The Village Money Market Revealed:
Credit Chains and Shadow Banking

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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 from loan-sharks to pay off formal sector loans. 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. Tedious but creative matching algorithms are utilized on the Townsend Thai survey data to identify loans, the identity of transaction partners, and multiple links in the credit refinancing chain. From risk sharing regressions, we find that borrowers surprisingly have higher income coefficient than non-borrowers. However, this is not because financial access is detrimental, but instead due to the self-selection into debt of more risk-tolerant individuals. Yet, those engaged in credit refinancing chains have the smoothest consumption against income shocks of all, as risk tolerance is dominated by low transaction and verification costs.

JEL: M41 G11 G21 O17 O16
0. Introduction

This paper is about shadow banking and money markets. Shadow banking refers to financial intermediation involved in the facilitation of credit among non-banks, that is, largely unregulated financial institution. 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 collateralize 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 pre-existing, administrative data, taking advantage of the formality of US financial markets. For Coco and Gomes (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 bonds. Municipal bond dealers intermediate round-trip trades not only 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 runs a simulation to see what might happen, as opposed to what has actually happened in the past. Das, Duffie, and Kapadia (2007) asked 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. Jorion and Xhang (2009) look at US corporate bankruptcies and the impact on largest claims holders, showing increased distress in years of debtor failure. Likewise, there are 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 2007-2011 using yearly financial statements and in particular bankruptcy proceedings that show

\(^1\) 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.
the identities 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 in turn 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 financial or sufficient cash holdings. Hence 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; Schnabl, 2010). But in poor and developing countries the issue of limited formal sector financial access looms large. That is, many households and SME businesses have little if any, access to the formal financial intermediaries. This in itself is a policy issue. But closely related is a measurement issue: there is typically a difficulty in developing countries in measuring any transaction outside of formal financial institutions.

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 business themselves. The data come from the Townsend Thai survey, with an extensive baseline beginning in Sept 1998 and continuing; the data we use here are from 1998-2007. 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, roll over, and refinancing strategies. Tedious but creative matching algorithms are utilized on the data to identify loans, the identity of transaction partners, and multiple links in credit refinancing chains.

Our major findings are the following:

- There is great variety in formal and informal lenders in the village data.
- There is a quite high correlation and 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, but a substantial amount is within the same household over time.
- 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 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 Repayment Loans are part of Credit Refinancing Chains: transactions involving two or more complementary links. For example, the 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 the proceeds of a new loan C allow repayment of the short-term loan B. The two repayment links in this chain are short to long and long to short. As we will see in Section 3a, there also exist more complicated chains involving multiple medium-term lenders.

- Half of Repayment loans are used to repay a loan of the same lender.

- A priori, we expect the two subsets (same-lender and credit refinancing chain) to 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 also part of chains  

- Among Repayment loans, we can trace the restructuring and refinancing throughout the years to find the original purpose. These original loans are usually taken out for consumption, and not investment. Investment loans have a larger size and longer ex-ante duration in the first place, so that deferment is not required/allowed. This explains why the behavior is not associated with investment smoothing.

- Another type of chain arises from loans which are borrowed to lend to someone else. This is borrow-to-relend loans. Lending is measured much less frequently in the data than borrowing, and household 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 linked transactions are again found via a matching algorithm.

  - When a borrower down the credit refinancing chain is late, what happens to the 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 providing insurance to the village. Interesting, when the downstream loan is early, the original loan is also repaid early. This happens most of the time (19/23).

- From risk sharing regressions, we find that borrowers surprisingly have higher income coefficient than non-borrowers. However, this is not because financial access is detrimental, but instead due to the self-selection of risk-tolerant individuals. Additionally, those engaged in credit refinancing chains have the smoothest consumption against income shocks as they benefit from low transaction and verification cost.
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. Part of the project involves household surveys. The impressive feature of these household surveys is that they continue, to this date, to survey the same households as it did a decade ago. Thus, they are among the longest socioeconomic panel data. This paper uses the monthly version of the household survey from the project, commonly known as the Townsend Thai Monthly Household Survey.

The long panel tracks how the household response to policy changes between now and then. 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. These funds are used to start village banks. The sum of the transfer is a sizable 1.5 percent of GDP, and in effect provide access to basic financial products, including the pledge saving accounts, to rural Thai villagers.

Robert Townsend initially designed the Townsend Thai project as a cross-sectional survey in 1997. The project chose two Thailand’s regions: the relatively rich central region, and the relatively poor northeastern region; and within each region, two provinces. These were selected deliberately (instead of randomized) to capture the variation in wealth level across the country.

Townsend chose a stratified random sample of households within each province. He divided the province into the forested and non-forested area using GIS data. From both strata, he selected a total of 12 sub-districts per province; and then 16 villages from each sub-district. The number of villages adds to 192. From each village, the survey team interviewed 15 households.

After, the 1997 economic crisis in Thailand, Townsend was motivated to continue with the project. The unexpected crisis put the survey in a unique position to collect panel data, with the first year serving as the pre-crisis baseline. The project also realized the need for increased detail, at a higher frequency. As such, in each province, one of the twelve sub-districts was chosen into the monthly version, while others remained in the existing annual format.

In each of the four sub-districts (one per province) of the Townsend Thai Monthly Household Survey, Townsend selected four of the original twelve villages. He compensated the reduction in village number by tripling the number household per village from 15 to 45; with the goal of capturing networks within the community. The increase in frequency from annual to monthly naturally reduces measurement error associated with recollection. However, the strength of the monthly version lies in its great detail; thousands of variables across twenty modules are collected monthly, from the same households.

The paper focuses on the borrowing and repayment of loans by households in this sample. The team conducted a baseline survey of these families over the summer of 1998. The team asked the household to count outstanding loans it owes, and 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.

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2http://cier.uchicago.edu/data/.
16F. Starting from September 1998 onward, the Thai team revisits each household monthly to document any changes in their life. 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 form or 16M form.

The data analyzed here extends to the 120th monthly visit in August 2008. Although more recent data has since been available, we do not expect it to change our results. Our data range includes the crucial year of 2001 when the Thai government implemented nationwide the Village Fund program. 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.

We exclude loans collected in the baseline to prevent reporting bias. For example, the survey team recorded a loan dating back to 1990 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 Townsend et. al. (2011). Some assets variables depend on lagged values, so we will exclude September 1998 to December 1998 to provide a buffer. Additionally, loans borrowed after 2007 were excluded to provide a buffer for repayment data. We now consider the remaining 14,109 loans borrowed by 694 households. We will later summarize the 2021 loans lent by households in section Appendix B.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
<th>Data Availability (% of Loan)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amount Borrowed</td>
<td>15F</td>
<td>99.8</td>
</tr>
<tr>
<td>Amount Repaid</td>
<td>15M</td>
<td>90.0</td>
</tr>
<tr>
<td>Purpose</td>
<td>15F</td>
<td>100</td>
</tr>
<tr>
<td>Lender</td>
<td>15F</td>
<td>100</td>
</tr>
<tr>
<td>Expected Duration</td>
<td>15F</td>
<td>97.7</td>
</tr>
<tr>
<td>Actual Duration</td>
<td>15F and 15M</td>
<td>90.0</td>
</tr>
<tr>
<td>Interest Rate</td>
<td>15F</td>
<td>96.7</td>
</tr>
</tbody>
</table>

We calculate Amount Borrowed (loan size), Loan Purpose, Lender, Expected Duration, and Interest Rate using data from 15F. We retrieved repayment from form 15M, which the survey team fills out for each outstanding loan. The household reports any loan repayment the family made since the surveyor’s last visit. We shall first provide a brief overview of the loan’s characteristic.

- **Loan Size:** Available on almost all loan except special cases with recall issues.

- **Duration:** We know the expected repayment date 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 is natural for loans are due in the 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 expected repayment date when actual repayment date is not available.

\( ^3 \text{Data from loans outside this range still plays a part in how it interacts with loans in the selected range.} \)
• **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. There are some loans without interest rate data, mainly because the use of land serves as payment instead of interest charge, or there is a fixed interest value on an open-ended loan. Overall, the interest rate figure is available for 94% of the loans.

• **Purpose:** The distribution of loans over purpose and time is the main interest of this paper and will be investigated in section 1A (borrowing). We shall give special consideration to the subset of loans that are used for Repayment of other loans.

