# Financial Lives and the Vicious Cycle of Debt among Thai Agricultural Households 

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# Financial lives and the vicious cycle of debt among Thai agricultural households 

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#### Abstract

This paper aims to explore drivers and dynamics of Thai agricultural households' vicious cycle of debt, currently impeding their development prospects. We use unique combination of nationwide representative survey of 720 households and longitudinal administrative and financial account data from the farmer registration, the Bank of Agriculture and Agricultural Cooperatives (BAAC) and the National Credit Bureau (NCB) to reflect households' financial problems from the lens of monthly income and expenditure flows, their financial attitudes and use of financial services from all sources to smooth consumption and debt dynamics and repayment behavior. The paper also tries to renew our understanding since Siamwalla et al. (1990) on the economic problems in Thai rural financial market and attempts to identify adverse impacts of debt moratorium policies, which are among the country's most extensive policies aiming to help Thai agricultural households. The unique granularity and coverage of our data allow us to provide better understanding of the dynamics of problems and the heterogenous patterns across households - necessary to shed some lights for the redesign of rural financial system and sustainable farmers' debt policies.


JEL Codes: D82, G20, G28, O12, O16, Q12, Q14
Keywords: Agricultural households, financial behavior, household debt, household debt policies, rural financial market, Thailand

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## 1. Introduction

This paper contributes to the better understanding of drivers and dynamics of Thailand's looming debt problems among Thai agricultural households. Over the past decade, the country observes widespread and persistent rise of debt among majority of 5 million agricultural households. And as found in Chantarat et al. (2019) and others, the rising debt burden could decrease households' incentive and ability to make productive investment and reduce resiliency to further shocks. And so persistent debt could naturally reinforce persistent poverty, especially among vulnerable agricultural households, who already lives with low and risky income prospects and so would both be greatly affected by debt problems as well as have trouble resolve debt problem. Better understanding of dynamics and heterogeneity of debt problems among these subpopulations would thus be critical for the design of both debt/financial system and development policies.

Unlike other rural household finance literatures that rely on survey data, this paper uses unique combination of nationwide representative survey of 720 households and longitudinal administrative and financial account data from the farmer registration, the Bank of Agriculture and Agricultural Cooperatives (BAAC) and the National Credit Bureau (NCB) that could allow us to better reflect households' financial problems from the lens of monthly income and expenditure flows, their financial attitudes and use of financial services from all sources to smooth consumption and debt dynamics and repayment behavior. The unique granularity and coverage of our data thus allow us to contribute both academically and empirically toward better understanding of the dynamics of problems and the heterogenous patterns across households - necessary to draw policy implications.

Economics and financial challenges of Thai agricultural households are not that different from rural households worldwide with low, irregular and uncertain income and expenditure streams. Our detailed monthly income and expenditure flows data from our representative survey allow us to identify the three financial challenges: insufficiency, illiquidity and instability similar to those in Morduch (2021), Townsend (2013) and Colins et al. (2009). These results, which could not been found with typical annual data, reveal households' striking challenges with only $15 \%$ having no liquidity problem in all months in a year, while $40 \%$ facing problems in 6 months or more and $18 \%$ facing negative net inflows in all years. These findings imply great financial difficulties among agricultural households and the importance of financial tools that could help them smooth their consumption.

But have households been able to utilize financial tools - saving, credit and insurance to resolve their financial challenges? Our results show similar results relative to rural households worldwide (Badarinza et al. 2018, among others) with low use of financial saving, especially among the poor and vulnerable groups. And while our agricultural households tend to be fully insured with life insurance, they are largely un or underinsured when it comes to income/crop insurance. Moreover, households appear to have low financial literacy especially related to debt management albeit their seemingly well financial attitude. Importantly, the data reveal that Thai agricultural households rely extensively on credit. This results however seem contrasting with the results elsewhere, where access to credit as key impediments (Banerjee and Duflo, 2012, Colins et al, 2009).

The combination of household survey and longitudinal financial accounts from BAAC and NCB that allow us to see households' debt and repayment behavior from all sources reveal striking debt problems. More than $90 \%$ of Thai agricultural households have debt and currently accumulate as large as 450,00 baht of debt per household on average. They use debt for multiple purposes and could acquire debt from multiple sources - and BAAC, village fund and leasing are among the three major lenders. Their averaged debt outstanding have been increasing over the past decade with old and newly incurred debt contributing to the annual debt growth. And when compared with household income and asset, we further found that more than half of households either have debt to income or debt to asset above $100 \%$ implying that majority of our agricultural households' debt burden could well be beyond their capacity to repay.

Our paper further reveals the vicious cycle of debt among our agricultural households. First, the loan repayment data allow us to uncover unhealthy cycle of loan repayment behaviors - paying only interest and/or rotating repayment from one loan to the next. And more interestingly, we estimate debt accumulation dynamics using longitudinal panel data of loan outstanding from BAAC and NCB and nonparametric estimation - similar to the estimation of welfare dynamics in poverty trap literatures (Barrett et al. 2006) - and find that in the long run, our agricultural households' debt outstanding tend to converge to long-run steady state level of debt at $70 \%$ of asset. This finding thus implies that without further intervention, our households' debt will converge to this level that would be very hard to revert - debt trap. This result further implies that efficient rural financial system and well-designed debt policies that could prevent some households from falling into debt trap or revert some out of the trap could yield great long-term impacts. The key research questions then become
'how well could our rural financial market provide inclusive and sustainable financial solutions to agricultural households?

Using our unique combination of data, the paper then attempts to renew the understanding on the economic problems in Thai rural financial market since the seminal paper Siamwalla et al. (1990). Similar to the 1990 results, we found that information asymmetry problem still largely prevail resulting in clear evidence of credit ratioing and so market segmentation (Hoff and Stiglitz 1990, Stiglitz and Weise, 1981). And so, on the one hand, information asymmetry results in unmet demand for credit for all groups. And on the other hand, over lending beyond households' repayment capacity has been widely evidenced, both among loan contracts within the same financial institution, and as a consolidated loan portfolio since many rural financial institutions do not have consolidated credit data.

We further found evidence of enforcement problems, whereby households tend to have default selection behaviors following their perceived cost of default. Community-based financial institutions such as village fund with stronger (social) enforcement mechanisms are among the very first lenders that households repay, whereas BAAC and cooperatives are among the very last. This result thus could imply that with variations in capacity to enforce loan repayment across institutions, one needs to consider household's debt from all sources when it comes to designing debt solution. Strikingly, we further found that joint liability loan or group loan - once acclaimed by Siamwalla et al. (1990) as innovation for rural loan enforcement mechanism - have performed poorly relative to other type of loans. This finding coincides well with other literatures (Ahlin and Townsend 2007, Gine et al. 2010, Fischer, 2013) that found the same results for microfinance loans, resulting in the rethinking and switching from group to individual loans among microfinance worldwide (Khandker, 2012).

Contract design also appears as another key impediments for rural financial market. Past literatures (Chawanote 2021 for example) show that better repayment contract design especially for rural households with the three financial problems - insufficiency, instability and illiquidity - should (i) match well with borrower's income/cash flows, (ii) flexible enough to accommodate instable and illiquid natures of income streams and (iii) have some tools and/or commitment device built in to help household repay despite the three financial problems. Using insights from Bauer et al. (2012) and Mullainathan \& Shafir (2013), we consider repayment contract of a typical working capital loan with annual repayment scheduled at the end of March, and analyze different impediments - especially with respect to behavioral problems - underpinning repayments for BAAC working capital loan contract.

Finally, the paper explores participations and impacts of debt moratorium policies, which are among the country's most extensive policies aiming to help Thai agricultural households - resulting in $44.1 \%$ of households being in debt moratoriums for more than 4 years. This paper estimates the impacts of agricultural debt moratoriums on households' debt, saving and agricultural investment dynamics using a unique panel data of 1 million representative households nationwide. We found that while the debt moratoriums could decrease delinquency propensity in the short run, they significantly resulted in higher debt accumulation, especially among those with larger debt and those with higher program intensity. The moratoriums had no significant impact on saving, while could increase agricultural investment especially among those with smaller debt. The debt moratorium policies thus could be one of the key drivers impeding agricultural households in long-term debt trap.

Putting all the results together, the paper reveals the full vicious cycle of debt among Thai agricultural households, which starts from (1) households' unavoidable financial challenges insufficiency, instability and illiquidity - (2) great reliance on credit as a tool to resolve all these challenges (3) problems in rural financial market - information asymmetry, enforcement problems and contract design problems - which further create overborrowing beyond households' repayment capacity and trapping households in the trajectory toward debt trap. Furthermore, debt trap could reinforce underdevelopment and so poverty trap as large debt burden reduces incentives and ability to make productive investment and make households less resilient from future shocks.

Our results imply that agricultural development policies should give priority to farmers' debt policies and the rethinking of how to make rural financial market work better for heterogenous agricultural households, especially with respect to resolving the three economic problems. On the other hand, our results further imply that household debt solution should be total solutions including not only debt policies but also development policies, financial literacy and safety nets. They should be well tailored to households with different debt situations, ability as well as willingness to repay.

The rest of the paper is organized as followings. Section 2 reveals the data sets we used. Section 3 explores the three financial problems of Thai agricultural households. Section 4 then tries to understand households' financial literacy and attitude, as well as, how households utilize financial tools to overcome financial problems. Section 5 explores and estimate the vicious cycle of debt and debt trap. Section 6 reveals problems in Thai rural financial market. Section 7 estimates potential impacts of debt moratorium policies and their mechanisms in trapping households in persistent debt. And section 8 concludes and draws some key policy implications.

## 2. Data

This paper utilizes and combines 4 sets of data. First, we use national representative survey of 720 randomly select rice farming households surveyed during 2019-2020. We used two-staged stratified sampling strategy to randomly select households, where we first randomly select 48 tambons - 12 from each of the 4 regions - from a sampling frame that contains all rice growing tambons in Thailand. We then randomly select 15 households from each tambon. And so we then conducted detailed household survey that include household demographics, detailed monthly income and expenditure from all members and all sources, financial literacy, attitude and use of all kinds of saving, credit and insurance from all sources (formal, semiformal and informal institutions). Moreover, the survey was especially designed to understand households' debt situation and so we include questions on loan-level information for each and every loan accounts, as well as, monthly loan repayment mechanisms. The survey also includes various behavioral biases measures.

## [Table 1 here]

The second set of data is the loan-level, 7 -year panel data of 1 million randomly selected rice farming households from BAAC. We randomly draw 1 million rice farmer borrowers from the sampling frame that contains all farmer borrowers in the BAAC loan portfolio. Since only one member per household can borrower from BAAC, selecting borrower is naturally the same as selecting household. Once, borrower was selected, all loan accounts of that borrower would be included in the data along with details of loan types, among, repayment and delinquency status. Moreover, we also draw detailed data of all saving accounts, assets, borrower and household characteristics. Altogether, the BAAC data contains 7.04 million loan accounts.
[Figure 1 here]

We further merge these 1 million randomly selected households from BAAC data with our third set of data - farmer registry available from the Ministry of Agriculture and Agricultural Cooperatives containing around 7.89 million farming households. With pre-agreed hashing mechanism, we thus are able to merge exact households in these two data sets using hashed national ID. This allows us to further see more detailed data on household demographics, land and other assets and more importantly plot-level farming activities including farm sizes, crop grown and further planting
information. These sets of data thus allow us to understand both agricultural practices as well as debt situation - though only those borrowed from BAAC.

The last set of data is the loan-level data from NCB, which contains all borrowers who borrow from NCB member institutions - and so mainly formal institutions. The data include around 4.7 million borrowers who have agricultural loan (with total of 30.3 million loan accounts) and so we use this information to flag them as farmers. And because the NCB data contain detailed loan information for all loans from the formal institutions, we use this data to reflect total loan outstanding of agricultural households from all formal institutions, which would include other formal institutions that lend to farmers beyond BAAC - majority of which are leasing and non-banks. And another key different between BAAC and NCB data are that the former only includes rice farmers, whereas the latter includes all farmers. Table 1 summarizes structure and coverage of each data set. Figure 1 further shows their geographical coverage nationwide. And Table 2 provides some key summary statistics from each data set.
[Table 2 here]

## 3. The three financial problems of Thai agricultural households

According to data from the PIER farmer financial survey, which we can analyze using monthly information, Thai agricultural households have three major financial problems: low income, high income instability, and facing liquidity problems. Most Thai agricultural households experience economic insecurity from both farms and non-farm incomes, together with systematic risks from natural disasters and fluctuated agricultural prices. In addition, the frequency and severity of natural disasters appear to be increasing due to climate change, leading to more uncertainty for agricultural households. As a result, their earnings are insufficient and volatile throughout the year, and they may continue to have more illiquidity issues in the future.

To see financial lives of farmer households in the PIER financial survey, Table 3 presents summary statistics of surveyed rice farmer households on share of cash income, share of expenditure, annual statistics of cashflow, and intra-year variation. The majority of Thai rice farmers' cash income still comes from agriculture, accounting for about $42 \%$ on average of all cash income, in which rice farmers in Central and Northern Thailand earn around half of cash income from agriculture. Although wage
and salary now make up the second-largest percentage of cash income, accounting for about 26-31\% of total cash income across regions, remittances have become a main source of cash income, around $20 \%$ on average in the Northeast. On the other hand, farmers in the South also earn from business income for around $13 \%$ of total cash income. Except for central and northern regions, Thai rice farmers earn more share from nonfarm income.

On the expenditure side (Table 3B), the two largest shares of expenditure are consumption and agricultural expenses, combining for around $60-75 \%$ of total expenditure. As expected from income shares, Central and Northern Thai farmers spend significantly on agricultural expenses as well. It is interesting to note that the share of temptation expenditure, which includes lottery, clothing, travelling, and other entertainment, accounts for $10 \%$ for all households, and $12 \%$ in the Northeast. Health and education spending, as well as social and transfer spending, account for approximately $6-7 \%$ of total spending.

