrowing coincidentally occurs after repayment in the same month. Unfortunately, the information on these credit refinancing chains is not readily available because the activity was not anticipated in the survey design. We manually read through the notes on the 2,422 15F loan forms, and in 753 cases we were able to deduce the loan number of one or more Target loans. For these cases, we use the following procedure to generate matches totaling 24.0 million Baht:

- One to One: In the most simple case, the surveyor notes that loan A is used to repay loan Z. Loan A could also be used for other purposes apart from repayment, but there is no other loan than loan Z mentioned. In this case, we match A to Z with the amount $min(Repay_Z, Borrow_A)$.
- Multiple Repayment Loans: In this case, Repayment loans A and B are used to repay Target loan Z. The general principle is to compare dates and first match events occurring the same month, then those occurring one month apart and so forth.
  - Example 1: Let A be borrowed at time t, B be borrowed at $t-1$, and Z be repaid at time t. We first match A and Z with the amount $min(Repay_Z, Borrow_A)$. We then move on to events that occur one month apart and match to B with remaining amount $min(Repay_Z - min(Repay_Z, Borrow_A), Borrow_B)$. Of course, this amount could be zero, in which case no match is made. One could imagine that in a more complicated case it is not zero and there could be loan C borrowed at $t-2$, and we would continue the matching process.
  - Example 2: Let A and B be borrowed at t; and Z repaid at t. In this case, we would match $min(Repay_Z, Borrow_A + Borrow_B)$ and attribute it proportionally.[9]
- Multiple Target Loans: In this case, loan A is used to repay loan Z and loan Y (and possibly more). The procedure is similar to the previous case, with the roles reversed. We follow the same principle of matching events occurring in the same month, and then those occurring one month apart and so forth. If the Target loans are repaid in the same month, then we match $min(Repay_Z + Repay_Y, Borrow_A)$ and attribute it to Z and Y proportionally.
- Further discussion of Multiple Repayment Loans and Multiple Target Loans can be found in Section A.4 of the Online Appendix.

[9] Proportionally means: $\frac{Borrow_A}{Borrow_A + Borrow_B} min(Repay_Z, Borrow_A + Borrow_B)$ to A and $\frac{Borrow_B}{Borrow_A + Borrow_B} min(Repay_Z, Borrow_A + Borrow_B)$ to B

(Flow of Repayment) % of Total (62.5 M Baht[11])		Target Loan										
		Agricultural Cooperative	BAAC	Commercial Bank	Other Institution	PCG	Village Fund	**Institution Total**	Kin Relationship	Non-Kin Relationship	**Informal Total**	**Total**
Repayment loan	Agricultural Cooperative	0.3	0.0	0.0	0.0	0.0	0.0	**0.4**	0.0	0.5	**0.6**	**1.2**
	BAAC	0.0	19.2	0.3	1.6	0.1	0.9	**22.0**	5.0	4.9	**9.9**	**32.4**
	Commercial Bank	0.0	0.1	0.1	0.0	0.0	0.0	**0.1**	0.0	0.0	**0.1**	**0.2**
	Other Institution	0.0	1.2	0.2	2.8	0.0	1.3	**5.5**	0.3	0.1	**0.4**	**5.9**
	PCG	0.0	0.0	0.0	0.0	0.1	0.1	**0.2**	0.0	0.0	**0.0**	**0.2**
	Village Fund	0.1	0.8	0.0	1.5	0.0	23.2	**25.6**	4.5	1.6	**6.2**	**32.0**
	Institution Total	**0.5**	**21.3**	**0.6**	**6.0**	**0.2**	**25.4**	**53.9**	**9.9**	**7.2**	**17.1**	**71.9**
	Kin Relationship	0.0	4.7	0.0	0.7	0.2	5.5	**11.1**	1.4	0.6	**2.0**	**13.5**
	Non-Kin Relationship	0.6	6.7	0.0	0.6	0.0	2.0	**9.9**	0.7	3.8	**4.5**	**14.7**
	Informal Total	**0.6**	**11.4**	**0.0**	**1.2**	**0.2**	**7.5**	**21.0**	**2.1**	**4.4**	**6.5**	**28.2**
	Total	**1.1**	**32.7**	**0.6**	**7.2**	**0.4**	**33.0**	**75.0**	**12.0**	**11.6**	**23.6**	**100.0**

Table 3: Repayment Loan as Source to Pay Off Target Loan

Table 3 describes the patterns of repayment and target loans, and is summarized here. Overall, exchanges between informal and institutional source are quite substantial at 38%, and also balanced: 17% of institutional repayment loans target informal loans vs. 21% of informal loans that target institutional sources. The majority (54%) of the Repayment flows are within the Institutional Lenders, and these are mainly from within the same lender: BAAC (19%) and Village Fund (23%). Meanwhile, the flows within the Informal source are small at 6.5%. The diagonal entries are flow within the same lender, and together they account for 51% of repayment flows.

We find this number surprisingly high because a careful lender will never allow a particular household to literally borrow a new loan to repay an old one. Even if the household does not make explicit its true purpose, the lender can easily deduce foul play. The lender could, of course, agree to restructure the loan. In this case, no money will actually exchange hands, but our survey will still record it as one loan paying off another. The possibility of restructuring makes the debt state-contingent. Townsend and Yaron (2008) documented the restructuring process for the BAAC, and found that it is accompanied by state verification. Apart from verification costs, households have other reasons to avoid verification. They might not be able to account for their investment, having instead consumed it, or they might have already received previous deferments from the lender and are not eligible for more.

To avoid verification, the insolvent household could mimic the behavior of a solvent household. The household will have to repay a loan **A** before borrowing a new loan **C** from the lender. The insolvent household can easily solve his liquidity constraint by borrowing a short-term Bridge loan **B** from another lender. Having proven his solvency, he can borrow loan **C** from the same lender. This explains the repayment flow between institution lenders and informal sources. The credit refinancing chain allows households to avoid verification, while still deferring repayment. A simple rule to distinguish a credit refinancing chain versus restructuring is to check whether repayment flows are between lender or within lender. The number is higher for the institutional sources because they allow restructuring. Meanwhile, informal loans are primarily used in the credit refinancing chain, so repayment flows to other lenders.

The figure for the Village Fund is unusually high, at 70 percent. [10] This contradicts anecdotal evidence that restructuring is not common for Village Fund loans. When we started writing this paper, we were not able to explain this discrepancy. To better understand this issue, we traveled to

[10]In the Online Appendix, Figure A.4 shows for each lender the percentage of flow that happens within lender.

the four provinces during the summer of 2011 and talked with the Village Fund loan officers. We found that a single Village Fund sometimes acts as two units separated by a "firewall," with one unit providing the Bridge loan for the household to overcome the liquidity constraint imposed by the other.

More generally, Village Fund officers may not want to officially defer loan repayment because they might well need to explain to the government why they approved a loan in the first place. They thus turn a blind eye as the households use the credit refinancing chain to avoid liquidity constraint. A local money lender can offer short-term Bridge loans. The Village Fund officer can help approve the new loan so that the household can in turn repay the informal Bridge loan within a couple of days. With such high turnaround, the money lender can lend out several Bridge loans within the month, all while earning a hefty fee for each loan.

Again, some Village Funds go a step further. They help households avoid these fees by providing the Bridge loan by themselves. They set aside an amount (usually from the savings account the household has with the Village Fund) and lend it off the books as a Bridge loan. These Village Funds boast to us how they complete this task with such efficiency. They only need an amount in the segregated Bidge loan fund equal to the biggest loan being deferred. The new loan can be approved within the same day the old one was returned. The same capital is used as a Bridge loan for every member of the village that needs deferment. We do not view this collusion against the government as being necessarily malicious. The Village Funds have a relatively low verification cost, and thus are able to optimally allocate loans to the households in need. From this perspective, the villagers have invented a scheme to overcome inflexible government rules.[11]

3.2 Duration of Repayment Loans

In this sub-section, we will use duration types to distinguish between restructuring versus credit refinancing chain. We have earlier indicated the high turnaround of the credit refinancing chain, with Bridge loans lasting only days. Nevertheless, we also observe less efficient cases that can take up to two months. To be safe, we shall include up to two months as the definition of a Short-term loan.[12] For lack of a better word, we define the remaining loans as Medium-term loans, with the understanding that most of these loans have a one-year duration.