<table>
<thead>
<tr>
<th>(Median) Duration and Rate weighted by Amount</th>
<th>Whole Set</th>
<th>Subset with Purpose==Repay</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Duration (Month)</td>
<td>Rate (%)</td>
</tr>
<tr>
<td>Agricultural Cooperative</td>
<td>7</td>
<td>8.0</td>
</tr>
<tr>
<td>Commercial Bank</td>
<td>12</td>
<td>5.5</td>
</tr>
<tr>
<td>PCG</td>
<td>12</td>
<td>12.0</td>
</tr>
<tr>
<td>Village Fund</td>
<td>12</td>
<td>6.0</td>
</tr>
<tr>
<td>BAAC</td>
<td>12</td>
<td>8.0</td>
</tr>
<tr>
<td>Other Institution</td>
<td>12</td>
<td>6.0</td>
</tr>
<tr>
<td>In total</td>
<td>12</td>
<td>7.0</td>
</tr>
<tr>
<td>Kin Relationship</td>
<td>10</td>
<td>0.0</td>
</tr>
<tr>
<td>Non-Kin Relationship</td>
<td>1</td>
<td>0.0</td>
</tr>
<tr>
<td>No Relationship</td>
<td>6</td>
<td>1.9</td>
</tr>
<tr>
<td>In total</td>
<td>1</td>
<td>0.0</td>
</tr>
<tr>
<td>Total</td>
<td>12</td>
<td>6.8</td>
</tr>
</tbody>
</table>

Above is a table which shows the median value of the loan duration, interest rate, and loan size. We present the corresponding value for the subset of Repayment loans to the right. We weight the median values for duration and interest rates by the amount borrowed. Upon interpreting these figures, one should keep in mind that they are not static. Informal loans are usually short-term loan with 1 month duration, while Institutional loans last for one year. In the Repayment loans subset, the loan size is larger for both institutional and informal sources. The most striking difference is that informal loans now have a positive interest rate, which is even higher than institutional loans. There is high demands for these loans. We will see in section 3 that they form a crucial component of the credit refinancing chain. At the same time, lenders know that informal Repayment loans are risky.5

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

5 Using Repayment loans is an indicator of liquidity constraint.
1a. Borrowing: Time Trend and Purpose

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 shows the amount borrowed, by province. The statistics presented in the following sections will weight each loan according to its size.

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borrowing two 30,000 baht loans should be equivalent to borrowing one 20,000 baht loan. The downside of this weighting scheme is that it creates an imbalance across households. Richer household borrows more than the poorer household. As seen in the box plot, the average loan size is greater in the two more prosperous provinces (Chachoengsao and Lopburi). Affluent households’ borrowings could eclipse the smaller loans from the low-income family. Another issue is whether we should also weight statistics by duration. We decide against this because we want to measure the flow of money between the households and lenders. Including duration in the weight will shift the focus to the amount of outstanding debt the family owes. The reader should always keep in mind that throughout this paper, we measure flow, as opposed to stock.
The total amount borrowed on the 14,109 selected loan totals 337 million Baht, and we tabulate it across lender and province. Households borrowed 82% of this sum from institutions while the remaining 18% comes from informal sources. BAAC (Bank for Agriculture and Agricultural Cooperatives) 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 find it 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 Sisaket. Commercial bank loans are rare but do show up at 3.3% due to their large loan size.

Agricultural Cooperative is significant in Chachoengsao but barely present elsewhere. The Production Credit Group is a precursor to Village Fund. The government promoted it in the villages but did not provide funding, hence the lack of lending from this institution. 'Other Institutions’ groups all institutional lenders that the survey does not code. These lenders are 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. Household 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 30% in Buriram.

\[\text{Chachoengsao’s figure is high due to a single 10 million baht loan}\]
The histogram above shows the amount borrowed from each lender over time. BAAC is the most dominant lender but is rather constant. 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. The peak in 2004 for Commercial bank is due to a single loan mentioned above. Agricultural Cooperative has been on the decline while the remaining lenders are relatively constant.
Other than tracking borrowing over time, we also investigated seasonality across calendar month. BAAC and Kin Relationship have the borrowing concentrated in the beginning and the end of the year. Commercial Bank has a single peak in January as a result of one single large loan. 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. We consider some plausible reasons behind seasonality:

- **Household** borrows to fund **Agricultural Activity**. The primary crop in Thailand is rice, which Thais usually start planting in May. However, we do not observe the aggregate shock in demand for loans around May. The peak occurs around December after the November
harvest. We speculate that lenders might choose to structure the loan such that repayment coincide with a positive cash flow event. Sripakdeecong (2015) finds that Thai families suffer from time inconsistency; they lack the self-control to set aside the income for loan repayment. Because an institutional loan usually has a duration of one year, the household would have to borrow at the same month of the prior year.

- There is Excess Demand for loans, especially at subsidized interest rates. The available funds might run out as soon as the institution starts lending, and might not replenish until the loans are repaid. Again, since institutional loans typically have a one-year duration, there will be a peak in lending at the same time every year. The data suggest that this is the case for Village Fund, which initially started operating in September 2001.

- Households are borrowing new loans for Repayment of older loans. These older loans are likely borrowed in the same month a year before.

We further investigate Repayment loans. The pie graph below shows the distribution of amount borrowed across self-reported purposes. 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 has the highest share at 34%. Meanwhile, household uses 16% of loans for Repayments of older loans. The utility of these Repayment loans is to defer repayment of institutional loans, usually by a year.

We will further investigate them in section 3. For now, we present a broad picture:

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8. Repayment not a coded choice in the survey. Instead, I use specific keywords to identify them from the free response answer.
• Household 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 household to avoid liquidity constraint.

• But there are also formal loan restructuring. We realize that this is a peculiar way to record such activity, but is due to a limitation in our survey design. In these cases money do 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 loan. Investment loans are present (8.9%) in the sample, but usually have multi-year duration from the onset and do not require deferment.

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

The table above shows the prevalence of Repayment loan across lender and province. Village fund and BAAC are the institutional sources with high percentages of Repayment loans. This is especially so in the poor provinces of Buriram and Sisaket. 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 formal restructuring, which is not very common in the rural economy. The large 50% figure for Sisaket 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. loan sharks) is only high in the poor provinces. The proportion of Repayment loans also vary 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. In section 3a, we will see that Village Fund plays a complementary role to both the BAAC and the Informal lenders in the credit refinancing chain.
2. Analysis of Covariance

We have earlier postulated the relationship between borrowing, its 12 months lag, and repayment. We calculate the listwise deletion correlation of the three series and find that all pairs are correlated at the 1% level. The correlation coefficient is highest for borrowing and repayment at 0.783. The autocorrelation in the borrowing series is 0.487, and repayment and lag borrowing correlate 0.567. Below we overlay the three series: lag(12) borrowing, borrowing, and repayment.

The direct links between borrowing and repayment must be dominant. Recall that the two direct links are Repayment Loans and Excess Demand. I replicate below the borrowing/repayment graph for the two biggest institutional lenders. Excess demand explains the Village Fund graph well. There was initial borrowing in 2001, which depletes the institution’s balance. Since the loans are lent at a subsidized rate, households will be waiting in queue to borrow. Unlike the Village Fund, the BAAC balance is not limited to a certain amount per village, so it must be Repayment Loans that is driving the result.

The correlation is not limited within lenders. Borrowing from lender $X$ is generally correlated with repayment from lender $Y$, usually at the 0.1% significance level. But does this translate to economic significance? To investigate this, we decompose the co-variance of borrowing $B_t$ and repayment $R_t$ across lenders $l \in L$. 


\[ B_t = \sum_{x \in L} B_{xt} \]

\[ R_t = \sum_{y \in L} R_{yt} \]

\[ \text{Cov}(B_t, R_t) = \sum_{x \in L} \sum_{y \in L} \text{Cov}(B_{xt}, R_{yt}) \]

We find pairs that generate high \( \text{Cov}(B_{xt}, R_{yt}) \). In the table below, \( \text{Cov}(B_{xt}, R_{yt}) \) figures are normalized by \( \text{Cov}(B_t, R_t) \). Borrowing and repayment within Village fund and BAAC generates a large portion of the co-variance. More surprising, there is also significant co-variation across these two lenders. The informal lenders do not generate much co-variance with itself. But, their series has substantial co-variance with the two institutional lenders.

<table>
<thead>
<tr>
<th>Between Lender Borrow (col)/Repay (row)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Normalized Covariance</td>
</tr>
<tr>
<td>---------------------------------------</td>
</tr>
<tr>
<td>1: Agricultural Cooperative</td>
</tr>
<tr>
<td>2: Commercial Bank</td>
</tr>
<tr>
<td>3: PCG</td>
</tr>
<tr>
<td>4: Village Fund</td>
</tr>
<tr>
<td>5: BAAC</td>
</tr>
<tr>
<td>6: Other Institution</td>
</tr>
<tr>
<td>7: Kin Relationship</td>
</tr>
<tr>
<td>8: Non-Kin Relationship</td>
</tr>
<tr>
<td>9: No Relationship</td>
</tr>
<tr>
<td>Total</td>
</tr>
</tbody>
</table>

There is evidence that a single household is borrowing and repaying multiple lenders during the same month. But the same result can also be generated if household \( i \) coincidentally borrows at the same time that household \( j \) repays. To distinguish the two cases, we further decompose the covariance across households \( i \in I \).

\[ B_{xt} = \sum_{i \in I} B_{ixt} \]

\[ R_{xt} = \sum_{i \in I} R_{iyt} \]

We calculate \( \text{Cov}(B_{ixt}, R_{iyt}) \) within household \( i \) for each \( x, y \) lender pair . We then sum this figure up across households. This process excludes the coincidental covariance \( \text{Cov}(B_{ixt}, R_{jyt}) \) generated by different households \( i \) and \( j \) going to the bank on the same month. Normalizing by \( \text{Cov}(B_{xt}, R_{yt}) \) from the previous table gives the portion of covariance generated within the households.
\[
Within(B_{xt}, R_{yt}) = \frac{\sum_{i \in I} Cov(B_{ixt}, R_{iyt})}{Cov(B_{xt}, R_{yt})}
\]

Above we list pairs from the previous table with a substantial amount of \(Cov(B_{xt}, R_{yt})\). In the next column, we list the percentage of covariation that occurs within the household. As equation (1) suggests, the product of the two column gives \(\sum_{i \in I} Cov(B_{ixt}, R_{iyt})\), in percentages.

