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Agricultural Credit and Conflict

Evidence from Myanmar

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ABSTRACT

Access to timely credit is widely viewed as an important determinant of improved agricultural investment and productivity. However, little is known about how agricultural credit markets function during prolonged conflict. This paper examines how conflict shapes both the receipt of agricultural credit and the provision of informal credit by agrifood businesses in Myanmar, where conflict has been widespread in after 2021. Using rare data from both farmers and firms, we document a substantial decline in formal credit after conflict, but stable receipt of informal credit. In conflict-affected areas, formal credit receipt declined sharply – most notably from government-supported schemes and from microfinance institutions – while informal credit was more resilient – especially from friends and family and agribusinesses. Using direct elicitation methods of credit constraint classifications, we show that farmers in high conflict areas are more likely to voluntarily withdraw from credit markets and shift to self-financing. On the supply side, conflict has insignificant relationships to farm-credit provision by input retailers and rice mills. Taken together, our findings highlight the informal segment of agricultural credit markets as an underappreciated source of resilience in conflict-affected settings.

1. INTRODUCTION

Agricultural credit can catalyze agricultural sector growth in transforming agrifood systems (AFS) by alleviating farm liquidity constraints and unlocking investment in productive inputs, ultimately increasing agricultural production and GDP in developing countries (e.g., Seven and Tumen, 2020). Yet, agricultural credit markets are often plagued by market failures, including asymmetric information and moral hazard in the relationship between creditors and farmers (Stiglitz and Weiss, 1981; Besley, 1994), leading to credit rationing and market segmentation between formal (e.g., banks, microfinance institutions (MFIs) and state-sponsored credit programs) and informal providers (see for example, Besley, 1995).

The formal credit sector has received more research attention, partly because data are easier to collect and more readily available, enabling more rigorous analyses. Rural bank expansion can reduce poverty (Burgess & Pande, 2005), while MFI expansion increased short-term credit, consumption, agricultural investment, and income growth in Thailand (Kaboski & Townsend, 2012). Yet, other evidence shows mixed or limited impacts of formal credit market participation (Morduch, 1999; Banerjee et al., 2015).

The informal credit sector has received less direct research attention, despite its importance and prevalence in rural areas, especially those with weak institutions. Existing research highlights the prevalence of informal credit from agribusinesses – e.g., traders and agro-input retailers – to farmers in diverse settings, and highlights the importance of relationships and trust (Fafchamps & Minten, 1999; Goeb et al., 2026a; Bell, 1988). Studies also show that formal and informal credit often coexist and interact rather than compete as substitutes (Bell, 1990). Barslund and Tarp (2008) estimate the determinants of both formal and informal credit demand in Vietnam, and highlight different drivers of demand from the two sources as well as large regional differences. Khoi et al. (2013) show significant interlinkages between both formal and informal credit.

However, most of this research is conducted in relatively stable contexts, and there is very little evidence of how formal and informal credit markets perform when conflict disrupts institutions, raises production risk, and weakens state capacity. With conflict increasing in many developing countries with transitioning agricultural economies (OECD, 2025), this is an important gap in the literature. The limited available evidence on conflict and farm credit focuses on the formal sector, showing that conflict-driven uncertainty is a significant demand side constraint (de Roux & Martinez, 2021). Informal credit may be particularly important in conflict-affected areas as repeated personal relationships may reduce problems of asymmetric information and moral hazard that hinder formal credit provision.

This paper studies rural agricultural credit markets – both formal and informal – in conflict-affected Myanmar where a military coup in 2021 induced widespread, prolonged conflict and disruptions to agrifood systems (Goeb et al., 2025), which employ almost two-thirds of the labor force (Diao et al., 2024). We make three main contributions. First, we document dynamics in farm-level credit receipt during prolonged conflict, disaggregating formal and informal sources. Second, we estimate relationships between local – township-level – conflict and farm credit markets, exploring farm credit receipt from different formal and informal sources, as well as credit constraints classified using direct elicitation methods (Boucher et al., 2009). Third, we analyze the supply side of informal agricultural credit during conflict using rare firm-level data from agribusinesses (input retailers and millers). We document changes in both credit lent out to farmers and credit taken in by agribusiness and estimate their relationships to conflict.

Our results reveal three main findings. First, conflict has opposing relationships with credit receipt from formal versus informal sources. Formal credit receipt declined sharply in conflict-affected areas

– largely driven by reductions in government-supported financing in conflict areas and to a lesser degree, reduced MFI lending – while receipt of informal credit was more resilient and increased under conflict – driven by loans from friends and family and credit from agribusinesses. Second, credit constraint classifications show that farmers in high conflict areas are more likely to exit credit markets voluntarily, particularly larger farmers that shift to self-financing. Third, our firm-level data show that spatial variations in conflict do not have significant relationships to farm-credit provision by agribusinesses, further underlining the resilience in informal lending under conflict. Together, these findings highlight significant limitations of formal credit in conflict settings, while documenting an underappreciated resilience of informal credit in these contexts.