When all cash income sources are combined into a yearly cashflow (Table 3C), we see that annual cash income (inflow) for rice farmer households in 2019 is approximately 382,128 Baht. With total annual expenditure (cash outflow) of 338,886 Baht, Thai rice farmers were left with only around 43,241 Baht for annual net cashflow. If we could consider this amount to be net income before debt payment, then there would be a critical issue for farmers, especially in the South. The annual net cashflow of Southern farmers is negative, around fifty thousand Baht on both mean and median, with $64 \%$ of households in the South having negative net cashflow. However, this could be our limitation of analysis due to the fact that the surveyed data was only available for one year. In any case, households with negative annual income are around $45 \%$ of all households. This means that nearly half of rice farmers face debt repayment difficulties and insufficient income.
[Table 3 here]

With monthly information, we can investigate instability and illiquidity problems within a year. This monthly data provides more advantages in analysis since it allows us to assess liquidity over the course of an entire year, especially when farm incomes frequently depend on the farming seasons and hence causing monthly fluctuations of income inflow. Figure 2(a) shows that a randomly selected household could experience net cash income up and down below zero in some months. Rural agricultural households find it difficult to manage cashflows across months. They need to smooth their nearly constant consumption every month while their cash inflows from seasonal farming are at
their peak in some months. Sometimes, they are faced with a lump sum payment, such as health and education expenses, that requires taking small amounts of money saved into a larger sum. Throughout the year, households need to simultaneously smooth and spike their money (Morduch, 2021).
[Figure 2 here]

We can also see from a high-frequency view in Figure 2 (b) - (e) that rice farmer households across regions encounter a variety of cashflow each month, indicating income instability within a year. This volatility with negative net cash income also reflects different liquidity issues based on different productions and income sources. Figure 3 exhibits heterogenous patterns of net cashflows of 720 sampled households. Table 3D also shows that only around $15 \%$ of all rice farmer households, with only $8 \%$ of households in the central region, have non-negative net cash income every month of the year. Around $31 \%$ of all households have negative net cash inflow for 1-6 months while more than $50 \%$ of them have negative net cash income for more than 6 months. Only in the Northeast do rice farmers face less severe liquidity issues, which could be attributed to a higher proportion of remittances than in other regions. It is worth mentioning that while central region farmers have on average the highest annual net income around 77,440 Baht, $65 \%$ of them encounter negative net cash income for more than 6 months. As we can see, farmers in the central region rely mostly on agricultural income. They are situated in irrigation areas where they can grow multiple cycles of rice farming to earn more income, but as it is seasonal, they have liquidity issues more often than others.
[Figure 3 here]

To summarize, Thai rural agricultural households are also facing the problems of insufficiency, illiquidity, and instability. People could be deprived and improved throughout the year, leading to chronic instability within a year. As a consequence, they need to put more efforts into distribute their insufficient and unstable incomes over the course of a year, as well as try to save for emergency or any shock that may occur at any time, thus the need to smooth consumption across years. Nonetheless, these households have to aggregate their money to pay a lump sum such as a medical bill or an agricultural investment. These financial problems are common for households in many developing countries, and that require a variety of appropriate financial tools to manage their financial lives (Collins et al., 2009; Morduch, 2021).

## 4. Using financial tools to overcome financial problems

The financial sector can play a significant role in assisting agricultural households if the system offers a variety of financial tools that are suitable and able to solve financial problems for heterogenous households. Rural households, facing different issues, need to appropriately use saving, insurance, and credit products in managing liquidity, accumulating wealth, and developing resilience in order to improve their quality of life. This section examines whether Thai agricultural households are able to use financial tools appropriately and sustainably by investigating financial awareness and attitudes, as well as the use of various financial tools.

### 4.1 Financial awareness and attitudes

Financial awareness and attitudes are crucial for individuals to be able to use financial tools to their advantage and manage their financial risks. In the PIER farmer financial survey, we tested farmers' financial awareness by asking them questions about credit, saving, and insurance products. For example, we asked if their collateral would be seized and they would have to pay a higher interest rate if they were late or delinquent. The score ranges from 1 to 5 , with a higher score indicating that they are more aware of the correct knowledge of that statement. Then, we analyzed based on heterogeneity of farmers by asset quantiles, with asset quantiles $1-3$ representing the poorest, middle, and richest total asset value, respectively. From Figure 4(a) we found that all asset quantile groups have lower financial awareness scores, especially on knowledge of saving products, consequence of joint-liability and delinquency, and loan protection life insurance. Only three topics, namely knowledge on jointliability loans, knowledge on interest rates, and saving as collateral, differ statistically significantly across the three asset quantile groups, with the richest group having higher awareness score than the others.

Despite having lower financial awareness scores, farmers appear to have higher scores on financial attitude. Figure 4(b) exhibits the score of farmers' self-evaluation on financial attitudes related to credit, saving, insurance, and management, across the three asset quantile groups. Overall, farmers have scores around 4 in each topic, suggesting that they understand what attitude should be. For example, they strongly agree that saving is essential even though they have low incomes. Farmers in the three asset quantiles have statistically significant differences in topics of incurring debt discipline, debt burden, saving discipline, and financial management, with the wealthier farmer group having better attitude scores. Although farmers in the third quantile have, but not statistically significant,
higher score on household accounting than the others, all three quantiles show lower scores on household accounting, indicating their perception of insignificance of doing household financial diary. The issues of financial diary appear to be difficult with households around the world (Morduch, 2021, Banerjee and Duflo 2012, Collins et al. 2009).
[Figure 4 here]

### 4.2 Saving and insurance patterns

Figure 5 presents the percentage share of farmer households having each type of savings or insurance products across three asset quantile groups. Most savings (Figure 5a) are in the form of illiquid assets such as land, livestock, and durable goods. Only $20 \%$ of the first quantile group and $40 \%$ of the second quantile group have savings in formal banks. Despite the fact that the third quantile group saves more in financial assets than the other groups, these products are savings accounts. As a result, the savings outcomes would not result in wealth accumulation. Figure 5(b), on the other hand, shows that while $90 \%$ of farmers in all groups have life insurance, or cremation fund, only a small proportion of farmers have social security or a pension fund, as well as income insurances, such as crop insurance which can help reduce income volatility. In sum, saving and insurance purchasing behaviors of farmer households do not support liquidity problem solving, wealth accumulation, or resilience for fluctuating incomes.
[Figure 5 here]

### 4.3 Credit

Credit is a main tool that farmers use to manage their financial issues since it is widely accessible from various sources. From the PIER farmer financial survey which asking debt information from formal, semi-formal, and informal lenders, Thai farmer households reported average level of total debt outstanding around 429,989 Baht in 2020 (Table 4A) ${ }^{2}$. More than $90 \%$ of surveyed households were indebted with on average 3.4 loan accounts per household. According to Figure 6(a) in which we rank surveyed farmer households by total outstanding debt percentile, we find that $30 \%$ of households

[^1]have outstanding debt more than 500,000 Baht. We can also see that each household has loans for a variety of purposes, including agriculture, consumption, asset purchasing, educational investment, and even debt repayment. As a result, we can conclude that farmer households commonly use credits for various purposes and indebtedness becomes a part of their financial lives.
[Table 4 here]

Sources of loan. Farmer households borrow from various sources. Specialized Financial Institutions (SFIs), such as the Bank for Agricultural and Agricultural Cooperatives (BAAC) and the Government Savings Bank (GSB), are the main sources of credit. From the PIER surveyed data, 65\% of farmer households have at least one loan account from SFIs. Similarly, community financial institutions such as village funds and saving groups are also major sources of loans in rural areas, accounting for $65 \%$ of farmer households as well. The next most common source is informal loans from agricultural input shops, relatives, or moneylenders, which are used by $31 \%$ of households. Surprisingly, leasing or non-bank financial institutions have grown in popularity, with $28 \%$ of households using them. Last but not least, cooperatives are used by $22 \%$ of households. These are five major sources of loan for farmer households. In terms of loan amount, Table 4A also presents the share of debt outstanding per household by lender. On average, each household uses SFIs for $47 \%$ share of debt outstanding, followed by village fund for $16 \%$, cooperatives for $12 \%$, informal sources for $10 \%$, and non-bank financial institutions for $8 \%$. These are also the same five major sources of loan amount for farmer households.

Figure 6(b) shows loan portfolios of different groups of households and the average debt outstanding balance for the borrowers in each group. The top combination of loan portfolio covers $20 \%$ of the farmer households with average debt outstanding of almost 400,000 Baht and the portfolio consists of mainly loans from SFIs (yellow) and small amount of loans from village fund and saving group (blue). The second rank portfolio comprises $10 \%$ of farmer households using SFIs, village fund and saving groups, and informal loan (dark blue), with an average debt outstanding of 450,000 Baht. The third rank is loan portfolio from only SFIs, accounting for $7 \%$ of households. The fourth rank is loan portfolio from commercial bank and non-bank institutions (red), SFIs, and village fund, accounting for another $7 \%$ of households. However, another $20 \%$ of farmer households do not have access to formal credit.
[Figure 6 here]

Loan purposes. Farmer households also borrow for different purposes, not only for agricultural or work-related purposes, but also for household expenses as well. According to the surveyed data (Table 4A), loan for agriculture purpose accounts for $45 \%$ of debt outstanding per household, with purchasing asset purpose accounting for $21 \%$, household expense accounting for $13 \%$, education purpose accounting for $7 \%$, and paying for other debts for another $7 \%$. When considering only loan products from BAAC (Table 4B), we find that working capital accounts for $60 \%$, the largest share, of debt outstanding per farmer. Term loan for agriculture account for $13 \%$ of total debt outstanding, followed by personal loans at $10 \%$ and home loans at $4 \%$. BAAC, as a major lender, also offers a variety of loan options to its farmer clients.

From aforementioned credit usage, farmers need several loan sources for a variety of loan objectives in order to manage their finances, emphasizing the crucial role of credit in rural Thai agricultural sector. On the other hand, for farmer households, having plenty access to credit sources may lead to over-indebtedness and over capacity for repayment (Alem \& Townsend, 2014).

Household debt accumulation. We observed constantly increasing debt outstanding during the past decade. Figure 7(a) plots the quarterly average of total loan outstanding per farmer borrower during 2017 - 2022 using the credit data from NCB. Only individuals with at least one account for agricultural loans are included in the graph, but total outstanding includes all types of loans from any financial institutions in NCB. We observe that previous loan balance from before 2015 has not been fully repaid, but is gradually declining. However, new loan amounts are increasing each year. From Table 4C based on NCB data, average annual debt growth during 2017-2022 accounts for 7.9\%. In addition, from Table 4B, 7-year loan growth of BAAC loans during 2014-2021 is $108 \%$, with average yearly loan growth during the same period for $6 \%$. This steadily increasing debt outstanding could eventually lead to a debt trap.

Relationship among debt to collateral ratio, ability to repay, and ability to obtain new loan. Due to the accumulation of household debt, several farmers are having difficulty repaying debts and obtaining new loans. Figure 7(b), using the data from BAAC, separates group of farmers into 5 quintiles of outstanding debt to collateral ratio. The higher quintiles indicate a greater debt burden based on collateral. More than $20 \%$ of farmers have a debt-to-collateral ratio higher than $100 \%$, with the fifth quintile having a median debt-to-collateral ratio of 1.2. We can see that the higher the debt-
to-collateral ration, the higher the rate of delinquency. The fifth quintile has an $11.4 \%$ delinquency rate while the first quintile has only $2.9 \%$ (Table 4B.2). Moreover, when considering the proportion of borrowers receiving new loan in each quintile, we find that higher quintiles appear to acquire a new loan in a smaller proportion. Only $11 \%$ of farmers in the fifth quintile receive a new loan, compared to $29 \%$ of farmers in the first quintile. With higher debt burden beyond collateral, we observe a lower repayment capacity and a reduced capacity to qualify for new loans, resulting in more challenging to manage household finances using credit tools in the future.
[Figure 7 here]
Unhealthy use of loans can be seen across areas, with heterogeneity of credit usage behaviors. Figure 8(a) exhibits average household outstanding debt in 2021 across regions, using the BAAC data. We observe that households in lower northern and upper central regions of Thailand where irrigation systems are located and agriculture is the primary source of income, appeared to have greater average debt outstanding due to these regions' higher cost of production and illiquidity problems. Figure 8(b) shows that households in the northeast and some areas in central regions experienced high debt growth during 2014 - 2021 as a result of low productivity from frequent natural disasters. Furthermore, as shown in Figure 8(c), farmer households widely participated in the debt moratorium program with the higher average number of years participating in the central region. We can see that households in the central region with larger levels of debt outstanding also participated in the debt moratorium program for longer periods.
[Figure 8 here]

## 5. The vicious cycle of debt

From the previous section, compared to savings and insurance, which are still in some aspects limited, credit is a key financial tool for farmer households with a variety of credit access and objectives. However, credit usage of agricultural households does not appear to be sustainable, and several households have been falling into a debt trap. This section further explores the vicious cycle of debt on the issues of debt burden, ability to repay, repayment behavior, and debt accumulation dynamics.

### 5.1 Debt burden and ability to repay (DTI \& DTA) distributions

Using the PIER financial survey data, Table 5A and Figure 9 (a-b) investigate debt burden to income (DTI), where supposed annual debt repayment divided by all sources of net incomes, and total outstanding debt to total asset (DTA). These two indicators can be combined to determine farmer households' ability to repay. From Table 5A, cutoff at the $95^{\text {th }}$ percentile, debt burden to income for all households with non-negative net income has a mean around 0.482 , meaning that farmers need to repay debt almost $50 \%$ of net income each year. When separated into three asset quantiles, farmers in the first asset quantile had a debt burden of approximately $58 \%$ of their net income, $47 \%$ for farmers in the second asset quantile, and $39 \%$ for wealthy farmers. Households with negative net income are around $20 \%$ across all asset quantiles. Moreover, the mean of debt to asset ratio for all households is 0.761 , indicating that their debt outstanding is approximately around $76 \%$ of their asset value. It can be observed that the higher the asset quantile, the lower the median of debt to asset ratio. It needs to be caution that poor farmers' debt outstanding is already 1.25 times their asset value, suggesting overindebtedness.