Intra-household covariation accounts for 27% of the total covariation between total borrowing and total repayment. First, we consider our two main institutional lenders, BAAC and Village Fund. There is still substantial (10.6 and 6.3) intra-household covariance within-lender. But cross-covariance between these two lenders is negligible. BAAC still retains covariance with the informal lenders, while this is lost for Village Fund. Finally, the covariance that Commercial Bank Borrowing has with Repayment of BAAC and Village Fund disappears at the household level.

The covariance between borrowing and repayment is in part generated by the flow of credit between institutional lenders (BAAC, Village Fund) and informal lenders (Kin, Non-Kin).

Informal loans used to repay an institutional loan is pretty standard practice, and we observe this even in developed economies. Using the institutional loan to repay an informal loan is somewhat more surprising. Furthermore, the reciprocity raises a red flag, as it brings to mind household switching between institutional and informal loans indefinitely.

More puzzling is that for both the Village Fund and BAAC, the same household is borrowing from and repaying to the same institution on the same month! Because we collect data monthly, we cannot technically distinguish whether borrowing or repayment occurred first. The household could be perfectly solvent, repaying the lender after harvesting their crop, and immediately borrowing again to invest on next years crop. For BAAC, this could just be due to the peculiar way of recording loan restructuring, without money physically changing hands. For Village Fund, we find that the process is literal, with households borrowing a new loan from the Village Fund and use to repay an older Village Fund loan.
3. Matching Loans

As mentioned earlier, out of the 14,109 loans, there are 2,422 Repayment loans which purpose is solely or at least partly repay an older loan. We want to match these Repayment loans to the 'Target' Loans which it repays. This approach will allow us to exclude the solvent households whose borrowing coincidentally occurs after repayment on 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 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. A could also be used for other purposes apart from repayment, but there is no other loan other than Z is mentioned. In this case, we match A to be Z with the amount $\min(\text{Repay}_Z, \text{Borrow}_A)$.

- 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 $\min(\text{Repay}_Z, \text{Borrow}_A)$. We then move on to events that occur one month apart and match to B with remaining amount $\min(\text{Repay}_Z-\min(\text{Repay}_Z, \text{Borrow}_A), \text{Borrow}_B)$. Of course, this amount could be zero in which case no match is made. One could imagine more complicated case 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 $\min(\text{Repay}_Z, \text{Borrow}_A + \text{Borrow}_B)$ 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 on the same month, then we match $\min(\text{Repay}_Z + \text{Repay}_Y, \text{Borrow}_A)$ and attribute it to Z and Y proportionally.

- Multiple Repayment Loan and Multiple Target Loans: This is the most complex case and combines the two previous cases. Consider Loan A and B used to repay loan Y and Z.

\[ \frac{Borrow_A}{Borrow_A+Borrow_B} \min(\text{Repay}_Y, \text{Borrow}_A + \text{Borrow}_B) \] to A and \[ \frac{Borrow_B}{Borrow_A+Borrow_B} \min(\text{Repay}_Z, \text{Borrow}_A + \text{Borrow}_B) \] to B.

---

$^9$
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 \( \min(\text{Repay}_B, \text{Borrow}_Y) \) 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 \( \min(\text{Repay}_A, \text{Borrow}_Y - \min(\text{Repay}_B, \text{Borrow}_Y)) \) and a match between B and Z with amount \( \min(\text{Repay}_B - \min(\text{Repay}_B, \text{Borrow}_Y), \text{Borrow}_Z) \). 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 \( \min(\text{Repay}_A - \min(\text{Repay}_A, \text{Borrow}_Y - \min(\text{Repay}_B, \text{Borrow}_Y)), \text{Borrow}_Z - \min(\text{Repay}_B - \min(\text{Repay}_B, \text{Borrow}_Y), \text{Borrow}_Z)) \).

Example 2: let A and B be borrowed at t, Y and Z be borrowed at t. Then we shall match amount \( \min(\text{Repay}_A + \text{Repay}_B, \text{Borrow}_Y + \text{Borrow}_Z) \). We shall attribute to each pair an amount proportional to their product.\(^{10}\)

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 Loan 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 Loan and Multiple Target Loans. Because this is a much broader criterion, we only match borrowing and repayment that occurs within 1 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 dataset and generated 62.5 million baht in repayment flow.

<table>
<thead>
<tr>
<th>Repayment loan</th>
<th>(Flow of Repayment) % of Total (62.5 M Baht(^{11}))</th>
<th>Target Loan</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Agricultural Cooperative</td>
<td>BAAC</td>
</tr>
<tr>
<td>Agricultural Cooperative</td>
<td>0.3</td>
<td>0.0</td>
</tr>
<tr>
<td>BAAC</td>
<td>0.0</td>
<td>19.2</td>
</tr>
<tr>
<td>Commercial Bank</td>
<td>0.0</td>
<td>0.1</td>
</tr>
<tr>
<td>Other Institution</td>
<td>0.0</td>
<td>1.2</td>
</tr>
<tr>
<td>PCG</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Village Fund</td>
<td>0.1</td>
<td>0.8</td>
</tr>
<tr>
<td>Institution Total</td>
<td>0.5</td>
<td>21.3</td>
</tr>
<tr>
<td>Kin Relationship</td>
<td>0.0</td>
<td>4.7</td>
</tr>
<tr>
<td>Non-Kin Relationship</td>
<td>0.6</td>
<td>6.7</td>
</tr>
<tr>
<td>Informal Total</td>
<td>0.6</td>
<td>11.4</td>
</tr>
<tr>
<td>Total</td>
<td>1.1</td>
<td>32.7</td>
</tr>
</tbody>
</table>

\(^{10}\)For example the pair A,Y would get \( \frac{\text{Repay}_A + \text{Repay}_B}{(\text{Repay}_A + \text{Repay}_B) + (\text{Borrow}_Y + \text{Borrow}_Z)} \)
This table is consistent with the intra-household covariance table. Overall, exchanges between informal and institutional source are quite substantial at 38%, and also balanced (17% vs. 21%). The majority (54%) of the repayment flows within the institutional lenders, and these are mainly from within 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 figure surprising high because a rational 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) documents the restructuring process for the BAAC, and find that it is accompanied by state verification. Apart from verification cost, Households have other reasons to avoid verification. They might not be able to account for their investment, having instead consumed it. The household might have already received previous deferments from the lender and is not eligible for more.

To avoid verification, the insolvent household will mimic the behavior of a solvent household. He 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 credit refinancing chain versus Restructuring is to check whether repayment flows between lender or within lender. We graph below for each lender, the percentage of flow that happens within lender. The figure 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.

\[\text{Calculate by dividing the diagonal entry by the rightmost total entry in the table above.}\]
The figure for the Village Fund is unusually high. 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 the four provinces during the summer of 2011 and talked to the Village Fund loan officers. We find that a single Village Fund sometimes acts as two units separated by a Chinese wall, with one unit providing the Bridge loan for the household to overcome the liquidity constraint imposed by the other.

- By Government policy, Village Fund should only approve investment loans. The Government envisions financial access promoting growth through occupational choice as in Lloyd-Ellis Dan Bernhardt (2000). The primary investment is in agricultural inputs, which yield output within the year. The government thus stipulate a 12-month duration in the by-laws. The Government can audit the Village Fund’s cash account which is deposited at the BAAC. As loans are lent out, and repayment received, the cash account should change accordingly.

- To circumvent this policy, Village Fund officers will record loans as an investment; even when used for consumption.

- The Village Fund lends at a subsidized rate, so there is excess demand. It is not costly to verify adverse shocks because the village is tightly knit. Households in trouble are given priority in loan deferment. Households doing well are asked to repay their loans, which are then lent out to those in need.
- Village Fund officers do not want to officially defer loan repayment because he would need to explain to the government why he approved a loan that was consumed instead of invested. They 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 household can repay 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. Some Village Fund goes a step further. They help household avoid these fees by providing the Bridge loan by themselves. They set aside an amount (usually from the savings account household have with the Village Fund) and lend it off the books as a Bridge loan. These Village Funds boast to us on how they complete this task with such efficiency. They only need an amount equal to the biggest loan being deferred. The new loan can be approved within the same day that 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 necessarily malicious. The Village Funds have a relatively low verification cost, and thus is able to optimally allocate loans to the households in need. From this perspective, the villagers have invented a scheme to overcome the inflexible government rules.
3a. Duration of Repayment Loans

In this section, we will use duration types to classify between restructuring and credit refinancing chain. We have earlier indicated the high turnaround of the credit refinancing chain, with Bridge loan 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. For lack of a better word, we shall define the remaining loans as medium-term loans, with the understanding that most of these loans have one-year duration. We can classify the repayment flow by the duration of the Repayment Loan and Target Loan, which has four possibilities. We can also check whether the repayment flows fits into the credit refinancing chain. This is done by pairing short ← medium and medium ← short repayments that share the same short-term loan.