This paper proceeds with contextual information on Myanmar's agricultural credit markets and conflict disruptions in Section 2, followed in Section 3 by a description of our farm- and firm-level data sources. Section 4 explains econometric methods, including the credit constraint classifications. We present our results in Section 5, starting with farm-level credit receipt and continuing with firm-level estimates. Section 6 concludes with a discussion of the results, study limitations, and the implications for policies and programs targeting credit markets in conflict-affected areas.

2. BACKGROUND

2.1. Agricultural credit in Myanmar

Myanmar's agricultural credit system is remarkably diverse, with multiple formal and informal credit providers (Turnell, 2009; Basu et al. 2020). We use established definitions of formal credit (i.e., state-supported providers and regulated institutions including microfinance institutions (MFIs) and commercial banks, often with formal contracts) and informal credit (i.e., lent by people and businesses outside of the regulated financial system and without written contracts, including agribusinesses, social networks, community funds, and private money lenders) (Besley, 1995).

The formal segment of agricultural credit provision in Myanmar has long been dominated by state-supported lending. The Myanmar Agricultural Development Bank (MADB) is historically the largest single source of farm credit with a network of 226 branches in 208 townships throughout the country (Aung et al., 2019). MADB extends seasonal loans for production of specific crops, with paddy being the highest priority and receiving most of the disbursements. Loans are given as a fixed amount per acre, and the seasonal interest rate since 2020 has been 5%. Since the military coup in 2021 MADB has been unable to operate many of their branches, especially in conflict areas. For example, all 14 branches in Rakhine have closed and only 20 of 32 branches in Sagaing were operating as of June 2026. Official documentation shows variation in MADB monsoon season lending amounts after the coup as follows: 2021, 498 billion MMK; 2022, 287 billion MMK; 2023, 440 billion MMK; 2024, 543 billion MMK; 2025, 495 billion MMK, though we note this has been a period of exchange rate depreciation and rising input prices making the real loan values lower in recent years. Other government-supported agricultural support mechanisms are much smaller than MADB disbursements, but two are worth mentioning. The first is a special assistance program that was made available to farmers starting in the 2023 monsoon season. The second are long-running loans provided to groups of farmers through the Department of Cooperatives.

The other historically important formal lenders are microfinance institutions (MFIs). Microfinance lending expanded rapidly in Myanmar in the decade to 2020 to around 6 million borrowers (Htay et al., 2024). The share of agricultural production loans in MFI portfolios has varied over time and has increased since 2020 as farm loans have been relatively more resilient to various shocks (TIGA, 2023). However, MFI agricultural lending declined sharply in 2023 when the main MFI (Pact Global Microfinance Fund) ceased operations due to increasing constraints under military control of the financial system. MFIs that maintained operations in Myanmar greatly decreased their portfolios, and ultimately the number of MFI loan recipients decreased sharply afterwards (Htay et al., 2024). Direct-to-farmer loans from commercial banks are near zero.

The informal sector of agricultural credit is highly diverse and, unlike the formal sector, not dominated by a single provider and relatively understudied. Agribusinesses – which are composed of diverse firms – extend a large amount of credit to farmers, relying on repeated, relationship-based transactions. Input retailers commonly provide fertilizer and other inputs on credit early in the growing season with repayment typically coming after harvest (Goeb et al., 2026a). Crop traders also commonly provide credit to farmers for inputs (MAPSA, 2024), as do rice millers though they tend to have less direct contact with farmers than input retailers or traders (Goeb et al., 2026b). Beyond agribusinesses, Myanmar's farmers receive credit from family and friends, community-based lending schemes – e.g., 'revolving funds' including Village Savings and Loans Associations (VSLAs) – and private money lenders. These sources vary in their loan terms and availability but share a reliance on local information and connections rather than collateral or formal contracts.

2.2. Conflict and disruptions

Myanmar has a long history of conflict, but from 2010 to 2020 there was relative stability under a quasi-democratic government. That stability was ruptured by a military coup in February 2021. The number of violent events increased nationally by 16-fold to more than 11,000 per year between 2021 and 2024, and the geographic scope of conflict expanded beyond the historically conflict-affected periphery to central Myanmar (Goeb et al., 2025). Figure 1 maps the share of months from 2021 through 2025 with at least one fatal violent event at the township level, highlighting the widespread conflict and the spatial intensity.