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\text { [Table } 5 \text { here] }
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Figure 9(a) shows the cumulative distribution of debt to income and debt to asset ratios by percentiles of borrowers. Cutting off at the $95^{\text {th }}$ percentile and including only non-negative income, median of debt to income is 0.273 and that of debt to asset is 0.35 . Figure 9(b) shows the discrete distribution of the borrower share across different values of the two ratios. Almost $40 \%$ of farmers (including negative income) have debt to income ratio greater than $100 \%$, and $34 \%$ of farmers have debt to asset greater than $100 \%$. $17 \%$ of farmers with both debt to income and debt to asset ratios greater than $100 \%$, which could be likely to have repayment issues. Less than half ( $43 \%$ ) of all surveyed households still have acceptable criteria on both indicators of repayment ability. $41 \%$ of them are prone to be over-capacity to repay.
[Figure 9 here]

### 5.2 The vicious cycle of borrowing and repayment behaviors

From the distributions of debt to income and debt to asset, there is a sign of over-borrowing beyond capacity to repay, reflecting in repayment behaviors. According to our surveyed data, the majority ( $64 \%$ ) of all households fully repaid at least one loan account during the year 2019 and only
$3 \%$ of all households did not repay any debt during the same period (Table 5B). This seems to be overall good repayment performance with only a few shares of households repaid nothing. However, from the surveyed interview, we often observed debt rotating behavior, when one borrows a loan to pay another loan and then re-borrow after repaid to pay for the other loan. In our surveyed data, we identify debt rotation from either having loan purpose for repaying other debts or having repayment method by using the other debt to repay. As shown in Table 5B, 27\% of households engaged with debt rotation, with $34 \%$ of the poor households, $29 \%$ of the middle asset quantile, and even $18 \%$ of the highest asset quantile.

When we further examine the details of repayment behavior, we would see 'only-interest payment'. It is a practice for a minimum payment by the BAAC's rule to assist farmers in paying only interest at due date of each round and sometimes also extending the principal repayment to the next round. Moreover, it could be argued that the debt moratorium (DM) program encouraged farmers to pay only the interest as the program suspended the outstanding debt. On the other hand, the repayment behavior during the period of participation in the debt moratorium scheme might not reflect the actual behavior. There were more than $50 \%$ of all households participating in the DM program at least one account for agricultural loans and village fund's loans. To evaluate the only-interest payment, we then consider only non-DM loans. Table 5B shows that $26 \%$ of households paid off solely the interest on at least one loan account for non-DM loans during the 2019 calendar year. Farmers with lower asset quantiles were more likely to repay only the interest, with $32 \%$ from the first asset quantile. Nonetheless, $20 \%$ of households in the highest asset quantile likewise only paid the interest on one or more loan accounts. Farmers appear to generally welcome this conduct and accumulate more debt without the strong need to repay. Thai farmer households may fall into debt traps as a result of continuously rising debts over the past ten years.

### 5.3 Debt accumulation dynamics

As mentioned in 4.3, debt accumulation is increasing over time. Figure 10 plots the non-parametric Kernel estimation exhibiting the relationship of debt to asset in period t and period $\mathrm{t}+6$, estimated from randomized 5,000 borrowers from 1 million randomly selected BAAC borrowers who have pledged collateral with the bank. We can conclude from the graph that the long-run steady state level of debt is at $70 \%$ of asset value. Those whose initial debt to asset ratio is below or above 0.7 will
eventually converge to 0.7 in the long-run. This could be considered as a potential debt trap that describes the debt accumulation path of Thai agricultural households.
[Figure 10 here]

## 6. Problems in Thai rural financial market

Economic theories emphasize that information asymmetry is a critical barrier to developing financial system for the poor. Stiglitz and Weiss (1981), Hoff and Stiglitz (1990), and Siamwalla et al. (1990) highlight problems caused by information asymmetry between lenders and borrowers, in particular when the lenders have no information of borrowers' behaviors and capabilities. This credit market's imperfect information creates high transaction costs in screening potential borrowers to avoid adverse selection, and in monitoring loan usage, as well as enforcing loan repayment in order to lessen the moral hazard problem. As a result, interest rates could be higher to offset default risks from borrowers. Furthermore, the interest rates could vary across households and financial institutions due to different transaction costs across lenders' ability in screening and monitoring their borrowers. On the other hand, to reduce these potential costs of information asymmetry, credit rationing occurs, in which lenders only provide loans to certain groups of borrowers despite more demands for loan in other groups, or the case where the interest rate cannot be used as a mechanism to clear the market.

Information asymmetry also leads to credit market segmentation. There are many lenders in the rural financial market, but these lenders provide loans to their particular targeted group in certain types of loan and varying interest rates. This could result in limited credit market access and insufficient loan availability. However, government intervention to help the poor by subsidizing low interest rate loans in many developing countries, without considering the issue of information asymmetry, does not lead to sustainability in developing rural financial markets (Armendáriz and Morduch, 2007)

In our study, we examine three related problems to information asymmetry. First, we present the landscape of loan usage and segmentation, still with unmet demand for loans. Second, enforcement problems are addressed to demonstrate a relative delinquency across financial institutions and inefficiency of group lending. Lastly, contract design is discussed to show current issues and possible solutions to increase repayment inventive. The key success is innovative and efficient in tackling the information problems entailed in lending.

### 6.1 Asymmetric information

Asymmetric information is a fundamental issue in Thai rural financial system, leading to incompatible with earnings capacity and households' demand for loan. Figure 11 presents the usage of debt, interest cost, and demand to borrow more by type of loans across three household asset groups. Evidence from the surveyed data in Figure 11 indicates that the Thai agricultural financial system may provide some type of credit more for some groups of households, but not enough for others.
[Figure 11 here]

Figure 11(a) exhibits the share of households who have debts by type of outstanding loans, including all-purpose loan, working capital loan, and long-term loan. From agricultural household's point of view, households in lower asset quantiles tend to have a higher proportion of all-purpose loans, and most of these loans come from SFIs and village fund or saving groups. It is interesting that poor households use a greater proportion of all-purpose loans from non-banks, SFIs, and cooperatives than the other asset quantiles. Loans for working capital and long-term loans show a higher proportion in the middle asset quantiles. We can see that borrowers cannot equally access all credit sources from all credit providers. From financial institutions' point of view, different institutions provide different loan purposes based on their role, or segmentation. SFIs are the major providers for working capital and long-term loans which mostly require formal collaterals such as land asset. On the other hand, village funds or saving groups supply short-term or all-purpose loans and some working capital loans. It is worth noting that informal lenders play a role for all three types of loans, particularly all-purpose and working capital loans, and they lend to all groups of households. This means that formal institutions cannot substitute some useful aspects of informal lenders (Siamwalla et al., 1990).

Figure 11(b) presents the interest rate distribution for each type of loans faced by each household group. Households in the lowest asset quantile experience diverse rates of interest with higher median interest rate than the others. This could reflect higher monitoring costs and a higher risk of default for the households with low collateral assets. Figure 11(c) reports that all groups of households still have more demand for loans, particularly working capital and all-purpose loans. While more households in the first and second asset quantiles need more working capital and all-purpose loans, wealthy potential households demand more long-term loans for production investments than the other two groups.

Despite some unmet demands for potential farmers, more credit is supplied to some household groups. Figure 12 plots the ratio of the principal amount of newly lent working capital loan to agricultural cost by percentiles. On average, newly lent working capital loan is 1.7 times agriculture cost 2020-2021. If the ratio is higher than 1 , it means that loan amount is higher than the actual cost of farming based on registered areas. As shown in the graph, $32 \%$ of new working capital loan from SFIs are greater than the actual cost of farming, indicating inappropriate loan screening and overlending.
[Figure 12 here]

In addition to aforementioned issues from asymmetric information, no clients' credit information across financial institutions, especially from semi-formal institutions and informal lenders, do not lead to sustainable credit providing when we have a variety of lenders. This could also lead to the cycle of persistent debt as mentioned previously.

### 6.2 Enforcement problems

Effective enforcement mechanism leads to high repayment rates. With asymmetric information in the credit market, monitoring is a major challenge to all credit providers after a loan has been provided to a borrower. In the formal credit sector, borrowing with collateral and credit scoring could alleviate screening and monitoring problems from adverse selection and moral hazard. When the default is about to occur, strict penalties become tools to govern the borrower's behavior. In the informal credit sector, other mechanisms, such as social sanctions and interlinkages, come into play. However, when confronted with multiple loan providers with varying enforcement mechanisms, agricultural households with limited liability may attempt to repay only some of the loans. In addition, joint liability or group lending, a common feature among microfinance institutions during the past decades, has become skeptical on its effectiveness, especially when the repayment performance depends on group characteristics (Khandker, 2012).

Relative delinquency. For agricultural households, there exist statistically significant differences in the likelihood of delinquency among the various credit sources. Table 6 presents average marginal effects from logit regressions of probability of delinquency, using the surveyed data. The dependent variable, delinquency, is equal to 1 when households reported that a particular loan had ever been overdue. Column (1) only regresses the binary of delinquency on dummy variables of financial
institutions with SFIs as a based case. In comparison to SFIs, only village funds and savings groups, as well as informal lenders, are statistically significantly less likely to be overdue. Cooperatives are likely to be more delinquent than SFIs, but not statistically significant. When ranking average marginal effects, as a relative order of delinquency, we find the following orders are less likely to be overdue compared to SFIs: commercial banks, nonbanks, village funds and savings groups, and the last one informal lenders. These orders are preserved for the other specifications. From columns (2) - (4), we control for loan principal value and other households' characteristics. When the loan principal has a higher value, it relates to a higher possibility of delinquency. Similarly, the number of debts within the household also lead to higher chance of overdue. Female household head and secondary school graduates are more likely to be delinquency. Young smart farmers and higher household asset value, as well as yearly debt burden, decrease the chance of loan to be overdue.
[Table 6 here]
The order of relative delinquency is coherent with intensity of enforcement mechanisms and perceived cost of default by households. From focus group interviews, we discover that local financial institutions have some effective enforcement practices. Due to their proximity to farmers and social monitoring, successful repayment is made possible. Moreover, dynamic incentives which require borrowers to repay all debt outstanding before applying for a new loan, could result in a high repayment rate. Joint liability, or group lending, is another mechanism that provides loans to those who lack sufficient collateral by allowing other group members to oversee loan usage and even repay the loan on their behalf if necessary. This enforcement mechanism encourages each borrower in the group to screen and monitor their group members closely, providing incentives for group members to enforce the loan repayment (Ghatak, 1999). Similarly, informal moneylenders also offer strong enforcement mechanisms such as seizing the collateral, using debt collectors, or imposing dynamic incentives. Another practice is trade-credit interlinkage by occupational lines or production relationship (Siamwalla et al., 1990). For example, rice mill's owner provides loans to local rice farmers, or agricultural input traders also lend to farmers in the same area. These mechanisms used by local financial institutions and informal moneylenders help reduce the likelihood of delinquency when compared to that of SFIs where there is no strong enforcement of delinquency. Farmers seem to perceive that the cost of default for SFI loan contracts is low, resulting in a relatively higher delinquency rate.

Group lending. A microfinance innovation adopted widely in many developing countries after Yunus's Grameen Bank is a group lending, using joint liability mechanism. Recently, the joint-liability lending has encountered some repayment difficulties. Shown in theory and lab experiments (Gine et al. 2010, Fischer 2013), default risk is increased because of free-riding from the implicit insurance mechanism when group members are required to pay for the default borrower. Another empirical study (Ahlin and Townsend, 2007), using Thai joint liability borrowing group survey, found the negative relationship of joint liability rate and repayment. In our study, we explore the current situation of joint liability loans and determinants of delinquency using group loan data from the BAAC.

Joint liability loans are well accepted by Thai farmers. Joint liability loan outstanding accounts for $25.8 \%$ of total debt portfolio of BAAC. One-third of farmers use joint liability loans, with $5 \%$ of farmers relying solely on joint liability loans without any collateral (Table 7). Those with joint liability loans have a joint liability loan that accounts for $30 \%$ of their total debt. Joint liability loan size, on average, accounts for around 359,696 Baht, almost as large as collateralized loan size of 422,040 Baht. As expected, the joint-liability delinquency rate by borrowers is higher than that of the collateralized loan, at $12.8 \%$ versus $4.6 \%$, respectively.
[Table 7 here]
Characteristics of group lending are varying across regions. We investigate group loans provided by SFIs in total of 171,771 groups. The number of joint-liability groups is distributed unevenly across regions, with the northeast region having a disproportionately large number (Table 8). Total debt outstanding per group in all regions is around 4 million Baht, with the south region having a largest amount of 6.6 million Baht. Group delinquency rate is $60.7 \%$, relatively high compared to individual loans' delinquency. There are four main factors of group lending that could lessen the efficiency of joint liability mechanisms. A large proportion of group members are landless, reducing the sense of shared responsibility and encouraging free-riding within the group. $20 \%$ of farmers nationwide and $40 \%$ of farmers in the central are landless. In addition, age differences, which could be a barrier to cooperate, are modest. The age standard deviation is around 9.5 , with small variation across areas. Furthermore, when income portfolios of group members are similar, it may create high risk of default when every group member faces the same shock, such as natural disasters. There is greater similarity of income portfolios, with score of 0.69, closer to one. On the good side, group members mostly live
within the same village, hence increasing benefits from monitoring. $67.7 \%$ of group members are in the same village. This could support the social monitoring within the area.
[Table 8 here]
We examine probability of delinquency for joint-liability loans using logit regressions. Table 9 presents average marginal effects of factors determining the likelihood of delinquency for group loans. As expected, landless of group members, higher age differences, more group members, higher joint liability loan outstanding to total loan outstanding of members, and having only joint-liability loans statistically significantly increase the probability of delinquency. There is still significant potential gain from monitoring to decrease the chance of delinquency. Also, higher size of land owned by farmers reduce the likelihood of delinquency. The models are robust with other regions as well, except for livelihood homogeneity. Only in the central region, higher similarity of income portfolio increases the probability of group loan delinquency while in other regions this factor shows statistically insignificant determinant.
[Table 9 here]

### 6.3 Contract design

Loan contract design and repayment schedules do not take financial difficulties or farmer behaviors into account, making them incompatible with repayment capability and offering little incentive to repay. Thus, farmers would not be able to repay and become debt-free eventually.

From Table 5C, considering only loans with yearly repayment schedule, $86 \%$ of all households have at least one loan account with yearly repayment. Most of them are due in March, with some due in December. In our surveyed data, these two months have the highest number of due dates. With the yearly schedule, only $2 \%$ of all households repay the yearly repayment loan more than once a year, with $4 \%$ of the second asset quantile repay more than regular. There are also those who do not repay the loan in the due month, which could be either before or after the due month, approximately $16 \%$ of all households.