<table>
<thead>
<tr>
<th>(Flow of Repayment)</th>
<th>Credit Chain</th>
<th>Not Credit Chain</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medium ← Medium</td>
<td>0.6</td>
<td>41.1</td>
<td>41.7</td>
</tr>
<tr>
<td>Short ← Medium</td>
<td>26.0</td>
<td>1.6</td>
<td>27.5</td>
</tr>
<tr>
<td>Medium ← Short</td>
<td>26.0</td>
<td>4.6</td>
<td>30.6</td>
</tr>
<tr>
<td>Short ← Short</td>
<td>0.0</td>
<td>0.2</td>
<td>0.2</td>
</tr>
<tr>
<td>Total</td>
<td>52.5</td>
<td>47.5</td>
<td>100</td>
</tr>
</tbody>
</table>

short ← 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 ← short, bridge ← medium new. We were able to pair most of short ← medium and medium ← short to form parts of the credit refinancing chain. The unpaired flows might be due to household forgetting to report the other part of the pair. There is more unpaired medium ← short than short ← medium. It is plausible that the households only intend to defer a medium-term loan for a few months. We also find that a small portion medium ← medium occurs during the duration of the short bridge loan and we classified it as part of a more complicated credit refinancing chain illustrated below. In general, medium ← medium flows are not in the credit refinancing chain and are associated with formal restructuring.

We formally define Restructuring as repayment flows that occur within the same lender but is not part of the credit refinancing chain. Although we do not restrict duration type, we find that almost all restructuring are medium ← medium, with a small portion of medium ← short. This is natural as the lender will either allow the household to defer repayment by either a year or a few months. We quantify restructuring in the following way:

1288% takes zero month, and 6% takes one month. Cases with longer time are usually when the borrowed loan is only used to pay a part of the Target loan.
\{Restructuring\} = \{WithinLender\} \setminus \{CreditChain\}

\rightarrow |\{Restructuring\}| = |\{WithinLender\}| - |\{WithinLender\} \cap \{CreditChain\}|

For Village Fund, we find that $|\{WithinLender\} \cap \{CreditChain\}|$ is 67.2% of repayment flow. We earlier found that Village Fund has 72.9% flow within lender. This implies that only 5.7% is restructuring. For other lenders, the $|\{WithinLender\} \cap \{CreditChain\}|$ should be zero, but in practice, due to misreporting we see a negligible amount. In the table below, we tabulate repayment flow by across lender and duration type. We also list the percentage of repayment flow classified as credit refinancing chain and Restructuring. They two are mutually exclusive by construction.

<table>
<thead>
<tr>
<th>Repaymen Loan Lender</th>
<th>Medium→Medium</th>
<th>Short←Medium</th>
<th>Medium→Short</th>
<th>Short←Short</th>
<th>Total Flow (Million Baht)</th>
<th>Credit Chain %</th>
<th>Restructuring %</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAAC</td>
<td>69.5</td>
<td>25.2</td>
<td>5.2</td>
<td>0.1</td>
<td>20.1</td>
<td>23.1</td>
<td>59.2</td>
</tr>
<tr>
<td>Village Fund</td>
<td>14.2</td>
<td>55.4</td>
<td>30.4</td>
<td>0.4</td>
<td>19.8</td>
<td>54.2</td>
<td>5.2</td>
</tr>
<tr>
<td>Institution Total</td>
<td>39.4</td>
<td>37.5</td>
<td>17.6</td>
<td>0.3</td>
<td>44.5</td>
<td>54.7</td>
<td>33.5</td>
</tr>
<tr>
<td>Kin Relationship</td>
<td>64.9</td>
<td>0.9</td>
<td>34.1</td>
<td>0.1</td>
<td>8.4</td>
<td>28.1</td>
<td>25.5</td>
</tr>
<tr>
<td>Non-Kin Relationship</td>
<td>16.9</td>
<td>1</td>
<td>82</td>
<td>0.1</td>
<td>9.1</td>
<td>73.8</td>
<td>7.6</td>
</tr>
<tr>
<td>Informal Total</td>
<td>39.9</td>
<td>1</td>
<td>59.1</td>
<td>0.1</td>
<td>17.5</td>
<td>49.1</td>
<td>16.8</td>
</tr>
<tr>
<td>Total</td>
<td>41.5</td>
<td>27.6</td>
<td>30.7</td>
<td>0.2</td>
<td>61.9</td>
<td>53</td>
<td>28.8</td>
</tr>
</tbody>
</table>

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

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 pretty lenient with its borrowers. It makes sense for the household to first try formal restructuring and use 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 are typically an informal method 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 institution verify income before granting deferment. It is not yet clear the extent in 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 (control
with credit line/wealth effect). But an improvement in these metrics on the part of the financial institution should be associated with improvement in risk sharing outcome for the households in the network. We develop the theoretical framework relating financial access to risk sharing in appendix A, and derive the risk sharing equation in section 4.

Our paper will focus on the risk sharing outcome of consumption and not investment. At first glance, one might suspect that these Repayment loans should also benefit investment smoothing. By allowing for these one-year loans to be deferred, the financial institution effectively turn an illiquid asset into a liquid liability. This fulfills the role of the bank as envisioned in Diamond and Dybvig (1983). However, we find that deferment is more commonly used on consumption loan. The table below compares the distribution over the purpose for the entire loan set versus the subset of Target Loans. We find that majority of Target loans are themselves Repayment loan. 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 have to look at the subset that is a Target Loan but NOT a Repayment to find the Original loan of each chain. For these loans, we see that the investment categories is small compared to consumption (6.0%, 5.3%, 4.5% vs. 37.9%). Investment loans have a larger size and longer ex-ante duration in the first place, so that deferment is not required/allowed.

<table>
<thead>
<tr>
<th>(Loan Purpose)</th>
<th>Repay Loan</th>
<th>B - agriculture input</th>
<th>C - livestock</th>
<th>E - business investment</th>
<th>J - consumption</th>
<th>O - other</th>
</tr>
</thead>
<tbody>
<tr>
<td>% of Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1999-2006 Loans</td>
<td>16.6</td>
<td>7.4</td>
<td>4.5</td>
<td>9</td>
<td>26</td>
<td>36.5</td>
</tr>
<tr>
<td>Target Loans</td>
<td>51.4</td>
<td>2.9</td>
<td>2.6</td>
<td>2.2</td>
<td>18.4</td>
<td>22.5</td>
</tr>
<tr>
<td>Target Loan (Excluding Repay Loan)</td>
<td>6.0</td>
<td>5.3</td>
<td>4.5</td>
<td>37.9</td>
<td>46.3</td>
<td></td>
</tr>
</tbody>
</table>
4. Risk Sharing Equation

In Appendix A, we illustrate through a simple three-period model how risk sharing continuously improves as the household moves from i) autarky, ii) savings only, iii) savings and borrowing, 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. 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 in household specific transaction costs and verification costs, which along with risk aversion, allows for heterogeneity in risk sharing results.

The economy consists of $J$ Networks, each with $I_J$ agents. $^{13}$ We abstract from labor decisions by excluding leisure from the model. $^{14}$ We define the following household lifetime utility:

$$U_i = \sum t \sum s t \beta^t_i u_i(c_i(s^t)) \text{ for all } i \in I_J, all J$$

We allow for heterogeneous discount rate, as well as heterogeneous risk aversion $\gamma_i$ in CARA utility:

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

The household can borrow a one period loan $b_i(s^t)$ at interest rate $R$. This generalize into lending, in which case $b_i(s^t) \leq 0$. The household’s income is private information, but the network achieves truth telling by allowing state verification as in Townsend (1979). The total verification cost 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 $\nu_i(b_i(s^t))$ and $\nu_k(b_k(s^t))$ per Townsend (1978). Theoretically, we want to distinguish these two costs, but in practice the financial fees are not separated into categories, and sometimes even combined into the interest rates. We will combine the two costs into a single term which vary with $b_i(s^t)$ in the following fashion:

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

$^{13}$The adjusted income variable is $y_i(s^t)$

$^{14}$A weaker assumption of linear separability will achieve the same result.
This is a departure from the fixed cost models of Townsend (1978) and Townsend (1979). In these settings, the household would borrow a single loan, which is subject to a single transaction cost and a single \textit{ex-ante} expected verification cost. In our setting, there is an artificial policy limit of loan size to 10,000 baht. So as \( b_i(s^t) \) increases, the number of transactions increases, and for each transaction the verification and transaction costs. Furthermore, the borrower and lender will endogenously transact with the counterparty that generates the least cost (e.g. kin before non-kin; village fund before BAAC), so that the cost function is convex in \( b_i(s^t) \). See that the cost function is symmetric in borrowing and lending. This 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. Note that one of the counterparties might be a financial institution, which we assume to have \( \phi = 0 \). The framework allows for autarky as an extreme case with \( \phi_i \to \infty \). The household budget constraint is given below. Note that we adjust\(^{16}\) income for depreciation and saving.