We classify the Repayment flow by the duration of the Repayment loan and Target loan. We can also check whether the repayment flows fit into the credit refinancing chain. This is done by pairing $medium \leftarrow short$ and then $short \leftarrow medium$ that share the same short-term loan, that is, short is used to pay off a medium loan and in turn a medium term loan used to repay that same short loan. See Table A.3 in the Online Appendix, which we now summarize here.

In general, $medium \leftarrow medium$ flows are not in the credit refinancing chain and are associated with formal restructuring. Likewise $short \leftarrow short$ is not part of the chain by design. Even outside the credit refinancing chain, this type is not prevalent because there is not much benefit from extending a Short-term loan for a month, especially when subjected to high fees.

As described earlier, the credit refinancing chain involves the equal and opposite flow between Short-term and Medium-term loans, $medium_{old} \leftarrow short_{bridge} \leftarrow medium_{new}$. We were able to pair most of $short \leftarrow medium$ and $medium \leftarrow short$ to form parts of these credit refinancing chains. The unpaired flows (not part of a credit chain) might be due to household forgetting to report the other part of the chain.

We also find that a small portion of $medium \leftarrow medium$ occurs during the duration of the $short_{bridge}$ loan, and we classified it as part of a more complicated credit refinancing chain, as illustrated in Table 4.

[11] See Ru and Townsend (2019) for related quantification of verification costs.

[12] Eighty-eight percent take zero months, and six percent take one month. Cases with longer times are usually when the borrowed loan is only used to pay a part of the Target loan.

Lender 1 **(Medium)**	Lender 2 (Short Term)	Lender 3 **(Medium)**
Loan A (Old)		Loan E (New)
	Loan B	
Loan C (New)	$\longrightarrow$	Loan D (Old)

Table 4: More Elaborate Credit Refinancing Chains

All the four main institutional lenders form a part of the simple credit refinancing chain $medium_{old} \leftarrow short_{bridge} \leftarrow medium_{new}$. Informal lenders provide the Short-term Bridge loan part, $medium_{old} \leftarrow short_{bridge}$, which allows the household to defer repayment of the BAAC loans. Village Fund is special in that it provides both the Short-term Bridge loan as well as the Medium-term loan being deferred. The Village Fund bridge loan is usually within lender, but we do see cases where it is used with medium-term BAAC loans. Village Fund $medium \leftarrow short$ is lower than $short \leftarrow medium$ because some Village Funds do not provide bridge loans. For those latter villages, informal bridge loans form the credit refinancing chain with medium-term Village Fund loans.

As anticipated, only 5% of Village Fund deferment is done through formal restructuring. The BAAC, on the other hand, has almost 60% restructuring. We know from Townsend and Yaron (2008) that the BAAC is lenient with its borrowers, through building in contingency clauses. It makes sense for the household to first try formal restructuring and use a credit refinancing chain as a last resort. Kin relationship has a substantial $medium \leftarrow medium$, but most of these are not loan restructuring (64.9% vs. 25.5%); the excess is repayment flow to other lenders. These represent an informal method of traditional refinancing, as Kin have cheap interest rates (on medium-term loans).

We have identified and quantified the Credit Refinancing Chain and Restructuring, two methods in which households can defer repayment of Medium-term loans. There is an insurance aspect, as institutions verify income before granting deferment. It is not yet clear the extent to which these products help households share risk. There is still a transaction cost every time a loan is borrowed and repaid, and there is verification cost when loan officers physically travel to audit the households. And even without these costs, the transfer amount is limited by loan size. But an improvement in these metrics on the part of the financial institution should be associated with improvement in risk sharing outcomes for the households in the network.

We find that majority of Target loans are themselves repayment loans.[13] This makes sense in the context of the credit refinancing chain. The bridge loan is used to repay another loan and is itself a target of repayment from a third loan. Households can receive multiple deferments so that the credit refinancing chain extends for several years. We look at the subset that is a Target loan but not a Repayment loan to find the original loan of each chain. For these loans, we see that investment categories are small compared to consumption. Investment loans have a larger size and longer ex-ante duration, so that deferment is not required/allowed (see Table A.4).

3.3 Borrowing to Relend

We retrieve lending data from modules 16F and 16M of the Townsend Monthly Survey. Between 1999 and 2007, households lent 2,021 loans totaling 28.6 million baht. The pie chart in Figure A.5 shows the distribution of the money source. For the cases with many sources, we split the loan into equal amounts. The biggest source is savings (40%) followed by borrowed money (30%) and business proceeds (13%). We combine sources with less than 5% into the 'Other' category. We will use 'Relend' to describe the lending of borrowed money. This process creates a network involving financial institutions and households. Out of the 2,021 loans, relending occurs in 332 loans

[13]See Table A.4 in the Online Appendix.

totaling 8.4 million baht.[14] Because households borrow money to relend, the counterpart exists in the borrowing data set. Indeed, we find that households borrowed 191 loans for relending.[15]

But what if the relent loan is not repaid on time? Because the relender still needs to repay his own loan, and he is in the middle, he is in the position to provide insurance.[16] To further study this issue, we want to link the 191 borrowed loans to the 332 relent loans. We do this by matching the cash flow based on the proximity of the transaction date. For each of the borrowed loans, we look for relending that occurs in the same month. If it does not exist, we continue looking at future months until a match is found, or never found.

In total, 6.7 million baht of borrowing can be linked to relending data.[17] Matching is difficult for the 59 borrowed loans with multiple purposes. The 132 loans solely used for relending has a much lower unmatched rate of 9%. For those matched, relending usually happens in the same month as borrowing, which can be seen in Figure A.6.

We can now compare repayment dates of the borrowed and relent loans using these links. A borrowed loan and its corresponding relent loan are more likely to be repaid in the same month if relending is the sole purpose (see Figure A.7). This is natural since the repayment the household receives should cover the amount of the corresponding borrowed loan. The figure shows the pairs where the repayment dates are not comparable. This happens when neither the borrowed nor the relent loan has been repaid.[18] In total, both loans are repaid in 81% of the cases. On average, the borrowed loan is repaid 0.8 months after the relent loan. The difference ranges from -37 to 74 months.

When a borrower down the credit refinancing chain is late in repaying, what happens to the upstream lender who had borrowed money in the first place? For some, the delays propagate, and both are late. This happens 19/28 times. However, in the remaining cases, the lender in the chain still repays the original loan, effectively absorbing the risk and providing loan-repayment insurance. Interesting and even more striking, when the downstream loan is repaid early, the original loan is also repaid early, a positive propagation back though the chain. This happens most of the time (19/23). TableA.5 summarizes the relationship between on time, early or late payment of borrowed and relent loans.

4 Risk Sharing Equation

Risk sharing continuously improves as the household moves from (i) autarky, to (ii) savings only, to (iii) savings and borrowing, and to (iv) state-contingent borrowing. Full state-contingency in loan repayment creates a complete market environment, resulting in Pareto optimal allocations characterized by full risk sharing (Townsend 1994). However, access to contingent loan products such as restructuring and credit refinancing chains does not necessarily achieve full insurance. With continuous income, it is unlikely that these products can be contingent on every state. For example, the lender might only be able to observe whether income is high or low and either demand full repayment or allow for full deferment. Furthermore, there are costs associated with the borrowing process. Therefore, we are in a partial insurance environment.

This section formally models household specific transaction costs and verification costs, which, along with risk aversion, allow for heterogeneity in risk sharing results.

The economy consists of J Networks, each with I_J agents.[19] We abstract from labor decisions by excluding leisure from the model.[20] We define the following household lifetime utility as:

[14] In 324 cases, borrowed money is the sole source, and in 8 cases it is one of the sources.

[15] We do not have in the sample the universe of all households.

[16] Furthermore, the relender personally verifies the negative shock that prevented repayment. He or she should be able to do it at a lower cost compared to institutions because of the relationship between the households.

[17] There are 202 total pairs. Some borrowed loans are relent into multiple smaller loans.

[18] Usually because these loans are not yet due as of the month surveyed.

[19] The adjusted income variable is $y_i(s^t)$.

[20] A weaker assumption of linear separability will achieve the same result.

$$U_i = \sum_t \sum_{s^t} \beta_i^t u_i(c_i(s^t)) \quad \text{for all } i \in I_J, \text{all } J \ ,$$

where s^tdenotes history up to and incluuding date t.