According to the BAAC data, most working capital loans are due yearly. Besides $59 \%$ of working capital accounts participated in the debt moratorium program, $28 \%$ of working capital accounts show no or partial repayment while only $13 \%$ were able to repay every year between 2018 - 2021. This could
be due to the mismatch between the repayment schedule and the household's cash inflow. Figure 13 illustrates sample cases of farmers' income, based on the observed facts from the survey. The due month in March may be suitable for households with income inflow in the same month such as households in irrigation areas with rice farming twice a year. On the other hand, if farmers outside irrigation areas can only grow rice once a year, their income will be received several months before March. This will become a problem when present bias or mental accounting are present (Bauer et al., 2012; Mullainathan \& Shafir, 2013). Farmers may be unable to save large sums of money received in November to repay the loan in March. There will be some temptation expenses or more necessary expenditure before the due date. In this case, there should be some incentive to let farmers repay ahead of the due date. Providing information that early repayment reduces the interest rate payment might not be enough. Some households may be afraid of unexpected expenses and thus prefer to keep money rather than repay debts that have not yet become due. Redraw facility product in Australia might be a good example to help solving this behavior. The last example is a case of farmer with remittance every month but only small income from farm activities. The matching repayment schedule to this case of income inflows could be small amount repayment in every month. This could assist in resolving the present bias problem by employing a commitment device to payback the loan on monthly basis. For loan contract design, structure is important to make sure the plans in commitment while flexibility needs to be incorporated to deal with uncertainties (Morduch, 2021).
[Figure 13 here]

## 7. Policy traps: Debt moratoriums

The last part, we explore participation and impacts of debt moratorium (DM) policies on households' debt accumulation and welfare. Over the past decade, debt moratoriums have been one of the most extensive policies aiming to help Thai agricultural households. DM programs have been common since 2014, with more than one ongoing DM program every year. The programs can be categorized into two broad types; shock-related DM programs and non-shock-related DM programs. Shock-related DM programs are mostly for disaster relief, except for a special case of COVID-19 shock in 2020. More than half of the DM programs are non-shock related, which can be further classified by whether the program is targeted or near universal. DM can be targeted to farmers planting certain types of crops or farmers in distress such as NPL borrowers and low-income farmers. DM
under Pracharat scheme18, which is considered as a landslide DM, is the largest in terms of the number of participants ( $69 \%$ of the borrowers).

Having overlapping DM programs back-to-back every year allows the hopping of the borrowers from one DM program to the next and enables the borrower to continuously stay in DM for many years. This also allows the borrowers to participate in more than one DM program at the same time by having multiple loan accounts that each enrolls in different programs. Figure 14a shows the share of borrowers by DM programs or combinations of DM programs participated over our sample period.
[Figure 14 here]
As a result of pervasiveness of DM programs, participation is widespread among Thai farmers. On average, $43.6 \%$ of the BAAC borrowers each year participate in DM, and the share amounts to $77.1 \%$ in 2021. The majority of borrowers (72.8\%) participate in both types of DM programs over the sample period, making it difficult to disentangle the impacts of shock- versus non-shock- related types of DM. Exploring intensity of DM participation, we found that $77.3 \%$ of the borrowers participated in more than one DM program, and $18.5 \%$ have received more than 4 DM programs. More importantly, Figure 14b shows that $41.1 \%$ of the borrowers have participated in DM for more than four years out of seven years that we can observe.

We further estimate the impact of DM participation on household debt growth. We identify DM impacts using panel regression that allow us to control for unobserved individual characteristics that might affect DM participation as well as the debt growth outcome. The specification is as follow:

$$
Y_{i t+1}=\beta D M_{i t}+\delta_{i}+\theta_{t}+\alpha X_{i t}+\varepsilon_{i t}
$$

where $Y_{i t+1}$ is debt growth the following year, $D M_{i t}$ reflects DM participation (in this paper, we only report result for impact of DM program intensity), $\delta_{i}, \theta_{t}$ are individual and time fixed effects in the panel regression and $X_{i t}$ controls for time-varying individual factors that might affect trends of individual outcomes. These include loan size, deposit size, number of loan accounts, number of new loan accounts, having DR/TDR accounts ( $0 / 1$ ), receiving disaster relief loans ( $0 / 1$ ), having personal loan ( $0 / 1$ ), having only working capital (WC) loans ( $0 / 1$ ), having collaterals pledged ( $0 / 1$ ), farming area (rai), being a landowner ( $0 / 1$ ), irrigated farming area $(0 / 1)$, receiving disaster relief transfer $(0 / 1$; proxy for shocks), having crop insurance ( $0 / 1$ ), borrower age, and age- squared. Various robustness
checks are carried out throughout the analysis and discussed in the notes of the tables or in the footnotes without the sub-section of its own. And Table 10 reports regression results.
[Table 10 here]
We found that participation in debt moratoriums resulted in higher debt accumulation, especially among those with larger debt and those with higher program intensity (Figure 14c). Ratanavararak and Chantarat (2023) explores impacts of DM in more detail and further found that there are two key mechanisms why being in DM could lead to larger debt growth: one is because most of DM participants did not repay even interest and so ended up accumulating large amount of interests while staying in the program and two is because most of DM participants could still take out new loan, and so this adds to the current debt in the program. Moreover, they found that DM has no significant impact on saving, while could increase agricultural investment especially among those with smaller debt. These findings thus could imply, on one hand, that DM policies thus could be one of the key drivers impeding agricultural households in long-term debt trap. On the other hand, these could imply that design of Thailand's popular debt moratoriums should be revisited, especially they should be more targeted and limited to short-term relief.

## 8. Conclusions and Policy Implications

Putting all the results together, this paper reveals the full vicious cycle of debt among Thai agricultural households, which starts from (1) households' unavoidable financial challenges insufficiency, instability and illiquidity - (2) great reliance on credit as a tool to resolve all these challenges (3) problems in rural financial market - information asymmetry, enforcement problems and contract design problems - which further create overborrowing beyond households' repayment capacity and trapping households in the trajectory toward debt trap. Furthermore, debt trap could reinforce underdevelopment and so poverty trap as large debt burden reduces incentives and ability to make productive investment and make households less resilient from future shocks.

Our results imply that agricultural development policies should give priority to farmers' debt policies and the rethinking of how to make rural financial market work better for heterogenous agricultural households, especially with respect to resolving the three economic problems. On the other hand, our results further imply that household debt solution should be total solutions including
not only debt policies but also development policies, financial literacy and safety nets. They should be well tailored to households with different debt situations, ability as well as willingness to repay.

More specifically, there are 6 policy priorities toward debt resolution and making rural financial market works for sustainable development of Thai agricultural households.

1. Making rural financial market works by resolving three economic problems which could include (i) creating better data that can reflect households' debt from all sources, ability and willingness to repay debt from Thailand's wealth of agricultural databases, encouraging better use of data for better design and target debt resolutions and for information-based lending as well as encouraging data exchange across rural financial institutions (ii) ensuring that the designs of financial products are well targeted and based on better understanding of capacity and need of different household groups and (iii) leveraging and empowering community financial institutions and interlinkages within the communities to ensure of more inclusive and sustainable rural financial market as these institutions could have lower screening and monitoring costs and can use social mechanisms and well-established business relationship to better enforce financial contracts relative to BAAC or other formal financial institutions.
2. Ensuring that households can repay and sustainably resolve existing debt which could include (i) redesigning repayment contracts and debt restructuring to match well with households' capacity to repay and having appropriate tools and commitment devices to enhance repayment (ii) using behavioral insights to nudge households' repayment especially among those currently lack willingness to repay (iii) scaling up community debt counselor.
3. Ensuring of more risk-based, more inclusive and more sustainable access to new loans which could include (i) ensuring more information and risk-based lending (ii) considering insured loan that could ensure households' loan repayment against key disaster shocks (iii) rethinking and redesigning joint liability or group loan to ensure that this can enforce loan repayment.
4. Enhancing household's economic growth to resolve financial challenges which could include (i) stimulating agricultural income growth by improving productivity and value added and resolving key structural problems in Thai agriculture (Attavanich et al. 2019) and (ii) improving availability and households' capacity and access to non-agricultural income.
5. Enhancing safety net and financial literacy which could include (i) ensuring households' access to crop and income insurance, (ii) incentivizing households to undertake adaptation and mitigation measures and (iii) enhancing financial awareness, attitude and behaviors especially in saving and financial management.
6. Transitioning out of destructive policies which could include (i) revisiting debt moratorium policies and ensuring that they are more targeted and limited to short-term relief, (ii) rethinking policy innovations to encourage finance for sustainable development.

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Figure 1 Distribution of Farmer Households in the Dataset


This figure plots the dataset used in this paper. Figure 1(a) shows the location of surveyed households across the country from PIER farmer household survey. One dot represents one Tambon. Twenty households are surveyed for each Tambon. Figure 1(b) shows the ratio of one-million sampled rice farmer borrowers from BAAC to total farmers at the Tambon level. The number of total farmers is taken from DOAE. Only Tambon with more than five rice farmer borrowers are plotted. Figure 1(c) presents the numbers of farmer borrowers by postcode using the NCB data as of 31 March 2022.

Figure 2 Monthly Cash flows by Type of Inflow and Outflow and by Region
(a) Monthly cash flows of a randomly selected household



This figure shows the intra-year variation of household income and expenses (represented by the bars), and net cash flow (represented by the black lines) using 2019-2020 farmer household survey data. The bars above zero represent cash income and the bars below zero represent expenditure. The percents in the parenthesis in Figure 2(b)-2(e) represent the share of farmer households by regions. This figure excludes financing cash flow (borrowing and repaying) and in-kind income and expenses. Wage income includes both non-owned on-farm and off-farm work. Salary income covers work as government officers, company employees, regional and local officers, and alike. Business includes processed agricultural products, handicraft, services, and off-farm trading. Government transfers include transfer for the elderly, for the poor, for the handicapped, for newborns, and for disaster relief. Other incomes include pension, lottery, gambling, winning prizes, and gifts. Consumption expenditure are food and beverages, utilities, transportation, groceries, and other household expenses. Temptation includes lottery, gambling, traveling, clothing, and other entertainment. Social expenditure covers donation and gifts to others. Investment includes insurance premiums and purchasing assets.

Figure 3 Heterogeneous Patterns of Monthly Net Cash Flows of 720 Sampled Households


This figure shows the intra-year variation of household net cash flow using 2019-2020 farmer household survey data. Each line represents the net cash flow of each household during January 2019 - January 2020. The lines above zero represent positive net cash flow and the lines below zero represent negative net cash flow. This figure excludes financing cash flow (borrowing and repaying) and in-kind income and expenses.

Figure 4 Financial Awareness and Attitude of Surveyed Farmer Households


This figure presents the score of farmers' self-evaluation in different areas of financial awareness and financial attitudes across 3 groups of households separated by the levels of household assets using the 2019-2020 farmer household survey data. All information is self-reported or self-evaluated. The highest score is 5 and the lowest score is 1 . High score of financial awareness means the farmers strongly agree (disagree) with the correct (wrong) knowledge in each topic. High score of financial attitude means the farmers evaluate themselves as strongly (strongly not) in line or strongly agree (disagree) with the good (bad) financial attitude and behavior. The financial attitude question in debt burden asks whether the farmer realizes that they are having a large amount of loan; thus, the lower score observed among the borrowers with higher assets (green line) might be because they do not have high debt in the first place. Asset quantile 1 = having total asset value below 416,400 Baht; Asset quantile 2 = having total asset value between 417,300-923,663 Baht; Asset quantile 3 = having total asset value above 924,600 Baht. Assets include land, machinery, automobiles, livestock, and financial assets. The difference across 3 groups of borrowers is tested using the overall Ftest by regressing the score on the dummies whether the borrower is in asset quantile 1,2 , or 3 . The asterisks *** $\mathrm{p}<$ $0.01,{ }^{* *} \mathrm{p}<0.05, * \mathrm{p}<0.1^{*}$ denote statistically significantly different.

Figure 5 Saving and Insurance Purchasing Behavior of Surveyed Farmer Households


This figure presents the share ( 0 to 1 ) of farmer households who have each type of savings or insurance across 3 groups of households separated by the levels of household assets using the 2019-2020 farmer household survey data. All information is self-reported. Asset quantile 1 = having total asset value below 416,400 Baht; Asset quantile 2 = having total asset value between 417,300-923,663 Baht; Asset quantile $3=$ having total asset value above 924,600 Baht. Assets include land, machinery, automobiles, livestock, and financial assets. $\mathrm{FN}=$ financial; ROSCA = rotating savings and credit association. The difference across 3 groups of borrowers is tested using the overall F-test by regressing the score on the dummies whether the borrower is in asset quantile 1,2 , or 3 . The asterisks $* * * \mathrm{p}<0.01$, ${ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1^{*}$ denote statistically significantly different.

Figure 6 Distribution of Household Outstanding Debt by Purpose and by Source of Loan


This figure presents the distribution of household outstanding debt by purpose and source of loan using the 20192020 farmer household survey data. Figure 6(a) ranks the borrower by debt percentile. The borrowers above the $95^{\text {th }}$ percentile are not plotted. The length of the bar represents the average debt outstanding balance for the borrowers in each percentile. The colors in the bar represent each type of loan purposes. Loans for agriculture purpose include loans for inputs, working capitals, loans for agriculture tools and machinery and loans for agriculture investment; loan for purchasing assets covers loans for land, house, automobile, motorcycles, and electrical appliances. Other purposes of borrowing in Figure 6(a) includes health, social expenses such as weddings and ceremonies, re-lending to other persons, and off-farm investment. Figure 6(b) shows the debt portfolio of different groups of households by the source of loan. The length of the bar represents the average debt outstanding balance for the borrowers in each group. The colors in the bar represent each type of lender. The top combination of debt portfolio (Rank \#1) covers 20\% of the farmer households with average debt outstanding of almost 400,000 Baht and the portfolio consists of mainly loans from SFIs (yellow) and small amount of loans from village fund and saving group (blue). Student Loan Fund (SLF) is not included in Figure 6(b) for the illustration purpose.

Figure 7 Dynamic of Household Debt Accumulation and the Relationship with the Ability to Repay and the Ability to Obtain New Loan
(a) Household debt accumulation by the opening year of the loan accounts (2017-2021)

(b) Debt to collateral ratio, the delinquency rate, and the proportion of borrowers receiving new loans (2020-2021)


Figure 7(a) plots the average of total loan outstanding per farmer borrower over time using the credit data from NCB. The borrowers are identified as farmers if they have loans for agriculture. The loan outstanding shown includes all types of loan from any financial institutions in NCB, inclusive of hire purchase loans from non-banks and nonagricultural loans from commercial banks. The height of the bar represents the average of the total loan outstanding and the colors of the bar represent the year the loan accounts were first opened. The data is from 2016Q2 to 2022Q1.