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

For simplicity, we shall assume\(^{17}\) 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 the network \( J \) resource constraint:

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

A nuanced part of this sequential problem is the transversality condition. The standard household transversality condition is

\[
\lim_{t \to \infty} \beta^t b_i(s^t)u'(c_i(s^t)) = 0 \text{ for all } i \in I_J, \text{ all } J
\]

This condition is usually viewed as a restriction against evergreening. But in our model, this condition actually prevent full risk sharing because with the condition in place, consumption can only be smoothed intertemporally as in PIH. For loans to be state-contingent, it must be possible to take out a loan in the final period and not repay it at all. The appropriate transversality condition is instead at the network level, which is automatically satisfied by the zero net borrowing condition. With this in mind, let \( \lambda_{j,t} \) be the Lagrange multiplier corresponding to the Network \( J \) resource constraint and \( \alpha_i \) be the Pareto weight of household \( i \). We solve for the first order condition of the Pareto problem with respect to \( c_i(s^t) \):

\(^{15}\) It is not that they don’t bear the cost, but they are able to push it all towards the household

\(^{16}\)This is because we are more interested in testing for risk sharing across household, rather than intertemporal smoothing. The adjustment allows us to avoid dealing with intertemporal decisions. We understand that intertemporal decision are endogenous, but hope that this process will disentangle intertemporal transfer from risk sharing between households.

\(^{17}\)more generally, we can allow it to be a time varying variable, as long it does not grow too fast
\[ \alpha_i \beta_i^t \gamma_i e^{-\gamma_i c_i(s^t)} = \lambda_{jst} (1 + \phi b_i(s^t)) \frac{\partial b_i(s^t)}{\partial c_i(s^t)} \]
\[ \approx \lambda_{jst} (1 + \phi b_i(s^t)) \]
\[ \rightarrow -\gamma_i c_i(s^t) + \log(\alpha_i \beta_i^t \gamma_i) \approx \log \lambda_{jst} + \phi b_i(s^t) \]
\[ \approx \log \lambda_{jst} + \phi [c_i(s^t) - y_i(s^t) + (R)b_i(s^{t-1})] \]

We assume that \( \frac{\phi_i}{\gamma_i + \phi_i} \) is relatively small so that \( \frac{\partial b_i(s^t)}{\partial c_i(s^t)} \) is approximately one. Next, take log on both sides and take the linear approximation of \( \log(1 + \phi b_i(s^t)) \) around 1. Finally we solve for \( c_i(s^t) \). For simplicity \( (R_2)b_i(s^{t-1}) \) will be omitted with the understanding that \( y_i(s^t) \) is now adjusted for loan repayments. In the risk sharing equation, consumption will depend directly on income, and therefore there is only partial insurance.

\[ c_i(s^t) \approx \frac{1}{\gamma_i + \phi_i} \log \alpha_i \gamma_i + \frac{t}{\gamma_i + \phi_i} \log \beta_i - \frac{1}{\gamma_i + \phi_i} \log \lambda_{jst} + \frac{\phi_i}{\gamma_i + \phi_i} y_i(s^t) \]  

(2)

\( \phi_i \) and \( \gamma \) together determine the degree of this dependency. 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 \( \gamma_i \). Risk averse households are willing to pay cost \( \phi_i \) to achieve smooth consumption. Risk tolerant households are willing to suffer consumption fluctuation to save on transfer cost. For a risk neutral household, \( \gamma_i = 0 \) and consumption moves one-to-one with income, as they are not affected by consumption shocks. The household that have more financial access should, all else equal, have a lower \( \phi_i \) and thus a lower income coefficient. The model can distinguish whether a smooth consumption arises from low transaction/verification cost or risk aversion.

After Deaton’s critique (1990), it has become fashionable to control for \( \lambda_{jst} \) with fixed effect for each risk sharing group. An example of this application on the dataset is Kinnan and Townsend (2012). But, with the heterogeneity in our model, OLS cannot estimate the equation, because \( \log \lambda_{jst} \) is not known. The term depends on both \( i \) and \( t \), and thus we cannot control for it using fixed or time effect. In previous papers, the general solution to this issue is to first estimate \( \gamma_i + \phi_i \). They then isolate \( \lambda_{jst} \) and control for it with fixed effect.

Schulhofer-Wohl (2011) assumes that \( \frac{\phi_i}{\gamma_i + \phi_i} \) is constant, which allows him to estimate \( \gamma_i \) through factor analysis. Townsend et al. (2014) estimates \( \gamma_i \) under the null hypothesis \( \phi_i = 0 \) using GMM.

These methods are not satisfactory for our current application because we want to measure \( \phi_i \) varying over \( i \). We take an alternative approach and proceed by solving for \( \lambda_{jst} \) in the spirit of Townsend (1994) and Mace (1991). We sum equation (2) across \( i \in J \) households and solve for \( \lambda_{jst} \).

We also take a time difference to remove the fixed effect term.

\[ \Delta c_i(s^t) \approx \frac{\phi_i}{\gamma_i + \phi_i} \Delta y(s^t) + \frac{1}{\gamma_i + \phi_i} \log \beta_i - \frac{1}{\gamma_i + \phi_i} \Delta \log \lambda_{jst} \]  

(3)

\[ \Delta \log \lambda_{jst} \sum_i \frac{1}{\gamma_i + \phi_i} \approx \Delta \sum_i \frac{\phi_i y_i(s^t)}{\gamma_i + \phi_i} + \sum_i \frac{\log \beta_i}{\gamma_i + \phi_i} - \Delta \sum_i c_i(s^t) \]
\[
\frac{\Delta \log \lambda_{j,t}}{\gamma_i + \phi_i} \approx \frac{\Delta \sum_i \phi_i y_i(s^t) + \sum_i \log \beta_i}{\gamma_i + \phi_i} - \Delta \sum_i c_i(s^t)
\]

Substitute \(\Delta \log \lambda_{j,t}\) back into equation (3) and rearrange

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

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

Our goal is to estimate the coefficient of \(\Delta y_i(s^t)\), and thus will need to control for the covariates.

- \(\frac{1}{\gamma_i + \phi_i} \left[ \log \beta_i - \sum_i \log \beta_i \right]\) 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 \(\frac{\phi_i}{\gamma_i + \phi_i}\), which will allow estimation, giving us an estimate of \(\frac{\phi_i}{\gamma_i + \phi_i}\) from the slope of \(\Delta \log y_i(s^t)\). However, \(\Delta \sum_i \frac{\phi_i y_i(s^t)}{\gamma_i + \phi_i}\) is not correctly measured, and the error is likely correlated with \(\Delta \log y_i(s^t)\), so there will be omitted variable bias. 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 hope that this will reduce omitted variable bias and in turn provide an improved estimate for \(\frac{\phi_i}{\gamma_i + \phi_i}\). We shall then iterate the regression until \(\frac{\phi_i}{\gamma_i + \phi_i}\) converges for all \(i\) households. The OLS equation on actual \(s^t\) realizations \(c_{it}\) and \(y_{it}\) is as follows:

\[
\Delta c_{it} = k_i + \delta_{1t} \Delta y_{it} + \delta_{2t} \Delta \sum_i c_{it} + \delta_{3t} \Delta \sum_i \frac{\phi_i y_{it}}{\gamma_i + \phi_i} + \varepsilon_{it}
\]

\(\varepsilon_{it}\) is the error term that represents approximation error, measurement error, as well as other shocks not included in the model. We cannot rule out the possibility that \(\varepsilon_{it}\) correlates across households \(i\) in \(I_J\). Since the coefficients are not common across the households, we can run OLS on equation (4) household-by-household. The correlation in \(\varepsilon_{it}\) does not prevent consistent estimates for both the coefficients and the co-variance matrix. But, seemingly unrelated regressions (SUR) is more efficient. Unfortunately, it is not feasible to estimate SUR in this scenario because we have more households than time periods. This is true even if we limit correlation to be within the network risk sharing group (\(I_J > T\)).
To estimate the CARA, we follow the portfolio choice method of Mehra and Prescott (1985). We mirror our strategy to that of Chiappori, Samphantarak, Shulhofer-Wohl (2013), which uses the same data set to estimate CRRA. Sripakdeeveong (2015) provides a detailed derivation. 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, Pawsutipaisit, and Townsend (2012) find that households hold large amount of cash, so that the risk-free rate of return is 1. This bounds CARA for each household to:

$$\hat{\gamma} = -\frac{\hat{E}[R_{t+1}^P] - 1}{\hat{\sigma}_{\Delta c} \hat{\sigma}_{\Delta R_{t+1}^P}} \text{Corr}[e^{\alpha(x_t^* - x_{t+1}^*)}, R_{t+1}^P]$$

(5)

- $\hat{E}[R_{t+1}^P]$ is expected return of household’s portfolio
- $\hat{\sigma}$ is the portfolio’s standard deviation
- $\hat{\sigma}_{\Delta c}$ is household’s consumption standard deviation
- $e^{-\alpha(x_{t+1}^* - x_t^*)}$ is the growth in marginal utility of consumption.

