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Flexible Debt Relief and Credit Behavior: Evidence from Loan-Level Data

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Abstract

This paper evaluates a flexible debt relief program that combines traditional debt forbearance with "principal-first" repayment incentive – whereby the very first baht of loan repayment during the program goes towards principal reduction. Using loan-level data from the National Credit Bureau and a fuzzy regression discontinuity design, we find that while the built-in forbearance reduces overall repayment probability, 49% of program participants maintain repayment. In addition, the principal-first feature successfully increases repayment intensity at the cutoff among those who make meaningful repayments. At the same time, the program significantly mitigates credit deterioration and generates positive spillovers, prompting borrowers to reallocate freed-up liquidity toward non-relief loans with stricter enforcement. These findings demonstrate that embedding repayment incentives within debt forbearance introduces contract flexibility that effectively reveals borrowers' latent repayment capacity. This allows the design to function simultaneously as a critical safety net for financially distressed borrowers and an active incentive for capable borrowers to accelerate debt reduction.

Keyword: Flexible contract, Debt relief, Debt restructuring, Farmer debt, Household debt

JEL codes: D90, G21, G50, G51, Q14

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1. Introduction

Globally, debt relief measures are widely deployed to support financially distressed borrowers. These interventions traditionally encompass three overlapping modalities: debt forbearance, debt restructuring, and debt forgiveness[2] (Indarte & Kanz, 2024). Despite their ubiquity, the impacts of these measures on borrowers' credit behavior remain empirically ambiguous. On the one hand, by alleviating liquidity constraints, debt relief can mitigate defaults and enhance repayment performance (Dobbie & Song, 2020; Fiorin et al., 2023; Aydin, 2024; Gyöngyösi & Verner, 2024), potentially generating positive spillovers onto non-relief obligations (Kim et al., 2024). On the other hand, the perception of repayment leniency can induce moral hazard, undermining repayment discipline (De & Tantri, 2016; Mishra et al., 2017; Giné & Kanz, 2018). And more importantly, the effectiveness of debt relief depends heavily on program design and targeting – that should align with the borrowers' true capacity (Mayer et al., 2014; Ganong & Noel, 2020).

Meanwhile, the microfinance literature increasingly emphasizes flexible debt contracts as vital financial instruments for vulnerable borrowers navigating insufficient, unstable, and illiquid incomes (Morduch, 2023). In contract theory, this marks a paradigm shift from rigid, fixed-term schedules toward risk-contingent terms that dynamically adjust to borrowers' fluctuating repayment capacity. Empirical evidence demonstrates that appropriate contractual flexibility can enhance debt discipline without compromising institutional credit performance (Field et al., 2012; Barboni & Agarwal, 2023; Battaglia et al., 2024). And the flexible design is especially effective for vulnerable borrowers, whose true capacity varies and remains largely unobserved.

The pervasive debt trap among Thai farmers provides an ideal empirical setting to unite these two strands of literature. Thai agricultural households face widespread indebtedness. They exhibit larger debt burdens and faster debt growth than other domestic households. Repayment remains problematic due to volatile incomes, excessive debt structures, and distorted incentives from public assistance. Chantarat et al. (2026a) shows that over the past 8 years, only 10-15% of borrowing

[2] Debt forbearance refers to any policies that allow borrowers to defer their loan repayments for a given period without incurring penalties, while leaving the amount of debt outstanding unchanged. Debt restructuring refers to a modification of a loan contract such as extension of the loan maturity and reducing the accrued interest and/or loan installment amount. There are two types of debt restructuring. First, general debt restructuring debt restructuring that financial institutions have incurred no losses from restructuring of debt. Troubled debt restructuring refers to debt restructuring cases where financial institutions incur losses from the restructuring. And debt forgiveness refers to a partially or entirely write off (haircut) a borrower's interest or loan outstanding. Sometimes, debt forgiveness could be viewed as a special case of debt restructuring.

farmers consistently repay loan principal, 17% are unable to repay, while the majority repay only interest annually – making them highly susceptible to a persistent debt trap. While comprehensive debt restructuring and interventions to stimulate repayment are necessary interventions to extricate borrowers from these long-term debt trap, historical measures have relied almost exclusively on blanket, forbearance-based relief to cushion farmers against recurring shocks. Consequently, Ratanavararak & Chantarat (2023) show that the widespread and continuous rollout of these traditional moratoria in the past decade have led to significantly higher debt accumulation and severely undermined incentive to repay.

This paper contributes and bridges the two strands of literatures by evaluating Thailand's flexible debt relief program for farmers recently introduced in 2023. The program uniquely integrates a debt restructuring incentive – a principal-first mechanism directing repayments toward principal reduction – into traditional debt forbearance. This design thus offers contractual flexibility that functions simultaneously as a safety net for distressed borrowers and an active incentive for capable households to accelerate debt reduction. Because borrowing farmers' true, time-varying repayment capacity are typically unobservable, this flexible debt relief that effectively reveals this latent capacity might sustainably address the long-standing debt and debt relief problems.

Empirically, we exploit granular, loan-level administrative data from the National Credit Bureau (NCB) spanning 2017–2025, which covers the universe of borrowing farmers and all formal credit sources to explore how flexible debt relief program bundling principal-first incentives and forbearance alter borrowers' credit behavior across repayments, credit quality, and new borrowing. The coverage of full borrowers' loan portfolio in NCB data further allows us to investigate if and how the program could generate spillover effects on non-relief loans. And because program eligibility is assigned based on a sharp institutional threshold, we employ a fuzzy regression discontinuity design to isolate causal effects at the cutoff.

Our empirical analysis yields three primary findings. First, the program triggers a distinct sorting effect on agricultural debt repayment at the eligibility threshold. Driven by the debt forbearance feature, the overall repayment probability decreases by approximately 27 percentage points; ultimately, around 25% of participants continue to make meaningful repayments over 1,000 Baht, while 49% maintain repayments. However, the add-on principal-first incentive drives a substantial surge along the intensive margin, increasing annual repayment amounts by approximately 26,000 baht at the threshold among active payees.

Second, the program mitigates the agricultural credit deterioration rate by 5 percentage points overall and by 16 percentage points for vulnerable borrowers at the cutoff, without inducing any corresponding expansion in new borrowing. And finally, we document positive liquidity spillovers onto non-agricultural liabilities. Borrowers strategically reallocate the liquidity freed by forbearance toward non-relief debts featuring stricter enforcement—such as auto and machinery loans—effectively utilizing the program as a safety net that shifts repayment priorities rather than eroding credit discipline. This behavioral pattern aligns with documented selective repayment strategies across multiple-loan portfolios among Thai agricultural households (Chantarat et al., 2023).

Collectively, these results demonstrate that embedding repayment incentives within debt forbearance introduces contract flexibility that effectively reveals borrowers' latent repayment capacity. This allows the design to function simultaneously as a critical safety net for financially distressed borrowers and an active incentive for capable borrowers to accelerate debt reduction. And although rooted in Thailand, our findings carry broad external validity for developing economies. This is because Thai agricultural debt landscape directly mirrors the structural frictions confronting rural populations globally in many aspects: low productivity and high vulnerability of households in farming economies, heavily reliance on public assistance and the concentration of public policies on short-term relief rather than long-term structural reforms.

The remainder of this paper is organized as follows. Section 2 positions our work within the literature on debt relief and flexible contract in microfinancing. Section 3 provides background on Thailand's agricultural debt and the 2023 flexible debt relief program design. Sections 4 and 5 outline the data, key variables, and our empirical identification framework. Section 6 reports the main empirical results, while Section 7 presents extensive robustness checks. Finally, Section 8 concludes with policy implications.

2. Related literature

This study connects two strands of literature in household finance. These are debt relief measures and flexible debt contracts.

2.1 Debt relief measures

Debt relief measures for households are generally categorized into three types, often used in combination to address different degrees of financial distress: (1) debt forbearance, (2) debt restructuring, and (3) debt forgiveness (Indarte & Kanz, 2024).

Debt forbearance, or a debt moratorium, provides short-term liquidity relief. The main goal is to prevent unnecessary defaults during temporary shocks. Experimental evidence from India shows that forbearance reduces short-term defaults (Fiorin et al., 2023). However, Aydin (2024), in a study of a European bank in Türkiye (Turkey), found that forbearance for delinquent borrowers failed to reduce long-term default, as it merely deferred the repayment burden. Furthermore, when applied broadly or over extended periods, as seen in the case of farmer debt in Thailand, forbearance leads to increased debt accumulation. It also induced moral hazard, resulting in lower repayments and long-term dependence on relief (Ratanavararak & Chantarat, 2023). Other studies further confirm that while forbearance improves short-term liquidity, it can also encourage additional borrowing (Tambunlertchai, 2004; Dinerstein et al., 2024; Kim et al., 2024).

Debt restructuring assists borrowers who are viable but have repayment capacities misaligned with their debt structures. The goal of debt restructuring is to enhance borrowers' loan repayment towards effective debt reduction by adjusting loan covenants like maturity, installments, or interest rates to match a borrower's actual ability to pay. Previous studies show that restructuring is effective only when precisely targeted or customized. For US credit card debt, reducing interest rates increased repayments and reduced defaults, while lowering installment amounts had no significant effect (Dobbie & Song, 2020). Similarly, interest rate reductions decreased long-term defaults for unsecured loans in Türkiye (Aydin, 2024). In the US mortgage market, lower installment amounts reduced defaults, while an equivalent amount of principal forgiveness had no impact (Ganong & Noel, 2020). However, poorly targeted programs can distort incentives. If restructuring is restricted to delinquent borrowers, solvent individuals may strategically default to qualify (Mayer et al., 2014).

Debt forgiveness targets insolvent borrowers who cannot repay their debts. It aims to break persistent debt cycles and lower institutional costs for maintaining non-performing loans (NPLs). However, principal haircuts carry moral hazard risks if applied to capable borrowers. This risk increases when future relief is highly anticipated. Evaluations of India's 2008 agricultural debt waiver show that broad forgiveness increased defaults without improving agricultural productivity or income (De & Tantri, 2016; Mishra et al., 2017; Giné & Kanz, 2018). Yet, some studies find heterogeneous effects. The same Indian waiver increased defaults among capable borrowers but successfully reduced defaults among truly distressed debtors (Mukherjee et al., 2018). In a different asset class, mortgage forgiveness in Hungary lowered default rates (Gyöngyösi & Verner, 2024). Unlike the anticipated Indian relief, this program was unexpected. It successfully alleviated debt overhang, which subsequently increased labor supply and household incomes.

Overall, recent literature implies that debt relief measures are most effective when targeting is precise and borrower capacity is explicitly identified. In practice, true repayment capacity for vulnerable debtors is hard to observe and varies over time. This information asymmetry makes both narrow targeting and blanket policies difficult to implement. These frictions underscore the need for dynamic designs that adjust to shifting financial circumstances.

2.2 Flexible debt contracts

Microfinance literature increasingly emphasizes flexible debt contracts as vital financial instruments for vulnerable debtors. In contract theory, this approach marks a shift from rigid, fixed-term structures to risk-contingent terms, which allow repayments to adjust dynamically to fluctuating income and capacity. Consequently, flexible contracts better serve vulnerable populations, typically face a combination of income insufficiency, high volatility, and cash-flow illiquidity (Morduch, 2023). Traditional contracts often fail these households because rigid installment structures prioritize repayment discipline over economic adaptability.

Empirical evidence shows that appropriate contractual flexibility can enhance repayment discipline without compromising institutional credit performance. Field et al. (2012) found that reducing payment frequency from weekly to monthly significantly lowered defaults for farmers with irregular incomes. Similarly, Barboni & Agarwal (2023) demonstrated that offering an optional three-month annual grace period incentivized earlier repayments and reduced reliance on emergency high-interest loans. Furthermore, Battaglia et al. (2024) showed that allowing borrowers to defer up to two installments also reduced default rates while generating positive spillovers on household investment and income. These choice-based designs allow borrowers to self-select relief based on their actual capacity.

However, excessive flexibility can be counterproductive. Czura et al. (2026) found that offering flexibility without built-in incentives reduces both the frequency and volume of repayments. Consistent with this, Brune et al. (2024) cautioned that extending maturity dates without appropriate screening mechanisms or conditional incentives also leads to higher default rates. Thus, while flexibility addresses the targeting gap, it requires clear boundaries and explicit repayment incentives to maintain credit discipline. Building on these insights, this study examines a flexible debt relief design that balances borrower flexibility with repayment incentives.

2.3 Our contribution to literature

This paper contributes to current literature in two ways. Conceptually, we evaluate a flexible debt relief design that bridges the gap between traditional forbearance and flexible contracting. Because vulnerable borrowers face highly uncertain incomes, their true repayment capacity is often unobservable to lenders. A flexible relief design addresses this asymmetry by allowing borrowers to self-select, thereby effectively revealing their latent capacity. Furthermore, the program embeds a principal-first incentive that directly appeals to households with debts far exceeding their repayment capacity. By pairing contractual flexibility with clear rewards for active payment, this framework builds on flexible contract theory and applies these established microfinance concepts directly to debt relief design.

Empirically, this study utilizes granular administrative data from the National Credit Bureau (NCB) to provide a comprehensive picture of borrower credit behavior. We track credit quantity outflows via repayments, credit inflows via new borrowing, and credit quality via default migration. While previous studies often rely on data from a single creditor, our dataset contains account-level records from all formal lenders. This comprehensive coverage thus allows us to distinguish between direct program impacts and cross-creditor spillovers across the broader financial ecosystem.

Ultimately, the paper demonstrates how embedding repayment incentives within traditional forbearance creates a dual-purpose design, functioning simultaneously as a critical safety net for distressed households and an active incentive for capable borrowers to accelerate debt reduction. And these findings carry broad external validity for developing economies because the Thai agricultural debt landscape directly mirrors structural frictions confronting rural populations globally e.g., low and highly volatile agricultural income, heavy reliance on public assistance, and a historical concentration of state policies on short-term relief rather than long-term structural reform.

3. Background and flexible debt relief program

3.1 Farmer debt problem in Thailand

The farmer debt problem in Thailand is structural rather than a mere liquidity issue. Chantarat et al. (2023) shows that the financial conditions of Thai agricultural households are largely consistent with those of rural populations worldwide, characterized by low, irregular, and uncertain income and expenditure streams (Morduch, 2023).