We allow for heterogeneous discount rate, β_i, as well as heterogeneous risk aversion γ_i in CARA utility:

$$u_i(c_i(s^t)) = 1 - e^{-\gamma_i c_i(s^t)}.$$

Household i can borrow a one period loan $b_i(s^t)$ at interest rate R. This generalizes into lending of the second party k, in which case $b_k(s^t) < 0$. The household's income is private information, but the network achieves truthtelling by allowing state verification as in Townsend (1979). The total verification costs borne by the two parties i and k are $v_i(b_i(s^t))$ and $v_k(b_k(s^t))$. Additionally the parties must also pay transaction costs $n_i(b_i(s^t))$ and $n_k(b_k(s^t))$, per Townsend (1978). Theoretically, we want to distinguish these two costs, but in practice the financial fees are not separated into categories and sometimes are combined into the interest rates. Here we combine the two costs into a single term, which varies with $b_i(s^t)$ in the following fashion:

$$n_i(b_i(s^t)) + v_i(b_i(s^t)) = \frac{\phi_i}{2}(b_i(s^t))^2 \text{ for } i \in I_J.$$

This is a departure from fixed cost models. In those settings, the household would borrow a single loan, which is subject to a single transaction cost and a single *ex ante* expected verification cost. In our setting, there is an artificial policy limit to loan size of 10,000 baht. So as $b_i(s^t)$ increases, the number of transactions increase, and for each transaction the verification and transaction costs increase. Furthermore, the borrower will endogenously transact with the lender that generates the least cost (e.g., Village Fund before BAAC), so that the cost function is convex in $b_i(s^t)$.[21] The convex cost function is first introduced in Schulhofer-Wohl (2011), which used it to capture the cost generated by resource reallocation associated with risk sharing. The framework allows for autarky as an extreme case with $\phi_i \to \infty$.

The household budget constraint is given below. Note that income is net of depreciation, investment and saving:[22]

$$c_i(s^t) = y_i(s^t) + [b_i(s^t) - (R)b_i(s^{t-1}) - \frac{\phi_i}{2}(b_i(s^t))^2].$$

For simplicity, we shall assume[23] that there is zero net borrowing at the Network level $\sum_i b_i(s^t) = 0$, which allows us to nicely sum up to the network J resource constraint:

$$\sum_i c_i(s^t) = \sum_i y_i(s^t) - \sum_i [\frac{\phi_i}{2}(b_i(s^t))^2] \text{ for all } s^t, J.$$

Let λ_{js^t} be the Lagrange multiplier corresponding to the Network J resource constraint and α_i be the Pareto weight of household i in that network. We solve for the first order condition of the Pareto problem with respect to $c_i(s^t)$.

In the risk sharing equation, consumption will depend directly on income, and therefore there is only partial insurance:

[21]For example, consider a network where $b_i(s^t) \geq 0$ and is small for all households in the network. This could simply be achieved by a single institution (i.e., Village Fund), allocating loans to households that need it ($b(s^t) > 0$), and demanding repayment from households that do not ($b_i(s^t) = 0$). On the other hand, suppose that a household suffers an extreme shock and require $b_i(s^t)$ that is much larger than 10,000 baht. This large transfer is more complex and costly because it must involve multiple institutional lenders, and even lending from other households in the network.

[22]We abstract away from these decisions as we are more interested in testing for risk sharing across households, rather than own intertemporal smoothing.

[23]More generally, we can allow it to be a time-varying variable, as long it does not grow too fast.

$$c_i(s^t) \approx \frac{1}{\gamma_i + \phi_i} log \alpha_i \gamma_i + \frac{t}{\gamma_i + \phi_i} \log \beta_i - \frac{1}{\gamma_i + \phi_i} \log \lambda_{js^t} + \frac{\phi_i}{\gamma_i + \phi_i} y_i(s^t). \tag{1}$$

The coefficients ϕ_i and γ_i together determine the degree of this dependency on income. The model can distinguish whether smooth consumption arises from low transaction/verification costs or from risk aversion. If $\phi_i = 0$, there is no cost, and the result reverts back to classical risk sharing. For $\phi_i > 0$, the degree of risk sharing depends on γ_i. Risk averse households are willing to pay cost ϕ_i to achieve smooth consumption. Risk tolerant households are willing to suffer consumption fluctuation to save on transfer cost. For a risk neutral household, $\gamma_i = 0$, consumption moves one-to-one with income, as they are not affected ex ante by consumption shocks. The household that has more financial access should, all else equal, have a lower ϕ_i and thus a lower income coefficient.

We sum equation (1) across $i \epsilon J$ households and solve for λ_{js^t}. We also take a time difference to remove the fixed effect term:

$$\Delta c_i(s^t) \approx \frac{\phi_i}{\gamma_i + \phi_i} \Delta y(s^t) + \frac{1}{\gamma_i + \phi_i} \log \beta_i - \frac{1}{\gamma_i + \phi_i} \Delta \log \lambda_{js^t}. \tag{2}$$

After algebraic manipulation, we get:

$$\Delta c_i(s^t) \approx \frac{\phi_i}{\gamma_i + \phi_i} \Delta \log y_i(s^t) + \frac{1}{\gamma_i + \phi_i} \log \beta_i - \left[\frac{\Delta \sum_i \frac{\phi_i y_i(s^t)}{\gamma_i + \phi_i} + \sum_i \frac{\log \beta_i}{\gamma_i + \phi_i} - \Delta \sum_i c_i(s^t)}{\gamma_i + \phi_i \sum_i \frac{1}{\gamma_i + \phi_i}} \right].$$

The goal is to estimate the coefficient on $\Delta y_i(s^t)$, and thus the need to control for the covariates:

- $\frac{1}{\gamma_i + \phi_i} \left[\log \beta_i - \sum_i \frac{\log \beta_i}{\gamma_i + \phi_i} \right]$ can be treated as household specific fixed effect;
- $\Delta \sum_i c_i(s^t)$ can be calculated for households within the risk sharing network;
- the problem lies with $\Delta \sum_i \frac{\phi_i y_i(s^t)}{\gamma_i + \phi_i}$, which requires that we know $\frac{\phi_i}{\gamma_i + \phi_i}$ from the onset.

We will initially assume a homogeneous $\frac{\phi_i}{\gamma_i + \phi_i}$, not dependent on i which will allow estimation, giving us an estimate of $\frac{\phi_i}{\gamma_i + \phi_i}$ from the coefficient on $\Delta \log y_i(s^t)$. Our strategy is to use this biased estimate of $\frac{\phi_i}{\gamma_i + \phi_i}$ to recalculate $\Delta \sum_i \frac{\phi_i y_i(s^t)}{\gamma_i + \phi_i}$, and then re-run the regression. We shall then iterate the regression until $\frac{\phi_i}{\gamma_i + \phi_i}$ converges for all i households.

To estimate the CARA, we follow the portfolio choice method of Mehra and Prescott (1988). We mirror our strategy to that of Chiappori et al. (2014), which uses the same data set to estimate CRRA. This method is consistent with our model as it works in the incomplete market framework, with the added assumption that asset returns are log-normally distributed. Alvarez, Pawasutipaisit, and Townsend (2018) find that households hold large amounts of cash, so that the risk-free rate of return is 1. This bounds CARA for each household to:

$$\hat{\gamma} = -\frac{\hat{E}[R^P_{t+1}] - 1}{\hat{\sigma}_{\Delta c} \hat{\sigma}_{\Delta R^P_{t+1}}} Corr[e^{\alpha(x^*_t - x^*_{t+1})}, R^P_{t+1}]. \tag{3}$$

where $\hat{E}[R^P_{t+1}]$ is the expected return of household's portfolio, $\hat{\sigma}$ is the portfolio's standard deviation, $\hat{\sigma}_{\Delta c}$ is household's consumption standard deviation, and $e^{-\alpha(x^*_{t+1} - x^*_t)}$ is the growth in marginal utility of consumption.

It is natural that $Corr[e^{\alpha(x^*_t - x^*_{t+1})}, R^P_{t+1}] < 0$ because with endogenous portfolio choice, households choose assets that have high return when endowment/income is low (insurance). Assuming that, on average, the household portfolio outperforms holding cash, we find that $\hat{\gamma} \epsilon [0, \frac{\hat{E}[R^P_{t+1}] - 1}{\hat{\sigma}_{\Delta x} \hat{\sigma}_{\Delta R^P_{t+1}}}]$. To pin down the value for $\hat{\gamma}$, we must further assume that households obtain the theoretical bound $Corr[e^{\alpha(x_i^*-x_{t+1}^*)}, R_{t+1}^P] = -1$.[24] Continuing, we get a standard error for $\hat{\gamma}_i$ by running bootstraps with replacement on blocks of 12 months. Finally, we use method of moments to back out an estimate for transaction cost ϕ_i by combining estimates on CARA $\hat{\gamma}_i$ and regression coefficient on income.