Figure 1. Share of months with fatal violent conflict by township, January 2021 – December 2025

Source: ACLED

The post-coup rise in conflict and instability has led to widespread disruptions across Myanmar's agrifood system, including persistent challenges for agribusinesses including in banking, transport blockages and rising fuel costs, telecommunications outages, and foreign exchange controls hindering essential imported agricultural inputs (Goeb et al., 2025). Fertilizer prices rose sharply, especially in high conflict areas (Takeshima et al., 2025). Marketing margins for rice, the staple food and most important crop for farmers, increased due to conflict (Minten et al., 2023). Welfare outcomes also deteriorated quickly as poverty estimates nearly doubled by late 2021 relative to before the coup (Boughton et al., 2023).

3. DATA

3.1. Farm-level data

Our farm-level data come from five rounds of the Myanmar Agricultural Performance Survey (MAPS) covering the monsoon growing seasons in 2020 through 2023, and 2025. MAPS is a nationally representative phone survey of farming households in Myanmar with sample sizes ranging from around 3,800 to 4,600 farmers across survey rounds (Table 1). Although a subset of farmers is interviewed in multiple rounds, the panel sample is limited and we use the data as repeated cross-sections. Throughout the analysis, we apply sampling weights to generate state and region-level representative estimates (Lambrecht et al., 2023). Sample means for selected variables are presented in Appendix Table A.1.

Table 1. Sample sizes by survey respondents and by monsoon season

		Agribusinesses	
	Farmers	Input Retailers	Rice Mills
Monsoon Season			
2020	3,827	235	--
2021	3,841	242	509
2022	4,616	241	438
2023	4,285	186	388
2024	--	170	196
2025	4,176	163	--
Representativeness	State/Region; National	N/A	N/A

Note: Farmer data are from the Myanmar Agricultural Performance Survey (MAPS). Input retailer data are from the Input Retailer Survey. Rice mill data are from the Rice Miller Survey. Samples are observations used in analysis.

In each survey round, MAPS collects farm-level credit use information – whether a household received agricultural credit for the monsoon season, and if so, from what sources – that are the main outcomes for our analysis. We split the credit sources into formal (government-administered, MFIs, and private banks) and informal (family/friends, agribusinesses – input retailers, crop traders, mills, and mechanization services providers – village funds, and private money lenders).

In the survey covering the 2025 monsoon season, MAPS included a detailed module to classify farmers into different credit constraint categories following the direct elicitation method developed by Boucher et al. (2009). Using survey responses, we assign farmers into one of four distinct groups (Appendix 2): (i) price-rationed borrowers, who received the credit they wanted at available costs; (ii) price-rationed non-borrowers, who did not receive credit but did not need it; (iii) quantity rationed, who either received less credit than they desired or did not receive credit at all despite wanting it;

(iv) risk and transaction cost rationed, who chose not to take credit due to perceived risks of repayment or high transaction costs.

We adapt the Boucher et al. (2009) approach in three important ways to better reflect the agricultural credit markets in Myanmar. First, while Boucher et al. (2009) consider only formal credit in their elicitation methods, we expand this to include informal credit sources. This change provides a more complete picture in Myanmar where the informal segment of credit markets is widespread (Goeb et al., 2026a). Excluding informal sources would misclassify many farmers that seek or obtain informal credit. Second, we modified slightly the response options to a few questions to also better reflect the conditions in Myanmar. Third, we combined both risk rationed and transaction cost rationed into a single category because we have few observations of transaction cost rationing. Both risk and transaction cost rationing are conceptually similar and represent not taking credit for non-price reasons. Thus, our elicitation approach is intended to characterize credit constraints in the Myanmar context rather than to enable direct comparisons with other studies.

3.2. Firm-level data

Our firm-level data come from two phone surveys of agribusinesses that play critical roles in Myanmar's agrifood value chains: input retailers and rice mills. While the surveys provide broad coverage of Myanmar's diverse agroecologies and main crop production regions, neither survey is nationally representative, and the analysis should be interpreted as descriptive of the surveyed firms rather than of the broader business populations.

The Input Retailer Survey provides data on agro-input retailers across six monsoon seasons from 2020 through 2025, with annual sample sizes between 163 and 242 retailers (Table 1). The Rice Miller survey provides data on rice mills across four monsoon seasons from 2021 to 2024, with annual sample sizes between 196 and 509 (Table 1). Both surveys collect similar information on business operations and disruptions. Of principal importance to our analysis, each survey round asks the firms two key credit questions: (i) if they provided any credit to farmers during the monsoon season, and (ii) if they took in any credit or loans for their business operations.[1]

3.3. Conflict data

To measure conflict we rely on publicly available data from the Armed Conflict and Location Event Data project (ACLED) which provides detailed information on locations, dates, and types of events (Raleigh et al., 2010). Following Steinhubel and Minten (2023), we construct a township-level Conflict Severity Index (CSI) using ACLED data that classifies townships by relative conflict severity into one of five levels – none, limited, moderate, high, or very high – based on the number of violent events and fatalities in a defined exposure window. We calculate CSI separately within each survey year, capturing within-year variations in township-level conflict.