Over 90% of Thai agricultural households have debt (Chantarat et al., 2023), averaging nearly 500,000 baht per household. As revealed in Figure 1A, the average debt per agricultural household has surged by nearly 40% over the past eight years, with most debt loads far exceeding the borrower's actual repayment capacity. Furthermore, Figure 1B illustrates a concerning pattern in repayment behavior where more than 50% of borrowers service only the interest to maintain their loan status. This implies that their outstanding principal remains unchanged despite continuous repayments. If this pattern persists, Chantarat et al. (2026a) estimates that over 52% of farmers across all age groups are unlikely to settle their debts before age 70, a critical threshold where income-generating capacity typically declines significantly.

[Figure 1 here]

The primary institutional vehicle for agricultural credit and relief efforts is the Bank for Agriculture and Agricultural Cooperatives (BAAC), which is by far the largest creditor for Thai farmers. However, historical debt relief programs administered through the BAAC have struggled to sustainably address the problem. Between 2014 and 2021, the BAAC implemented thirteen major forbearance programs, with over 40% of agricultural households participating for four or more consecutive years (Ratanavararak & Chantarat, 2023). These programs failed to resolve long-term debt stress; instead, they contributed to higher debt accumulation and an increased risk of loan default, while yielding no statistically significant effects on savings or investment. Because these measures lacked dynamic incentives and condition for borrowers to continually service interest, they trapped farmers in a cycle of debt maintenance rather than resolution. This aligns with earlier evidence from Tambunlertchai (2004), who found that conventional debt forbearance did not stimulate household consumption or investment growth.

The core hurdle in designing effective debt relief lies in the severe information asymmetry regarding a borrower's true repayment capacity. While blanket relief policies have been proved to undermine repayment discipline and foster moral hazard especially among capable payers, customized, tailor-made relief could be too costly and operationally challenging to implement for millions of households. Because farmers' financial conditions shift constantly, they require debt relief that adapts to the idiosyncratic timing of their cash flows. For instance, they may need immediate forbearance during climate or crop disease shocks, yet they require structured incentives to accelerate repayments when harvests are sold or non-farm income is realized. Ultimately, without this built-in flexibility, debt relief remains misaligned with a borrowers' moving capacity, perpetuating a vicious cycle rather than enabling a sustainable path to debt reduction.

3.2 Flexible debt relief program

In September 2023, the Thai government introduced a new three-year flexible debt relief program implemented through the BAAC. Fulfilling a post-election campaign promise, the program's initial objective was to provide short-term debt forbearance for farmers whose incomes were still recovering unevenly from the COVID-19 pandemic. Crucially, the program was designed with explicit recognition of the unintended consequences generated by the preceding relief schemes. Consequently, this new intervention diverges from historical programs in three fundamental ways.

First, alongside the deferral of principal repayments, the program provides complete interest forgiveness, with the government subsidizing all interest expenses for three years on an annually renewable basis. This structural change protects highly distressed borrowers by removing the requirement to service interest to avoid delinquency. In contrast, past programs required continuous interest payments simply to prevent accounts from degrading into non-performing loans, causing unpaid interest to pile up over time. The current framework eliminates both pitfalls by directly alleviating credit deterioration while ensuring borrowers do not exit the program burdened by a massive backlog of accrued interest.

Second, because the government subsidizes the accrued interest, any payment made by a participant is directly allocated toward reducing the outstanding principal. This mechanism thus embeds a principal-first incentive that functions as a form of subsidized debt restructuring to accelerate debt reduction. Active repayment during the program thus becomes highly rewarding for borrowers who regain their financial capacity, presenting a rare opportunity given borrowers' debt structure.

During the program's first year, however, public announcements heavily mirrored past schemes by focusing primarily on the forbearance component, which limited borrower awareness of this principal-first feature. To remedy this, the BAAC implemented more targeted communication strategies in the second year to explicitly highlight this repayment incentive. And so ultimately, by combining temporary relaxation with structured incentives, the program achieves built-in flexibility – safeguarding vulnerable households while encouraging capable borrowers to accelerate debt reduction.

Third, the program utilizes a voluntary, opt-in enrollment mechanism rather than automatic enrollment. To qualify, borrowers must have an outstanding balance not exceeding 300,000 baht as of September 30, 2023. Upon choosing to opt in, participants are subject to a strict credit constraint that caps new loans[3] from the BAAC at 100,000 baht. In contrast, most previous initiatives automatically defaulted borrowers into relief schemes unless they actively opted out, and they failed to impose subsequent borrowing limits to prevent further debt accumulation.

The application window spanned from October 1, 2023, to March 31, 2024. And by October 2024, the program registered 1.4 million participants (BAAC, 2024), accounting for 67% of the total eligible borrower pool. Table 1 comprehensively details these eligibility criteria and the corresponding program benefits.

[Table 1 here]

4. Data

4.1 The loan-level data

This study utilizes monthly, loan-level administrative data from the Thai National Credit Bureau (NCB) spanning 2017 to 2025. This comprehensive dataset tracks detailed loan transactions – capturing both credit quality and quantity – alongside lender and borrower characteristics. The coverage encompasses majority of formal financial institutions, including domestic commercial banks, foreign bank branches,

[3] New borrowing is restricted to occupational rehabilitation loans. Any additional disbursements from pre-existing credit lines drawn after program participation are permitted but remain ineligible for the flexible relief measure.

non-bank financial institutions, and state-owned banks such as the BAAC. And because these raw records are submitted directly by member institutions for regulatory reporting, measurement error is expected to be negligible.

To account for substantial variations in contractual features – such as repayment schedules, interest rates, enforcement intensity, and maturities – we disaggregate our analysis across five distinct loan types: agricultural, automotive hire-purchase, machinery hire-purchase, housing, and personal loans. And because the 2023 flexible debt relief program applies exclusively to agricultural loans, these accounts capture the program's direct effects. To particularly account for the unique variation in inherent credit risk of agricultural loans, we analyze these loans both in the aggregate and disaggregated by their portfolio-specific restructuring status prior to the intervention—specifically separating non-troubled debt restructuring (non-TDR) and troubled debt restructuring (TDR) accounts. Conversely, non-agricultural portfolios are ineligible, allowing us to interpret behavioral changes in those accounts as cross-creditor spillovers. Evaluating both dimensions simultaneously is crucial in the Thai context, where approximately one-third of farmers typically borrow from multiple formal institutions and exhibit strategic portfolio repayment selection (Chantarat et al., 2023). This disaggregated approach therefore ensures clean identification and consistent interpretation across heterogeneous credit behaviors.

4.2 Key variables

This study examines how the flexible debt relief program shapes borrower credit behavior from April 2024 to July 2025 across three key outcome domains: repayment, credit deterioration, and new borrowing.

Repayment outcomes capture both the extensive margin – whether borrowers repay – and the intensive margin – how much they repay. Specifically, the extensive margin is measured using a binary repayment indicator, while the intensive margin is captured by the total repayment amount. Together, these complementary metrics reflect the combined strength of the program's built-in repayment incentives and its forbearance-based safety net.

Credit deterioration outcomes evaluate the program's safety-net effects, though their underlying interpretation varies by asset class. For agricultural loans, deterioration reflects the counterfactual credit risk that borrowers would have faced in the absence of the program, given that participating accounts mechanically retain their pre-program credit classifications. For non-agricultural portfolios, credit deterioration captures actual changes in credit quality driven by freed-up liquidity or shifting repayment priorities across alternative creditors.

Borrowing outcomes track how the program influences subsequent credit inflows. We employ a new borrowing indicator to identify whether a borrower originates any new loans during the sample period, alongside a continuous measure capturing the total value of newly originated credit. These variables allow us to assess whether repayment deferral, enhanced liquidity, or improved credit standings alter borrowers' extra loaning from the BAAC or other lenders.

Table 2 presents descriptive statistics for the key variables utilized in this study. The analytical sample is restricted to borrowers near the eligibility threshold, specifically those with outstanding loan balances between 100,000 and 500,000 baht as of September 30, 2023. All metrics are initially calculated at the loan account level before being aggregated to the borrower level.

[Table 2 here]

The summary statistics in Table 2 reveal a distinct divergence in credit behavior between agricultural and non-agricultural portfolios. Agricultural loans exhibit lower repayment and lower credit deterioration rates compared to non-agricultural obligations, such as automotive and mortgage loans. In terms of demographics, the average borrower age is 55.4 years, with approximately one-third of the sample holding accounts across multiple creditors and three-quarters classified as performing debtors at the program's onset. Notably, these baseline credit classifications reflect institutional reporting practices, as Thai state-owned banks, including the BAAC, do not strictly adhere to international accounting standards for loan classification.

5. Identification strategy

The primary empirical challenge in this study is establishing a valid counterfactual for program participants. Because enrollment is voluntary, treatment status may be systematically correlated with both observed and unobserved borrower characteristics. Factors such as baseline credit quality, liquidity constraints, and intrinsic repayment preferences can jointly influence both the decision to participate and subsequent credit outcomes. Consequently, a simple comparison of outcomes between participants and non-participants would confound the program's causal effects with these pre-existing differences, ultimately leading to biased estimates.

To identify the causal effects of the flexible debt relief program, we employ a regression discontinuity (RD) framework. This identification strategy is uniquely suited to our setting because program eligibility was determined by a strict institutional threshold, causing the probability of treatment assignment to shift abruptly at a known cutoff. Consequently, individuals with outstanding loan balances just above this threshold can serve as a valid counterfactual for those whose balances lie just below it. The validity of the estimated causal effects relies on compliance with four core econometric assumptions outlined by Lee & Lemieux (2010): (1) imprecise control; (2) discontinuity of first-stage status at the threshold; (3) excludability; and (4) monotonicity.

The first and foundational assumption of the regression discontinuity design is that borrowers lack precise control over the running variable near the eligibility threshold. Under this condition, treatment assignment immediately surrounding the cutoff behaves stochastically, meaning that variation in program participation is locally as good as random. The primary threat to this assumption is strategic sorting, where debtors precisely manipulate their outstanding balances ahead of the key date to guarantee assignment into their preferred treatment status (Cattaneo & Titiunik, 2022). Such manipulation would introduce confounding discontinuities in other observed or unobserved covariates at the cutoff. Formally, this continuity assumption requires that all unobserved determinants of the outcome evolve smoothly with respect to the running variable within a neighborhood around the threshold. When continuity holds, any abrupt change in outcomes at the cutoff can be confidently attributed to the program itself rather than to underlying baseline differences between borrowers.

We formally evaluate the imprecise control assumption by testing for a discontinuity in the density of the running variable at the eligibility threshold. The McCrary density test reveals a statistically significant discontinuity at the cutoff ($T = 20.8$, $p < 0.001$), thereby formally rejecting the null hypothesis of a continuous density function. While this density jump might initially raise concerns regarding the strategic manipulation of outstanding loan balances around the threshold, two key institutional and empirical considerations indicate that this discontinuity does not reflect strategic sorting by borrowers.

First, the density spike at exactly 300,000 baht reflects a long-standing pattern of round-number bunching in credit markets rather than a strategic response to the policy. As shown in Appendix Figure A1, identical mass points at the 300,000 baht threshold appear consistently in historical placebo data from 2019 and 2021, well before the program's inception. This recurring distribution strongly suggests that the observed discontinuity does not stem from deliberate borrower manipulation.

Second, although borrowers theoretically had a four-day window between the program's announcement on September 26, 2023, and the official eligibility determination date on September 30, 2023, operational and institutional frictions rendered large-scale manipulation highly implausible. During this brief interim, the BAAC had insufficient time to widely disseminate policy specifics, leaving borrower awareness exceptionally low. Furthermore, executing any balance adjustments would have required formal, in-person branch visits and contract amendments. Empirically, only 0.11% of eventually enrolled borrowers executed repayments during this four-day window that altered their eligibility status—a fraction far too negligible to account for the observed density discontinuity. This lack of strategic sorting is further corroborated by the program's sluggish initial take-up; enrollment remained below 10,000 participants at the end of 2023, before climbing to approximately 600,000 in February 2024, and ultimately reaching 1.4 million by the close of the registration window in March 2024.

To further evaluate the validity of the imprecise control assumption, we conduct falsification tests examining baseline covariates and pre-intervention credit quality within the neighborhood of the eligibility threshold. Utilizing the same estimation procedure and bandwidth selection as our main analysis, we test whether these variables exhibit any discontinuous jumps at the cutoff. As reported in Table 3, the estimated discontinuities are statistically indistinguishable from zero across nearly all placebo variables, with the minor exceptions of borrower age and the number of creditors. To safeguard the robustness of our causal estimates against these local imbalances, we include both variables as additional controls in all RD specifications. Collectively, these results demonstrate that borrowers on either side of the threshold are systematically comparable prior to the intervention, thereby supporting the local randomization framework.

[Table 3 here]

The second assumption is the first-stage assumption, which requires a robust relationship between actual program enrollment and eligibility assignment at the cutoff. This condition is satisfied if there is a significant, discontinuous jump in the probability of participation at the threshold point. Among the eligibility criteria outlined in Table 1, we select the outstanding loan balance as our running variable because it continuously captures assignment proximity, outperforming discretized criteria such as a borrower's legal bankruptcy status. As reported in Table 4, this first-stage relationship is highly and statistically significant ($p < 0.01$), yielding an F-statistic well exceeding 10,000.

[Table 4 here]

Figure 2 provides visual evidence of the first-stage discontinuity, confirming a robust relationship with a compliance jump of approximately 0.7 at the cutoff. The graphical evidence also reveals imperfect compliance in the form of "no-shows" (eligible but non-participants) and "cross-overs" (ineligible but participants). This non-compliance can be attributed to several institutional and empirical factors.

First, the occurrence of no-shows was heavily driven by the transition to a voluntary opt-in protocol, marking a significant departure from historical default-enrollment (opt-out) schemes. Borrowers long accustomed to automatic relief may have lacked awareness of the new requirements, while the enrollment process itself introduced substantial transaction costs, including travel distances, complex paperwork, and mandatory in-person reviews. Second, our empirical running variable relies strictly on the outstanding balance threshold, thereby omitting certain unobserved institutional criteria detailed in Table 1 that could mechanically disqualify seemingly eligible borrowers. Third, some solvent debtors may have actively chosen to forego the program to avoid the subsequent credit caps and borrowing restrictions documented in Appendix Table A2.

Conversely, the cross-over anomaly primarily arises from the unavoidable inclusion of Public Service Account (PSA) loans within the broader agricultural loan balance. While data constraints prevent us from precisely isolating and removing these specific accounts from the running variable, this empirical friction is negligible, as the cross-over rate stands at a mere 0.38%.