We investigate the income coefficient, denoted $\hat{\delta}_i$, at the household level. The histograms of the coefficients are plotted in Figure A.8. We exclude 20 households that either have $\hat{\delta}_{1i} < 0$ or $\gamma_i \hat{<} 0$.[25]

With household level coefficients, we can distinguish whether a high $\hat{\delta}_i$ is due to high cost $\hat{\phi}_i$ or low risk-aversion $\hat{\gamma}_i$. Furthermore, we can investigate how these two factors vary with financial access by running a regression against group indicators. The results are presented in Table 5. Since the dependent variables are themselves estimates, we also run the weighted regression, using as weight the inverse of the estimated variance.

	Income Coefficient $\hat{\delta}_i$		CARA $\hat{\gamma}_i$		Cost Parameter $\hat{\phi}_i$	
	OLS	weighted	OLS	weighted	OLS	weighted
I.Borrow	0.00640*	0.00563	-0.550***	-0.561***	-0.0160	-0.0324*
	(1.97)	(1.58)	(-5.17)	(-6.02)	(-1.14)	(-2.47)
I.Contingent	-0.00188	-0.00204	-0.128	-0.0533	-0.00214	0.00172
	(-0.77)	(-0.89)	(-1.60)	(-0.90)	(-0.20)	(0.20)
I.Chain	-0.0105***	-0.0101***	-0.0587	-0.0668	-0.0424***	-0.0365***
	(-4.29)	(-4.48)	(-0.73)	(-1.13)	(-4.04)	(-4.37)
r2_a	0.113	0.132	0.0980	0.105	0.0975	0.119
N	475	475	475	475	475	475
t statistics in parentheses						
="* p<0.05	** p<0.01	*** p<0.001"				|

Table 5: Decomposition of Income Coefficients

The result of the $\hat{\delta}_i$ regression tells a consistent story. Borrowing is associated with a higher income coefficient, and within borrowers, the credit refinancing chain is associated with a lower income coefficient. From the $\hat{\gamma}_i$ regression, we see that borrowers are more risk-tolerant than non-borrowers. Additionally, from the weighted $\hat{\phi}_i$ regression, borrowing is associated with lower transaction/verification cost.

At first glance, it might seem that borrowers are worse off from a risk-sharing perspective, but in fact, borrowers receive less insurance because it is optimal for them to bear the volatility. The $\hat{\phi}_i$ regression shows access to credit refinancing loan is associated with lower transaction/verification cost, beyond that of normal borrowing. When $\hat{\phi}_i$ is close to zero, even risk-tolerant households can enjoy full risk sharing. This explains why households with access to credit refinance chain have smooth consumption, despite being relatively risk-tolerant.

[24]This potentially creates a systemic bias. The assumption is more likely to hold for households with better access to complete market (low ϕ_i).

[25]The presence of estimates outside the range restricted by the model is possible due to the small sample size.

It is not surprising that users of the credit refinancing chain enjoy the lowest cost $\hat{\phi}_i$. Recall that this scheme is usually associated with the Village Fund and lenders from the informal sector. As these lenders are physically located within the village, they have a natural advantage in verifying income. Furthermore, remember that these households also have access to restructuring loans, so effectively they always have a choice between two contingent loan products. A note of caution: As is standard in OLS, correlation does not imply causation. We cannot claim that access to credit refinancing chain reduces ϕ_i. It is entirely possible that the household with inherently low ϕ_i self-selects into using the scheme.

5 Conclusion

We conclude with a report on the chronology of this project, including aspects not yet reported in the text. This project started out with a simple macro-level observation on the correlation between the borrowing and repayment time series of the Townsend Thai Monthly data. The covariance was then broken down between lenders and across households. The surprisingly high amount of co-variation between an individual household borrowing to its own repayment led us to postulate the existence of credit refinancing chains – the usage of a short-term bridge loan to extend the duration of medium-term loans. These chains are identified through intensive but creative matching algorithms. In particular, we can distinguish bridge loans and chains from the standard restructuring process, which, like the credit refinancing chain, also allows for state-contingent deferment/repayment. Along the way, we document the unorthodox firewall within Village Funds that allows for the entire credit refinancing chain to occur within the same lender.

From the theory side, risk sharing continuously improves as the household moves from (i) autarky, to (ii) savings only, to (iii) savings and borrowing, and to (iv) state-contingent borrowing. We examined this prediction empirically by estimating the risk-sharing income coefficient across groups with the varying level of financial access, but ignoring heterogeneity in risk aversion and transaction costs (as in Kinnan and Townsend 2012).[26] Users of the credit refinancing chains have the smoothest consumption against income shocks. On the other hand, it might seem odd that general borrowing is detrimental towards risk-sharing, or put more precisely borrowers have the highest covariance of consumption with income. This is what motivated us to extend the risk sharing regression to allow for heterogeneity in both the transaction/verification cost as well as the coefficient of risk aversion. We deduced that risk-tolerant households are self-selecting into using loans, and thus borrowers receive less insurance because it is optimal for them to bear more volatility. On the other hand, those with access to credit refinancing chains face a smaller transaction/verification cost, such that even the risk tolerant individuals can enjoy something close to full insurance.

This paper illustrates the synergy between theory and empirics. We postulated and identified a unique state-contingent repayment scheme, which motivated us to extend the standard risk-sharing model to allow for heterogeneity. The model, in turn, ultimately enabled us to quantify how users of the scheme are able to benefit from it through the sharing of risk.

[26] See Table A.6 in the Online Appendix.

6 Reference

1. Alvarez, Fernando, Anan Pawasutipaisit and Robert M. Townsend. "Cash Management in Village Thailand: Positive and Normative Implications." Working Paper, 2018.

2. Boissay, Frederic, and Reint Gropp. 2013. "Payment Defaults and Interfirm Liquidity Provision." *Review of Finance* 17 (6): 1853–1894. doi:10.1093/rof/rfs045.

3. Chiappori, Pierre-Andre, Krislert Samphantharak, Sam Schulhofer-Wohl, and Robert M. Townsend. 2014. "Heterogeneity and Risk Sharing in Village Economies." *Quantitative Economics* 5 (1): 1–27. doi:http://qeconomics.org/ojs/index.php/qe/issue/archive.

4. Cocco, João F., Francisco J. Gomes, and Nuno C. Martins. 2009. "Lending Relationships in the Interbank Market." *Journal of Financial Intermediation* 18 (1): 24–48. doi:10.1016/j.jfi.2008.06.003.

5. Das, Sanjiv R., Darrell Duffie, Nikunj Kapadia, and Leandro Saita. 2007. "Common Failings: How Corporate Defaults Are Correlated." *Journal of Finance* 62 (1): 93-117. doi:10.1111/j.1540- 6261.2007.01202.x.

6. Deaton, Angus. 1991. "Saving and Liquidity Constraints." *Econometrica* 59 (5): 1221-1248. doi:10.2307/2938366.

7. Jacobson, Tor, and Erik von Schedvin. 2015. "Trade Credit and the Propagation of Corporate Failure: An Empirical Analysis." *Econometrica*, 83 (4): 1315-1371. doi:10.3982/ECTA12148.

8. Jorion, Philippe, and Gaiyan Zhang. 2009. "Credit Contagion from Counterparty Risk." *Journal of Finance*, 64 (5): 2053-2087.

9. Kaboski, Joseph P., and Robert M. Townsend. 2011. "A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative." *Econometrica* 79 (5): 1357-1406.

10. Kaboski, Joseph P., and Robert M. Townsend. 2012. "The Impact of Credit on Village Economies." *American Economic Journal: Applied Economics* 4 (2): 98-133. doi:10.1257/app.4.2.98.

11. Khwaja, Asim Ijaz, and Atif Mian. 2008. "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market." *American Economic Review* 98 (4): 1413–42. doi:10.1257/aer.98.4.1413.

12. Kinnan, Cynthia, and Robert Townsend. 2012. "Kinship and Financial Networks, Formal Financial Access, and Risk Reduction." *American Economic Review* 102 (3): 289-93. doi:10.1257/aer.102.3.289.

13. Mehra, Rajnish, and Edward C. Prescott. 1988. "The Equity Risk Premium: A Solution?" *Journal of Monetary Economics* 22 (1): 133–36. doi:10.1016/0304-3932(88)90173-0.

14. Pozsar, Zoltan. 2014. "Shadow Banking: The Money View." US Department of Treasury, Office of Financial Research Working Paper 14-14.