Farmer input purchases – and therefore credit demand – are concentrated before and just after planting, which follows the onset of monsoon rains. Thus, we define our timing window for conflict events as the 60 days before and 30 days after expected planting date, which is defined at township-level using the modal planting month reported by farmers.

We test the robustness of our results to alternative conflict measures including: (i) the full CSI categorical variable, (ii) a binary indicator of any conflict (CSI>=1), (iii) a binary variable of high conflict (CSI>=3), and (iv) the total number of conflict-related fatalities during the exposure window,

[1] Sample means for selected variables are presented in Appendix Tables A13 and A14.

transformed using the inverse hyperbolic sine which approximates a logarithmic transformation but allows for zero values to be included.

4. METHODS

4.1. Farm-level credit receipt and conflict

We assess the associations between localized conflict and farm-level credit receipt in Myanmar using the following linear probability model estimated by ordinary least squares:

$$Y_{ijt} = Conflict'_{jt}\boldsymbol{\alpha} + X'_{ijt}\boldsymbol{\beta} + \gamma_k + \delta_t + \varepsilon_{ijt} \qquad (1)$$

where Y_{ijt} is the dependent variable for household i in township j at time t. We estimate (1) separately for an overall indicator of any farm-credit receipt and indicators of receipt from different sources including the MADB, an MFI, a private money lender, a village fund, family or friends, and agribusinesses (input retailers, mills, or crop traders). X'_{ijt} is a vector of covariates that control for household factors that might also affect farm-level credit use, including farm size (log of acres cultivated), an asset index constructed as the first principal component from seven indicator variables for ownership of productive assets, indicator variables for key crops grown (rice, maize, pulses and oilseeds, tree crops, and horticultural crops), farm decision-maker demographics (education, age, and gender), and measures of remoteness defined as travel times to the nearest input retailer and to the township city center.[2] γ_k is a state/region fixed effect and δ_t is a year fixed effect. These controls better isolate the relationships between conflict and credit use, where $Conflict_{jt}$ is our conflict variable and $\boldsymbol{\alpha}$ is our main coefficient vector of interest. Finally, ε_{ijt} is the error term clustered within townships to match the level defining our conflict variable.

As discussed above in Section 3.3, $Conflict_{jt}$ is a township-level categorical variable representing relative local conflict intensity during the 60 days before and 30 days after expected planting date. By using the township-level expected planting month rather than each household's actual planting month we reduce concerns of endogeneity from conflict affecting actual planting dates. However, conflict intensity at the township level may be endogenous with farm credit market conditions through two possible pathways. First, the relationship may be bi-directional, as has been shown between conflict and food security (Shemyakina, 2022). Second, unobserved township characteristics may jointly determine both conflict intensity and credit markets. Thus, we interpret our estimates as conditional associations, which still have important implications targeting agricultural credit interventions regardless of the causal pathway.

With indicator variables for state/region as well as year, we are estimating within state/region and within year variations in conflict and their relationships with credit use. The state/region variables themselves account for a lot of the overall variation in conflict throughout the country. For example, Yangon, Naypyitaw, and Ayeyarwady are military strongholds and show limited conflict throughout the study period. Yet importantly, there is still meaningful variation within townships in the same state/region (Appendix Table A.2).

As an extension of equation (1), we examine whether the relationship between conflict and credit receipt varies by farm size. Smaller and larger farms may differ in their access to credit under conflict conditions. The variation may come from several channels including differences in collateral and relationships with lenders. Understanding this heterogeneity has important welfare implications, as smaller farms may face tighter budget constraints and, without credit, may be less able to purchase inputs for production. To test this, we use the following model

[2] Appendix Table A.1 shows the full list of regression variable means by monsoon season year.

$$Y_{ijt} = Conflict'_{jt}\boldsymbol{\alpha} + \left[Conflict_{jt}\ x\ Size_{it}\right]'\boldsymbol{\mu} + X'_{ijt}\boldsymbol{\beta} + \gamma_k + \delta_t + \varepsilon_{ijt} \qquad (2)$$

where all variables are as defined above but with the addition of interactions between the conflict variable and $Size_{it}$ which is a vector of indicator variables for farm size terciles. $\boldsymbol{\mu}$ is then the coefficient vector of interest showing differences in conflict relationships by farm size.

4.2. Farm credit constraint classification and conflict

Using our adaptation of the credit constraint direct elicitation methodology developed by Boucher et al. (2009) applied to the 2025 monsoon season data, as discussed above in section 3.1, we categorize farmers as price-rationed borrowers, price-rationed non-borrowers, quantity rationed, or risk and transaction cost rationed. These classifications provide richer detail on farmer credit constraints than our simple borrower/non-borrower distinctions.