[Figure 2 here]

The third assumption is excludability or exclusion restriction, which requires that treatment assignment affects the outcomes of interest solely through actual program participation. Potential violations of this assumption could emerge from two primary channels: first, the presence of concurrent financial or debt relief policies utilizing an identical eligibility threshold (confounding policies); or second, information effects, where the mere awareness of assignment status independently alters borrower credit behavior. To rule out these confounding factors, we conducted a comprehensive review of debt relief initiatives across Thai financial institutions and prudential regulations enacted by the Bank of Thailand. This institutional assessment confirms that the 300,000 baht threshold was not officially utilized by any other institution or concurrent relief scheme. Furthermore, historical debt interventions administered by the BAAC never employed this specific cutoff, and all such prior programs had fully expired before the inception of the 2023 framework.

The fourth assumption is monotonicity, which requires that the eligibility assignment affects program participation in a uniform direction, thereby ruling out the presence of "defiers" near the cutoff. In this econometric framework, defiers represent individuals who actively pursue the exact opposite of their assigned treatment status. This assumption is highly compelling in our setting because the introduction of a subsidized, nearly risk-free flexible debt relief program is expected to monotonically shift borrower incentives in a single direction—namely, toward enrollment. While isolated, idiosyncratic exceptions might theoretically occur on a case-by-case basis, the proportion of systematic defiers is likely to be negligible, thereby safeguarding the Local Average Treatment Effect (LATE) interpretation.

Given the empirical evidence of imperfect compliance presented in Table 4 and Figure 2 when utilizing the outstanding loan balance as the running variable, we employ a fuzzy regression discontinuity (FRD) design to identify causal effects. The econometric framework is specified as follows:

$$\frac{\lim_{\varepsilon\uparrow 0} E[Y|X=c+\varepsilon]-\lim_{\varepsilon\downarrow 0} E[Y|X=c+\varepsilon]}{\lim_{\varepsilon\uparrow 0} E[D|X=c+\varepsilon]-\lim_{\varepsilon\downarrow 0} E[D|X=c+\varepsilon]} = E[\,\beta_i \mid \text{unit is complier},\ \mathrm{X} = c] \tag{1}$$

where Y is the outcome variable;

D is the status of joining the flexible debt relief program;

X is the running variable, which is the loan outstanding balance;

c is the cutoff, which is the loan outstanding threshold set at 300,000 baht;

ε is distance from the cutoff

In essence, this fuzzy RD estimator scales the reduced-form effect of eligibility assignment on the outcome by the first-stage effect on actual treatment receipt. This ratio is numerically analogous to a two-stage least squares (2SLS) instrumental variable estimation (Hahn et al., 2001), operationalized via the following system of equations:

First stage equation:

$$D_i = \pi_0 + \pi_1 Z_i + f(X_i - c) + [Z_i \cdot f(X_i - c)] + N_i' \delta_D + v_i \tag{2}$$

Second stage equation:

$$Y_i = \beta_0 + \beta_1 \widehat{D}_i + g(X_i - c) + \left[\widehat{D}_i \cdot g(X_i - c)\right] + N_i' \delta_Y + \mu_i \tag{3}$$

In this system, π_1 captures differences in the likelihood of participating in the flexible debt relief program between those just above and just below the cutoff. Z_i is the assignment status of eligibility for the program, which can be written as Z = I[$X_i \leq c$]. N_i' represents individual characteristics. f(.) and g(.) are the orders of the local polynomials, while v_i and μ_i are error terms. The main explanatory variable of interest is *D*.

The FRD estimate (β_1) can be interpreted as LATE, which is the average treatment effect at the cutoff for compliers. Compliers refer to individuals who participate in the program when they are assigned to the treatment condition and remain untreated when they are assigned to the control condition. When FRD estimates are obtained, there is a bias and variance trade-off. The use of observations only near the cutoff would result in a small bias but large variation if the sample size is small.

However, an increase in bandwidth further from the cutoff could reduce variance at the expense of increased bias. To find the optimal point of bias and variance, we adopted a principled data-driven procedure of minimization of the mean square error (MSE) criterion to find optimal bandwidth for observations above and below the cutoff (Imbens & Kalyanaraman, 2012; Calonico et al., 2014).

To evaluate the external validity of our findings, we complement our primary analysis with a Difference-in-Differences (DiD) specification in the robustness section. While the FRD design yields a precise local estimate tailored to compliers near the threshold, the DiD framework allows us to examine whether these behavioral impacts extend across the broader population. By demonstrating that the DiD estimates align closely with our baseline FRD results, we establish that the observed policy effects are not idiosyncratic to threshold compliers but are potentially generalizable to the agricultural population at large

6. Results

This section presents estimation results, including the regression discontinuity estimates that serve as LATE at the eligibility threshold. These estimates are accompanied by selected graphical RD plots for statistically significant outcomes, visually confirming the discontinuities at the cutoff.

6.1 Direct effect on agricultural loan repayment

Table 5 presents the program's direct impact on agricultural loan repayment behavior, capturing responses across the extensive margin. Program participation induces a statistically significant decrease in the probability of repayment of 26.8 percentage points (Column 1). This contractionary effect is notably more pronounced for borrowers who have undergone Troubled Debt Restructuring (TDR borrowers), who exhibit a 28.9 percentage point decline (Column 3) compared to a 23.9 percentage point drop among non-TDR borrowers (Column 2). This empirical divergence indicates that the program's forbearance component is particularly binding for the TDR segment, underscoring its role as a critical liquidity safety net for the most financially distressed debtors.

The estimated impact on the repayment amount further corroborates this forbearance narrative for the financially vulnerable cohort. Specifically, TDR borrowers experience a statistically significant reduction in total repayments of approximately 1,736 baht (Column 6). This decline implies that the program's inherent flexibility effectively preserves the liquidity of distressed debtors, rather than accelerating early repayments through its principal-first incentive structure. Crucially, the widespread contraction in repayment probability across all borrower segments should not be misconstrued as a policy failure. Instead, it represents a direct consequence of the program's design, which enables borrowers to strategically leverage forbearance benefits during the intervention window. Consequently, non-repayment within this flexible framework does not automatically constitute evidence of opportunistic moral hazard.

[Table 5 here]

While the extensive margin highlights the program's role in providing liquidity forbearance, the intensive margin reveals a significant surge in repayment intensity conditional on making a payment. As reported in Table 6, participants at the threshold increased their agricultural loan repayments by approximately 26,886 baht (Column 1) – an effect that is both statistically significant and economically substantial. This surge is most prominent among non-TDR borrowers with a single creditor, where the repayment amount jumps by 28,517 baht (Column 5). Even within the financially vulnerable TDR cohort, active repayers increased their intensity by 8,696 baht (Column 7). These findings provide robust evidence that the principal-first incentive effectively motivates borrowers with sufficient repayment capacity, leading directly to a more pronounced reduction in outstanding loan principal.

[Table 6 here]

Taken together, the findings from Tables 5 and 6 demonstrate a bifurcated direct impact on agricultural loan repayment, illustrating how the program's flexible architecture simultaneously supports two distinct borrower segments. For liquidity-constrained debtors, the policy provides critical forbearance; for those with sufficient financial capacity, the principal-first incentive accelerates debt reduction relative to the counterfactual. Figure 3 visually confirms this behavioral duality. The discontinuous drop in Panel (A) illustrates the contraction in repayment probability among borrowers leveraging forbearance benefits, while the sharp upward jump in Panel (B) captures the heightened repayment intensity driven by the incentive mechanism among active repayers.

[Figure 3 here]

6.2 Spillover effect on non-relief loans

The liquidity unlocked by the program's flexible framework is actively deployed by borrowers. Specifically, we document robust evidence of positive cross-creditor spillovers onto non-agricultural obligations, indicating that borrowers strategically reallocate their liberated funds across their broader credit portfolios. As reported in Table 7 (Panel A), program participation induces a statistically significant increase in repayment amounts for automotive and machinery hire-purchase loans by approximately 10,931 baht and 3,684 baht, respectively.

[Table 7 here]

This narrative of strategic liquidity reallocation is even more pronounced among the sub-sample of borrowers who deferred their agricultural loan payments (Panel B). For individuals who fully leveraged the program's forbearance benefits by pausing or minimizing their BAAC repayments, participation substantially increases both the probability (extensive margin) and intensity (intensive margin) of repayment toward non-agricultural obligations held with external creditors. Specifically, the probability of timely repayment for automotive hire-purchase loans rises by 4.3 percentage points (Column 1), while the corresponding repayment amount surges by 18,213 baht (Column 5). Statistically significant expansions are also observed in the repayment probabilities for machinery hire-purchase loans (7.5 percentage points) and personal loans (5.9 percentage points).

Figure 4 provides visual confirmation of these discontinuous jumps in non-agricultural loan repayment behavior at the cutoff for the forbearance sub-sample. This strategic liquidity reallocation toward non-agricultural obligations can be rationalized through the framework of relative delinquency, wherein borrowers prioritize repayments based on the perceived severity of credit enforcement mechanisms and the idiosyncratic costs associated with default. This behavioral pattern is tightly aligned with findings by Chantarat et al. (2023), who document that Thai farmers systematically prioritize obligations to commercial banks and non-banks over community-based lenders and state-owned institutions, placing the BAAC at the bottom of their repayment hierarchy. Collectively, these results demonstrate that rather than eroding overall credit discipline, the flexible debt relief program dynamically reshapes repayment priorities toward higher-stake obligations – such as automotive hire-purchase, machinery hire-purchase, and personal loans – which typically feature higher interest rates and more stringent default penalties.

[Figure 4 here]

Furthermore, the results presented in Table 7 (Panel C) for the active repayers sub-sample reveal no statistically significant spillovers across either the extensive or intensive margins. This indicates that for borrowers who expand their agricultural debt repayment, there is no detectable substitution effect; that is, they do not contract repayments on alternative obligations to finance their increased BAAC contributions. Interestingly, an experimental study by Chantarat et al. (2026b), which layered prize-linked incentives onto a similar principal-first framework, found that while the combined mechanism successfully boosted agricultural loan repayments, it induced negative cross-creditor spillovers by reducing the repayment probability of ineligible obligations at external financial institutions.

6.3 Direct and spillover effects on credit deterioration

Table 8 presents the program's impact on credit deterioration, defined as the transition of a loan account from performing to non-performing status. In the full sample, program participation reduces the probability of agricultural loan deterioration by 5.0 percentage points (Column 1). This mitigating effect is particularly pronounced within the financially vulnerable cohort; specifically, the likelihood of migrating to non-performing status among TDR agricultural accounts decreases by 16.3 percentage points (Column 3).

[Table 8 here]

Figure 5 provides visual confirmation of this direct impact, depicting a sharp contraction in the probability of agricultural loan credit deterioration at the threshold for the full sample and the TDR sub-sample in Panels (A) and (B), respectively. Crucially, interpreting these estimates requires an understanding of the program's institutional mechanics: by design, enrolled accounts are administratively shielded from downward accounting reclassification during the observation window. Consequently, these FRD estimates identify the counterfactual state – effectively quantifying the latent default rates that would have materialized in the absence of the policy intervention. For instance, our findings imply that without this regulatory safety net, nearly one in six distressed TDR borrowers would have transitioned into NPL status.

[Figure 5 here]

Furthermore, the results reported in Columns 4 through 7 of Table 8 reveal no statistically significant spillovers onto the credit deterioration of non-agricultural loan portfolios. While our previous findings demonstrate that borrowers strategically reallocate liquidity to service alternative debts, the estimates here confirm that this policy-induced reallocation occurred without systematically shifting credit risk to external lenders or precipitating a buildup of defaults across other loans.

6.4 Direct and spillover effects on new borrowing

Table 9 presents the program's impact on subsequent borrowing behavior across both agricultural and non-agricultural credit categories. Across all analyzed portfolios, the estimated effects are statistically indistinguishable from zero for both the extensive margin of new credit origination (the probability of securing a new loan) and the intensive margin of total loan volume.

[Table 9 here]

Several institutional and empirical factors may explain this documented null effect. First, the program's structural design did not condition new credit lines on a dynamic incentive mechanism; participants remained eligible to draw BAAC funds up to their pre-existing limits without being required to achieve full debt clearance. Second, beneficiaries retained active access to alternative credit channels, particularly within unobserved informal markets that are not captured in our administrative dataset. This data constraint is highly relevant, as prior evidence indicates that nearly one-third of Thai agricultural households systematically rely on informal financing, such as agricultural input suppliers, relatives, and unregulated lenders (Chantarat et al., 2023). Third, the absence of significant variations may stem from temporal limitations, given the relatively constrained 16-month observation window. Complex behavioral adjustments – such as structurally shifting credit demand or strategically accumulating liquidity prior to embarking on new borrowing cycles – typically require a more extended horizon to fully manifest.

Importantly, our findings stand in stark contrast to prior evaluations of agricultural debt relief initiatives in Thailand. For instance, Ratanavararak & Chantarat (2023) document that traditional debt moratoriums induced significant debt accumulation, particularly among borrowers with medium-to-high baseline debt levels. Distinct from these conventional interventions, the flexible debt relief program incorporates binding credit caps for participants. These constraints ensure that subsequent credit originations at the BAAC are restricted to productive purposes – such as human capital upskilling – thereby mitigating the risk of compounding indebtedness. Consequently, these insights suggest that bundling borrowing restrictions alongside liquidity forbearance and a principal-first incentive effectively preempts "debt rotation" – the strategic practice wherein borrowers secure new credit primarily to service pre-existing obligations.

6.5 Understanding participants' perceptions and behavioral responses

To provide deeper context for our empirical findings, we complement our administrative analysis with supplementary data from a specialized nationwide survey. This instrument was specifically designed to elicit borrowers' subjective comprehension of debt relief mechanisms, policy salience, psychological attitudes toward indebtedness, and self-reported repayment intentions alongside structural liquidity constraints. The final sample comprises 1,831 program-enrolled farmers across 19 provinces, with the survey administered between January and March 2025.

Panel (A) of Figure 6 illustrates that borrowers entering the program generally comprehend the structural severity of their debt obligations. Specifically, 86.2% of respondents recognize that stagnant principal reduction poses a long-term financial threat, even though nearly half of the surveyed cohort perceive the implicit costs of default to be relatively negligible. This low perceived cost of default is likely driven by historical institutional leniency, as the BAAC rarely deploys stringent delinquency enforcement mechanisms, such as collateral foreclosure.