Figure 7(b) plots (1) debt to collateral ratio by quintiles in the blue bars, (2) delinquency rate by the quintiles of debt to collateral ratio in orange line, and (3) the share of borrowers who obtain new loans by the quintiles of debt to collateral ratio in navy line using data from BAAC. Figure 7(b) does not plot the borrowers with no collateral pledged with the bank. Outstanding debt to collateral ratio is calculated using the principal outstanding from every collateralized loan account observed in March 2020, exclusive of interest outstanding. Delinquent borrowers refer to the borrowers who have at least one loan with a classification of substandard or lower based on the conservative approach. Obtaining a new loan is determined by two criteria: (1) the borrowers open a new loan account and (2) there must be at least $10 \%$ increase in total debt, in order to exclude a new loan account resulting from TDR. Delinquency rate and proportion of borrowers receiving new loans are considered during April 2020 - March 2021.

Figure 8 Debt Outstanding, Debt Growth, and the Number of Years Participating in Debt Moratorium Scheme by Tambon


This figure plots the average household outstanding debt, 7 -year debt growth during 2014-2021, and the average number of years participating in the debt moratorium program using data from BAAC. Darker colors mean higher intensities.

Figure 9 Distribution of Debt Burden to Income and Total Debt to Asset Ratios
(a) Distribution of debt burden to income and total debt outstanding to asset

(b) The share of households by debt burden to income and total debt outstanding to asset

| Debt to <br> income | Debt to asset |  |  | Total |
| :---: | :---: | :---: | :---: | :---: |
|  | $0-1$ | $1-2$ | $>2$ |  |
| $0-1$ | $43 \%$ | $11 \%$ | $6 \%$ | $60 \%$ |
| $1-2$ | $6 \%$ | $1 \%$ | $3 \%$ | $9 \%$ |
| $>2$ <br> or negative income | $18 \%$ | $6 \%$ | $7 \%$ | $30 \%$ |
| Total | $66 \%$ | $18 \%$ | $16 \%$ | $100 \%$ |

Figure 9(a) shows the cumulative distribution of debt to income (navy line) and debt to asset (red line) ratios by percentiles of borrowers using 2019-2020 farmer household survey data. The values plotted are the median of the debt to income and debt to asset in each percentile. Debt to income and debt to asset above the $95^{\text {th }}$ percentile and debt to income with negative income are excluded. This corresponds to panel A in Table 5. Debt to income is the ratio of supposed annual debt repayment to annual income from all sources net of agriculture expenses. The net income comprises of net agriculture income, on-farm wage, off-farm income, remittance, government transfer, and other cash income. The annual debt repayment is yearly debt burden estimated from the interest rate multiplied with debt outstanding or principal. The median interest rate by loan-lender type is used when the interest rate data is missing. Debt to asset is the ratio of total outstanding debt balance to total asset values the households possess. Assets include land, machinery, automobiles, livestock, and financial assets.

Figure 9(b) shows the discrete distribution of the borrower share across different values of the two ratios using 2019-2020 farmer household survey data. It includes all borrowers, inclusive of the borrowers with negative income and the borrowers who have debt to income or debt to asset above the $95^{\text {th }}$ percentile; thus, Figure 9(b) is not entirely equivalent to Figure 9(a). The grouping by colors in Figure 9(b) is based on the authors' judgment.

Figure 10 Nonparametric Estimation of 6-year Debt to Asset Dynamics


These figures plot the non-parametric Kernel estimation employing randomized 5,000 borrowers from 1 million randomly selected BAAC borrowers who have pledged collateral with the bank. The borrowers who have debt outstanding below the $1^{\text {st }}$ percentile or above the $99^{\text {th }}$ percentile are excluded before randomization. Debt to asset ratio is calculated from the ratio of total loan outstanding to the values of collaterals. The collaterals included are real estate, deposit, bond, and BAAC saving lottery (sa-lak-oam-sap).

Figure 11 Debt Usage, Interest Cost, and Demand to Borrow More
(a) Share of households who have debts by type of outstanding loans and level of household asset (\%)

(b) Interest rate by type of outstanding loans and level of household asset (\%)

(c) Share of households who have demand to borrow more by type of needed loans and level of household asset (\%)

$1=$ Asset quantile 1; $2=$ Asset quantile $2 ; 3=$ Asset quantile 3

This figure presents the usage of debt, interest cost, and demand to borrow more by type of loans across 3 groups of households separated by the levels of household assets using the 2019-2020 farmer household survey data. Allpurpose loans are short-term loans for consumption and liquidity such as household expenditure, paying other debt, and for health expenses. Working capital (WC) loans are short-term revolving loans mainly to buy agriculture inputs. Long-term loans include medium- to long-term loans for purchasing agricultural land, houses, automobiles, education, and investment. Figure 11(b) uses the highest interest rate the borrowers need to pay for each type of loan excluding borrowing with zero interest rate such as borrowing from relatives. Asset quantile $1=$ having total asset value below 416,400 Baht; Asset quantile $2=$ having total asset value between 417,300-923,663 Baht; Asset quantile $3=$ having total asset value above 924,600 Baht. Assets include land, machinery, automobiles, livestock, and financial assets.

Figure 12 Distribution of the Ratio of Newly Lent Working Capitals to Agriculture Cost


This figure plots the ratio of the principal amount of newly lent working capital loan to agriculture cost across the percentiles of the ratio using BAAC data. The agriculture cost is approximated by the amount of actual planting area during 2020-2021 multiplied with the cost of 5,000 Baht per rai. The percentiles above the $95^{\text {th }}$ are not plotted. The time period is April 2020 to March 2021.

Figure 13 Example of the Current Mismatched Debt Contract Under One-size-fit-all Design

Example 2: A farmer in non-irrigated area normally grows rice once a year. The farmer receives large income once a year in November.


The proportion of WC accounts by repayment pattern between 2018-2021

| No or partial <br> repayment | Participated in Debt <br> Moratorium | Able to repay <br> every year |
| :---: | :---: | :---: |
| $28 \%$ | $59 \%$ | $13 \%$ |
| Hillill |  |  |

This figure illustrates working capital debt contract with yearly repayment (red bar), hypothetical cases of farmers' income (yellow bars), and the actual loan repayment using data from BAAC (gray box). From the survey, the majority of BAAC and cooperatives loans with yearly repayment are due in March and $41 \%$ of the farmer households in the survey have at least one yearly-repayment loan that are due in March each year (the red bar). The hypothetical cases are designed by the authors based on the observed facts from the survey.

For the loan repayment in the gray box, being able to repay is considered from the actual yearly repayments that are above the supposed-to-repay amount. The supposed-to-repay amount is proxied by the principal divided by the loan term in years. Zero repayment can be observed from the data, but partial repayment is estimated as the residual from all loans minus loans under debt moratorium, loans that can be repaid, and loans with zero repayment. Hence, this number might not reflect the actual situation. Repayment is considered during April 2017 - March 2022.

Figure 14 Intensity of Participation in Debt Moratorium and the Impact on Farmer Debt Growth
(a) Share of borrowers by DM program participation 2015-2021


(b) Share of borrowers by number of years in debt moratorium

(c) Impact of number of years in debt moratorium on debt growth by debt size


This figure plots the farmers' participation in debt moratorium (DM) scheme and the impact on debt growth using the randomly selected 1 million rice farmers from BAAC data.

Figure 14(a) shows the share of borrowers by DM program participation from 2015 to 2021. One color corresponds to one DM program or one combination of DM programs. Other DM programs are flood 2016, NPL borrowers, fruit farmers, cassava farmers, and farmers in 3 southern provinces. Blue-toned bars are non-shock-related DMs. Red-toned bars are shock-related DMs. Green-toned bars are combinations of DM programs. Pracharat is a government scheme that aims to support agricultural sector reform. Alleviating debt burden through debt deferral is one of its sub-programs.

Figure 14(b) shows the cumulative number of years the farmers participated in DM scheme out of 7 years over the period of 2015-2021.

Figure 14(c) plots the estimated coefficients (solid line) and the associated $95 \%$ confidence intervals (dashed line) of the number of years in DM from four fixed effect panel regressions, each represented by each line. Low, medium, high debts are grouping of debt deciles based on similarity of the regression results by each decile group. Low debt $=$ borrowers in the $1^{\text {st }}$ debt decile with outstanding debt below 37,000 Baht; medium debt $=$ borrowers in the $2^{\text {nd }}$ to $7^{\text {th }}$ deciles with outstanding debt between $37,000-292,000$ Baht; high debt $=$ borrowers in the $8^{\text {th }}$ to $10^{\text {th }}$ decile with outstanding debt above 292,000 Baht. The number of years in DM enters the model as dummy variables. The regressions are at the borrower-year level. Dependent variable is 1-year loan growth. Borrower controls include lagged
dependent variables, loan size, deposit size, number of loan accounts, number of new loans in previous year, having DR/TDR accounts ( $0 / 1$ ), receiving disaster relief loans $(0 / 1)$, having P-loan ( $0 / 1$ ), having only WC loans ( $0 / 1$ ), collaterals pledged $(0 / 1)$, farming area, landowner $(0 / 1)$, irrigated farming area $(0 / 1)$, receiving disaster relief transfer $(0 / 1)$, receiving crop insurance $(0 / 1)$, age, and age-squared. All regressors are lagged except age. See Ratanavararak and Chantarat (2022) for more discussion on the impact of debt moratorium on farmer debt.

Table 1 Summary of Main Data Sources

|  | Year | Households | Individuals | Loans |
| :--- | :--- | :--- | :--- | :--- |
|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ |
| 1. PIER Farmer Household Survey | $2019-2020$ | 720 | 2,632 | 3,559 |
| 2. Loans and deposits of sampled farmers from BAAC | $2014-2021$ | - | $1,000,000$ | $7,038,178$ |
| 3. Farmer registration from DOAE | $2016-2022$ | $7,873,948$ | $17,854,449$ | - |
| 4. Formal loans from NCB | $2016-2022$ | - | $4,732,532$ | $30,285,699$ |

The table presents a summary of the four main data sources. Column 2-4 shows the number of total households, individual farmers, and loan accounts respectively. PIER = Puey Ungphakorn Institute for Economic Research; BAAC = Bank for Agriculture and Agricultural Cooperatives; DOAE $=$ Department of Agriculture Extension; NCB $=$ National Credit Bureau.

Table 2 Descriptive Statistics of Farmer Households by Data Source 2014-2022

|  | N | Mean | SD | Median |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) |
| A. PIER Farmer Household Survey (household level) |  |  |  |  |
| Age of respondent (year, in 2020) | 711 | 52.92 | 9.79 | 53 |
| Debt outstanding (Baht, in 2020) | 665 | 429,898 | 551,945 | 251,500 |
| Number of types of formal institutions used per household (out of 3 types: banks, non-banks, SFI) | 584 | 1.31 | 0.50 | 1 |
| Number of types of semi-formal institutions used per household (out of 4 types: village fund, cooperative, saving group, Student Loan Fund) | 532 | 1.37 | 0.60 | 1 |
| Number of types of informal lenders used per household (out of 4 types: relative, shop credit, moneylender, other) | 364 | 1.34 | 0.60 | 1 |
| Number of loan accounts per household (in 2020) | 665 | 3.42 | 2.10 | 3 |
| B. Loans and deposits from BAAC (individual level) |  |  |  |  |
| Age (year, in 2021) | 989,047 | 59.01 | 10.36 | 59 |
| Debt outstanding (Baht, yearly average) | 983,732 | 253,540 | 301,224 | 177,073 |
| Debt outstanding (Baht, 2021) | 835,990 | 344,135 | 429,587 | 235,729 |
| Deposit (Baht, yearly average) | 999,631 | 31,165 | 121,892 | 9,892 |
| Number of loan accounts per farmer (yearly average) | 983,793 | 2.84 | 1.77 | 2.38 |
| Delinquency (0/1) | 983,793 | 0.12 | 0.32 | 0 |
| Collateralization (0/1) | 983,793 | 0.73 | 0.44 | 1 |
| C. Farming activities from $D O A E$ merged with $B A A C$ (household level) |  |  |  |  |
| Planting area (rai, yearly average) | 999,989 | 19.30 | 14.02 | 15.75 |
| Landowner (0/1) | 999,999 | 0.94 | 0.24 | 1 |
| Participating in agricultural growth policy 2018 (0/1) | 998,542 | 0.13 | 0.34 | 0 |
| D. Loans from NCB (individual level) |  |  |  |  |
| Age (year, in 2022) | 4,730,103 | 58.42 | 12.13 | 58 |
| Debt outstanding (Baht, yearly average) | 4,732,458 | 356,914 | 926,141 | 192,201 |
| Number of types of formal institutions used per household (out of 3 types: banks, non-banks, SFI) | 4,732,532 | 1.38 | 0.62 | 1 |
| Number of formal institutions used per household | 4,732,532 | 1.70 | 1.30 | 1 |
| Number of loan accounts per farmer (yearly average) | 4,732,532 | 3.48 | 2.46 | 2.8571 |
| Delinquency (0/1) | 4,732,532 | 0.35 | 0.48 | 0 |

The table presents summary statistics at the household or farmer level for the main variables from four data sources. Only the survey data in panel A uses the statistics based on the latest 2020 data, which is the time when the interviews took place. The data for 2019 is based on recalling memories of the respondents which can likely be more inaccurate. Other databases use yearly average of data over the entire sample period. Dummy variables are considered during the whole period of data and equal to 1 if the borrower falls into the criteria at least once in any year. The number of types of financial institutions are considered during the whole sample period for each dataset. Debt outstanding and number of loan accounts are only summarized for the farmers who have non-zero debt outstanding. The farmers who do not borrow are excluded. The data from BAAC is annually as of 31 March each year. Loan outstanding from BAAC only refers to the outstanding principal, and does not cover the accrued interest amount. The data from NCB that are used to compute the statistics in this table is annually as of 31 December each year, except 2022, which uses the data as of 31 March because it was the latest data at the time the analysis in this paper was carried out. Loans from NCB only include banks, non-banks, and SFI. SFI is Specialized Financial Institution. Student Loan Fund is not included as formal loans so that the formal loans in panel A can be compared to those from NCB in panel D . The loan delinquency for BAAC data is based on the loan classification using the conservative approach; if any of the farmer's active loan is classified as substandard (SS) or lower, that borrower is classified as delinquent. The loan delinquency for NCB data is based on the number of days past due using the conservative approach; if any of the farmer's active loan is more than 90 days past due, that borrower is classified as delinquent.