To go beyond the descriptive classifications, we assess their associations with localized conflict using the following linear expression of a multinomial logit (MNL) model estimated by maximum likelihood:

$$CredClass_{ijl} = \alpha Conflict_j + X'_{ijl}\boldsymbol{\beta} + \gamma_l + \varepsilon_{ijl} \qquad (3)$$

where $CredClass_{ijl}$ is the credit classification for farmer i in township j and agro-ecological zone l. X'_{ijl} is the same set of covariate controls used in equation (1). γ_l is a set of indicators for agro-ecological zones, replacing the state/region variables used in equation (1) to reduce the risk of incidental parameters bias and ensure sufficient observations within each group.[3] $Conflict_j$ is a high conflict indicator variable defined as equal to one if CSI takes values of three or four, and zero otherwise. Again standard errors are clustered at the township level. We report average partial effects (APEs) computed from the coefficients for easier interpretation.

To assess heterogeneity in conflict relationships across farm size, we calculate APEs separately for each farm size tercile with coefficients from (3). Note that we do not include interaction terms directly in the MNL due to challenges with interaction term effects in non-linear models (Ai and Norton, 2003). Thus, computing APEs at different values of farm size tercile provides a more reliable characterization of conflict relationships.

4.3. Conflict and agribusiness credit provision and receipt

The farm-level analysis estimates relationships of conflict to farm credit use and credit constraint classifications. We complement this with analysis of the supply side of informal credit markets, examining if conflict has strong associations to credit provision and receipt among agribusinesses. Using our firm-level data from input retailers and rice mills, we use a regression framework analogous to equation (1) adapted to business-level data. We assess the relationships between conflict and firm-level credit provision and receipt using the following linear probability model estimated by ordinary least squares separately for mills and input retailers data:

$$W_{fjt} = Conflict'_{jt}\boldsymbol{\alpha} + Z'_{fjt}\boldsymbol{\beta} + \gamma_l + \delta_t + \varepsilon_{fjt} \qquad (4)$$

where W_{fjt} is the outcome variable for firm f in township j at time t. We estimate (4) separately for indicators for the firm (i) providing credit to farmers and (ii) taking in credit or loans for their business.

Z'_{fjt} is a vector of firm-level covariates, including manager characteristics (education, age, and gender), an urban indicator variable for businesses in urban areas, years of mill experience, and a proxy for business size defined as the inverse hyperbolic sine of the number of permanent

[3] Myanmar's state and regions are grouped into four distinct agro-ecological zones: (i) Hills and mountains – Chin, Kachin, Shan, Kayah, and Kayin; (ii) Coastal – Rakhine, Mon, and Tanintharyi; (iii) Central Dry Zone – Magway, Mandalay, Naypyitaw, and Sagaing; and (iv) Delta – Ayeyarwady, Bago, and Yangon.

employees. γ_l is an agro-ecological zone fixed effect and δ_t is a year fixed effect. $Conflict'_{jt}$ is again the conflict severity index indicators vector and $\boldsymbol{\alpha}$ is our main coefficient vector of interest. Finally, ε_{fjt} is the error term clustered within townships to match the level defining our conflict variable.

5. RESULTS

We begin our analysis by examining credit outcomes at the farm level, first with descriptive trends over time (Section 5.1) then with regression results showing the associations between conflict and credit (Section 5.2). We proceed after with analyses of agribusiness credit provision and receipt, again leading with descriptive trends (Section 5.3) and proceeding with associations between conflict and credit outcomes (Section 5.4).

5.1. Farm-level agricultural credit receipt

Overall agricultural credit receipt declined sharply after the coup, falling from 60% of farmers in the 2020 monsoon season (the last before the military takeover) to 41% in the 2025 monsoon season (Table 2). This decline was driven largely by contractions in formal credit. Government-provided credit receipt (predominantly MADB loans) fell by almost half from 38% of farmers in 2020 to 20% in 2025, while MFI loan receipt fell from 9% in 2020 to just 2% in 2025. Private bank loans were negligible over the period, reaching 1% or less of farmers in each year.

In contrast, credit receipt from informal sources held relatively steady, declining from 24% in 2020 to a low of 20% in 2023 before rebounding to 25% in 2025. The informal credit sector is not dominated by a single source: credit from family/friends, agribusinesses, village funds, and money lenders reached between 6 and 8% of farmers in 2020 and 2021. Credit from village funds and money lenders fell to just 4% and 3% of farmers by 2025, respectively. Credit from family and friends still reached 8% of farmers, while agribusiness credit receipt increased to 12%.