Conversely, Panel (B) of Figure 6 reveals that a substantial proportion of participants harbor pronounced misconceptions regarding the specific operational terms and underlying benefits of this flexible debt relief framework. For instance, 41.8% of respondents incorrectly believe that they are strictly prohibited from executing any loan repayments throughout the program's duration. This systemic misunderstanding underscores the critical role of policy nomenclature and informational framing. Although institutional considerations led to the initial promotion of the scheme under the conventional label of "debt forbearance," this branding generated a severe communication barrier. Having been heavily conditioned by successive blanket moratoria for nearly a decade, rural borrowers reflexively anchored on the assumption that all repayment mechanisms were entirely suspended. Such cognitive frictions – particularly regarding mechanisms engineered to directly reward active debt servicing – inevitably distort optimal credit behaviors. Consequently, establishing transparent communication channels and active institutional engagement to rectify these information asymmetries are paramount. Cultivating a precise understanding of the program's conditional design – specifically its capacity-based window for accelerated principal reduction – is essential to maximizing overall policy efficacy.

[Figure 6 here]

Furthermore, the survey results presented in Figure 7 indicate that approximately one-quarter of participating borrowers expanded their debt service. This magnitude aligns tightly with our prior empirical findings regarding the heightened agricultural loan repayments observed along the intensive margin. This positive response underscores the behavioral efficacy of the principal-first incentive structure, whereby voluntary repayments are channeled directly toward reducing the outstanding principal balance. Conversely, approximately 30% of respondents reported either contracting or entirely suspending their payments. The primary drivers behind this non-repayment behavior bifurcate into two distinct rationales: first, borrowers strategically leveraging the non-mandatory nature of the forbearance window (15%); and second, individuals who harbored the intention to repay but faced binding liquidity constraints (12%) or logistical frictions, including transit barriers to bank branches (1%).

[Figure 7 here]

For the liquidity-constrained segment, the program functions as a critical safety net that prevents vulnerable debtors from transitioning into severe credit deterioration. Conversely, for the logistically-constrained cohort, mitigating transaction costs—specifically in terms of transit time and travel expenses—can substantially amplify overall policy efficacy. We explore this mechanism by examining variations in local institutional enforcement; our analysis reveals that the program induces significantly higher repayment intensity among borrowers residing in sub-districts characterized by intensive on-site debt collection, where BAAC officers conduct monthly village-level visitations (see Table A2 in the Appendix). This finding aligns tightly with experimental evidence from Chantarat et al. (2026b), who demonstrate that minimizing spatial and logistical frictions through mobile on-site collection services effectively enables agricultural borrowers to enhance both their repayment frequency and total debt contributions.

7. Robustness check

To ensure the validity of our empirical design, we rigorously evaluate the robustness of our main estimation results and address the potential for false positives across our significant outcomes. Specifically, we subject our core fuzzy regression discontinuity (FRD) estimates to a battery of sensitivity tests, varying the local polynomial orders, kernel functions, and bandwidth selections.

Regarding orders of local polynomials, we include orders up to three to mitigate concerns regarding overfitting and excessive influence from observation far from the cutoff (Cattaneo et al., 2019). As for kernel choices, besides Triangular, we add Epanechnikov and Uniform. For alternative bandwidth ranges, we choose windows that are smaller than the optimal bandwidth to ensure the reliability of the covariate balance test (Cattaneo et al., 2024). The outputs in Tables 10 and Tables A3-A9 show that the estimation results are robust when different setups are applied.

[Table 10 here]

Beyond conventional regression discontinuity robustness checks, we employ Difference-in-Differences (DiD) framework to account for time-invariant unobservable heterogeneities and further corroborate the validity of our core estimation results. By tracking outcomes for eligible and ineligible borrowers before and after the policy's implementation, this complementary approach ensures that the observed discontinuities are genuinely driven by the regulatory intervention rather than confounded by pre-existing baseline differences at the threshold.

The DiD estimates for repayment behavior and credit deterioration, presented in Tables A10-A13, strongly confirm the empirical consistency of our baseline FRD findings. On the extensive margin of repayment, the DiD estimate reported in Table A10 (Column 4) indicates a 22.5 percentage point reduction in the agricultural loan repayment probability, which aligns closely with the baseline FRD estimate of 25.6 percentage points.

Specifically, for the active repayers sub-sample, the DiD estimates in Table A11 document a robust expansion in repayment intensity across the full sample, non-TDR, and TDR cohorts, faithfully mirroring the baseline FRD findings. Parallel to this, for the sub-sample of borrowers who deferred their agricultural obligations, the DiD estimates in Table A12 corroborate the strategic reallocation of liquidity toward non-agricultural credit categories. Statistically significant increases are observed across both the extensive margin of repayment probability (Panel A) and the intensive margin of repayment magnitude (Panel B) for non-agricultural debts, encompassing automotive hire-purchase, machinery hire-purchase, and personal loans.

Finally, the DiD estimates presented in Table A13 regarding the probability of agricultural loan credit deterioration further substantiate the robustness of our primary results. The full-sample estimate indicates a 6.5 percentage point reduction in the probability of deterioration (Column 4), while the mitigating effect for the financially vulnerable TDR cohort reaches a substantial 15.8 percentage points (Column 6). These findings are highly consistent with our baseline FRD estimates of 5.0 percentage points and 16.3 percentage points, respectively, providing robust cross-methodological confirmation that the program effectively insulated high-risk debtors from severe credit distress.

The empirical cross-validation between the FRD and DiD frameworks demonstrates that our findings are highly robust to alternative identification strategies. The stark consistency between these two distinct empirical approaches – encompassing both direct policy impacts and cross-creditor spillovers – substantiates the internal validity of our estimates and strengthens the causal interpretation of the documented behavioral responses.

8. Conclusion

This paper evaluates a flexible debt relief program for agricultural households, designed to mitigate the interconnected challenges of income insufficiency, cash flow volatility, and liquidity constraints through a synchronized combination of repayment incentives and a traditional debt forbearance. Our empirical findings demonstrate that this design effectively uncovers the latent repayment capacity of borrowers. By deploying a "principal-first" incentive, the program successfully induces financially capable debtors to accelerate debt reduction. Concurrently, as a structural safety net, the policy generates positive cross-creditor spillovers; it enables liquidity-constrained borrowers to strategically defer agricultural obligations while optimizing debt service on non-agricultural portfolios characterized by more stringent enforcement mechanisms and higher default penalties. Simultaneously, the program shields vulnerable debtors from severe credit deterioration.

Ultimately, these results indicate that bundling performance-based incentives with structural flexibility serves as an efficient screening and self-selection mechanism in credit markets characterized by asymmetric information. By allowing borrowers to dynamically choose between repayment and forbearance based on their current financial capacity and idiosyncratic shocks, the policy minimizes distortions. In addition, clear policy communication and active institutional engagement are vital to boosting program efficacy; otherwise, legacy perceptions and long-standing expectations from a decade of blanket moratoria can easily obfuscate the program's repayment incentives and distort borrower repayment behavior. For policymakers, this study offers a critical blueprint for shifting away from rigid, one-size-fits-all debt moratoria toward more nuanced, incentive-compatible frameworks that secure sustainable debt resolution and foster long-term financial resilience for agricultural households.

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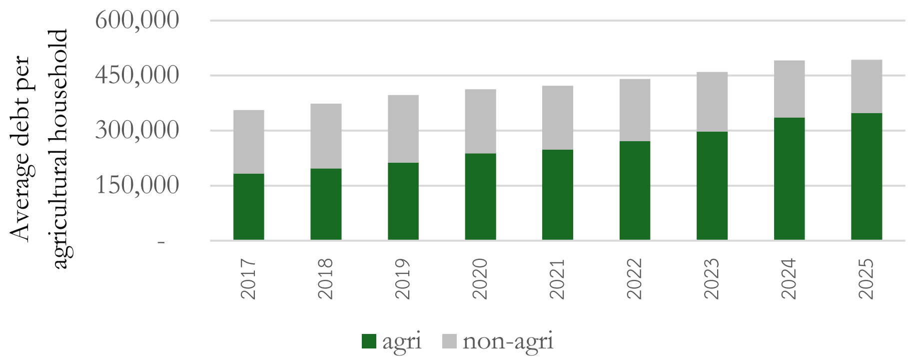
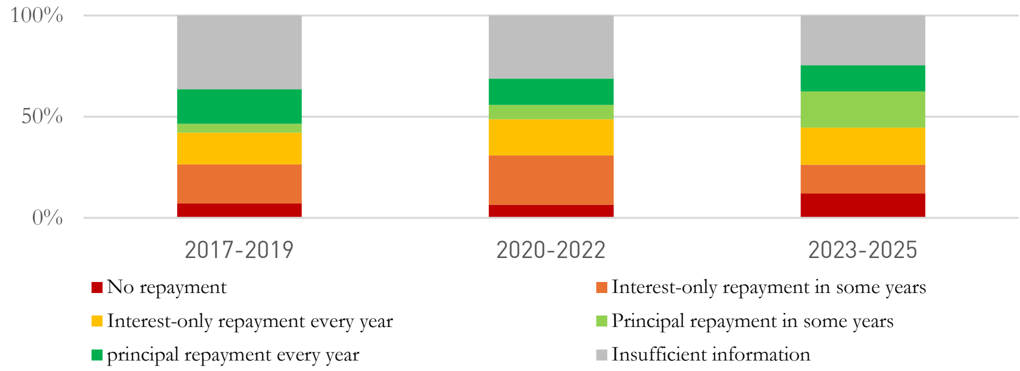
Figure 1: Dynamics of debt and repayment

(A) Average debt per household (2017-2025)

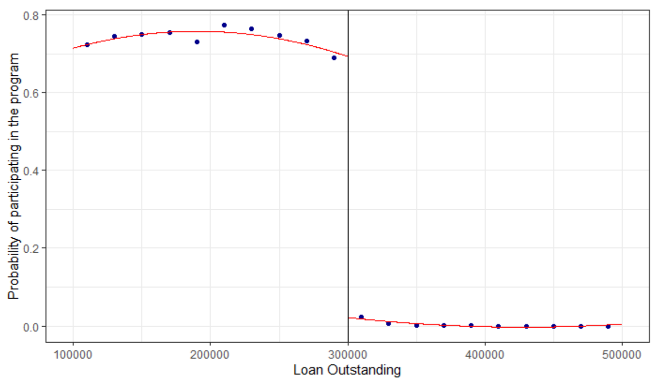


(B) Distribution and dynamics of debt repayment (2017-2025)



Note: The figure provides an overview of Thai farmers' debt and repayment capacity over time. Panel (A) shows the average outstanding debt per borrower (in baht) as of March each year, separately for agricultural and non-agricultural loans. Panel (B) illustrates the distribution of repayment behavior among agricultural households, classified based on changes in outstanding loan balances and credit quality over time. The figure is based on authors' calculations using National Credit Bureau (NCB) data.

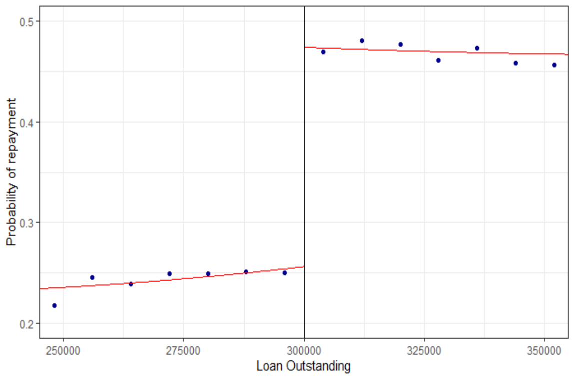
Figure 2: First-stage plot



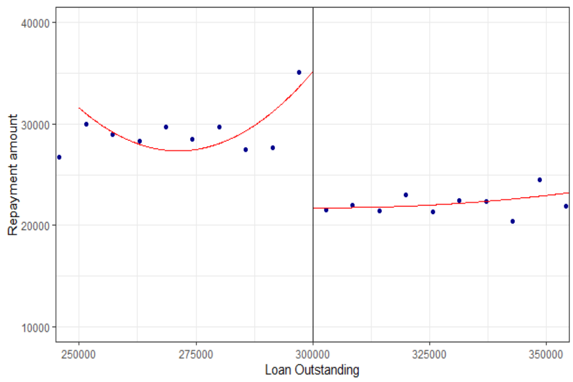
Note: The figure presents the first-stage relationship between program eligibility and participation at the borrower level. The vertical axis shows the program participation rate, while the horizontal axis displays outstanding debt as of September 30, 2023. The dots represent binned averages of participation rates, and the solid lines show fitted values from local polynomial regressions estimated separately on each side of the cutoff. The vertical line indicates the eligibility threshold at 300,000 baht of outstanding debt. Participation is defined by enrollment status as of March 2024 (program registration closure). The estimation uses a regression discontinuity design with a triangular kernel and a quadratic local polynomial.