15. Ru, Hong, and Robert M. Townsend. 2019. "Enhanced Informal Network: Costly State Verification and Village Fund Intervention." Working Paper, Massachusetts Institute of Technology.

16. Schulhofer-Wohl, Sam. 2011. "Heterogeneity and Tests of Risk Sharing." *Journal of Political Economy* 119 (5): 925–58. doi:10.1086/662720.

17. Srivisal, Narapong, Anan Pawasutipaisit, Archawa Paweenawat, Krislert Samphantharak, and Robert Townsend. 2011. "User's Manual Townsend Thai Monthly Survey Household Financial Accounting." Internal Mimeo.

18. Townsend, Robert M. 1978. "Intermediation with Costly Bilateral Exchange." *Review of Economic Studies* 45 (3): 417-25. doi:10.2307/2297244.

19. Townsend, Robert M. 1979. "Optimal Contracts and Competitive Markets with Costly State Verification." *Journal of Economic Theory* 21 (2): 265-293. doi:10.1016/0022-0531(79)90031-0.

20. Townsend, Robert M. 1994. "Risk and Insurance in Village India." *Econometrica* 62 (3): 539-591. doi:10.2307/2951659.

21. Townsend, Robert M., and Jacob Yaron. 2001. "The Credit Risk-Contingency System of an Asian Development Bank." *Economic Perspectives* 25 (3): 31-48.

A Online Appendix

A.1 Source of Data by Module

The following table summarizes the source of data by variable and availability.

Variable	Source	Data Availability (% of Loan)
Amount Borrowed	15F	99.8
Amount Repaid	15M	90.0
Purpose	15F	100
Lender	15F	100
Expected Duration	15F	97.7
Actual Duration	15F and 15M	90.0
Interest Rate	15F	96.7

Table A.1: Source of Data by Module

A.2 Loan Size

There are differences across provinces in the amount borrowed. Figure A.1 displays the box plot for each province depicting the median, inter-quartile range and outliers.

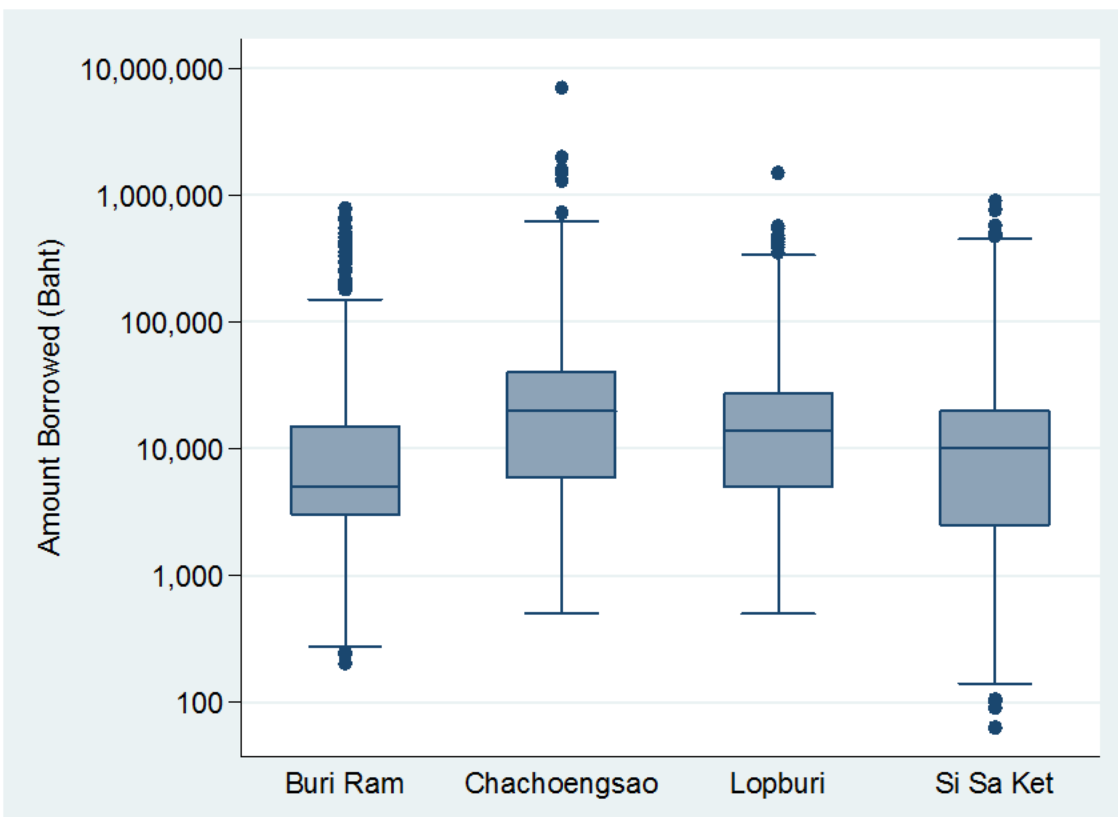

Figure A.1: Box Plot: Loan Size by Province

A.3 Heterogeneity and Changes Over Time

The BAAC is the most dominant lender but is rather constant, as is displayed in Figure A.2. Village Fund has been growing fast since its inception in 2001 and overtook BAAC in 2005. However, its growth has stalled since, allowing BAAC to retake the lead. 'Other institutions' is also growing, albeit at a slower rate; mainly due to newer organizations not coded in the survey entering the village money market. Agricultural Cooperative has been on the decline while the remaining lenders are relatively constant.We track borrowing over time and investigate seasonality across calendar month. BAAC and Kin Relationship have borrowing concentrated in the beginning and end of the year. Agricultural Cooperative borrowing occurs more during the first half of the year, while Village Fund loans seems to lead BAAC borrowing by a few months. The amounts borrowed from other lenders are relatively constant throughout the year.

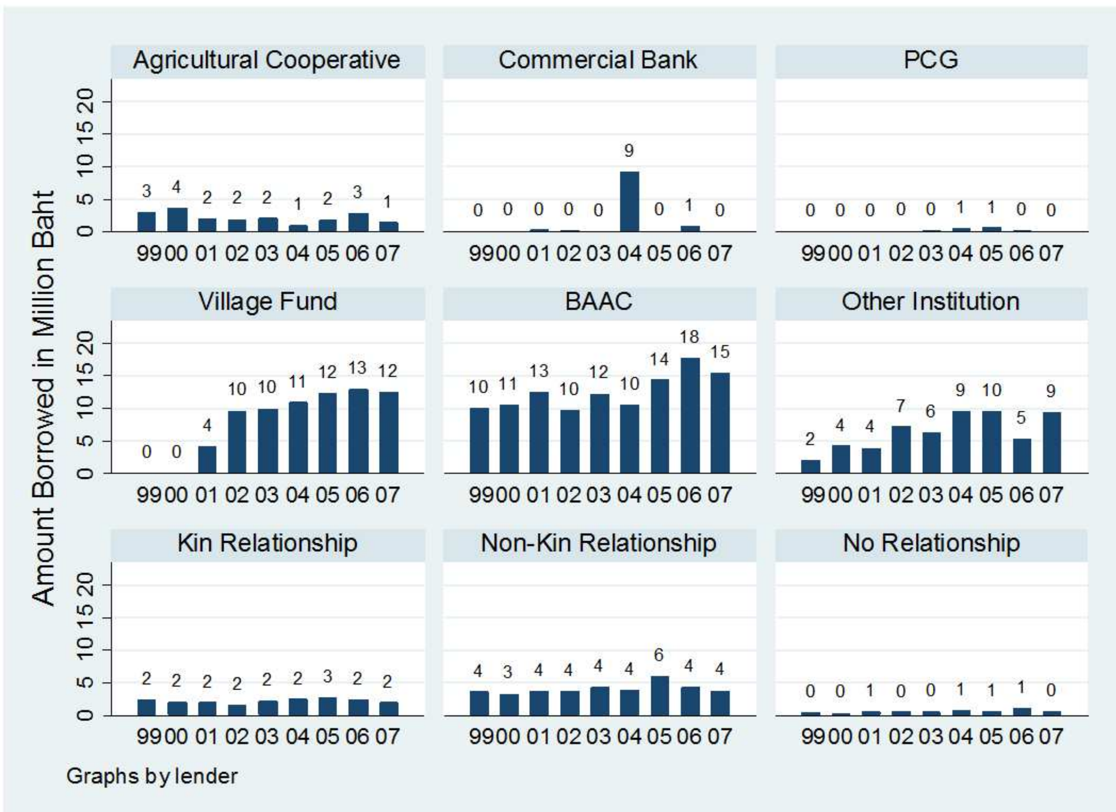

Figure A.2: Distribution of Loan Amount Across Lender and Year

Here and in the text, we exclude loans collected in the baseline to prevent reporting bias. For example, the survey team recorded a loan dating back to 1960 as currently in arrears. Another loan from 1960 that the household already paid off will not show up. We supplement our loan data with financial accounting data from Srivisal et. al. (2011). Some asset variables depend on lagged values, so we exclude September 1998 to December 1998 to provide a buffer. Additionally, loans borrowed after 2007 were excluded to provide a buffer for repayment data.