One rai equals 0.16 hectare. Agricultural growth policies are the large farming program and the after-rice planting program.

Table 3 Yearly Share of Cash Income, Expenditure, and Net Cash flow by Source and Region

|  | All households ( $\mathrm{N}=713$ ) |  |  | Northeast ( $\mathrm{N}=310$ ) |  |  | Central ( $\mathrm{N}=157$ ) |  |  | North (N=163) |  |  | South ( $\mathrm{N}=80$ ) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Mean | SD | Median | Mean | SD | Median | Mean | SD | Median | Mean | SD | Median | Mean | SD | Median |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| A: Yearly share of cash income by source (\%) |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Agriculture | 0.42 | 0.31 | 0.39 | 0.31 | 0.25 | 0.24 | 0.59 | 0.29 | 0.63 | 0.50 | 0.32 | 0.47 | 0.39 | 0.32 | 0.37 |
| Wage | 0.15 | 0.21 | 0.03 | 0.16 | 0.21 | 0.00 | 0.11 | 0.18 | 0.02 | 0.17 | 0.24 | 0.03 | 0.13 | 0.22 | 0.00 |
| Salary | 0.14 | 0.23 | 0.00 | 0.13 | 0.21 | 0.00 | 0.14 | 0.22 | 0.00 | 0.13 | 0.23 | 0.00 | 0.18 | 0.29 | 0.00 |
| Business | 0.09 | 0.20 | 0.00 | 0.09 | 0.20 | 0.00 | 0.06 | 0.15 | 0.00 | 0.09 | 0.22 | 0.00 | 0.13 | 0.22 | 0.00 |
| Remittances | 0.12 | 0.21 | 0.00 | 0.20 | 0.25 | 0.07 | 0.06 | 0.15 | 0.00 | 0.05 | 0.14 | 0.00 | 0.07 | 0.16 | 0.00 |
| Government transfer | 0.05 | 0.11 | 0.02 | 0.05 | 0.11 | 0.03 | 0.03 | 0.04 | 0.01 | 0.06 | 0.13 | 0.03 | 0.08 | 0.18 | 0.03 |
| Return on assets and others | 0.03 | 0.09 | 0.00 | 0.05 | 0.13 | 0.01 | 0.02 | 0.04 | 0.00 | 0.00 | 0.02 |  | 0.02 | 0.08 | 0.00 |
| B: Yearly share of expenditure by source (\%) |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Consumption | 0.32 | 0.16 | 0.31 | 0.32 | 0.15 | 0.29 | 0.26 | 0.14 | 0.24 | 0.35 | 0.15 | 0.34 | 0.43 | 0.18 | 0.44 |
| Agriculture expenses | 0.34 | 0.20 | 0.31 | 0.27 | 0.17 | 0.24 | 0.44 | 0.21 | 0.44 | 0.40 | 0.20 | 0.38 | 0.30 | 0.19 | 0.26 |
| Health and education | 0.07 | 0.10 | 0.03 | 0.08 | 0.10 | 0.04 | 0.07 | 0.08 | 0.04 | 0.07 | 0.10 | 0.02 | 0.06 | 0.09 | 0.03 |
| Temptation | 0.10 | 0.08 | 0.08 | 0.12 | 0.10 | 0.09 | 0.09 | 0.08 | 0.07 | 0.09 | 0.08 | 0.06 | 0.08 | 0.05 | 0.06 |
| Social and transfer | 0.06 | 0.11 | 0.02 | 0.09 | 0.12 | 0.04 | 0.07 | 0.09 | 0.03 | 0.02 | 0.08 | 0.00 | 0.05 | 0.12 | 0.00 |
| Rent and investment | 0.10 | 0.12 | 0.06 | 0.13 | 0.13 | 0.09 | 0.07 | 0.08 | 0.04 | 0.06 | 0.10 | 0.03 | 0.09 | 0.15 | 0.03 |
| C: Annual income, expenditure, and net cash flow |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Annual cash income (cash inflow, Baht) | 382,128 | 387,773 | 290,500 | 375,322 | 372,185 | 295,713 | 536,623 | 502,566 | 395,500 | 314,863 | 313,227 | 248,400 | 251,485 | 200,108 | 215,400 |
| Annual expenditure (cash outflow, Baht) | 338,886 | 285,285 | 255,972 | 309,000 | 245,127 | 228,249 | 459,183 | 373,489 | 358,605 | 300,295 | 266,708 | 236,160 | 304,485 | 199,068 | 250,377 |
| Annual net cash flow (Baht) | 43,241 | 295,236 | 16,804 | 66,323 | 318,509 | 33,619 | 77,440 | 322,530 | 36,366 | 14,568 | 234,201 | -3,675 | -52,999 | 238,978 | -51,243 |
| Share of households with negative annual income (\%) | 0.45 | 0.50 |  | 0.39 | 0.49 |  | 0.40 | 0.49 |  | 0.51 | 0.50 |  | 0.64 | 0.48 |  |
| D: Intra year variation: Share of households by months with negative income |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Never (having non-negative income every month) | 0.15 | 0.36 |  | 0.21 | 0.41 |  | 0.08 | 0.28 |  | 0.10 | 0.30 |  | 0.16 | 0.37 |  |
| 1-6 months | 0.31 | 0.46 |  | 0.35 | 0.48 |  | 0.27 | 0.45 |  | 0.28 | 0.45 |  | 0.24 | 0.43 |  |
| 7-11 months | 0.37 | 0.48 |  | 0.33 | 0.47 |  | 0.52 | 0.50 |  | 0.39 | 0.49 |  | 0.25 | 0.44 |  |
| Every month | 0.18 | 0.37 |  | 0.11 | 0.31 |  | 0.13 | 0.33 |  | 0.23 | 0.42 |  | 0.35 | 0.48 |  |

This table presents the summary statistics of household incomes, expenditures, and net cash flow using the 2019-2020 farmer household survey data. The overall statistics are reported in column $1-3$. The statistics separated by regions are reported in column 4-15. The in-kind income is not considered. Wage income includes both non-owned on-farm and off-farm work. Salary income covers work as government officers, company employees, regional and local officers, and alike. Business includes processed agricultural products, handicraft, services, and off-farm trading. Government transfers include transfer for the elderly, for the poor, for the handicapped, for newborns, and for disaster relief. Other incomes include pension, lottery, gambling, winning prizes, and gifts. Consumption expenditure are food and beverages, utilities, transportation, groceries, and other household expenses. Temptation includes lottery, gambling, traveling, clothing, and other entertainment. Social expenditure covers donation and gifts to others. Investment includes insurance premiums and purchasing assets.

Table 4 Summary Statistics of Farmer Household Borrowing

|  | N | Mean | SD | Median |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) |
| A. PIER Farmer Household Survey (bousehold level) |  |  |  |  |
| Debt outstanding (Baht, in 2020) | 665 | 429,898 | 551,945 | 251,500 |
| Number of loan accounts per household (in 2020) | 665 | 3.420 | 2.095 | 3 |
| Share of debt outstanding per household by purpose (\%) |  |  |  |  |
| Agriculture | 665 | 0.449 | 0.417 | 0.339 |
| Purchasing assets | 665 | 0.208 | 0.336 | 0 |
| Household expense | 665 | 0.134 | 0.266 | 0 |
| Education | 665 | 0.070 | 0.221 | 0 |
| Paying other debts | 665 | 0.068 | 0.195 | 0 |
| Others | 665 | 0.072 | 0.209 | 0 |
| Share of debt outstanding per household by lender (\%) |  |  |  |  |
| Specialized Financial Institutions (SFI) | 665 | 0.473 | 0.408 | 0.544 |
| Non-bank financial institutions | 665 | 0.079 | 0.209 | 0 |
| Commercial banks | 665 | 0.014 | 0.109 | 0 |
| Village fund | 665 | 0.160 | 0.254 | 0.055 |
| Agriculture and saving cooperatives | 665 | 0.120 | 0.269 | 0 |
| Saving groups | 665 | 0.017 | 0.081 | 0 |
| Student Loan Fund | 665 | 0.019 | 0.112 | 0 |
| Agriculture shop credit | 665 | 0.008 | 0.058 | 0 |
| Relatives and friends | 665 | 0.065 | 0.206 | 0 |
| Moneylender | 665 | 0.027 | 0.129 | 0 |
| Others | 665 | 0.018 | 0.093 | 0 |
| B. Loans and deposits from BAAC merged with farmer registration from DOAE (individual level) |  |  |  |  |
| Debt outstanding (Baht, yearly average) | 983,732 | 253,540 | 301,224 | 177,073 |
| Debt outstanding (Baht, 2021) | 835,990 | 344,135 | 429,587 | 235,729 |
| 7-year loan growth 2014-2021 | 758,765 | 1.077 | 2.432 | 0.333 |
| Average yearly debt growth 2014-2021 | 982,659 | 0.060 | 0.331 | 0.053 |
| Number of years in Debt Moratorium programs (out of 7 years) | 981,085 | 3.564 | 2.125 | 4 |
| Ratio of newly lent working capital loan to agriculture cost 2020-2021 | 132,281 | 1.705 | 6.459 | 0.717 |
| Share of debt outstanding per farmer by product type (\%, yearly average 2014-2021) |  |  |  |  |
| Working capital | 968,221 | 0.604 | 0.331 | 1 |
| Term loan for agriculture | 968,221 | 0.125 | 0.223 | 0 |
| Personal loan | 968,221 | 0.098 | 0.158 | 0 |
| Home loan | 968,221 | 0.044 | 0.141 | 0 |
| Business | 968,221 | 0.041 | 0.139 | 0 |
| Other | 968,221 | 0.089 | 0.247 | 0 |
| B.1 Ability to repay and capacity to obtain new loan |  |  |  |  |
| Debt to collateral ratio 2020-2021 by quintiles of debt to collateral ratio |  |  |  |  |
| No collateral | 325,655 |  |  |  |
| Quintile 1 | 103,828 | 0.062 | 0.051 | 0.062 |
| Quintile 2 | 103,828 | 0.230 | 0.045 | 0.230 |
| Quintile 3 | 103,828 | 0.394 | 0.051 | 0.393 |
| Quintile 4 | 103,828 | 0.619 | 0.088 | 0.610 |
| Quintile 5 | 98,637 | 1.644 | 1.179 | 1.188 |
| Delinquency headcount 2020-2021 by quintiles of debt to collateral ratio |  |  |  |  |
| No collateral | 325,655 | 0.092 | 0.289 | 0 |
| Quintile 1 | 101,319 | 0.029 | 0.167 | 0 |
| Quintile 2 | 103,700 | 0.035 | 0.183 | 0 |
| Quintile 3 | 103,742 | 0.050 | 0.217 | 0 |
| Quintile 4 | 103,774 | 0.071 | 0.257 | 0 |
| Quintile 5 | 103,749 | 0.114 | 0.317 | 0 |

Ratio of borrowers receiving new loan 2020-2021 by quintiles of debt to collateral ratio

|  | N | Mean | SD | Median |
| :--- | :--- | :--- | :--- | :--- |
|  | $(1)$ | $(2)$ | $(3)$ | $(4)$ |
| No collateral | 330,623 | 0.154 | 0.361 | 0 |
| Quintile 1 | 103,828 | 0.294 | 0.456 | 0 |
| Quintile 2 | 103,828 | 0.186 | 0.389 | 0 |
| Quintile 3 | 103,828 | 0.141 | 0.348 | 0 |
| Quintile 4 | 103,828 | 0.113 | 0.317 | 0 |
| Quintile 5 | 103,828 | 0.114 | 0.317 | 0 |
|  |  |  |  |  |
| C. Loans from NCB (individual level) |  |  |  |  |
| Debt outstanding (Baht, yearly average) | $4,732,458$ | 356,914 | 926,141 | 192,201 |
| Debt outstanding (Baht, 2021) | $4,006,666$ | 440,825 | $1,079,876$ | 235,399 |
| Average yearly debt growth 2017-2022 | $4,154,650$ | 0.079 | 0.422 | 0.015 |

This table presents the summary statistics of farmer household borrowing in various dimensions. They are the statistics for Figure 6-8 and Figure 12. Loan growth above the $99^{\text {th }}$ percentile is excluded in all panels.

Panel A shows the borrowing by purpose of loan and by type of lenders using the farmer household survey data between 2019-2020. Loans for agriculture purpose include loans for inputs, working capitals, loans for agriculture tools and machinery and loans for agricultural lands. Loan for purchasing assets covers loans for land, house, automobile, motorcycles, and electrical appliances. Other purposes of borrowing in panel A includes health, social expenses such as weddings and ceremonies, re-lending to other persons, and off-farm investment.

Panel B shows the borrowing characteristics using the BAAC data. For the ratio of newly lent working capital loan to agriculture cost, the agriculture cost is approximated by the amount of actual planting area during 2020-2021 multiplied with the cost of 5,000 Baht per rai. Panel B. 1 focuses on the ability to repay and to obtain new loans. Debt to collateral ratio is calculated using the principal outstanding from every collateralized loan account observed in March 2020, exclusive of interest outstanding. Delinquent borrowers refer to the borrowers who have at least one loan with a classification of substandard or lower based on the conservative approach. Obtaining a new loan is determined by two criteria: (1) the borrowers open a new loan account and (2) there must be at least $10 \%$ increase in total debt, in order to exclude a new loan account resulting from TDR. Delinquency rate and proportion of borrowers receiving new loans are considered during April 2020 - March 2021. Debt to collateral ratio above $99^{\text {th }}$ percentile is excluded in the summary statistics of debt to collateral ratio, resulting in a smaller number of borrowers in Quintile 5 (98,637 farmers).

Panel C shows the debt outstanding and growth over time using the credit data from NCB. The borrowers are identified as farmers if they have loans for agriculture. The loan outstanding shown includes all types of loan from any financial institutions in NCB, inclusive of hire purchase loans from non-banks and non-agricultural loans from commercial banks. The data from NCB that are used is annually as of 31 December each year, except 2022, which uses the data as of 31 March because it was the latest data at the time the analysis in this paper was carried out.