Figure 3: RD plot for agricultural loan repayment

(A) Overall agricultural loan repayment probability (full sample)

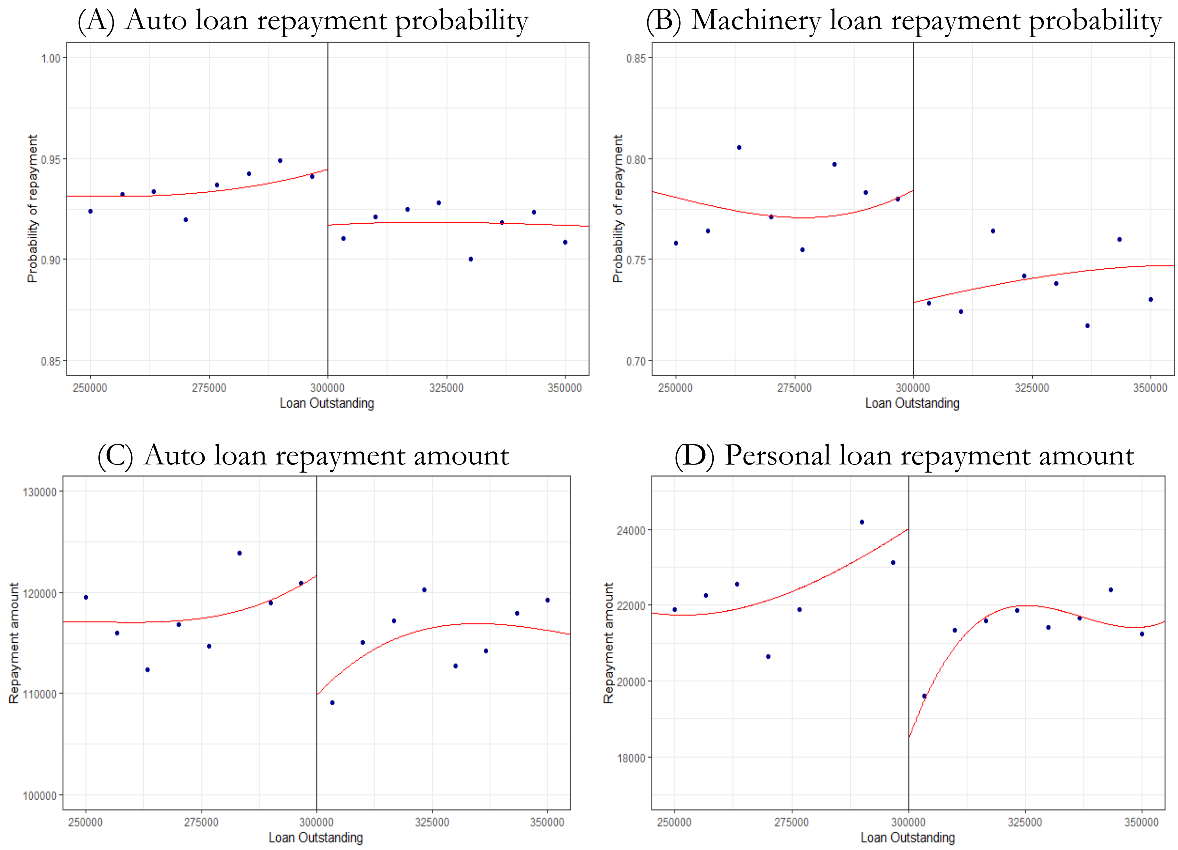


(B) Overall agricultural loan repayment amount (paid sample)



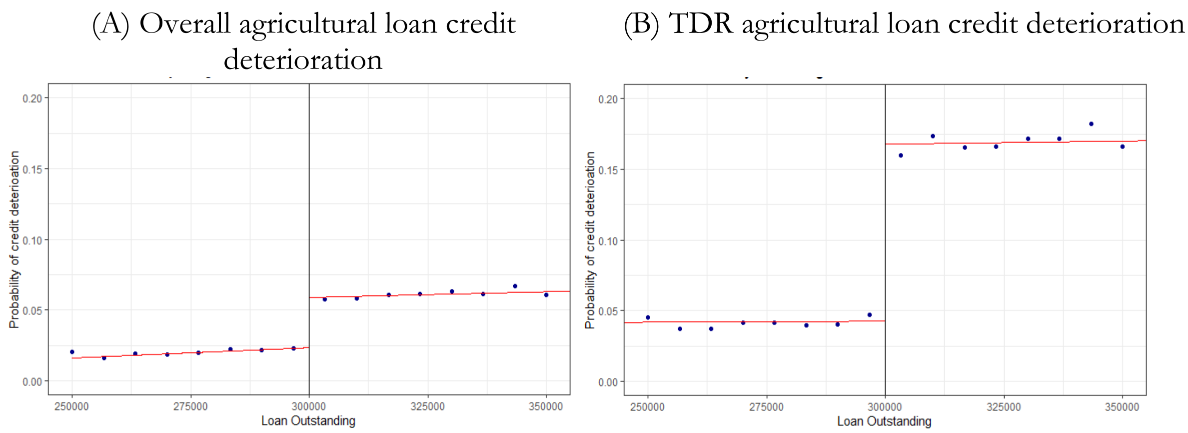
Note: The figure presents regression discontinuity (RD) estimates of the impact of program eligibility on agricultural loan repayment outcomes at the borrower level. The vertical axis shows the outcome variable, while the horizontal axis displays outstanding debt as of September 30, 2023. The dots represent binned averages, and the solid lines show fitted values from local polynomial regressions estimated separately on each side of the cutoff. The vertical line indicates the eligibility threshold at 300,000 baht of outstanding debt. In Panel (A), the outcome is repayment probability, defined as an indicator equal to one if the borrower made at least one payment exceeding 1,000 baht between April 2024 and July 2025. In Panel (B), the outcome is repayment amount, measured by the reduction in outstanding loan balance over the same period, and is estimated on the subsample of borrowers who made payments exceeding 1,000 baht during this period. The estimation uses a triangular kernel and a quadratic local polynomial.

Figure 4: RD plot for non-relief repayment (unpaid subsample)



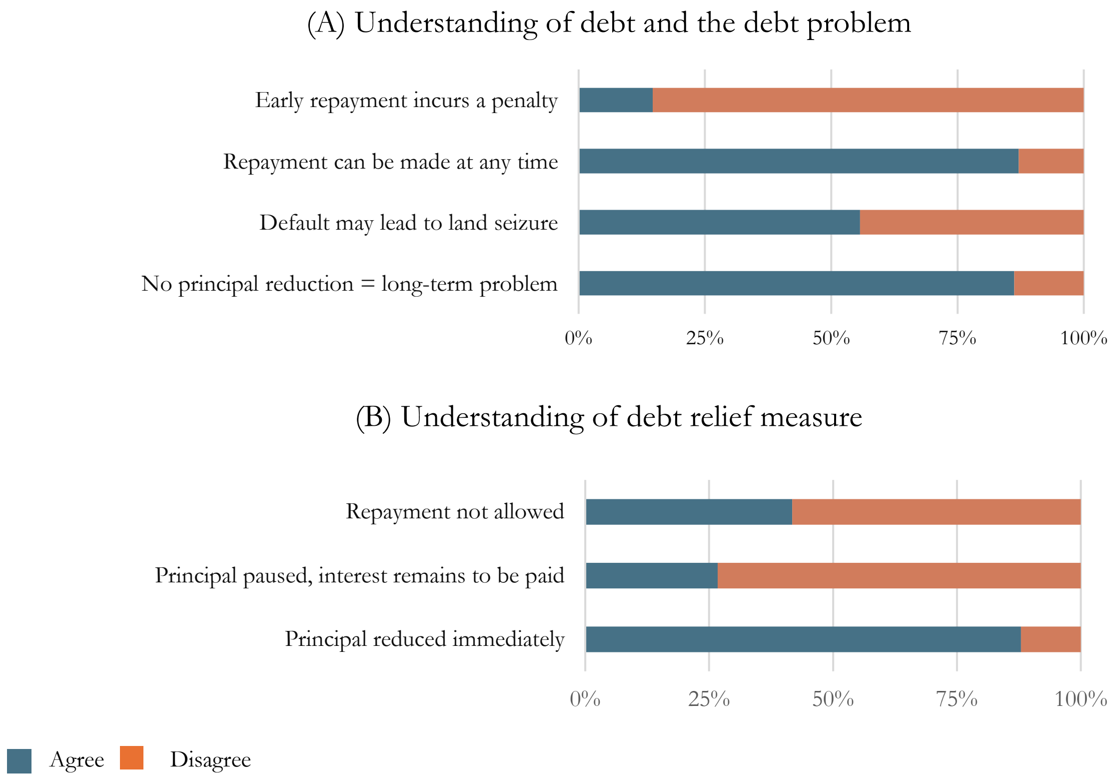
Note: The figure presents regression discontinuity (RD) estimates of the impact of program eligibility on non-agricultural loan repayment outcomes at the borrower level for the unpaid subsample. The vertical axis shows the outcome variable, while the horizontal axis displays outstanding debt as of September 30, 2023. The dots represent binned averages, and the solid lines show fitted values from local polynomial regressions estimated separately on each side of the cutoff. The vertical line indicates the eligibility threshold at 300,000 baht of outstanding debt. Panels (A) and (B) show repayment probability for auto and machinery loans, respectively. Panels (C) and (D) show repayment amount for auto and personal loans, respectively, measured by the reduction in outstanding loan balance between April 2024 and July 2025. The unpaid subsample consists of borrowers who did not make any payments exceeding 1,000 baht on agricultural loans during this period, consistent with the repayment definition in Figure 3. The estimation uses a triangular kernel and a quadratic local polynomial.

Figure 5: RD plot for agricultural loan credit deterioration



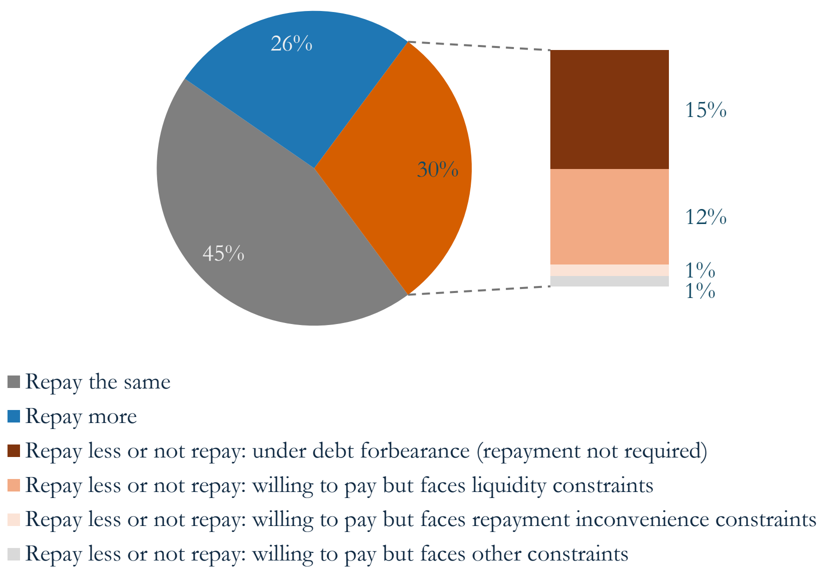
Note: The figure presents regression discontinuity (RD) estimates of the impact of program eligibility on agricultural loan credit deterioration at the borrower level. The vertical axis shows the credit deterioration probability, while the horizontal axis displays outstanding debt as of September 30, 2023. The dots represent binned averages, and the solid lines show fitted values from local polynomial regressions estimated separately on each side of the cutoff. The vertical line indicates the eligibility threshold at 300,000 baht of outstanding debt. Credit deterioration is defined as an indicator equal to one if the borrower's loan classification deteriorates from performing to non-performing between April 2024 and July 2025. Panel (A) reports results for overall agricultural loans, while Panel (B) focuses on TDR agricultural loans. The estimation uses a triangular kernel and a quadratic local polynomial.

Figure 6: Understanding of debt, debt problem and flexible debt relief program



Note: The figure presents borrower-level statistics on (1) understanding of debt and debt-related risks and (2) understanding of the debt relief program, shown in Panel (A) and Panel (B), respectively. The data are drawn from a nationwide survey of 1,831 program participants across 19 provinces, conducted between January and March 2025. The figures are based on the authors' calculations. In Panel (A), the expected responses are "disagree", "agree", "agree", and "agree" (from top to bottom), while in Panel (B), the expected responses are "disagree", "disagree", and "agree", respectively.

Figure 7: Understanding of flexible debt relief program participants' repayment behavior



Note: The figure presents borrower-level repayment behavior among sample participants in the flexible debt relief program. The pie chart shows the overall distribution of repayment outcomes: repaying the same (45%), repaying more (26%), and repaying less or not repaying (30%). The stacked bar provides a breakdown of the "repay less or not repay" group by underlying reasons, including being under a debt moratorium (repayment not required), facing liquidity constraints, facing repayment inconvenience, and facing other constraints. The data are drawn from a nationwide survey of 1,831 program participants across 19 provinces, conducted between January and March 2025. Percentages are based on authors' calculations.

Table 1: Program eligibility and benefits

(A) Eligibility requirements

	Category	Criteria
1	Creditor	The borrower must be an existing client (member) of BAAC as of September 2023.
2	Loan quality classification	Performing or underperforming, or non-performing loan
3	Loan type	Must not be an overdraft or a promissory note, or a Public Service Loan Account (PSA)
4	Loan outstanding	The total amount of the remaining balance of an applicant's loan at BAAC must not exceed 300,000 baht as of September 30, 2023.
5	Debtor characteristic	Must not be under prosecution or bankruptcy

(B) Program benefits

	Category	Benefit
1	Debt restructuring (Principal-first incentive)	Full interest expense forgiveness for up to three years. Specifically, the government repays interest expenses on behalf of beneficiaries. The subsidy is paid directly to BAAC. A beneficiary can take full advantage of the subsidy by repaying during the program: every "baht" of repayment will directly deduct the loan principal outstanding. In the case where a beneficiary has accrued interest expense, half of the amount of repayment will be allotted to repayment of accrued interest, and the other half will be allotted to repayment of the loan principal.
2	Debt forbearance	A voluntary deferral of principal repayments for a period up to three years without any penalty or additional credit classification. Any loan accounts under the program are allowed to retain their pre-program credit quality classification.
3	Training course	Free training courses are provided for 300,000 program participants. The objective is to equip beneficiaries with the necessary technical and entrepreneurial skills.
4	New borrowing	A maximum of 100,000 baht of additional credit from BAAC. The amount of new credit is determined by BAAC, depending mainly on the debtor's ability and willingness to repay. This additional rehabilitating credit must be used for human capital upskilling, working capital, agricultural investment, or for business recovery. A participant who fails to comply with this new borrowing rule is required to quit the program.

Note: Public Service Accounts (PSA) refers to loan accounts under government programs that were implemented by Specialized Financial Institutions as approved by the cabinet. Such programs rely on service models with more accommodative conditions and have various objectives such as rehabilitating loans to assist those affected by disasters. The operation of PSA is different from standard practice in several aspects such as easing credit consideration criteria and provision of grace period. USD 1 was approximately Baht 32.61 as of May 15, 2026 (Bank of Thailand).