A.4 Multiple Repayment Loan and Multiple Target Loans: More Details

This is the most complex case and combines the two previous cases.

Consider Loan A and B used to repay loan Y and Z.

- Example 1: Let A be borrowed at $t-1$, B be borrowed at t, Y be repaid at t and Z be repaid at $t+1$. Then we first match B and Y with amount $min(Repay_B, Borrow_Y)$ because they occurred in the same month. We then match the remaining amount on events occurring one month part; this will include a match between A and Y with amount $min(Repay_A, Borrow_Y - min(Repay_B, Borrow_Y))$ and a match between B and Z with amount $min(Repay_B - min(Repay_B, Borrow_Y), Borrow_Z)$. Of course, these amounts may be zero, in which case no match is made. We would finally match A and Z with whatever amounts remained unmatched $min(RepayA - min(Repay_A, Borrow_Y - min(Repay_B, Borrow_Y)), Borrow_Z - min(Repay_B - min(Repay_B, Borrow_Y), Borrow_Z))$.

- Example 2: let A and B be borrowed at t, Y and Z be borrowed at t. Then we match amount $min(Repay_A + Repay_B, Borrow_Y + Borrow_Z))$. We attribute to each pair an amount proportional to their product.[27]

Apart from actual Target loan number, we were able to deduce the lender of some Target loans. In these cases, we proceed as if there were multiple Repayment loans and multiple Target loans. For example, we might know that loans A and B are repaid to Target loans borrowed from BAAC. Then we would compile a list of BAAC loans repaid within 12 months and proceed as if they were loans Y and Z from the above case. From this procedure, we match an additional 2.2 million Baht. Finally, we consider the repayment loans without any information on the target loan. We add into this list any repayment from the cases above that remained unmatched. Again we proceed as if there were multiple Repayment loans and multiple Target loans. Because this is a much broader criterion, we only match borrowing and repayment that occurs within one month of each other. From this procedure, we match an additional 35.8 million Baht. This matching process was done using every loan in the data set and generated 62.5 million baht in repayment flow.

A.5 Distribution of Loan Amount Across Purpose

The purpose of loans is displayed in Figure A.3 highlighting repay loans.

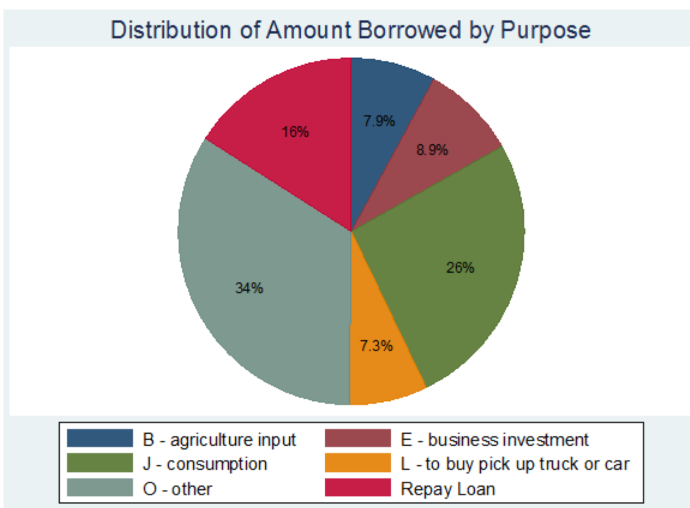

Figure A.3: Distribution of Loan Amount across Purpose

A.6 Borrow to Repay

The percentage of loans with the stated purpose of repaying another loan varies across lenders, both formal and informal, and across provinces.

[27]For example, the pair A,Y would get $\frac{Repay_A * Borrow_Y}{(Repay_A + Replay_B)*(Borrow_Y + Borrow)}$.

% of loans with purpose 'Repay Loan' (weighted by amount borrowed)	Buri Ram	Chachoengsao	Lopburi	Si Sa Ket	**Total**
Agricultural Cooperative	N/A	1.6	0.0	38.0	**2.5**
Commercial Bank	3.5	0.3	0.0	50.0	**0.8**
PCG	5.8	0.0	0.0	3.4	**4.8**
Village Fund	24.3	0.7	2.8	55.2	**25.7**
BAAC	22.5	21.0	6.1	18.9	**14.2**
Other Institution	8.7	0.0	1.3	7.3	**3.9**
Institution Total	**18.2**	**8.1**	**4.3**	**36.1**	**13.7**
Kin Relationship	35.1	58.6	25.4	38.5	**43.1**
Non-Kin Relationship	49.2	6.4	6.4	58.2	**19.6**
No Relationship	22.6	3.7	19.9	35.9	**21.4**
Informal Total	**39.9**	**48.6**	**9.3**	**48.2**	**27.1**
Total	**23.6**	**12.1**	**5.5**	**37.4**	**16.1**

Table A.2: Characteristics of Borrow to Repay Loans

A.7 Flow within Lender

The percentage of loans for which the borrowed loan is used to repay a loan from the same lender varies by lender type.

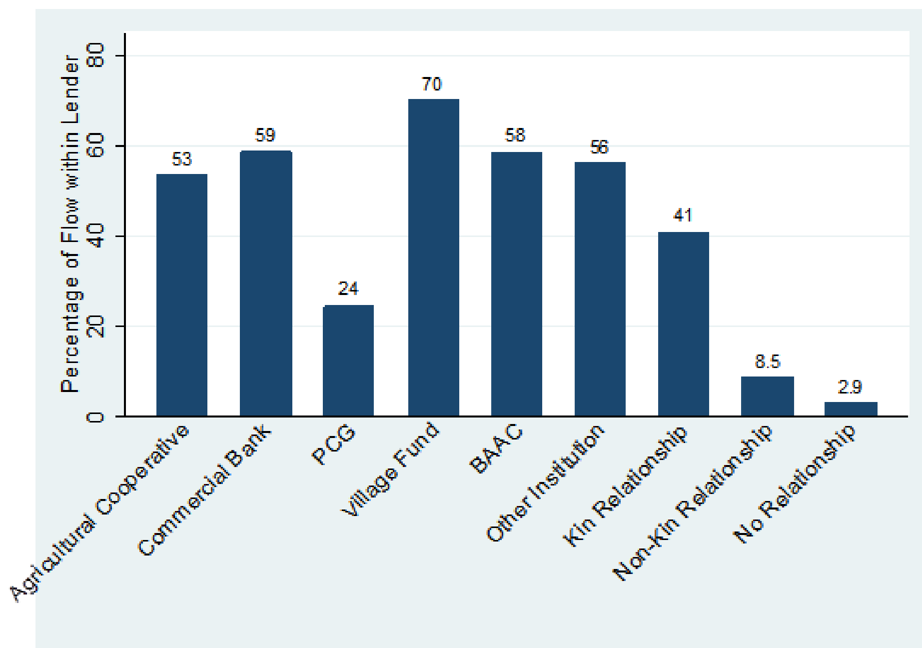

Figure A.4: Flow within Lender

A.8 Duration of Repayment and Target Loans, and the Role of Credit Chains

Duration of flows, short, medium and long, within credit chains and outside credit chains, is displayed in Table A.3.

(Flow of Repayment) % of Total	Credit Chain	Not Credit Chain	Total
Medium ← Medium	0.6	41.1	41.7
Short ← Medium	26.0	1.6	27.5
Medium ← Short	26.0	4.6	30.6
Short ← Short	0.0	0.2	0.2
Total	52.5	47.5	100

Table A.3: Duration of Repayment and Target Loans, and the Role of Credit Chains

A.9 Loan Purpose

The first row of Table A.4 shows the purpose of borrowing by sector, also featuring borrowing to repay another loan. The second row shows the original purpose of those repay loans, the target loans, featuring those loans that were themselves borrowed to repay yet another loan.