Table 5 Ability to Repay and Repayment Behavior

|  | All households |  |  |  | Asset quantile 1 |  |  |  | Asset quantile 2 |  |  |  | Asset quantile 3 |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | N | Mean | SD | Median | N | Mean | SD | Median | N | Mean | SD | Median | N | Mean | SD | Median |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) |
| A. Ability to repay |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Having negative income | 713 | 0.202 | 0.402 | 0 | 218 | 0.200 | 0.401 | 0 | 234 | 0.195 | 0.397 | 0 | 261 | 0.211 | 0.409 | 0 |
| Debt burden to non-negative net income | 500 | 0.482 | 0.574 | 0.273 | 153 | 0.584 | 0.659 | 0.376 | 157 | 0.466 | 0.522 | 0.250 | 190 | 0.394 | 0.514 | 0.223 |
| Total debt to total asset | 678 | 0.761 | 1.026 | 0.350 | 184 | 1.253 | 1.332 | 0.853 | 233 | 0.838 | 0.935 | 0.593 | 261 | 0.269 | 0.419 | 0.086 |
| B. Repayment behavior |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Share of households fully repaying at least one loan account in the previous year | 683 | 0.637 | 0.481 | 1 | 210 | 0.590 | 0.493 | 1 | 228 | 0.730 | 0.445 | 1 | 245 | 0.589 | 0.493 | 1 |
| Share of households not repaying any debt | 683 | 0.026 | 0.158 | 0 | 210 | 0.030 | 0.170 | 0 | 228 | 0.000 | 0.000 | 0 | 245 | 0.048 | 0.214 | 0 |
| Share of households who borrow to repay (debt rotation) | 683 | 0.268 | 0.443 | 0 | 210 | 0.343 | 0.476 | 0 | 228 | 0.294 | 0.457 | 0 | 245 | 0.180 | 0.385 | 0 |
| Share of households participating in DM program | 683 | 0.545 | 0.498 | 1 | 210 | 0.638 | 0.482 | 1 | 228 | 0.509 | 0.501 | 1 | 245 | 0.485 | 0.501 | 0 |
| Share of households repaying only the interest in non-DM loans |  | 0.257 | 0.437 | 0 | 210 | 0.322 | 0.468 | 0 | 228 | 0.246 | 0.431 | 0 | 245 | 0.201 |  | 0 |
| C Yearl-repayment loan |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Share of households having yearly repayment debt | 670 | 0.859 | 0.348 | 1 | 208 | 0.862 | 0.346 | 1 | 224 | 0.917 | 0.276 | 1 | 238 | 0.796 | 0.403 | 1 |
| Due in March | 670 | 0.413 | 0.493 | 0 | 208 | 0.435 | 0.497 | 0 | 224 | 0.441 | 0.498 | 0 | 238 | 0.359 | 0.481 | 0 |
| Due in December | 670 | 0.244 | 0.430 | 0 | 208 | 0.229 | 0.421 | 0 | 224 | 0.267 | 0.443 | 0 | 238 | 0.237 | 0.426 | 0 |
| Share of households repaying yearly repayment loan more than once a year | 670 | 0.021 | 0.144 | 0 | 208 | 0.003 | 0.057 | 0 | 224 | 0.040 | 0.195 | 0 | 238 | 0.021 | 0.144 | 0 |
| Share of households repaying the loan not in the due month | 592 | 0.156 | 0.363 | 0 | 188 | 0.163 | 0.370 | 0 | 201 | 0.139 | 0.347 | 0 | 203 | 0.167 | 0.374 | 0 |

This table shows the repayment behavior of farmer households in 3 areas across 3 groups of borrowers based on their asset size (asset quantile 1-3) using the 2019-2020 farmer household survey data. Asset quantile $1=$ having total asset value below 416,400 Baht; Asset quantile $2=$ having total asset value between 417,300-923, 663 Baht; Asset quantile $3=$ having total asset value above 924,600 Baht. Assets include land, machinery, automobiles, livestock, and financial assets.

Panel A shows the ability to repay from debt burden to net income and total debt to total asset. Debt to income is the ratio of supposed annual debt repayment to annual income from all sources net of agriculture expenses. The net income comprises of net agriculture income, on-farm wage, off-farm income, remittance, government transfer, and other cash income. The annual debt repayment is yearly debt burden estimated from the interest rate multiplied with debt outstanding or principal. The median interest rate by loan-lender type is used when the interest rate data is missing. Debt to asset is the ratio of total outstanding debt balance to total asset values the households possess. Assets include land, machinery, automobiles, livestock, and financial assets. The debt to income and debt to asset ratios above the $95^{\text {th }}$ percentiles and the debt to negative income are excluded in the statistics. This corresponds to Figure 9(a).

Panel B shows the overall repayment behavior. The behavior of borrowing one loan to pay another loan or debt rotation is identified by both the repayment of the loan with the source of fund as borrowing money or the borrowing of the loan with the purpose to use it to repay other debt. Debt moratorium (DM) suspends the repayment of the loan for a certain period of time; thus, the repayment behavior during participation in the DM scheme might not reflect the actual behavior. The households repaying only the interest in nonDM loans refer to the households that repay at least one loan account during the past year in the amount below the yearly debt burden. Fully repaying a loan account might or might not suggest capacity to repay as it is possible that the households borrow loan from other sources to pay off another loan

Panel C focuses on the repayment of loans that require repayment only once a year (yearly-repayment loan). The statistics under panel C aims to show the possible mismatching between the required loan repayment period and the actual loan repayment by the borrowers.

Table 6 Impact of Lender Type on Loan Delinquency

|  | Dependent variable: delinquency (0/1) |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) |
| Sources of loan: (base - SFIs) Cooperatives (0/1) | $\begin{aligned} & 0.021 \\ & (0.0254) \end{aligned}$ | $\begin{aligned} & 0.026 \\ & (0.0254) \end{aligned}$ | $\begin{aligned} & 0.030 \\ & (0.0260) \end{aligned}$ | $\begin{aligned} & 0.038 \\ & (0.0259) \end{aligned}$ |
| Commercial Banks (0/1) | $\begin{aligned} & -0.012 \\ & (0.0606) \end{aligned}$ | $\begin{aligned} & -0.019 \\ & (0.0609) \end{aligned}$ | $\begin{aligned} & 0.009 \\ & (0.0599) \end{aligned}$ | $\begin{aligned} & 0.005 \\ & (0.0599) \end{aligned}$ |
| Non-bank (0/1) | $\begin{aligned} & -0.024 \\ & (0.0247) \end{aligned}$ | $\begin{aligned} & -0.026 \\ & (0.0247) \end{aligned}$ | $\begin{aligned} & -0.022 \\ & (0.0246) \end{aligned}$ | $\begin{aligned} & -0.022 \\ & (0.0244) \end{aligned}$ |
| Village funds/Saving groups (0/1) | $\begin{aligned} & -0.091^{* * *} \\ & (0.0183) \end{aligned}$ | $\begin{aligned} & -0.074 * * * \\ & (0.0199) \end{aligned}$ | $\begin{aligned} & -0.089^{* * *} \\ & (0.0183) \end{aligned}$ | $\begin{aligned} & -0.053 * * * \\ & (0.0201) \end{aligned}$ |
| Informal lenders (0/1) | $\begin{aligned} & -0.100^{* * *} \\ & (0.0204) \end{aligned}$ | $\begin{aligned} & -0.079 * * * \\ & (0.0218) \end{aligned}$ | $\begin{aligned} & -0.096^{* * *} \\ & (0.0202) \end{aligned}$ | $\begin{aligned} & -0.059 * * * \\ & (0.0215) \end{aligned}$ |
| Principal amount (ln) |  | $\begin{aligned} & 0.013 * * \\ & (0.0054) \end{aligned}$ |  | $\begin{aligned} & 0.027 * * * \\ & (0.0060) \end{aligned}$ |
| Number of debts per household |  |  | $\begin{aligned} & 0.015 * * * \\ & (0.0025) \end{aligned}$ | $\begin{aligned} & 0.018^{* * *} \\ & (0.0025) \end{aligned}$ |
| Household head age |  |  | $\begin{aligned} & -0.002^{* *} \\ & (0.0009) \end{aligned}$ | $\begin{aligned} & -0.002^{* *} \\ & (0.0009) \end{aligned}$ |
| Female household head (0/1) |  |  | $\begin{aligned} & 0.027 * \\ & (0.0145) \end{aligned}$ | $\begin{aligned} & 0.027 * \\ & (0.0145) \end{aligned}$ |
| Household head education: (base - primary school) |  |  |  |  |
| - Secondary school (0/1) |  |  | $\begin{aligned} & 0.041^{*} \\ & (0.0223) \end{aligned}$ | $\begin{aligned} & 0.044^{*} \\ & (0.0225) \end{aligned}$ |
| - High school (0/1) |  |  | $\begin{aligned} & 0.020 \\ & (0.0200) \end{aligned}$ | $\begin{aligned} & 0.016 \\ & (0.0198) \end{aligned}$ |
| - Higher education (college an above) (0/1) |  |  | $\begin{aligned} & 0.002 \\ & (0.0286) \end{aligned}$ | $\begin{aligned} & -0.003 \\ & (0.0278) \end{aligned}$ |
| Having farmer credit card (0/1) |  |  | $\begin{aligned} & 0.001 \\ & (0.0148) \end{aligned}$ | $\begin{aligned} & 0.005 \\ & (0.0148) \end{aligned}$ |
| Young smart farmer (0/1) |  |  | $\begin{aligned} & -0.202^{* * *} \\ & (0.0702) \end{aligned}$ | $\begin{aligned} & -0.202 * * * \\ & (0.0695) \end{aligned}$ |
| Asset value (ln) |  |  | $\begin{aligned} & -0.018^{* * *} \\ & (0.0056) \end{aligned}$ | $\begin{aligned} & -0.020^{* * *} \\ & (0.0056) \end{aligned}$ |
| Yearly debt burden (ln) |  |  | $\begin{aligned} & -0.016^{*} \\ & (0.0086) \end{aligned}$ | $\begin{aligned} & -0.031 * * * \\ & (0.0088) \end{aligned}$ |
| Pseudo R2 | 0.0213 | 0.0242 | 0.0642 | 0.0739 |
| Number of observations | 2,719 | 2,707 | 2,661 | 2,649 |

This table reports the average marginal effects from logit regressions using 2019-2020 farmer household survey data. The data are at the loan level. Each column represents one regression. Only loans that have been repaid during the past 12 months at the time of survey or the on-going loans are included. The dependent variable is delinquency which equals to 1 when the households reported that a particular loan had ever been overdue. Standard errors are in parentheses. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$.

Table 7 Summary Statistics of Joint-liability Loans - Borrower Level

|  | N | Mean | SD | Median |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) |
| A. Share of joint-liability loan |  |  |  |  |
| Share of joint-liability loan outstanding to total debt per borrower | 222,449 | 0.308 | 0.229 | 0.241 |
| B. Share of farmers by loan type (borrower level) |  |  |  |  |
| Having only joint-liability loans | 816,674 | 0.059 | 0.235 | 0 |
| Having joint-liability loans with other types of loans | 816,674 | 0.272 | 0.445 | 0 |
| Do not have joint-liability loans | 816,674 | 0.669 | 0.471 | 1 |
| C. Size of loan by loan type (Babt, borrower-loan type level) |  |  |  |  |
| Joint-liability loan | 270,260 | 359,696 | 342,255 | 281,071 |
| Collateralized loan | 343,182 | 422,040 | 533,022 | 289,990 |
| Other loans | 203,232 | 198,545 | 264,120 | 101,123 |
| D. Borrower delinquency by loan type (\%, borrower-loan type level) |  |  |  |  |
| Joint-liability loan | 270,260 | 0.128 | 0.334 | 0 |
| Collateralized loan | 343,182 | 0.046 | 0.209 | 0 |
| Other loans | 203,232 | 0.069 | 0.254 | 0 |

This table reports the summary statistics of joint liability loans at the borrower level using randomly selected 1 million borrowers from BAAC data. Joint-liability loans are identified from 2 criteria: (1) the loan account is backed with the guarantor (2) the borrower of the loan belongs to a group. Other types of loans in panel B refer to assetcollateralized loans and loans with neither pledged collateral or guarantor. Other loans in panel C refer to loans with neither pledged collateral or guarantor. Asset collaterals include real estate, deposit, bond, BAAC saving lottery (sa-lak-oam-sap) and pledged agricultural products. Panel C and D aggregate the data at the borrower-loan type level (not the account level). The borrowers with two joint-liability loans are summed up and reported under the Joint-liability loan. The borrowers with both joint-liability loan and collateralized loan are reported under both loan types. Delinquent borrowers refer to the borrowers who have at least one loan with a classification of substandard or lower based on the conservative approach.

Table 8 Summary Statistics of Joint-liability Loans - Group Level

|  | All groups ( $\mathrm{N}=171,752$ ) |  |  | Northeast (N=108,307) |  |  | Central (N=14,850) |  |  | North (N=46,616) |  |  | South ( $\mathrm{N}=1,979$ ) |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Mean | SD | Median | Mean | SD | Median | Mean | SD | Median | Mean | SD | Median | Mean | SD | Median |
|  | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| Number of members | 12.631 | 6.544 | 11 | 12.343 | 6.241 | 11 | 13.089 | 6.626 | 12 | 13.035 | 7.070 | 11 | 15.424 | 7.771 | 14 |
| Total debt outstanding per group (Baht, 2021) | 4,069,965 | 3,345,022 | 3,245,742 | 3,828,678 | 2,900,838 | 3,139,669 | 4,596,151 | 4,561,193 | 3,472,855 | 4,355,408 | 3,625,600 | 3,409,474 | 6,603,068 | 5,588,659 | 5,366,541 |
| Group delinquency | 0.369 | 0.482 | 0 | 0.313 | 0.464 | 0 | 0.481 | 0.500 | 0 | 0.465 | 0.499 | 0 | 0.293 | 0.455 | 0 |
| Share of delinquent accounts to total number of accounts | 0.115 | 0.190 | 0 | 0.091 | 0.167 | 0 | 0.175 | 0.239 | 0 | 0.153 | 0.213 | 0 | 0.101 | 0.192 | 0 |
| Decrease sense of joint liability (\% landless) | 0.209 | 0.239 | 0.143 | 0.144 | 0.186 | 0.091 | 0.404 | 0.306 | 0.357 | 0.299 | 0.261 | 0.250 | 0.190 | 0.222 | 0.125 |
| Potential gain from monitoring (\% in the same village) | 0.677 | 0.197 | 0.667 | 0.694 | 0.200 | 0.700 | 0.607 | 0.181 | 0.588 | 0.664 | 0.189 | 0.667 | 0.587 | 0.175 | 0.571 |
| Livelihood homogeneity (similarity of income portfolio) | 0.691 | 0.223 | 0.592 | 0.710 | 0.225 | 0.622 | 0.729 | 0.233 | 0.646 | 0.639 | 0.206 | 0.553 | 0.623 | 0.197 | 0.551 |
| Barrier to cooperate (age difference as proxied by age SD) | 9.517 | 2.945 | 9.427 | 9.454 | 2.948 | 9.317 | 10.192 | 2.936 | 10.162 | 9.439 | 2.919 | 9.435 | 9.784 | 2.758 | 9.703 |

This table reports the summary statistics of joint liability loans at the group level using BAAC data. The group characteristics are constructed from all the members of the group that have active loan accounts. The statistics exclude groups with only 1 active borrowers, which could be because the other borrowers already paid off their loans or because the borrowers take out the loan guaranteed by other members, but the guarantor members do not take out the loan. Decrease sense of joint liability is proxied by the share of the members who do not have owned land to the total number of members within a group (\% landless). Potential gain from monitoring is proxied by the share of members who live in the same village to the total number of members within a group ( $\%$ in the same village). Livelihood homogeneity in the context of similarity of income portfolio is proxied by 1-SD of whether the members grow rice ( $0 / 1$ ). Barrier to cooperate is proxied by age difference (age SD). Delinquent groups refer to the groups who have at least one joint-liability loan with a classification of substandard or lower based on the conservative approach.