Table 2. Percentage of farmers receiving farm credit by source and by monsoon season

	2020	2021	2022	2023	2025
Any Source	60	47	44	46	41
Formal Sources					
Any Formal Source	44	30	27	30	21
Government	38	24	22	27	20
MFI	9	7	6	3	2
Private Bank	1	1	0	1	0
Informal Sources					
Any Informal Source	24	22	22	20	25
Family/Friend	8	8	8	7	8
Agribusiness	6	6	6	7	12
Village Fund	7	6	4	3	4
Money Lender	6	6	6	4	3

Source: Data from Myanmar Agricultural Performance Survey (MAPS) 2020-23 and 2025 survey rounds. No data available for 2024.

5.2. Conflict and farm credit receipt

Our regression results show that farmers in high-conflict areas were substantially less likely to receive farm credit from any source (Table 3, with full results in Appendix Table A.3). Townships with high conflict (CSI values of 3 or 4) were more than 11 percentage points (pp) less likely to receive credit than farmers in townships with near zero conflict (column 1). The negative relationship between conflict and credit receipt was driven by decreases in formal credit. The coefficients on all CSI conflict values are negative and increasing in magnitude with higher conflict: the highest conflict townships were 16 pp less likely to receive formal credit, and CSI values 2, 3, and 4 are each significantly different from the near-zero base category.

Table 3. Conflict severity and farm credit receipt by source

	Any Source	Formal Sources			Informal Sources		
		Any Formal	Gov't	MFI	Any Informal	Family/ Friend	Agribusi-ness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Conflict Severity Index							
Low (CSI = 1)	0.013	-0.004	-0.006	-0.011	0.020	0.008	0.024 **
	(0.018)	(0.017)	(0.017)	(0.008)	(0.015)	(0.007)	(0.010)
Medium (CSI = 2)	-0.031	-0.054 **	-0.057 ***	-0.001	0.025 *	0.018 **	0.022 **
	(0.019)	(0.021)	(0.020)	(0.009)	(0.015)	(0.009)	(0.011)
High (CSI = 3)	-0.117 ***	-0.131 ***	-0.123 ***	-0.016 **	0.008	0.009	0.008
	(0.027)	(0.023)	(0.022)	(0.008)	(0.022)	(0.014)	(0.010)
Highest (CSI = 4)	-0.111 ***	-0.157 ***	-0.150 ***	-0.016 **	0.040 **	0.049 ***	0.018
	(0.023)	(0.019)	(0.019)	(0.008)	(0.017)	(0.013)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Region Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,745	20,745	20,745	20,745	20,745	20,745	20,745
R2	0.095	0.133	0.166	0.036	0.047	0.019	0.043

Notes: Estimates from linear probability models (LPM). Dependent variables are binary indicators equal to one if the household received credit from the indicated source in the survey year. Conflict severity index is defined at the township level and discussed in Section 3.3, and the control variables discussed in Section 4.1. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Within the formal sector, declines in government-supported credit in conflict areas were most pronounced with negative and increasing in magnitude with conflict to -15 pp for the highest conflict category. MFI agricultural loan receipt also shows statistically significant negative relationships to high levels of conflict, but with smaller coefficients and starting from a lower share of farmers receiving.

In contrast to the formal sector, receipt from informal credit sources shows some positive relationships with conflict. Farmers in the highest conflict townships were 4 pp more likely to receive informal credit relative to the lowest conflict townships. This relationship in high conflict areas is driven by lending from family and friends, while receipt from agribusinesses shows significant positive relationships with low levels of conflict (CSIs 1 and 2).

We conduct several extensions and robustness checks on these findings. First, we use three alternative definitions of the conflict variable (each using the same time window around the expected growing calendar as our main results) including indicators for any conflict (CSI>0) and high conflict (CSI>=3), and the number of fatalities in the township (Appendix Table A.4). The results are consistent with the patterns shown in Table 3, giving us confidence that the estimates are not driven by the CSI variable construction. Second, we show that estimates of average partial effects from a probit model are similar to our LPM estimates (Appendix Table A.5), implying that our results are not driven by the choice of statistical model. Third, we restrict the estimation to rice farmers only, who are disproportionately targeted for government-supported credit schemes (Appendix Table A.6). Again, the results are consistent with Table 3, and the coefficients for high conflict in estimations on formal and government sources are of larger magnitude than the full sample. Fourth, we test the generalizability of our results by excluding the farmers from Sagaing Region (Appendix Table A.7). Sagaing is both a productive agricultural area and highly contested with many townships experiencing sustained, intense conflict. The patterns of estimates are similar to those in the full sample, so our estimates are not driven by this important region alone.