It is natural that $\text{Corr}[e^{\alpha(x_t^* - x_{t+1}^*)}, R_{t+1}^P] < 0$ 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 outperform holding cash, we find that $\hat{\gamma} \in [0, \frac{\hat{E}[R_{t+1}^P] - 1}{\hat{\sigma}_{\Delta c} \hat{\sigma}_{\Delta R_{t+1}^P}}]$. To pin down the value for $\hat{\gamma}$, we must further assume that households obtain the theoretical bound $\text{Corr}[e^{\alpha(x_t^* - x_{t+1}^*)}, R_{t+1}^P] = -1$. If this assumption does not hold, then we overestimate $\alpha$. Finally, we get standard error for $\hat{\gamma_i}$ by running bootstrap with replacement on blocks of 12 months. Finally, we use method of moments to back out an estimate for transaction cost $\phi_i$ by combining estimates on CARA $\hat{\gamma_i}$ and regression coefficient $\hat{\delta_{1i}}$.

---

18 This potentially creates a systemic bias. The assumption is more likely to hold for households with better access to complete market (low $\phi_i$)
5. 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. As a starting point, we will first present regression results that follow this methodology. The regression equation from section 4 is reproduced below:

\[
\Delta c_{it} = k_i + \delta_{1i} \Delta y_{it} + \delta_{2i} \Delta \sum_i c_{it} + \delta_{3i} \Delta \frac{\phi_i y_{it}}{\gamma_i + \phi_i} + \epsilon_{it}
\]

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 the table below. 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.

**Consumption Risk Sharing Regression**

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\Delta c_{it})</td>
<td>0.0151***</td>
<td>0.00278</td>
<td>0.00278</td>
<td>0.00280</td>
</tr>
<tr>
<td></td>
<td>(3.42)</td>
<td>(1.43)</td>
<td>(1.43)</td>
<td>(1.45)</td>
</tr>
<tr>
<td>[l_{Borrow} \times \Delta y_{it}]</td>
<td>0.0129**</td>
<td>0.0132*</td>
<td>0.0132*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.61)</td>
<td>(2.09)</td>
<td>(2.08)</td>
<td></td>
</tr>
<tr>
<td>[l_{Contingent} \times D.Net]</td>
<td>-0.000978</td>
<td></td>
<td>0.0105</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-0.12)</td>
<td>(1.14)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>[l_{Chain} \times D.Net]</td>
<td>-0.0239**</td>
<td></td>
<td></td>
<td>-0.0239**</td>
</tr>
<tr>
<td></td>
<td>(-3.25)</td>
<td></td>
<td></td>
<td>(-3.25)</td>
</tr>
<tr>
<td>(r^2_a)</td>
<td>0.00419</td>
<td>0.00433</td>
<td>0.00431</td>
<td>0.00509</td>
</tr>
<tr>
<td>(N)</td>
<td>59371</td>
<td>59371</td>
<td>59371</td>
<td>59371</td>
</tr>
<tr>
<td><strong>t statistics in parentheses</strong></td>
<td><em><em>&quot;</em> (p&lt;0.05)</em>*</td>
<td><strong>&quot;</strong> (p&lt;0.01)**</td>
<td>*** (p&lt;0.001)**</td>
<td></td>
</tr>
</tbody>
</table>

In the first column, we assume that the income coefficient \(\frac{\phi_i}{\gamma_i + \phi_i}\) 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%) \(^{19}\) and non-borrowers (6%). Note that being in the same

\(^{19}\)We define this as a household that has borrowed at least once during the survey.
'group' does not mean that households in different Tambons are sharing risk. We merely allow them to have the same income coefficient \( \frac{\phi_i}{\gamma_i+\phi_i} \). 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 (1991). 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 uses restructuring (12%) and those that uses BOTH credit refinancing chain and restructuring (40%). The relationship is represented in the equation below. Note the implication that household that uses credit refinancing chain is a subset of household that uses restructuring.

\[
[I\text{-Contingent}] = [I\text{-Restructuring}] \cup [I\text{-Chain}] = [I\text{-Restructuring}]
\rightarrow
[I\text{-Chain}] \subseteq [I\text{-Restructuring}]
\]

The regression table shows that using state-contingent loans does not affect the income coefficient. However, the subgroup that uses credit refinancing chain has a significantly lower income coefficient. The improvement in risk sharing is hardly surprising, as state-contingency contribute towards complete markets.

But, it is not yet clear why the restructuring scheme does not provide the same benefit. To further understand what makes the credit refinancing chain special, we move beyond the homogeneous model and investigate the income coefficient \( \hat{\delta}_i \) instead at the household level. The histograms of the coefficients are plotted below. Recall that \( \hat{\phi}_i \) is estimated from \( \hat{\delta}_i = \frac{\hat{\phi}_i}{\gamma_i+\hat{\phi}_i} \) and \( \hat{\gamma}_i \) by using the method of moments. We exclude 20 households that either has \( \hat{\delta}_{1i} < 0 \) or \( \hat{\gamma}_i < 0^{20} \).

---

\footnote{The presence of estimates outside the range restricted by the model is possible due to small sample.}
With household level coefficients, we can distinguish whether a high $\delta_i$ is due to high cost $\phi_i$ or low risk-aversion $\gamma_i$. Furthermore, we can investigate how these two factors vary with financial access by running a regression against group indicators. The results are presented in the table below. Since the dependent variables are themselves estimates, we also run the weighted regression, using as weight the inverse of the estimated variance. In interpreting the result, keep in mind that credit refinancing chain users are a subset of contingent loans users, which is itself a subset of borrowers.

<table>
<thead>
<tr>
<th></th>
<th>Income Coefficient $\delta_i$</th>
<th>CARA $\gamma_i$</th>
<th>Cost Parameter $\phi_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>weighted</td>
<td>OLS</td>
</tr>
<tr>
<td>I.Borrow</td>
<td>0.00640*</td>
<td>0.00563</td>
<td>-0.550***</td>
</tr>
<tr>
<td></td>
<td>(1.97)</td>
<td>(1.58)</td>
<td>(-5.17)</td>
</tr>
<tr>
<td>I.Contingent</td>
<td>-0.00188</td>
<td>-0.00204</td>
<td>-0.128</td>
</tr>
<tr>
<td></td>
<td>(-0.77)</td>
<td>(-0.89)</td>
<td>(-1.60)</td>
</tr>
<tr>
<td>I.Chain</td>
<td>-0.0105***</td>
<td>-0.0101***</td>
<td>-0.0587</td>
</tr>
<tr>
<td></td>
<td>(-4.29)</td>
<td>(-4.48)</td>
<td>(-0.73)</td>
</tr>
<tr>
<td>r2_a</td>
<td>0.113</td>
<td>0.132</td>
<td>0.0980</td>
</tr>
<tr>
<td>N</td>
<td>475</td>
<td>475</td>
<td>475</td>
</tr>
<tr>
<td>t statistics in parentheses</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The result of the $\delta_i$ regression is consistent with the result of the pooled (homogeneous) risk-sharing regression. Borrowing is associated with higher income coefficient, and within borrowers, the credit refinancing chain is associated with lower income coefficient. From the $\gamma_i$ regression, we see that borrowers are more risk-tolerant than non-borrowers. Additionally, from the weighted $\phi_i$ 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 $\phi_i$ regression shows access to credit refinancing loan is associated with lower transaction/verification cost, beyond that of normal borrowing. When $\phi_i$ is close to zero, even risk-tolerant households can enjoy full risk sharing. This explains why household with access to credit refinance have smooth consumption, despite being relatively risk-tolerant.

It is not surprising that users of the credit refinancing chain enjoy the lowest cost $\phi_i$. 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. Finally, given the complexity of the credit refinancing chain, we do not rule out the possibility the savviest household self-select into using it.
6. Conclusion

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 is then broken down between lenders and across households. The surprising 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 tedious but creative matching algorithms. In particular, we can distinguish it from the standard restructuring process, which like credit refinancing chain, also allows for state-contingent deferment/repayment. Along the way, we document the unorthodox Chinese wall within Village Funds, which allows for the entire credit refinancing chain to occur within the same lender.

From the theory side, we illustrate through a simple three-period model how risk sharing continuously improves as the household moves from i) autarky, ii) savings only, iii) savings and borrowing, to iv) state-contingent borrowing. We test the model’s prediction empirically by estimating the risk-sharing income coefficient across groups with the varying level of financial access; the credit refinancing chain being the highest level. As predicted, users of the credit refinancing chains have the smoothest consumption against income shocks. Meanwhile, at first glance, it seems that general borrowing is detrimental towards risk-sharing. This motivated us to extend the risk sharing regression to allow for heterogeneity in both the transaction/verification costs as well as the coefficient of risk aversion. This allows us to deduce 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-adverse individual can enjoy full insurance.