Table 2: Descriptive statistics

Variables	Mean	Median	Std. Dev.	Obs.
Repayment (0/1)				
agricultural loan	0.324	0	0.468	1,484,514
auto loan	0.923	1	0.267	175,036
machinery loan	0.733	1	0.442	97,344
mortgage loan	0.908	1	0.289	24,399
personal loan	0.760	1	0.427	206,601
Repayment amount (baht)				
agricultural loan	8,129	0	24,214	1,484,514
auto loan	116,645	103,245	115,293	175,036
machinery loan	18,343	11,437	30,679	97,344
mortgage loan	65,606	41,241	123,020	24,399
personal loan	33,053	9,801	71,897	206,601
Credit deterioration (0/1)				
agricultural loan	0.035	0	0.183	1,484,514
auto loan	0.084	0	0.277	175,036
machinery loan	0.102	0	0.303	97,344
mortgage loan	0.068	0	0.252	24,399
personal loan	0.148	0	0.355	206,601
New borrowing (0/1)				
agricultural loan	0.118	0	0.324	1,484,514
auto loan	0.019	0	0.139	1,484,514
machinery loan	0.051	0	0.221	1,484,514
mortgage loan	0.001	0	0.032	1,484,514
personal loan	0.118	0	0.323	1,484,514
New borrowing amount				
agricultural loan	15,476	0	78,763	1,484,514
auto loan	11,573	0	99,319	1,484,514
machinery loan	2,080	0	19,985	1,484,514
mortgage loan	797	0	44,563	1,484,514
personal loan	10,412	0	69,583	1,484,514
Borrower characteristics				
borrower's age	55.4	57	11.0	1,484,514
female (0/1)	0.514	1	0.500	643,355
multi-creditor (0/1)	0.312	0	0.463	1,484,514
commercial bank borrowing (0/1)	0.099	0	0.299	1,484,514
yearly repayment schedule (0/1)	0.972	1	0.166	1,484,514
monthly repayment schedule (0/1)	0.310	0	0.463	1,484,514
performing debtor (0/1)	0.753	1	0.432	1,484,514
in repeated flood area (0/1)	0.135	0	0.341	1,484,514

Note: The table reports summary statistics for the main variables at the borrower level. Repayment is defined as an indicator equal to one if the borrower made at least one payment (exceeding 1,000 baht) on the respective loan during the period from April 2024 to July 2025. Repayment amount is measured as the reduction in outstanding loan balance over the same period. Credit deterioration is defined as an indicator equal to one if the borrower's loan classification transitions from performing to non-performing (new default) between April 2024 and July 2025. New borrowing is defined as an indicator equal to one if the borrower takes out a new loan during this period, and new borrowing amount measures the total amount of new loans originated. Borrower characteristics are measured as of September 2023. The number of observations (Obs.) corresponds to the number of borrowers. For loan-specific outcomes (e.g., auto, machinery, mortgage, and personal loans), the sample is restricted to borrowers who hold the respective loan type.

Table 3: Falsification test of null treatment effect

Variable	Bandwidth (L|R)	RD Estimate	*p*-value	CI	Eff. Obs.
NPL agricultural loan	83,238 | 71,076	-0.001	0.256	[-0.005, 0.001]	545,248
NPL non-TDR agricultural loan	32,732 | 47,152	-0.001	0.787	[-0.008, 0.006]	210,591
NPL TDR agricultural loan	70,187 | 94,962	-0.003	0.782	[-0.022, 0.017]	109,649
NPL auto loan	77,413 | 94,348	0.003	0.753	[-0.018, 0.025]	58,896
NPL machinery loan	116,699 | 130,764	-0.034	0.174	[-0.083, 0.015]	47,972
NPL mortgage loan	68,109 | 71,815	-0.023	0.535	[-0.097, 0.050]	7,426
NPL personal loan	69,918 | 81,217	-0.017	0.414	[-0.059, 0.024]	62,571
Age	10,152 | 15,064	-7.63	0.000	[-8.36, -6.91]	78,222
Male	17,207 | 22,206	0.018	0.512	[-0.036, 0.072]	44,636
Repeated flood	17,337 | 20,446	-0.008	0.500	[-0.032, 0.016]	97,055
Number of creditors	13,660 | 20,794	0.119	0.000	[0.081, 0.156]	87,461

Note: The table reports regression discontinuity (RD) estimates for a set of predetermined borrower characteristics and credit quality outcomes prior to the program to assess the validity of the identification strategy. Each row corresponds to a separate RD regression in which the outcome variable is the characteristic listed in the first column. The reported estimates capture the discontinuity at the eligibility threshold. Bandwidths are optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion and the number of observations reflects the effective sample used in each estimation. All specifications use a triangular kernel and a quadratic local polynomial.

Table 4: First-stage regression

	Agricultural loan			Non-agricultural loan			
	(1) Overall	(2) Non-TDR borrowers	(3) TDR borrowers	(4) Auto loan	(5) Machinery loan	(6) Mortgage loan	(7) Personal loan
RD Estimate	0.669***	0.673***	0.696***	0.627***	0.599***	0.559***	0.590***
	(0.003)	(0.004)	(0.007)	(0.008)	(0.013)	(0.022)	(0.009)
Observations	223,898	170,122	96,335	54,760	29,468	8,685	51,318
Bandwidth (L| R)	24,479 | 36,780	29,689 | 53,893	28,251 | 51,504	51,146 | 75,064	48,823 | 75,696	100,307 | 128,417	43,043 | 67,715
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Local Poly (p)	2	2	2	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports first-stage regression results from a regression discontinuity (RD) design at the borrower level. The outcome variable is an indicator for program participation, measured as of March 2024. The estimates capture the discontinuity in participation at the eligibility threshold. Columns differ by loan type, where each specification restricts the sample to borrowers holding the respective loan type. The number of observations reflects the effective sample used in each estimation within the selected bandwidth. Bandwidths are determined using optimal procedures on either side of the cutoff. All specifications use a triangular kernel and a quadratic local polynomial. Borrower-level control variables are included in all regressions. The variables include demographics, baseline creditor profile and credit quality characteristics and an indicator for climate risk exposure (repeated flood areas) as presented in Table 2. Robust standard errors are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5: Effects on agricultural loan repayment

	Direct effect					
	Repayment			Repayment amount		
	(1) Overall	(2) Non-TDR borrowers	(3) TDR borrowers	(4) Overall	(5) non-TDR borrowers	(6) TDR borrowers
RD Estimate	-0.268***	-0.239***	-0.289***	344.5	250.0	-1,736***
	(0.009)	(0.010)	(0.018)	(566.9)	(584.2)	(629.6)
Observations	254,318	191,701	64,012	199,448	177,820	106,481
Bandwidth (L| R)	37,236 | 63,045	32,547 | 48,221	47,081 | 61,609	26,290| 50,585	26,176 | 48,213	86,125 | 110,150
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Local Poly (p)	2	2	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports fuzzy regression discontinuity (RD) estimates of the impact of program participation on agricultural loan repayment outcomes at the borrower level. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment is defined as an indicator equal to one if the borrower made at least one payment exceeding 1,000 baht between April 2024 and July 2025. Repayment amount is measured as the reduction in outstanding loan balance over the same period. Columns (1)–(3) report effects on repayment probability, while Columns (4)–(6) report effects on repayment amount. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications use a triangular kernel and a quadratic local polynomial, with borrower-level control variables included. Robust standard errors are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 6: Effects on loan repayment amount, paid debtor subsample

	Direct effect								
	Repayment amount								
	(1) Overall	(2) Overall	(3) Overall	(4) Non-TDR	(5) Non-TDR	(6) Non-TDR	(7) TDR	(8) TDR	(9) TDR
RD Estimate	26,886***	28,640***	20,302***	27,801***	28,517***	17,949***	8,696***	10,267***	4,332
	(1,203)	(1,331)	(2,382)	(1,300)	(1,398)	(2,626)	(1,843)	(2,286)	(2,964)
Observations	138,070	100,090	47,015	107,535	87,879	38,995	41,354	28,831	13,919
Bandwidth (L| R)	59,307 | 102,485	47,041 | 87,292	87,158 | 103,780	39,095 | 70,473	42,323 | 76,509	86,597 | 102,682	97,923 | 120,788	96,723 | 119,282	97,660 | 123,893
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Local Poly (p)	2	2	2	2	2	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Single creditor	Multiple creditor	Full	Single creditor	Multiple creditor	Full	Single creditor	Multiple creditor

Note: The table reports fuzzy regression discontinuity (RD) estimates of the impact of program participation on agricultural loan repayment amounts at the borrower level, estimated on the subsample of borrowers who made payments exceeding 1,000 baht between April 2024 and July 2025. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment amount is measured as the reduction in outstanding loan balance over the same period. Columns present results separately for overall, non-TDR, and TDR agricultural loans, with further breakdowns by borrower type (full sample, single-creditor, and multiple-creditor). The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications use a triangular kernel and a quadratic local polynomial, with borrower-level control variables included. Robust standard errors are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

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Table 7: Effects on non-relief loan repayment

	Spillover effect							
	Repayment				Repayment amount			
	(1) Auto loan	(2) Machinery loan	(3) Mortgage loan	(4) Personal loan	(5) Auto loan	(6) Machinery loan	(7) Mortgage loan	(8) Personal loan
Panel A: Full sample								
RD Estimate	-0.002	0.010	-0.047	0.014	10,931**	3,684**	-21,495	-1,991
	(0.012)	(0.027)	(0.032)	(0.024)	(5,513)	(1,480)	(20,548)	(3,083)
Observations	62,998	30,915	6,994	43,057	60,068	29,153	8,606	58,533
Bandwidth (L| R)	86,998 | 103,141	71,460 | 84,587	51,773 | 72,653	51,389 | 73,907	79,603 | 97,258	59,099 | 70,677	71,193 | 89,984	59,956 | 74,631
Sample	Full	Full	Full	Full	Full	Full	Full	Full
Panel B: Unpaid debtor								
RD Estimate	0.043**	0.075**	0.054	0.059*	18,213***	2,748	2,329	5,376*
	(0.019)	(0.035)	(0.037)	(0.034)	(6,449)	(1,962)	(7,176)	(2,942)
Observations	32,325	22,949	2,627	17,448	32,959	16,668	2,290	21,892
Bandwidth (L| R)	91,065 | 106,864	104,962 | 122,020	81,425 | 89,356	49,289 | 67,161	97,167 | 111,783	71,548 | 81,227	67,686 | 82,922	65,896 | 71,689
Sample	Unpaid debtor	Unpaid debtor	Unpaid debtor	Unpaid debtor	Unpaid debtor	Unpaid debtor	Unpaid debtor	Unpaid debtor
Panel C: Paid debtor								
RD Estimate	-0.006	0.048	0.008	0.039	14,472	1,982	39,693	10,192
	(0.021)	(0.057)	(0.408)	(0.040)	(12,439)	(4,488)	(39,033)	(6,581)
Observations	19,094	5,864	2,537	14,120	19,410	5,445	1,688	14,099
Bandwidth (L| R)	103,573 | 114,929	94,720 | 105,676	105,683 | 118,692	103,986 | 114,575	96,606 | 105,970	78,259 | 90,556	97,944 | 103,483	110,447 | 122,937
Sample	Paid debtor	Paid debtor	Paid debtor	Paid debtor	Paid debtor	Paid debtor	Paid debtor	Paid debtor
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Local Poly (p)	2	2	2	2	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports fuzzy regression discontinuity (RD) estimates of the spillover effects of program participation on non-agricultural loan repayment outcomes at the borrower level. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment is defined as an indicator equal to one if the borrower made at least one payment exceeding 1,000 baht between April 2024 and July 2025, while repayment amount is measured as the reduction in outstanding loan balance over the same period. Columns (1)–(4) report effects on repayment probability, and Columns (5)–(8) report effects on repayment amount for auto, machinery, mortgage, and personal loans, respectively. Panel A presents results for the full sample, Panel B restricts the sample to borrowers who did not make payments exceeding 1,000 baht on agricultural loans during this period, and Panel C restricts the sample to those who did. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications use a triangular kernel and a quadratic local polynomial, with borrower-level control variables included. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Effects on credit deterioration

	Direct effect			Spillover effect			
	Agricultural loan			Non-agricultural loan			
	(1) Overall	(2) Non-TDR	(3) TDR	(4) Auto loan	(5) Machinery loan	(6) Mortgage loan	(7) Personal loan
RD Estimate	-0.050***	-0.034***	-0.163***	0.008	0.010	0.006	0.026
	(0.004)	(0.004)	(0.011)	(0.014)	(0.020)	(0.036)	(0.020)
Observations	344,471	237,073	113,233	76,219	34,649	11,565	52,580
Bandwidth (L| R)	55,099 | 69,216W	46,870 | 63,484	85,385 | 119,959	103,438 | 113,080	98,482 | 116,453	110,982 | 127,271	61,775 | 69,845
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular	Triangular
Local Poly (p)	2	2	2	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports fuzzy regression discontinuity (RD) estimates of the impact of program participation on credit deterioration at the borrower level. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Credit deterioration is defined as an indicator equal to one if the borrower's loan classification transitions from performing to non-performing between April 2024 and July 2025. Columns (1)–(3) report the direct effects on agricultural loan credit deterioration, while Columns (4)–(7) report spillover effects on non-agricultural loans, including auto, machinery, mortgage, and personal loans. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications use a triangular kernel and a quadratic local polynomial, with borrower-level control variables included. Robust standard errors are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 9: Effects on new borrowing

	Direct effect	Spillover effect			
	(1) Agricultural loan	(2) Auto loan	(3) Machinery loan	(4) Mortgage loan	(5) Personal loan
Panel A: New borrowing probability					
RD Estimate	0.008	0.003	0.002	-0.000	0.006
	(0.007)	(0.003)	(0.005)	(0.001)	(0.008)
Observations	182,488	243,222	231,609	272,297	208,628
Bandwidth (L| R)	15,448 | 28,644	23,038 | 27,302	24,787 | 30,534	28,672 | 30,305	21,978 | 29,189
Panel B: New borrowing amount					
RD Estimate	2,246	2,737	596.1	6.92	1,227
	(2,122)	(2,324)	(477.8)	(1,145)	(2,478)
Observations	177,192	204,709	195,952	268,286	225,868
Bandwidth (L| R)	21,230 | 30,175	20,479 | 24,943	22,938 | 29,452	31,025 | 39,857	22,052 | 28,543
Kernel	Triangular	Triangular	Triangular	Triangular	Triangular
Local Poly (p)	2	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes

Note: The table reports fuzzy regression discontinuity (RD) estimates of the impact of program participation on new borrowing outcomes at the borrower level. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. New borrowing is defined as an indicator equal to one if the borrower takes out a new loan between April 2024 and July 2025, while new borrowing amount measures the total amount of new loans originated over the same period. Columns report effects separately for agricultural loans (direct effects) and non-agricultural loans, including auto, machinery, mortgage, and personal loans (spillover effects). Panel A presents results for new borrowing probability, while Panel B reports results for new borrowing amounts. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications use a triangular kernel and a quadratic local polynomial, with borrower-level control variables included. Robust standard errors are reported in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