(Loan Purpose) % of Total	Repay Loan	B - agriculture input	C - livestock	E - business investment	J – consumption	O - other
1999-2006 Loans	16.6	7.4	4.5	9	26	36.5
Target Loans	51.4	2.9	2.6	2.2	18.4	22.5
Target Loan (Excluding Repay Loan)		6.0	5.3	4.5	37.9	46.3

Table A.4: Loan Purpose

A.10 Lending

This section focuses on lending by source of funds and early and late repayment chains for loans borrowed to lend.

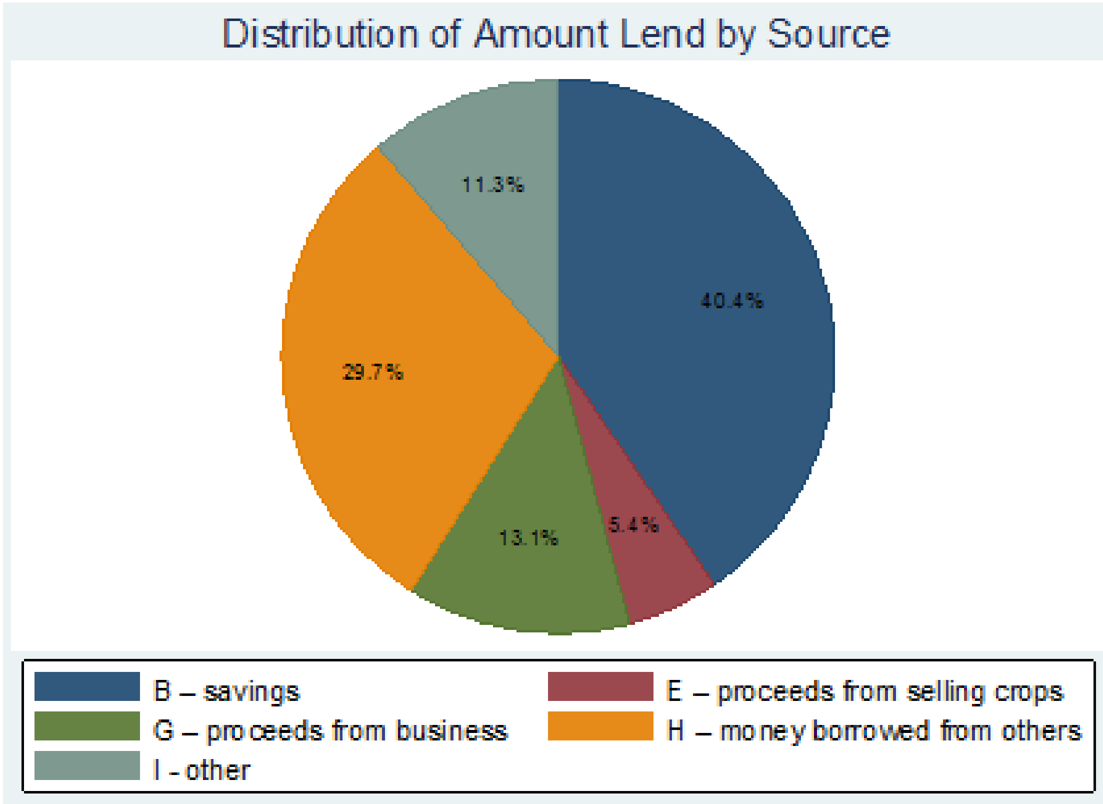

Figure A.5: Distribution of Amount Lend by Source

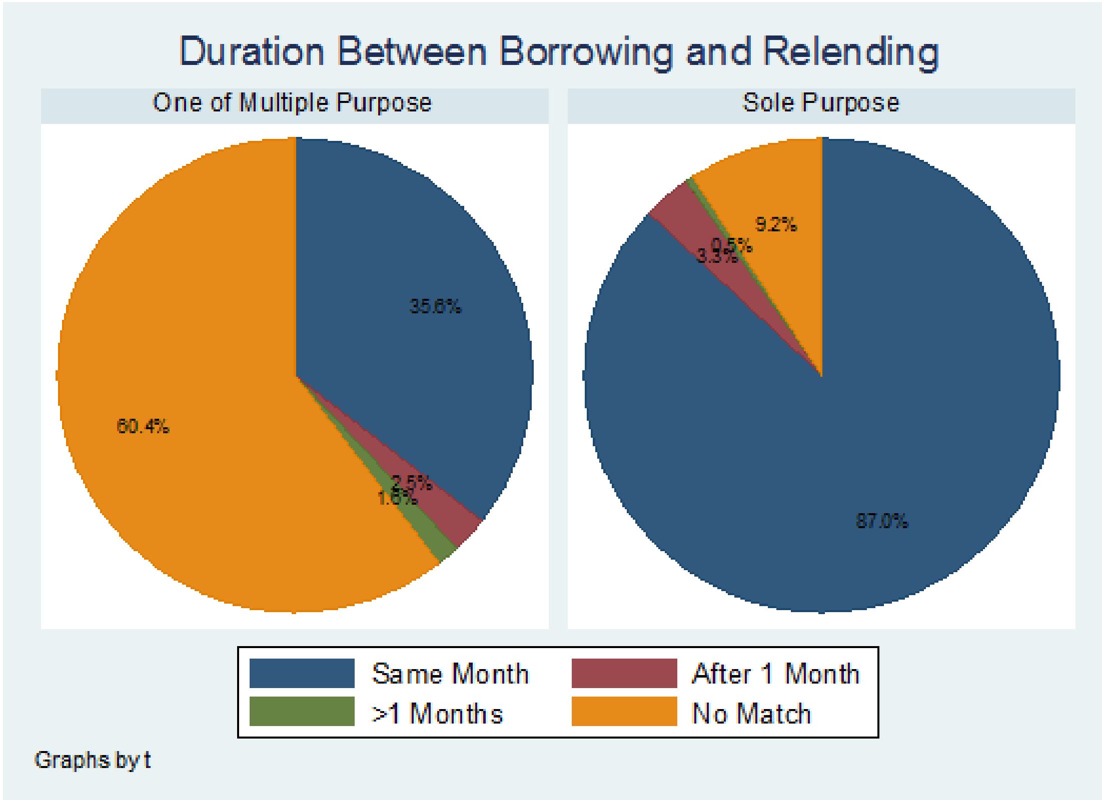

Figure A.6: Duration Between Borrowing and Relending

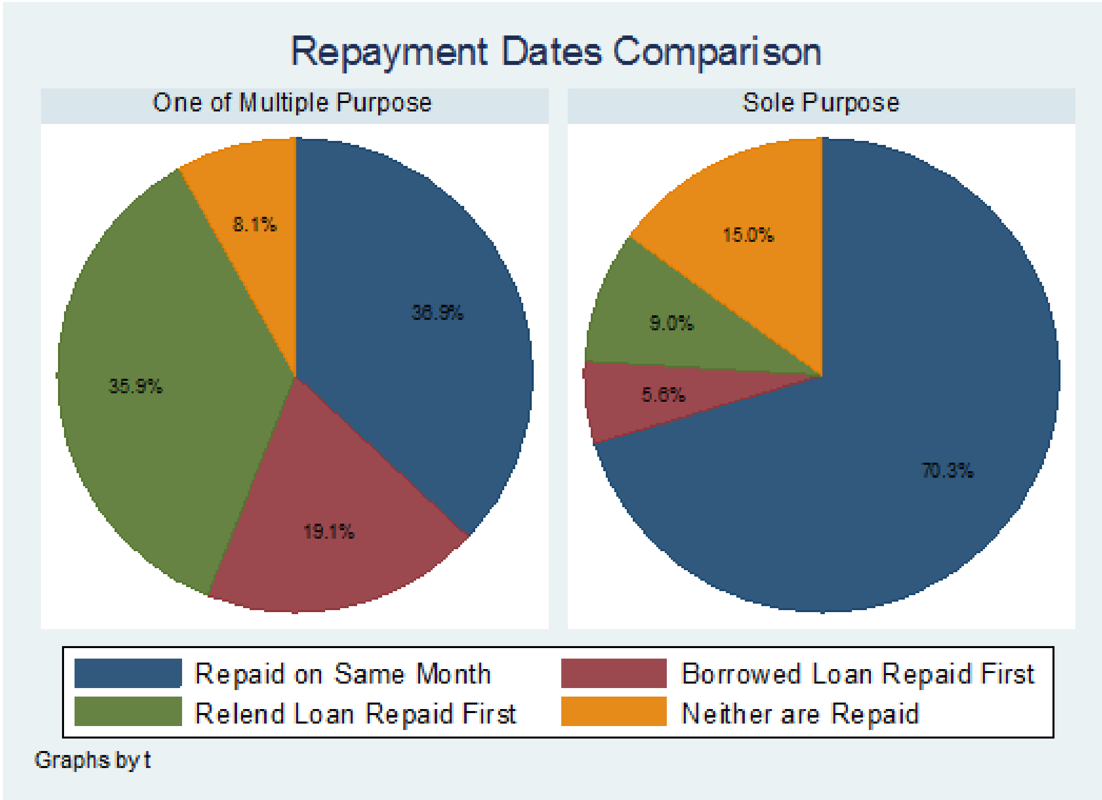

Figure A.7: Repayment Dates Comparison

Weighted % of Total		Lent Loan Early	On Time	Late	Total
Borrowed Loan	Early	19%	1%	1%	22%
	On Time	2%	45%	8%	54%
	Late	1%	4%	19%	24%
	Total	23%	49%	28%	100%