This paper illustrates the synergy between theory and empirics. We postulate 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 risk sharing.
Appendix A. Risk Sharing Theory

To understand the benefits of borrowing along with state-contingent loan deferment, we shall first refresh the reader with a basic pure exchange economy under uncertainty. There are three dates \( T = 0, 1, 2 \) and two agents \( I = 1, 2 \). For simplicity we shall assume that at \( t = 0 \), there is no consumption and income. There is also no uncertainty so that there is only one state \( S_0 = 0 \). For \( t \in \{1, 2\} \), there are two states \( S_t = a, b \). As such there shall be 1 history node at \( S^0 = 0 \), 2 nodes at \( S^1 = (0, a), (0, b) \), and 4 nodes at \( S^2 = (0, a, a), (0, a, b), (0, b, a), (0, b, b) \). We shall assume that there is no dependence between state across time, so the histories have the following probability.

\[
\pi(s^t) = \begin{cases} 
\pi(0) & s^t=(0) \\
\pi(a) & s^t=(0,a) \\
\pi(b) & s^t=(0,b) \\
\pi(a)\pi(b) & s^t=(0,b,a) \text{ or } s^t=(0,a,b) \\
\pi(b)^2 & s^t=(0,a,a) \text{ or } s^t=(0,a,a) \\
\pi(a)^2 & s^t=(0,a,a) \text{ or } s^t=(0,a,a) 
\end{cases}
\]

Income \( y_i(s_t) \) is state dependent with

\[
y_i(s_t) = \begin{cases} 
1 & i=1 \text{ and } s_t=a \\
0 & i=2 \text{ and } s_t=a \\
0 & i=1 \text{ and } s_t=b \\
1 & i=2 \text{ and } s_t=b 
\end{cases}
\]

See that \( y_1(s_t) + y_2(s_t) = 1 \), so that there is no aggregate uncertainty. For now we shall have homogeneous discount rate \( \beta \) and Bernoulli utility function \( u(c_i(s^t)) \). For all \( i \in I \), household \( i \) lifetime utility is given by

\[
U_i = \sum \sum s^t \pi(s^t) \beta^t u(c_i(s^t))
\]

Define household \( i \) Pareto weight as \( \alpha_i \). The Pareto problem is given by

\[
\max_{c_i(s^t)} \int_\alpha_i U_i
\]

subjected to the market clearing condition with Lagrange multiplier \( \lambda(s^t) \)
\[
\int_i c_i(s^t) = \int_i y_i(s^t)
\]

Note that we have not allowed for any storage or investment technology. As such, resource cannot be transferred across \( s^t \) at the aggregate level. This makes it very clear that this problem can be solved pointwise at each \( s^t \)

\[
\max_{c_i(s^t)} \int_i \alpha_i u(c_i(s^t))
\]

\[
c_i(s^t) = Y(s^t)
\]

We see that \( Y(s^t) \) encodes the entire information from \( s^t \). Also note that \( \pi(s^t) \) does not appear. Excluding \( s_t = (0) \), the remaining histories all have the same aggregate income, so the Pareto optimum allocation must be sunspot free with a constant \( c_i(s^t) = c_i^* \). \(^{21}\) For tractability, we shall now assume a CARA form for \( u(c_i(s^t)) \) and solve out the actual allocation function.

\[
u(c_i(s^t)) = 1 - e^{-\gamma c_i(s^t)}
\]

\[
\alpha_i \gamma e^{-\gamma c_i(s^t)} = \lambda(s^t)
\]

\[
\rightarrow \log \alpha_i + \log \gamma - \gamma c_i(s^t) = \log \lambda(s^t)
\]

\[
\rightarrow c_i(s^t) = \frac{\log \alpha_i + \log \gamma - \log \lambda(s^t)}{\gamma}
\]

\[
\rightarrow \gamma C(s^t) = \int_i \left[ \log \alpha_i + \log \gamma - \log \lambda(s^t) \right]
\]

\[
\rightarrow \log \lambda(s^t) = \int_i \left[ \log \alpha_i + \log \gamma \right] - \gamma C(s^t)
\]

\[
\rightarrow c_i(s^t) = \frac{\log \alpha_i - (\log \alpha_1 + \log \alpha_2)/2 + C(s^t)}{\gamma} + \frac{C(s^t)}{2}
\]

We shall call this \( c_i(s^t) = g_i(C(s^t)) \). Note that we have achieved a full risk-sharing, since individual income is not present in the equation. Of course, there is no intertemporal consumption smoothing at the aggregate level, but the allocation is constrained Pareto optimal given the lack of technology. Next, we will add in a price-taking firm with linear investment technologies. For an investment of \( k(s^t) \) at \( s^t \), the firm generates \( Rk(s^t) \) on all successor \( s^{t+1}|s^t \). To be clear, it is not possible to transfer to another history branch (e.g. \( s^t = (0, a) \) to \( s^t = (0, b, a) \) is not possible). To be precise there is a separate technology at each node \( s^t \) (indexed by the subscript) with the following feasibility set

\(^{21}\)If this were not the case, then by the concavity of \( u(c_i(s^t)) \), there is a Pareto improvement from consuming instead the average, \( \bar{c}_i = \frac{\sum s_{t+1} c_i(s^t)}{\sum s_{t+1}} \).
The resource constraint now includes production

\[ Rk_{st}(s^t) + k_{st}(s^{t+1}|s^t) = 0 \text{ for all } s^t \]

We can simplify this by substituting in the production function

\[ \int_i c_i(s^t) = \int_i y_i(s^t) + k_{st}(s^t) + k_{st-1}(s^t) \]

In this form, the subscript will always match the argument, so for brevity we can drop the the subscript

\[ \int_i c_i(s^t) = \int_i y_i(s^t) + k(s^t) - Rk(s^{t-1}) \]

We want to be clear about how access to financial assets affects consumption smoothing, so it is important to note that individual household can only access consumption smoothing through the market or central planner. We will not allow household to store/invest by itself in autarky, because access to such technologies mimics the effect of financial access. The Pareto problem now maximizes with respect to both \( c_i(s^t) \) and \( k(s^t) \)

\[ \max_{c_i(s^t), k(s^t)} \int_i \alpha_i U_i \]

We shall purposely add a choice variable \( C(s^t) \) and the constraint \( \int_i c_i(s^t) = C(s^t) \). This will allow us to decompose the problem into the problem two subproblem, one which we already solved.

\[ \max_{C(s^t), k(s^t)} \sum_t \sum_{s^t} \pi(s^t) \beta^t \max_{c_i(s^t)} \int_i \alpha_i u(G_i(C(s^t))) \]

\[ \int_i c_i(s^t) = C(s^t) \]

\[ C(s^t) = \int_i y_i(s^t) + k(s^t) - Rk(s^{t-1}) \]

We already solved the consumption allocation problem given \( C(s^t) \), so the problem reduces to

\[ \max_{C(s^t), k(s^t)} \sum_t \sum_{s^t} \pi(s^t) \beta^t \int_i \alpha_i u(g_i(C(s^t))) \]
\[\pi(s^t)C(s^t) = \pi(s^t) \left[ \int y_i(s^t) + k(s^t) - Rk(s^{t-1}) \right] \]

The risk sharing equation \(g_t(C(s^t))\) is still the same. The only difference is that \(C(s^t)\) is now allocated optimally across period. The first order condition with respect to \(C(s^t)\)

\[
\beta^t \int_{1}^{\alpha_t} e^{-\gamma_1(C(s^t))} \frac{\gamma e^{-\gamma}}{\int_{1}^{\alpha_t}} = \mu(s^t)
\]

\[
\beta^t e^{-\gamma C(s^t)/I_{t+1}} \left[ \int_{1}^{\alpha_t} e^{-[\log_1 - (\log_1 + \log_2)/2]} \right] = \mu(s^t)
\]

\[
\mu(s^t) = E[R\mu(s^{t+1})|s^t] = E_t[R\mu(s^{t+1})]
\]

We know that there is no aggregate uncertainty in \(C(s^t)\) so this reduces to

\[
\mu(s^t) = R\mu(s^{t+1})|f_{s^t+1} = (s^t, s_{t+1})
\]

\[
e^{-\gamma C(s^t)/f_{s^t+1}} = R\beta e^{-\gamma C(s^{t+1})/f_{s^t+1}}
\]

\[
C(s^t) = -\frac{\log(R\beta)}{\gamma} + C(s^{t+1})
\]

\[
Y(s^1) - k(s^1) = -\frac{\log(R\beta)}{\gamma} + Y(s^2) + Rk(s^1)
\]

\[
k(s^1) = \frac{\log(R\beta)}{\gamma(R+1)}
\]

\[
C(s^1) = 1 - \frac{\log(R\beta)}{(R+1)\gamma}
\]

\[
C(s^2) = 1 + \frac{R\log(R\beta)}{\gamma(R+1)}
\]

**Price Equilibrium:**
By second welfare theorem, the Pareto optima can be supported as a price equilibrium with transfer. However, it is hard to imagine that the rural economy have access to contingent commodities. Even in our simple economy where the numerae is consumed directly, there would still be six commodities, one for each $s^{t}$. Instead we shall consider Radner equilibrium under different level of financial access (asset availability). We shall find that with access to loan with contingent deferment in addition to traditional saving, the Pareto optima can be supported. This is not surprising since at each time period there is only two states $s_{t}$, so it is possible to achieve complete asset structure with only two (linearly independent) assets. In such case, the Radner equilibrium is equivalent to Arrow-Debreu equilibrium and is therefore Pareto optimal. We demonstrate this for our economy by investigating how consumption changes as we increase asset availability from autarky starting point.