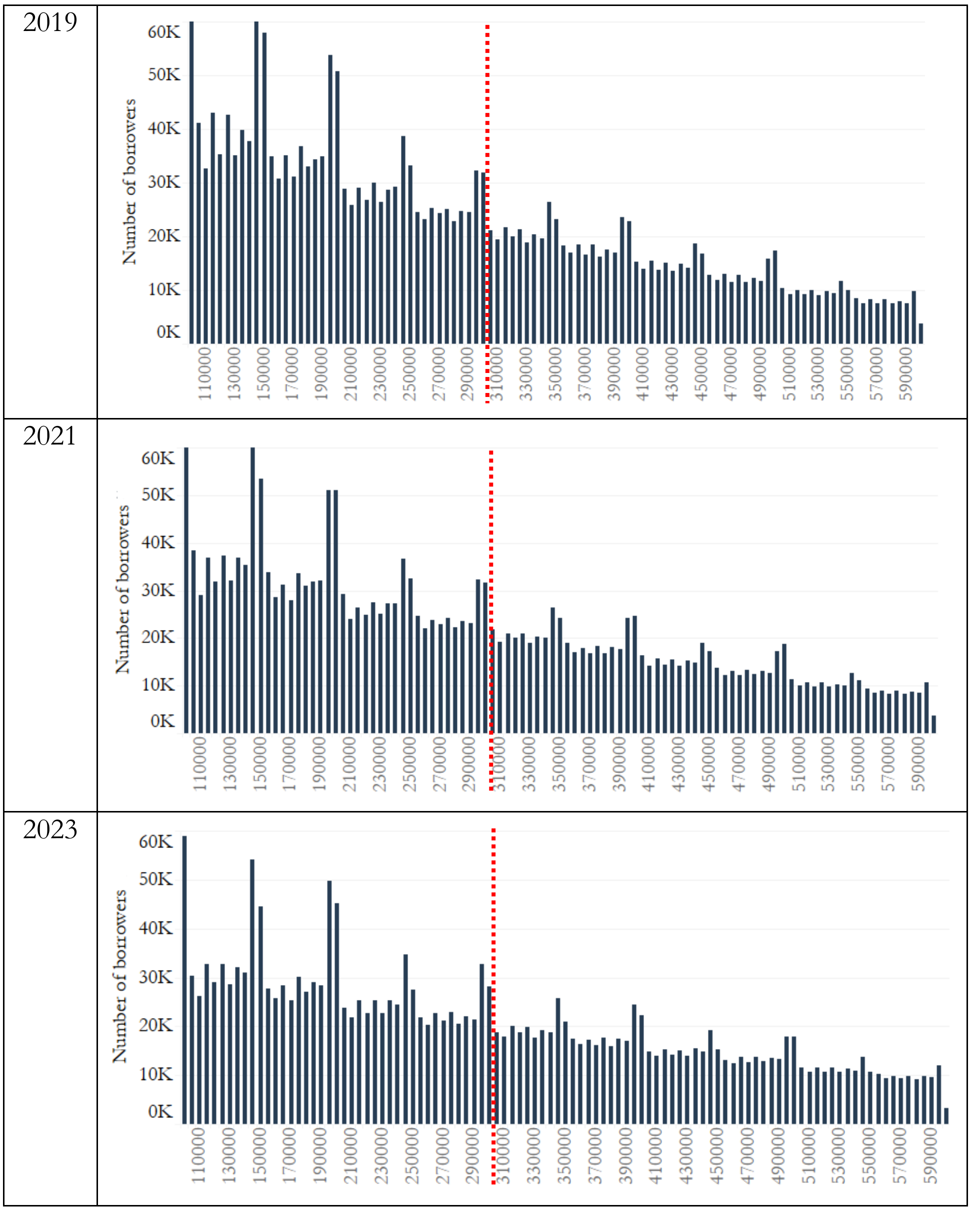
Table 10: Robustness check for agricultural loan repayment probability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Overall (non-TDR and TDR)							
RD Estimate	-0.276***	-0.268***	-0.257***	-0.271***	-0.270***	-0.254***	-0.241***
	(0.008)	(0.009)	(0.010)	(0.010)	(0.009)	(0.015)	(0.022)
Observations	163,345	254,318	313,047	193,790	248,073	150,357	84,356
Bandwidth (L| R)	21,523 | 45,855	37,236 | 63,045	44,935 | 64,067	29,035 | 49,945	36,657 | 61,624	20,000 | 20,000	10,000 | 10,000
Panel B: non-TDR							
RD Estimate	-0.255***	-0.239***	-0.226***	-0.243***	-0.252***	-0.228***	-0.216***
	(0.009)	(0.010)	(0.011)	(0.011)	(0.009)	(0.017)	(0.024)
Observations	141,900	191,701	231,077	184,612	231,053	121,434	68,457
Bandwidth (L| R)	24,961 | 43,078	32,547 | 48,221	35,636 | 52,058	35,666 | 46,350	42,543 | 57,896	20,000 | 20,000	10,000 | 10,000
Panel C: TDR							
RD Estimate	-0.287***	-0.289***	-0.297***	-0.283***	-0.287***	-0.306***	-0.355***
	(0.014)	(0.018)	(0.020)	(0.017)	(0.017)	(0.031)	(0.048)
Observations	45,494	64,012	96,081	57,507	62,054	33,397	18,045
Bandwidth (L| R)	34,225 | 71,064	47,081 | 61,609	63,507 | 76,021	41,004 | 79,475	44,606 | 62,888	20,000 | 20,000	10,000 | 10,000
Kernel	Triangular	Triangular	Triangular	Uniform	Epanechnikov	Triangular	Triangular
Local Poly (p)	1	2	3	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports robustness checks for the regression discontinuity (RD) estimates of the impact of program participation on agricultural loan repayment probability at the borrower level. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment is defined as an indicator equal to one if the borrower made at least one payment exceeding 1,000 baht between April 2024 and July 2025. Panels A–C present results for overall, non-TDR, and TDR agricultural loans, respectively. Across columns, specifications vary by order of the local polynomial, kernel function, and the choice of bandwidth. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications include borrower-level control variables. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix

Figure A1: Density distribution



Note: The figure shows the distribution of borrower-level outstanding loan amounts in 2019, 2021, and 2023. Each bar represents the number of borrowers in each loan-size bin. The horizontal axis reports outstanding loan amounts (in baht) as of September of each year, and the vertical axis reports the number of borrowers. The dashed red line indicates the eligibility threshold at 300,000 baht.

Table A1: Comparison of borrower characteristics by program participation (conditional on quantitative eligibility)

Variable	Participated (Mean)	Did Not Participate (Mean)	Difference	t-statistic	*p*-value
Inquiry for New Loan (0/1)	0.161	0.210	-0.049***	64.857	0.000
Number of Loan Inquiries	0.349	0.489	-0.140***	48.785	0.000
Age (years)	58.33	57.75	0.576***	-24.885	0.000
Female (0/1)	0.516	0.504	0.012***	-8.073	0.000
Flood Exposure (0/1)	0.137	0.148	-0.012***	17.415	0.000

Note: This table reports mean comparisons between borrowers who participated in the program and those who did not participate, conditional on being quantitatively eligible. The "Participated" and "Did Not Participate" columns report group means. The "Difference" column reports the difference in means between the two groups (participants minus non-participants). Statistical significance is based on two-sample t-tests. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample consists of 1,450,937 observations.

Table A2: Direct effect on agricultural loan repayment, on-site debt collector subsample

	(1) Repayment	(2) Repayment amount
RD Estimate	-0.111	6,304*
	(0.079)	(3,307)
Observations	3,906	3,392
Bandwidth (L| R)	88,743 | 104,815	74,867 | 97,863
Kernel	Triangular	Triangular
Local Poly (p)	2	2
Controls	Yes	Yes

Note: The table reports fuzzy regression discontinuity (RD) estimates of the impact of program participation on agricultural loan repayment at the borrower level. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment is defined as an indicator equal to one if the borrower made at least one payment exceeding 1,000 baht between April 2024 and July 2025. Repayment amount is measured as the reduction in outstanding loan balance over the same period. The sample is restricted to borrowers who reside in sub-districts with intensive on-site debt collection, where BAAC officers come to collect repayment in the village monthly. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications use a triangular kernel and a quadratic local polynomial, with borrower-level control variables included. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Robustness check for overall agricultural loan repayment amount, paid subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Overall (Single and multiple creditors)							
RD Estimate	25,469***	27,801***	28,771***	25,582***	21,388***	32,790***	33,876***
	(1,159)	(1,300)	(1,345)	(1,294)	(1,222)	(2,421)	(3,515)
Observations	66,493	107,535	161,818	101,287	129,948	42,886	23,265
Bandwidth (L| R)	27,456 | 72,129	39,095 | 70,473	56,177 | 78,239	50,161 | 95,126	74,980 | 114,823	20,000 | 20,000	10,000 | 10,000
Panel B: Single creditor							
RD Estimate	28,647***	28,640***	30,667***	27,006***	24,919***	36,310***	37,757***
	(1,232)	(1,331)	(1,388)	(1,405)	(1,273)	(2,391)	(3,262)
Observations	59,809	100,090	153,473	80,517	110,282	36,867	19,738
Bandwidth (L| R)	24,439 | 65,369	47,041 | 87,292	67,210 | 106,141	34,706 | 69,603	64,504 | 105,617	20,000 | 20,000	10,000 | 10,000
Panel C: Multiple creditor							
RD Estimate	21,220***	20,302***	23,494***	18,316***	19,534***	27,124***	24,843***
	(2,117)	(2,382)	(2,536)	(2,255)	(2,314)	(5,426)	(8,241)
Observations	26,709	47,015	61,646	44,146	48,218	14,499	7,824
Bandwidth (L| R)	38,405 | 68,805	87,158 | 103,780	72,764 | 101,051	63,375 | 93,402	99,016 | 109,126	20,000 | 20,000	10,000 | 10,000
Kernel	Triangular	Triangular	Triangular	Uniform	Epanechnikov	Triangular	Triangular
Local Poly (p)	1	2	3	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports robustness checks for the regression discontinuity (RD) estimates of the impact of program participation on overall (Non-TDR and TDR) agricultural loan repayment amounts at the borrower level, estimated on the subsample of borrowers who made payments exceeding 1,000 baht between April 2024 and July 2025. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment amount is measured as the reduction in outstanding loan balance over the same period. Panels A–C present results for overall borrowers, single-creditor borrowers, and multiple-creditor borrowers, respectively. Across columns, specifications vary by the order of the local polynomial, kernel function, and bandwidth choice. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications include borrower-level control variables. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Robustness check for non-TDR agricultural loan repayment amount, paid subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Overall (Single and multiple creditors)							
RD Estimate	25,469***	27,801***	28,771***	25,582***	21,388***	32,790***	33,876***
	(1,159)	(1,300)	(1,345)	(1,294)	(1,222)	(2,421)	(3,515)
Observations	66,493	107,535	161,818	101,287	129,948	42,886	23,265
Bandwidth (L| R)	27,456 | 72,129	39,095 | 70,473	56,177 | 78,239	50,161 | 95,126	74,980 | 114,823	20,000 | 20,000	10,000 | 10,000
Panel B: Single creditor							
RD Estimate	26,460***	28,517***	30,021***	25,914***	22,393***	34,416***	35,746***
	(1,299)	(1,398)	(1,481)	(1,490)	(1,314)	(2,563)	(3,542)
Observations	50,569	87,879	128,032	68,761	101,297	31,178	16,854
Bandwidth (L| R)	26,260 | 69,133	42,323 | 76,509	65,683 | 98,022	35,629 | 68,578	71,156 | 110,801	20,000 | 20,000	10,000 | 10,000
Panel C: Multiple creditor							
RD Estimate	17,944***	17,949***	21,349***	17,076***	17,045***	24,270***	23,083**
	(2,237)	(2,626)	(2,963)	(2,657)	(2,525)	(6,397)	(10,243)
Observations	24,768	38,995	46,136	33,566	44,723	11,708	6,411
Bandwidth (L| R)	39,406 | 68,829	86,597 | 102,682	65,856 | 85,329	71,742 | 104,490	102,012 | 111,697	20,000 | 20,000	10,000 | 10,000
Kernel	Triangular	Triangular	Triangular	Uniform	Epanechnikov	Triangular	Triangular
Local Poly (p)	1	2	3	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports robustness checks for the regression discontinuity (RD) estimates of the impact of program participation on non-TDR agricultural loan repayment amounts at the borrower level, estimated on the subsample of borrowers who made payments exceeding 1,000 baht between April 2024 and July 2025. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment amount is measured as the reduction in outstanding loan balance over the same period. Panels A–C present results for overall borrowers, single-creditor borrowers, and multiple-creditor borrowers, respectively. Across columns, specifications vary by the order of the local polynomial, kernel function, and bandwidth choice. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications include borrower-level control variables. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Robustness check for TDR agricultural loan repayment amount, paid subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Overall							
RD Estimate	8,763***	8,696***	8,980***	8,808***	8,886***	9,930**	9,352*
	(1,689)	(1,843)	(2,278)	(1,804)	(1,874)	(3,869)	(4,881)
Observations	24,451	41,354	44,839	36,643	36,990	11,627	5,952
Bandwidth (L| R)	52,441 | 73,462	97,923 | 120,788	86,971 | 103,864	82,568 | 113,674	93,423 | 119,404	20,000 | 20,000	10,000 | 10,000
Panel B Single creditor							
RD Estimate	10,423***	10,267***	10,887***	9,397***	10,341***	12,351**	12,229**
	(2,133)	(2,286)	(2,807)	(2,112)	(2,264)	(4,824)	(5,985)
Observations	17,377	28,831	33,481	28,013	27,723	7,777	3,945
Bandwidth (L| R)	50,575 | 71,078	96,723 | 119,282	90,539 | 105,722	87,501 | 117,916	92,555 | 117,019	20,000 | 20,000	10,000 | 10,000
Kernel	Triangular	Triangular	Triangular	Uniform	Epanechnikov	Triangular	Triangular
Local Poly (p)	1	2	3	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports robustness checks for the regression discontinuity (RD) estimates of the impact of program participation on TDR agricultural loan repayment amounts at the borrower level, estimated on the subsample of borrowers who made payments exceeding 1,000 baht between April 2024 and July 2025. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment amount is measured as the reduction in outstanding loan balance over the same period. Panels A–B present results for overall borrowers and single-creditor borrowers, respectively. Across columns, specifications vary by the order of the local polynomial, kernel function, and bandwidth choice. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications include borrower-level control variables. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Robustness check for non-relief loan repayment amount