Table A.5: Early or Late Repayment

A.11 Relative to Standard Risk Sharing Results

The standard method of investigating risk sharing is to compare the income coefficient across groups with different levels of financial access. The crucial feature of these studies is that within each group, the income coefficient is assumed to be homogeneous. We present regression results that follow this method. The regression equation from Section 4 is reproduced below in reduced form notation:

$$\Delta c_{it} = k_i + \delta_{1i}\Delta y_{it} + \delta_{2i}\Delta \sum_i c_{it} + \delta_{3i}\Delta \sum_i \frac{\phi_i y_{it}}{\gamma_i + \phi_i} + \varepsilon_{it}.$$

Recall that $\delta_{1i} = \frac{\phi_i}{\gamma_i+\phi_i}$. This implies that the $\delta_{3i}\Delta\sum_i \frac{\phi_i y_{it}}{\gamma_i+\phi_i}$ term can be controlled for by network-level time effects when the regression is conducted over the entire panel data. Our panel data consists of 495 households that did not leave the sample throughout the 120 months period. Recall that in each province, only one Tambon (collection of nearby villages) is surveyed. The Tambon provides a natural way to divide households into networks. We present the regression result in Table A.6. Apart from the fixed and group-time effect, we also control for wealth, age, gender and household size to account for potential features missing from the model. These variables are generally not statistically significant, and we omit the coefficients from the table.

	(1)	(2)	(3)	(4)
	Δc_{it}			
Δy_{it}	0.0151***	0.00278	0.00278	0.00280
	(3.42)	(1.43)	(1.43)	(1.45)
I.Borrow x Δy_{it}		0.0129**	0.0132*	0.0132*
		(2.61)	(2.09)	(2.08)
I.Contingent x D.Net			-0.000978	0.0105
			(-0.12)	(1.14)
I.Chain x D.Net				-0.0239**
				(-3.25)
r2_a	0.00419	0.00433	0.00431	0.00509
N	59371	59371	59371	59371
t statistics in parentheses				
="* p<0.05	** p<0.01	*** p<0.001"		

Table A.6: Risk Sharing Regression

In the first column, we assume that the income coefficient is homogeneous across the entire sample. The estimate is positive and significantly different from zero, rejecting full risk sharing. In the second column, the interaction term with income allows us to compare the income coefficient between the two groups: borrowers (94%)[28] and non-borrowers (6%). Note that being in the same 'group' does not mean that households in the different Tambons are sharing risk. We merely allow them to have the same income coefficient. The base income coefficient corresponds to the non-borrower group, and the interaction coefficient measures the difference in income coefficient across the groups. Our model predicts that financial access should improve risk sharing, per the argument of Deaton (1989). Surprisingly the interaction coefficient is positive, signifying a worsening in risk sharing. Furthermore, full risk sharing cannot be rejected for non-borrowers.

In column 3, the borrower group can be further separated by whether the borrower uses state-contingent (52%) loans. In column 4, the state-contingent group can be further separated by the schemes defined in Section 3: restructuring and credit refinancing chain. This is done by adding the interaction term of income with the subgroup indicator. Again, we assign indicator by checking whether the household used the particular borrowing scheme during the course of the survey. Recall that at the loan level, restructuring and credit refinancing chains are mutually exclusive. However, a household can use both schemes over time. It turns out that every household that uses a state-contingent loan is also a user of restructuring. This means that the group can be separated into households that only use some kind of restructuring (12%) and those that use both credit refinancing chain and restructuring (40%). Note the implication that households that use a credit refinancing chain is a subset of households that use restructuring.

[28] We define this as a household that has borrowed at least once during the survey.

The subgroup that uses credit refinancing chain has a significantly lower income coefficient. The improvement in risk sharing is hardly surprising, as state-contingency contributes towards complete markets.

A.12 Histograms of Income Coefficients, CARA Risk Aversion and Cost Parameters

These histograms break down the income regression coefficients into risk aversion and cost components.

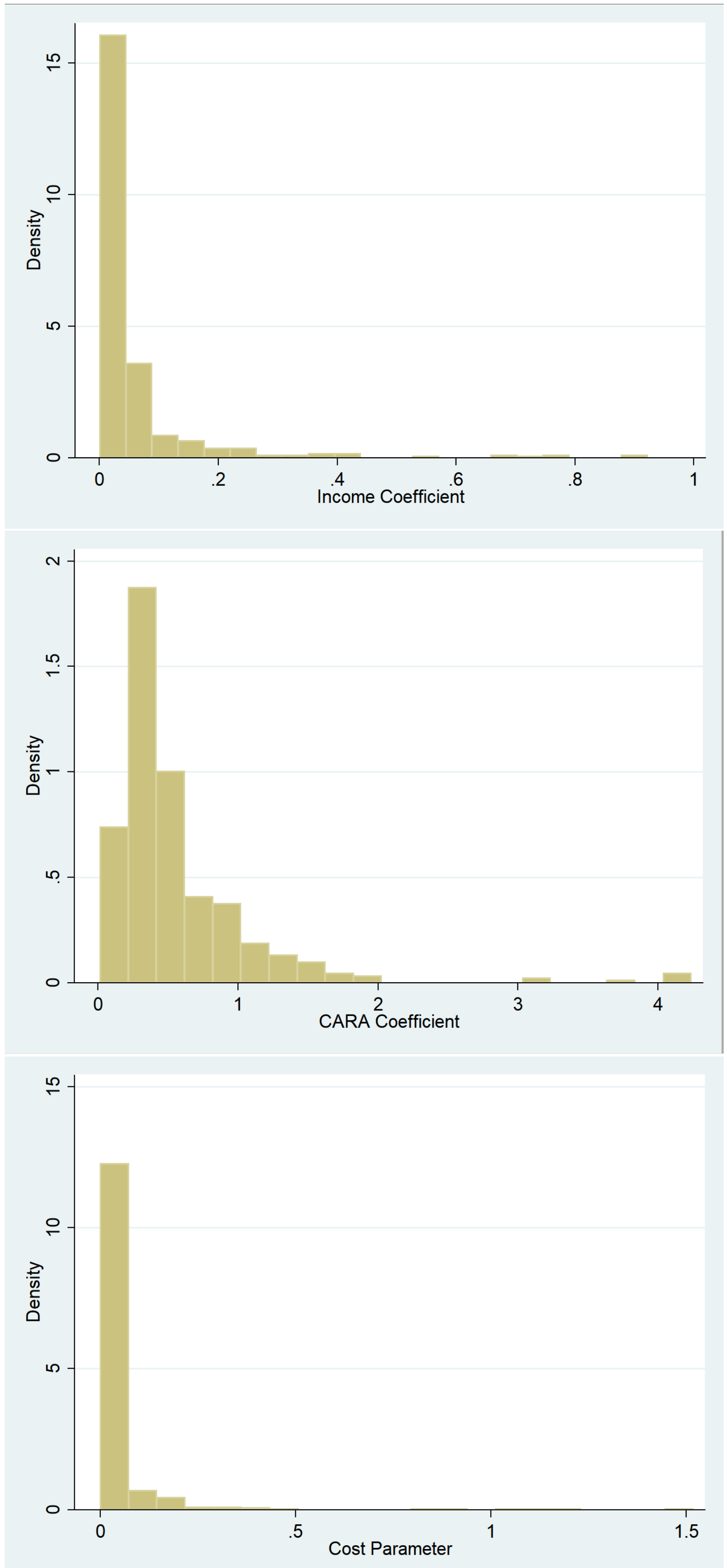

Figure A.8: Histograms of Income Coefficients, CARA Risk Aversion and Cost Parameters