Finally, we test for differences in conflict timing by splitting our defined conflict window into two separate time periods – pre-planting (60 days before expected plant date) and post-planting (30 days after) – and calculating our conflict variables within those two windows (Appendix Table A.8). Estimates of formal credit conflict receipt are of similar magnitude in both the pre- and post-planting windows. For informal sources, conflict pre-planting has larger relationships than post-planting conflict, particularly for family and friends. Agribusiness credit shows positive and similar magnitude, but insignificant, coefficients in pre- and post-planting windows.

We next examine whether the above conflict relationships vary by farm size, as smaller farmers may have less land, fewer assets, and weaker lender relationships which may particularly affect access to formal credit (Table 4). Larger farms (terciles 2 and 3) are more likely to receive agricultural credit, particularly from government sources, while the relationships between terciles and informal credit receipt are insignificant. Focusing on conflict estimates, the interactions between high conflict and terciles show that the negative associations increase in magnitude with farm size, particularly for government supported credit. For informal sources, the conflict coefficient for the smallest farms (tercile 1) is positive and significant, particularly for credit from family/friends. Interestingly, the interaction terms show negative and significant coefficients for family and friend credit, implying that the informal lending in conflict areas is concentrated among smaller farms which may be less able to self-finance their inputs. Relationships between high conflict and receipt of credit from agribusinesses do not significantly vary across farm size terciles, implying that the observed increase in conflict areas in Table 3 is not directed differently to farmers of different sizes.

Table 4. Heterogeneity effects of farm size in conflict severity and farm credit receipt by source

	Any Source	Formal Sources			Informal Sources		
		Any Formal	Gov't	MFI	Any Informal	Family/ Friend	Agribusi-ness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Conflict Indicator (CSI >= 3)	-0.053 **	-0.085 ***	-0.072 ***	-0.012	0.036 **	0.047 ***	0.005
	(0.024)	(0.018)	(0.017)	(0.008)	(0.018)	(0.015)	(0.009)
Farm Size							
Medium (Tercile 2)	0.048 ***	0.057 ***	0.068 ***	-0.001	0.002	-0.012	0.004
	(0.017)	(0.016)	(0.014)	(0.007)	(0.013)	(0.009)	(0.008)
Large (Tercile 3)	0.079 ***	0.099 ***	0.105 ***	-0.001	0.006	-0.011	0.008
	(0.021)	(0.019)	(0.018)	(0.010)	(0.017)	(0.011)	(0.011)
Interactions (High Conflict x Farm Size)							
High Conflict x Medium	-0.095 ***	-0.084 ***	-0.090 ***	-0.006	-0.031	-0.038 **	-0.004
	(0.031)	(0.022)	(0.022)	(0.009)	(0.023)	(0.016)	(0.012)
High Conflict x Large	-0.139 ***	-0.113 ***	-0.122 ***	0.003	-0.055 **	-0.048 ***	-0.014
	(0.029)	(0.028)	(0.028)	(0.010)	(0.023)	(0.017)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Region Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,745	20,745	20,745	20,745	20,745	20,745	20,745
R2	0.098	0.135	0.169	0.036	0.047	0.019	0.042

Notes: Estimates from linear probability models (LPM) using MAPS data 2020-23, and 2025. Dependent variables are binary indicators equal to one if the household received credit from the indicated source in the survey year. Conflict severity index is defined at the township level and discussed in Section 3.3 and the control variables in Section 4.1. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

The results above examine the extensive margin of credit receipt but do not distinguish constrained farmers from voluntary non-participation in credit markets. Using credit market classifications available in the 2025 monsoon survey round, Table 5 shows how conflict relates to farmer credit market positions inclusive of informal credit sources. The overall sample shares show that the majority of farmers are price rationed in rural credit markets in Myanmar – either actively borrowing (26%) or choosing not to borrow at available rates (49%). The latter is consistent with a credit market where many farmers are able to self-finance production without credit. Smaller, but meaningful, shares of farmers are quantity rationed (16%) and risk and transaction cost rationed (9%).

Table 5. Conflict and credit market classification – sample shares and average partial effects

	Price-rationed Borrower	Quality Rationed	Risk and Transaction Cost Rationed	Price-rationed Nonborrower
	(1)	(2)	(3)	(4)
Sample Shares by Classification				
Full Sample	0.26	0.16	0.09	0.49
Low Conflict (CSI <3)	0.28	0.17	0.08	0.46
High Conflict (CSI >=3)	0.19	0.13	0.11	0.57
MNL Average Partial Effects of High Conflict Indicator (CSI >=3)				
Full Sample	-0.077 ***	-0.011	0.014	0.074 **
	(0.029)	(0.019)	(0.013)	(0.035)
By Farm Size (Land Tercile)				
Small (Tercile 1)	-0.069 ***	-0.014	0.015	0.068 **
	(0.026)	(0.017)	(0.016)	(0.033)
Medium (Tercile 2)	-0.082 ***	-0.011	0.014	0.079 **
	(0.031)	(0.020)	(0.012)	(0.036)
Large (Tercile 3)	-0.086 **	-0.008	0.013	0.081 **
	(0.034)	(0.022)	(0.011)	(0.037)
Controls	Yes	Yes	Yes	Yes
Agro-ecological Zone Effects	Yes	Yes	Yes	Yes
N	4,176	4,176	4,176	4,176