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Auto loan							
RD Estimate	10,740**	10,931**	11,440*	12,275**	10,675*	18,968*	18,806
	(5,096)	(5,513)	(6,091)	(5,966)	(5,691)	(9,757)	(13,996)
Observations	39,179	60,068	89,679	43,354	55,357	18,247	10,591
Bandwidth (L| R)	56,902 | 84,618	79,603 | 97,258	112,872 | 134,848	54,216 | 74,799	71,071 | 89,895	20,000 | 20,000	10,000 | 10,000
Panel B: Machinery loan							
RD Estimate	2,574*	3,684**	3,949**	3,746**	3,116**	1,683	2,987
	(1,420)	(1,480)	(1,649)	(1,505)	(1,398)	(3,192)	(4,676)
Observations	20,384	29,153	39,616	26,853	29,951	9,917	5,877
Bandwidth (L| R)	55,809 | 85,615	59,099 | 70,677	85,680 | 102,664	52,862 | 75,641	56,205 | 69,512	20,000 | 20,000	10,000 | 10,000
Kernel	Triangular	Triangular	Triangular	Uniform	Epanechnikov	Triangular	Triangular
Local Poly (p)	1	2	3	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports robustness checks for the regression discontinuity (RD) estimates of the spillover effects of program participation on non-agricultural loan repayment amounts at the borrower level. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment amount is measured as the reduction in outstanding loan balance between April 2024 and July 2025. Panels A–B present results for auto loans and machinery loans, respectively. Across columns, specifications vary by the order of the local polynomial, kernel function, and bandwidth choice. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications include borrower-level control variables. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Robustness check for non-relief loan repayment probability, unpaid subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Auto loan							
RD Estimate	0.039**	0.043**	0.041**	0.037**	0.039**	0.047	0.005
	(0.017)	(0.019)	(0.020)	(0.018)	(0.018)	(0.038)	(0.054)
Observations	18,561	32,325	37,727	27,450	33,038	8,801	5,292
Bandwidth (L| R)	50,364 | 72,826	91,065 | 106,864	97,057 | 104,035	69,739 | 105,185	93,326 | 113,884	20,000 | 20,000	10,000 | 10,000
Panel B: Machinery loan							
RD Estimate	0.071**	0.075**	0.079*	0.089**	0.077**	0.093	0.090
	(0.029)	(0.035)	(0.043)	(0.036)	(0.036)	(0.101)	(0.152)
Observations	12,637	22,949	19,877	15,547	19,184	4,518	2,800
Bandwidth (L| R)	54,322 | 75,347	104,962 | 122,020	84,590 | 95,647	69,153 | 85,541	99,111 | 118,108	20,000 | 20,000	10,000 | 10,000
Panel C: Personal loan							
RD Estimate	0.025	0.059*	0.060*	0.052	0.056*	0.073	0.050
	(0.022)	(0.034)	(0.035)	(0.032)	(0.033)	(0.066)	(0.093)
Observations	18,968	17,448	27,629	17,086	18,147	7,996	4,853
Bandwidth (L| R)	48,853 | 72,426	49,289 | 67,161	67,129 | 78,444	40,809 | 62,656	47,417 | 66,664	20,000 | 20,000	10,000 | 10,000
Kernel	Triangular	Triangular	Triangular	Uniform	Epanechnikov	Triangular	Triangular
Local Poly (p)	1	2	3	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports robustness checks for the regression discontinuity (RD) estimates of the spillover effects of program participation on non-agricultural loan repayment probability at the borrower level, estimated on the subsample of borrowers who did not make payments exceeding 1,000 baht on agricultural loans between April 2024 and July 2025. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment is defined as an indicator equal to one if the borrower made at least one payment exceeding 1,000 baht on the respective non-agricultural loan over the same period. Panels A–C present results for auto, machinery, and personal loans, respectively. Across columns, specifications vary by the order of the local polynomial, kernel function, and bandwidth choice. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications include borrower-level control variables. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Robustness check for non-relief loan repayment amount, unpaid subsample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Auto loan							
RD Estimate	16,921***	18,213***	20,774***	18,686***	17,233***	26,089**	23,190
	(5,561)	(6,449)	(6,270)	(5,589)	(6,240)	(12,255)	(15,861)
Observations	21,993	32,959	40,181	29,103	37,994	8,801	5,292
Bandwidth (L| R)	62,238 | 87,035	97,167 | 111,783	98,521 | 110,001	71,605 | 91,917	101,161 | 128,683	20,000 | 20,000	10,000 | 10,000
Panel B: Machinery loan							
RD Estimate	3,929	5,376*	6,119**	5,727*	5,289*	5,672	4,054
	(2,407)	(2,942)	(3,052)	(2,972)	(2,997)	(4,838)	(6,397)
Observations	22,422	21,892	31,037	23,192	20,826	7,996	4,853
Bandwidth (L| R)	74,649 | 85,429	65,896 | 71,689	96,893 | 100,921	75,813 | 86,039	60,967 | 67,699	20,000 | 20,000	10,000 | 10,000
Kernel	Triangular	Triangular	Triangular	Uniform	Epanechnikov	Triangular	Triangular
Local Poly (p)	1	2	3	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports robustness checks for the regression discontinuity (RD) estimates of the spillover effects of program participation on non-agricultural loan repayment amounts at the borrower level, estimated on the subsample of borrowers who did not make payments exceeding 1,000 baht on agricultural loans between April 2024 and July 2025. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Repayment amount is measured as the reduction in outstanding loan balance over the same period. Panels A–B present results for auto loans and machinery loans, respectively. Across columns, specifications vary by the order of the local polynomial, kernel function, and bandwidth choice. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications include borrower-level control variables. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Robustness check for agricultural loan credit deterioration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Overall (Non-TDR and TDR)							
RD Estimate	-0.050***	-0.050***	-0.052***	-0.051***	-0.050***	-0.056***	-0.057***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.007)	(0.010)
Observations	259,115	344,471	416,674	246,895	357,726	150,357	84,356
Bandwidth (L| R)	46,052 | 54,878	55,099 | 69,216	65,198 | 82,607	36,157 | 55,127	60,663 | 71,729	20,000 | 20,000	10,000 | 10,000
Panel B: Non-TDR							
RD Estimate	-0.035***	-0.034***	-0.034***	-0.035***	-0.035***	-0.034***	-0.029***
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.007)	(0.009)
Observations	212,355	237,073	326,709	215,046	222,142	121,434	68,457
Bandwidth (L| R)	49,010 | 58,832	46,870 | 63,484	60,854 | 77,797	36,380 | 55,498	38,585 | 56,826	20,000 | 20,000	10,000 | 10,000
Panel C: TDR							
RD Estimate	-0.162***	-0.163***	-0.164***	-0.167***	-0.164***	-0.161***	-0.192***
	(0.010)	(0.011)	(0.013)	(0.011)	(0.011)	(0.022)	(0.034)
Observations	59,969	113,233	158,983	94,844	108,883	37,750	20,530
Bandwidth (L| R)	43,051 | 76,809	85,385 | 119,959	110,199 | 130,958	68,060 | 108,537	82,002 | 118,084	20,000 | 20,000	10,000 | 10,000
Kernel	Triangular	Triangular	Triangular	Uniform	Epanechnikov	Triangular	Triangular
Local Poly (p)	1	2	3	2	2	2	2
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The table reports robustness checks for the regression discontinuity (RD) estimates of the impact of program participation on agricultural loan credit deterioration at the borrower level. The reported estimates correspond to local average treatment effects (LATE) for compliers around the eligibility threshold. Credit deterioration is defined as an indicator equal to one if the borrower's loan classification transitions from performing to non-performing between April 2024 and July 2025. Panels A–C present results for overall (non-TDR and TDR), non-TDR, and TDR agricultural loans, respectively. Across columns, specifications vary by the order of the local polynomial, kernel function, and bandwidth choice. The number of observations reflects the effective sample used in each estimation within the optimal bandwidth on either side of the cutoff, selected using a mean squared error (MSE) criterion. All specifications include borrower-level control variables. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Robustness check for agricultural loan repayment probability with difference-in-differences

	Repayment					
	(1) Overall	(2) Non-TDR	(3) TDR	(4) Overall	(5) Non-TDR	(6) TDR
DiD estimate	−0.256***	−0.232***	−0.228***	−0.225***	−0.204***	−0.188***
	(0.003)	(0.003)	(0.004)	(0.001)	(0.001)	(0.002)
Observations	612,430	459,682	196,350	5,292,550	4,299,576	1,325,398
R^2	0.044	0.030	0.117	0.044	0.039	0.096
Optimal bandwidth	Yes	Yes	Yes	No	No	No

Note: The table reports difference-in-differences (DiD) estimates of the impact of the program on agricultural loan repayment probability at the borrower level. The reported coefficient ("DiD estimate") corresponds to the interaction between an indicator for program participation (equal to one for participating borrowers and zero otherwise) and a post-policy period indicator (equal to one for observations in the post-policy period and zero otherwise). Repayment is defined as an indicator equal to one if the borrower made at least one payment exceeding 1,000 baht during the respective observation period. Columns (1)–(3) restrict the estimation sample to observations within an RD-optimal bandwidth around the assignment threshold, while Columns (4)–(6) use the full sample. Columns are further disaggregated by loan type: overall (non-TDR and TDR), non-TDR, and TDR agricultural loans. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Robustness check for overall agricultural loan repayment amount, paid debtor, with difference-in-differences

	Repayment amount					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Overall						
DiD estimate	12,622***	12,187***	11,952***	3,742***	2,406***	6,682***
	(347)	(444)	(584)	(338)	(330)	(910)
Observations	367,393	213,071	122,060	1,668,022	1,170,357	497,454
R^2	0.005	0.005	0.004	0.005	0.007	0.004
Panel B: Non-TDR						
DiD estimate	10,462***	10,333***	9,884***	1,557***	335	4,388***
	(364)	(465)	(612)	(356.304)	(348.472)	(968.609)
Observations	314,512	184,391	102,181	1,434,252	1,019,575	414,484
R^2	0.003	0.004	0.003	0.007	0.010	0.004
Panel C: TDR						
DiD estimate	7,721***	5,178***	8,446***	2,737***	1,359	4,897**
	(921)	(1,226)	(1,455)	(964)	(949)	(2,258)
Observations	64,970	35,269	24,506	287,877	185,190	102,665
R^2	0.005	0.005	0.006	0.002	0.001	0.002
Optimal bandwidth	Yes	Yes	Yes	No	No	No
Sample	Full	Single creditor	Multiple creditor	Full	Single creditor	Multiple creditor

Note: The table reports difference-in-differences (DiD) estimates of the impact of the program on agricultural loan repayment amounts at the borrower level, estimated on the subsample of paid borrowers. The reported coefficient ("DiD estimate") corresponds to the interaction between an indicator for program participation (equal to one for participating borrowers and zero otherwise) and a post-policy period indicator (equal to one for observations in the post-policy period and zero otherwise). Repayment amount is measured as the reduction in outstanding loan balance during the respective observation period. Panel A presents results for overall agricultural loans, while Panels B and C report results separately for non-TDR and TDR agricultural loans, respectively. Within each panel, Columns (1)–(3) restrict the estimation sample to observations within an RD-optimal bandwidth around the assignment threshold, whereas Columns (4)–(6) use the full sample. Columns further distinguish borrowers by creditor structure: full sample, single-creditor borrowers, and multiple-creditor borrowers. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Robustness check for non-relief loan repayment, unpaid subsample, with difference-in-differences

	(1) Auto loan	(2) Machinery loan	(3) Mortgage loan	(4) Personal loan	(5) Auto loan	(6) Machinery loan	(7) Mortgage loan	(8) Personal loan
Panel A: Repayment								
DiD estimate	0.022***	0.080***	−0.006	0.043***	0.024***	0.098***	−0.010	0.037***
	(0.005)	(0.008)	(0.018)	(0.009)	(0.004)	(0.006)	(0.011)	(0.005)
Observations	77,466	43,338	5,694	42,654	168,068	89,006	15,180	165,340
R^2	0.094	0.278	0.002	0.080	0.097	0.280	0.004	0.075
Optimal bandwidth	Yes	Yes	Yes	Yes	No	No	No	No
Panel B: Repayment amount								
DiD estimate	3,230**	1,829**	−2,380	215	1,663	2,118***	−1,179	−516
	(1,509)	(716)	(4,580)	(640)	(1,079)	(411)	(3,230)	(415)
Observations	82,568	33,842	4,794	76,082	168,068	89,006	15,180	165,340
R^2	0.010	0.026	0.003	0.010	0.011	0.030	0.001	0.010
Optimal bandwidth	Yes	Yes	Yes	Yes	No	No	No	No

Note: The table reports difference-in-differences (DiD) estimates of the impact of the program on non-agricultural loan repayment outcomes at the borrower level, estimated on the subsample of borrowers who did not make payments exceeding 1,000 baht on agricultural loans between April 2024 and July 2025. The reported coefficient ("DiD estimate") corresponds to the interaction between an indicator for program participation (equal to one for participating borrowers and zero otherwise) and a post-policy period indicator (equal to one for observations in the post-policy period and zero otherwise). Panel A reports results for repayment probability, while Panel B reports results for repayment amounts. Repayment probability is defined as an indicator equal to one if the borrower made at least one payment exceeding 1,000 baht on the respective non-agricultural loan during the observation period, while repayment amount is measured as the reduction in outstanding loan balance over the same period. Columns (1)–(4) restrict the estimation sample to observations within an RD-optimal bandwidth around the assignment threshold, whereas Columns (5)–(8) use the full sample. Results are reported separately by loan type: auto, machinery, mortgage, and personal loans. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13: Robustness check for agricultural loan credit deterioration with difference-in-differences

	(1) Overall	(2) Non-TDR	(3) TDR	(4) Overall	(5) Non-TDR	(6) TDR
DiD estimate	−0.066***	−0.053***	−0.173***	−0.065***	−0.052***	−0.158***
	(0.001)	(0.001)	(0.001)	(0.0002)	(0.0002)	(0.001)
Observations	894,358	611,494	370,510	5,292,550	4,299,576	1,325,398
R^2	0.046	0.036	0.124	0.047	0.038	0.107
Optimal bandwidth	Yes	Yes	Yes	No	No	No

Note: The table reports difference-in-differences (DiD) estimates of the impact of the program on agricultural loan credit deterioration at the borrower level. The reported coefficient ("DiD estimate") corresponds to the interaction between an indicator for program participation (equal to one for participating borrowers and zero otherwise) and a post-policy period indicator (equal to one for observations in the post-policy period and zero otherwise). Credit deterioration is defined as an indicator equal to one if the borrower's loan classification transitions from performing to non-performing during the observation period. Columns (1)–(3) restrict the estimation sample to observations within an RD-optimal bandwidth around the assignment threshold, while Columns (4)–(6) use the full sample. Columns are further disaggregated by loan type: overall (non-TDR and TDR), non-TDR, and TDR agricultural loans. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.