**Autarky**

In the Radner equilibrium, household has access to spot market, one for each $s^{t}$. As such the household faces seven budget constraint, one for each $s^{t}$. There is only one consumption good in our model, so no spot trading takes place. The spot market can be augmented by financial market, which provide instrument for agent to redistribute income across $s^{t}$. We first consider the Autarky case, where the financial market does not exist. In this case, consumption simply equals income for each $s^{t}$.

$$c_{t}(s^{t}) = y_{t}(s^{t})$$

**Savings and Borrowing**

Allowing for Savings and Borrowing yield the standard result from the PIH literature.

Consumption is affected by temporary income shock. This dependency is greatest in the last period, and diminish as the number of future period grows, but does not completely disappear even at the limit. The income dependency is clear in our model since it only has 2 consumption periods. Furthermore as shown in Caballero (1990), there is precautionary saving, and thus consumption is skewed towards period 2 compared to the certainty equivalent.

Borrowing and Savings has linearly dependent return vector, so one would be redundant if we were to introduce both. Instead we shall only introduce the asset $a_{st}$, which yield 1 unit of consumption in all successor nodes $s^{t+1} = (s^{t}, s_{t+1})$, with the understanding that $a_{st} < 0$ indicate borrowing, while the $a_{st} > 0$ represent saving. Since there is only one consumption good at each period, we shall normalize its price to one. Let $p(x, s^{t})$ be the price of $x$ at history $s^{t}$. By our normalization, we have the trivial identity $p(c(s^{t}), s^{t}) = 1$. Since $a_{s_{t}...}$yields one unit of consumption at all $s^{t}e(s^{t-1}, s_{t})$, by abritage we find that $p(a_{s_{t-1}}, s^{t}) = 1$. Also by abritage

$$p(a_{s_{t-1}}, s^{t-1}) = \sum_{s^{t}e(s^{t-1}, s_{t})} p(c(s^{t}), s^{t-1})$$
But there does not exist a market for $c(s')$ at $s'^{-1}$, so $p(c(s'), s'^{-1})$ is indeterminate. The firm profit maximization for each $k(s')$ is

$$max_{k(s')} \left[ Rq_{a(s')} - 1 \right] k(s')$$

So for $k^*(s')$ to be bounded so that the market clears $\int a(s') = k(s')$, we need $q_{a(s')} = 1/R$. Note that in equilibrium the firm does not generate profit, so firm ownership does not affect consumption allocation.

The consumer solves

$$max_{c_i(s') a_i(s')} U_i = \sum_t \sum_{s'} \pi(s') \beta^t u(c_i(s'))$$

subjected to the lifetime budget constraint

$$a_i(s^0) = 0 \text{ by assumption since } c_i(s^0) = y_i(s^0) = 0$$

$$c_i(s^1) + (1/R)a_i(s^1) = y_i(s^1) + a_i(s^0) \text{ for all } s^1$$

$$c_i(s^2) + (1/R)a_i(s^2) = y_i(s^2) + a_i(s^1) \text{ for all } s^2|s^1$$

Note that $a_i(s^2) = 0$ since the world ends after $t = 2$. Combine to get lifetime constraint

$$c_i(s^1) + (1/R)c_i(s^2) = y_i(s^1) + (1/R)y_i(s^2) \text{ for all } s^2 = (s^1, s^2)$$

The FOC is

$$e^{-\gamma c_i(s^1)} = E[R \beta e^{-\gamma c_i(s^2)}|s^1]$$

$$e^{-\gamma c_i(s^1)} = R \beta E \left[ e^{-\gamma [y_i(s^1) + (1/R)y_i(s^2) - c_i(s^1)]} | s^1 \right]$$

$$e^{-2\gamma c_i(s^1)} = R \beta e^{-\gamma y_i(s^1)} E \left[ e^{-\gamma (1/R)y_i(s^2)} | s^1 \right]$$
From this equation, we see that $c_i(s^1)$ is increasing with $y_i(s^1)$. And likewise, $c_i(s^2)$ is increasing with $y_i(s^2)$. Note that $c_i(s^3)$ is also increasing in $\text{var}[y_i(s^2)]$ due to precautionary savings as shown in Caballero (1990). Risk is not shared across households and the Pareto Optima is not supported. Nevertheless, there is still intertemporal smoothing, so this is an improvement from Autarky. Additionally, in the spirit of Deaton (1991), this allocation is superior to the savings only as $a_i(s^1) > 0$ would bind when $y_i(s^1)$ is low (or if we were to induce more precautionary savings via $\text{var}[y_i(s^2)]$).

**State-contingent Loan**

Loans in which repayment can be deferred allows for stage-contingency. In the most simple case where there is no interest rate, the discount rate decreases the net present value of repayment, implying that less can be paid when facing a bad state. This is true even with interest rate, if the rate is low enough (which we think is true in our environment due to subsidy). Without going through the derivation, intuitively we know that stage contingent transfer move the price equilibrium from savings and borrowing only towards the Pareto optimum. The discussion above shows that with increasing financial access, the income coefficient in the risk sharing regression move closer to zero. This is consistent with previous works:

- In a static model with adverse selection, income risk cannot be contracted and diversified upon. Townsend (1982) shows that this problem is alleviated in repeated game setting by tyring future payments to present claims. Nevertheless there is still income depency as formally shown in Kinnan (2017). Townsend (1979) highlights the auditing (state verification) role of intermediaries. Auditing upon negative income shock allows for truth telling. As auditing cost falls from infinity to zero, the economy move towards full risk sharing.

- Townsend (1978) highlights the insurance role of intermediaries under the costly bilateral exchange. Alem and Townsend (2011) formally derive how this insurance effect enters the risk sharing equation. Kinnan and Townsend (2012) test it empirically on the same data set as this paper. As the number of transactions, as well as the cost per transaction, move towards zero, the economy moves towards full risk-sharing.
Appendix B. Lending

We retrieve lending data from module 16F and 16M of the Townsend Monthly Survey. Between 1999 and 2007, households lent 2021 loans totaling 28.6 million baht. The pie chart below shows the distribution of the money source. For the cases with many sources, we split the loan across in equal amounts. The biggest source is savings (40%) followed by borrowed money (30%), 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 2021 lent loans, relending occurs in 332 loans totaling 8.4 million baht. Because households borrow money to relend, the counterpart exists in the borrowing dataset. Indeed we find that households borrowed 191 loans for relending.

![Pie chart showing distribution of amount lend by source.](image)

Often, money flows right through the relender so that the net cash flow is zero. But what if the relent loan is not repaid on time? Because the relender still needs to repay his own loan, he in effect provides insurance. 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, I look for relending that occurs in the same month. If it does not exist, I continue looking at future months until I find a match.

---

22:24 cases where borrowed money is the sole source and 8 cases where it is one of the source.
23: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.
In total, 6.7 million baht of borrowing can be linked to relending data. 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. We can now compare repayment the dates of the borrowed and relent loans using these links.

24 total pairs. Some borrowed loans are relent into multiple smaller loans.
A borrowed loan and its corresponding relent loan are more likely to be repaid on the same month if relending is the sole purpose. This is natural since the repayment the household receives should cover the amount of the corresponding borrowed loan. Orange represents the pairs where the repayment dates are not comparable. This happens when neither the borrowed and relent loan has been repaid.\footnote{Usually because these loans are not yet due as of the month surveyed.} 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.
The high correlation in repayment dates suggests financial contagion as described in Adrian and Shin (2008). Above, I plot the duration late values for the 187 loan pairs. The negative values indicate early repayment. The slope is less than identity at 0.308, but still significant with $t = 2.77$ under robust regression. Instead of actual duration, we can instead classify by late, on time, or early. We can see that the borrowed and relent loan are likely to have the same status. A Chi-Square test against the null hypothesis of no relationship is significant at the 0.1% level. Even so, insurance is still provided in the 8% (of the 28%) where the relender repaid his loan on time even though he did not receive repayment from the relent loan.

<table>
<thead>
<tr>
<th>Weighted % of Total</th>
<th>Lent Loan</th>
</tr>
</thead>
<tbody>
<tr>
<td>Borrowed Loan</td>
<td>Early</td>
</tr>
<tr>
<td></td>
<td>Total</td>
</tr>
<tr>
<td>Early</td>
<td>19%</td>
</tr>
<tr>
<td>On Time</td>
<td>2%</td>
</tr>
<tr>
<td>Late</td>
<td>1%</td>
</tr>
<tr>
<td>Total</td>
<td>23%</td>
</tr>
</tbody>
</table>

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26 Attenutation bias likely to play a part here