Table 9 Impact of Composition of Joint-liability Loans on Group Delinquency

|  | Dependent variable: group delinquency (0/1) |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | All groups | Northeast | Central | North | South |
|  | (1) | (2) | (3) | (4) | (5) |
| Decrease sense of joint liability (\% landless) | $\begin{aligned} & 0.146 * * * \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.084^{* * *} \\ & (0.008) \end{aligned}$ | $\begin{aligned} & 0.118^{* * *} \\ & (0.014) \end{aligned}$ | $\begin{aligned} & 0.036 * * * \\ & (0.009) \end{aligned}$ | $\begin{aligned} & 0.047 \\ & (0.054) \end{aligned}$ |
| Potential gain from monitoring (\% in the same village) | $\begin{aligned} & -0.235^{* * *} \\ & (0.006) \end{aligned}$ | $\begin{aligned} & -0.213^{* * *} \\ & (0.007) \end{aligned}$ | $\begin{aligned} & -0.208^{* * *} \\ & (0.022) \end{aligned}$ | $\begin{aligned} & -0.234^{* * *} \\ & (0.012) \end{aligned}$ | $\begin{aligned} & -0.107 * \\ & (0.059) \end{aligned}$ |
| Livelihood homogeneity (similarity of income portfolio) | $\begin{aligned} & -0.014^{* * *} \\ & (0.005) \end{aligned}$ | $\begin{aligned} & -0.002 \\ & (0.006) \end{aligned}$ | $\begin{aligned} & 0.103^{* * *} \\ & (0.018) \end{aligned}$ | $\begin{aligned} & 0.001 \\ & (0.011) \end{aligned}$ | $\begin{aligned} & 0.083 \\ & (0.053) \end{aligned}$ |
| Barrier to cooperate (age difference as proxied by age SD) | $\begin{aligned} & 0.003^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.003^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.005^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.004 * * * \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.001 \\ & (0.004) \end{aligned}$ |
| Number of members | $\begin{aligned} & 0.013^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.011 * * * \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.014^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.016^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.010^{* * *} \\ & (0.001) \end{aligned}$ |
| Joint liability loan outstanding to total loan outstanding of members | $\begin{aligned} & 0.240^{* * *} \\ & (0.009) \end{aligned}$ | $\begin{aligned} & 0.232 * * * \\ & (0.012) \end{aligned}$ | $\begin{aligned} & 0.282 * * * \\ & (0.033) \end{aligned}$ | $\begin{aligned} & 0.281 * * * \\ & (0.017) \end{aligned}$ | $\begin{aligned} & 0.182^{*} \\ & (0.094) \end{aligned}$ |
| Having joint liability loans only (0/1) | $\begin{aligned} & 0.497 * * * \\ & (0.011) \end{aligned}$ | $\begin{aligned} & 0.427 * * * \\ & (0.013) \end{aligned}$ | $\begin{aligned} & 0.641^{* * *} \\ & (0.035) \end{aligned}$ | $\begin{aligned} & 0.548 * * * \\ & (0.020) \end{aligned}$ | $\begin{aligned} & 0.267 * * * \\ & (0.086) \end{aligned}$ |
| Size of land owned | $\begin{aligned} & -0.000^{*} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.005^{* * *} \\ & (0.002) \end{aligned}$ |
| Pseudo R2 | $0.0707$ | 0.0537 | 0.0917 | 0.0731 | 0.0382 |
| Number of observations | 170,446 | 107,837 | 14,475 | 46,111 | 1,912 |

This table reports the average marginal effects from logit regressions using BAAC and DOAE data. The data are at the group level. Each column represents one regression. The dependent variable is delinquency which takes the value of one if the groups have at least one joint-liability loan with a classification of substandard or lower based on the conservative approach. The group characteristics are constructed from all the members of the group that have active loan accounts. The regressions exclude groups with only 1 active borrowers, which could be because the other borrowers already paid off their loans or because the borrowers take out the loan guaranteed by other members, but the guarantor members do not take out the loan. Decrease sense of joint liability is proxied by the share of the members who do not have owned land to the total number of members within a group (\% landless). Potential gain from monitoring is proxied by the share of members who live in the same village to the total number of members within a group ( $\%$ in the same village). Livelihood homogeneity in the context of similarity of income portfolio is proxied by 1 -SD of whether the members grow rice $(0 / 1)$. Barrier to cooperate is proxied by age difference (age SD). Standard errors are in parentheses. ${ }^{* * *} \mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$.

Table 10 Impact of the DM Participation Intensity on Debt Growth

|  | Dependent variable: loan growth |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | All | Low debt | Medium debt | High debt |
|  | (1) | (2) | (3) | (4) |
| Number of years in DM dummies |  |  |  |  |
| 1 year in DM | $\begin{aligned} & 0.109 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.065^{* * *} \\ & (0.007) \end{aligned}$ | $\begin{aligned} & 0.165^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.095^{* * *} \\ & (0.003) \end{aligned}$ |
| 2 years in DM | $\begin{aligned} & 0.175 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.110 * * * \\ & (0.009) \end{aligned}$ | $\begin{aligned} & 0.266^{* * *} \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.137 * * * \\ & (0.005) \end{aligned}$ |
| 3 years in DM | $\begin{aligned} & 0.229^{* * *} \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.057^{* * *} \\ & (0.010) \end{aligned}$ | $\begin{aligned} & 0.344 * * * \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.181^{* * *} \\ & (0.006) \end{aligned}$ |
| 4 years in DM | $\begin{aligned} & 0.287 * * * \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.035^{* * *} \\ & (0.012) \end{aligned}$ | $\begin{aligned} & 0.420 * * * \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.232 * * * \\ & (0.007) \end{aligned}$ |
| 5 years in DM | $\begin{aligned} & 0.344^{* * *} \\ & (0.004) \end{aligned}$ | $\begin{aligned} & 0.026^{*} \\ & (0.014) \end{aligned}$ | $\begin{aligned} & 0.495^{* * *} \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.279 * * * \\ & (0.009) \end{aligned}$ |
| 6 years in DM | $\begin{aligned} & 0.402^{* * *} \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.021 \\ & (0.016) \end{aligned}$ | $\begin{aligned} & 0.567^{* * *} \\ & (0.006) \end{aligned}$ | $\begin{aligned} & 0.329 * * * \\ & (0.010) \end{aligned}$ |
| 7 years in DM | $\begin{aligned} & 0.457^{* * *} \\ & (0.006) \end{aligned}$ | $\begin{aligned} & -0.019 \\ & (0.024) \end{aligned}$ | $\begin{aligned} & 0.638 * * * \\ & (0.007) \end{aligned}$ | $\begin{aligned} & 0.381^{* * *} \\ & (0.011) \end{aligned}$ |
| Lagged dependent variable | $\begin{aligned} & -0.040^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.161^{* * *} \\ & (0.003) \end{aligned}$ | $\begin{aligned} & -0.029^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.015^{* * *} \\ & (0.001) \end{aligned}$ |
| Loan size (ln) | $\begin{aligned} & -0.759^{* * *} \\ & (0.003) \end{aligned}$ | $\begin{aligned} & -0.309^{* * *} \\ & (0.006) \end{aligned}$ | $\begin{aligned} & -0.816^{* * *} \\ & (0.003) \end{aligned}$ | $\begin{aligned} & -0.914^{* * *} \\ & (0.005) \end{aligned}$ |
| Deposit size (ln) | $\begin{aligned} & -0.006^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.008^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.007 * * * \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.000) \end{aligned}$ |
| Number of loan accounts | $\begin{aligned} & 0.017 * * * \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.145^{* * *} \\ & (0.007) \end{aligned}$ | $\begin{aligned} & 0.021^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.018 * * * \\ & (0.000) \end{aligned}$ |
| Number of new loans | $\begin{aligned} & 0.192^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.464^{* * *} \\ & (0.006) \end{aligned}$ | $\begin{aligned} & 0.264^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & 0.120^{* * *} \\ & (0.001) \end{aligned}$ |
| Having DR/TDR accounts (0/1) | $\begin{aligned} & 0.019 * * * \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.187^{* * *} \\ & (0.030) \end{aligned}$ | $\begin{aligned} & 0.030^{* * *} \\ & (0.005) \end{aligned}$ | $\begin{aligned} & -0.034^{* * *} \\ & (0.003) \end{aligned}$ |
| Receiving disaster relief loans (0/1) | $\begin{aligned} & -0.015^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.048 \\ & (0.037) \end{aligned}$ | $\begin{aligned} & 0.001 \\ & (0.003) \end{aligned}$ | $\begin{aligned} & 0.004^{* *} \\ & (0.002) \end{aligned}$ |
| Having p-loan (0/1) | $\begin{aligned} & 0.012^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.210^{* * *} \\ & (0.021) \end{aligned}$ | $\begin{aligned} & 0.031^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.011^{* * *} \\ & (0.002) \end{aligned}$ |
| Having only WC loans (0/1) | $\begin{aligned} & 0.056^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.159 * * * \\ & (0.014) \end{aligned}$ | $\begin{aligned} & 0.055^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.049 * * * \\ & (0.003) \end{aligned}$ |
| Collaterals pledged (0/1) | $\begin{aligned} & -0.142^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.206 * * * \\ & (0.012) \end{aligned}$ | $\begin{aligned} & -0.124^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.084^{* * *} \\ & (0.003) \end{aligned}$ |
| Farming area | $\begin{aligned} & 0.000^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.001^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & 0.001^{* * *} \\ & (0.000) \end{aligned}$ |
| Landowner (0/1) | $\begin{aligned} & 0.013 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.001 \\ & (0.009) \end{aligned}$ | $\begin{aligned} & 0.016 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.017 * * * \\ & (0.003) \end{aligned}$ |
| Irrigated farming area (0/1) | $\begin{aligned} & 0.008^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.011 \\ & (0.009) \end{aligned}$ | $\begin{aligned} & 0.009^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.009^{* * *} \\ & (0.002) \end{aligned}$ |
| Receiving disaster relief transfer (0/1) | $\begin{aligned} & -0.009^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.027^{* * *} \\ & (0.006) \end{aligned}$ | $\begin{aligned} & -0.011^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & -0.000 \\ & (0.002) \end{aligned}$ |
| Receiving crop insurance (0/1) | $\begin{aligned} & 0.005^{* * *} \\ & (0.001) \end{aligned}$ | $\begin{aligned} & -0.059^{* * *} \\ & (0.005) \end{aligned}$ | $\begin{aligned} & 0.013 * * * \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.013 * * * \\ & (0.002) \end{aligned}$ |
| Age | $\begin{aligned} & 0.078^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.119 * * * \\ & (0.006) \end{aligned}$ | $\begin{aligned} & 0.057^{* * *} \\ & (0.002) \end{aligned}$ | $\begin{aligned} & 0.075 * * * \\ & (0.002) \end{aligned}$ |
| Age-squared | $\begin{aligned} & -0.001^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.001^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.001^{* * *} \\ & (0.000) \end{aligned}$ | $\begin{aligned} & -0.001^{* * *} \\ & (0.000) \end{aligned}$ |
| Borrower FE | Y | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| Year*region FE | Y | Y | Y | Y |
| Number of borrowers | 920,972 | 68,369 | 565,922 | 286,681 |
| Number of observations | 4,518,016 | 243,751 | 2,777,895 | 1,496,370 |
| R-squared | 0.318 | 0.244 | 0.345 | 0.351 |
| Prob $>$ F | 0.000 | 0.000 | 0.000 | 0.000 |

This table reports the regression results from fixed effect panel regressions. The data are at the borrower-year level. Each column represents one regression. The dependent variable is 1-year loan growth. Debt outstanding includes all type of loans, which are working capitals, term loans for agriculture, personal loans, home loans, and farmer credit cards. The number of years in DM enters the model as dummy variables. All regressors are lagged except age. Low, medium, high debts are grouping of debt deciles based on similarity of the regression results by each decile group. Low debt $=$ borrowers in the 1 st debt decile with outstanding debt below 37,000 Baht; medium debt $=$ borrowers in the 2nd to 7th deciles with outstanding debt between 37,000-292,000 Baht; high debt = borrowers in the 8th to 10th decile with outstanding debt above 292,000 Baht. Robust standard errors are in parentheses. *** $\mathrm{p}<0.01,{ }^{* *} \mathrm{p}<0.05,{ }^{*} \mathrm{p}<0.1$. See Ratanavararak and Chantarat (2022) for more discussion on the impact of debt moratorium on farmer debt.


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[^1]:    ${ }^{2}$ According to Table 4B, debt outstanding from randomly selected farmers from BAAC data is around 344,135 Baht in 2021. This number is smaller as it is from only one major source of loan for farmers. Table 4C displays farmers' total debt outstanding, based on NCB data, which is approximately 440,825 Baht in 2021 and 356,914 Baht yearly average during 2017-2021. This number includes all types of loan from any financial institutions in NCB, including banks and non-banks, but excludes semi-formal and informal sources.