Notes: Classifications are discussed in Section 3.1. Average partial effects (APEs) are from multinomial logit (MNL) estimation using MAPS 2025. Full sample APEs are computed over all observations. Tercile-specific APEs are computed over the subpopulation in each farm size tercile, defined by log cultivated land area within each survey year. Data are from the 2025 survey round only. Controls are discussed in Section 4.2. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Comparing across high and low conflict, farmers in high conflict townships are less likely to be price-rationed borrowers and quantity rationed, and more likely to be risk or transaction cost rationed and price-rationed nonborrowers. The average partial effects (APEs) from the MNL model confirm these descriptive patterns. High conflict is associated with a 7.7 pp reduction in the probability of being a price-rationed borrower. High conflict is also significantly associated with a 7.4 pp increase in price-rationed nonborrowing, meaning more farmers are unconstrained but not borrowing, consistent with reduced demand. Notably, high conflict is not significantly associated with either quantity rationing or risk and transaction cost rationing, though the coefficients are directionally the same as simple sample shares.

The APEs by farm size terciles reveal subtle, but important heterogeneity. First, larger farms show larger probability declines in being classified as a price-rationed borrower. This aligns with the results in Table 4 showing larger declines in credit receipt for larger farms in conflict areas, mostly from MADB loans. Second, larger farms are more likely to be classified as price-rationed nonborrowers.

5.3. Agribusiness credit provision and receipt

The overall stability of informal credit receipt at the farm-level and the increase in agribusiness credit receipt in conflict-affected areas highlights the importance of informal credit from agribusinesses and raises the question of how agribusiness credit itself has changed during conflict. We now address that question by turning to firm-side analysis with data from input retailers and rice mills.

Table 6 presents the shares of input retailers and rice mills in our sample that provided credit to farmers or took in credit or loans for their businesses for available years of data for monsoon seasons between 2020 and 2025. The samples change across years and the broad patterns should therefore be interpreted with caution.

Table 6. Credit provided to farmers and borrowed in by agribusinesses (%), by year

	Input Retailers		Rice Mills	
Year	Credit out to farmers	Credit taken in	Credit out to farmers	Credit taken in
2020	60	.	.	.
2021	58	.	23	18
2022	49	22	17	10
2023	70	39	18	11
2024	70	37	14	16
2025	70	42	.	.

Note: Share of businesses reporting credit provision to farmers (credit out) and borrowing for business operations (credit taken in) by monsoon season year. Missing values (.) indicate survey round not conducted for that business type.

Input retailers are substantially more active in credit markets than rice mills, with 70% of retailers providing credit to farmers in 2025 compared to just 14% of rice mills in 2024. They are also more likely to take credit in – 42% of retailers in 2025 compared to 16% of mills in 2024. The nature of credit taken in differs substantially across the business types, with input retailers almost exclusively taking inputs on credit from suppliers, and rice mills taking formal credit or loans mostly for purchasing paddy to mill (about ¾ of credit taken) and some taking credit for machinery investments (about ¼).

The share of input retailers providing credit to farmers declined between 2020 and 2022 coinciding with the onset of the conflict, with a low of 49% in 2022, but quickly rebounded to higher than pre-coup levels, flattening to 70% from 2023 to 2025. The share taking in credit increased markedly between 2022 and 2023, but then stabilized at about 40% through 2025.

In contrast, the share of rice mills providing credit to farmers declined from 23% in 2021 to 14% in 2024, while share taking credit in also declined. Thus, input retailer credit markets have proven more resilient than those of rice mills.

5.4. Conflict and agribusiness credit provision and receipt

Regression results reveal no significant relationships between conflict and credit provision or credit receipt among either input retailers or rice mills (Table 7), though smaller sample sizes limit statistical power. These firm-side results are consistent with the farm-level evidence showing no declines in agribusiness credit receipt in conflict-affected areas. These results are robust to alternative conflict definitions (Appendix Table A.10). Descriptive analysis of reported credit-related challenges by year shows no consistent worsening (Appendix Table A.9), and supplemental regressions on reported credit disruptions show no increases in credit challenges in conflict-affected areas (Appendix Table A.11 and Table A.12).

Table 7. Conflict and credit provided to farmers and borrowed in by agribusinesses, by year

	Input Retailers		Rice Mills	
	Credit out to farmers	Credit taken in	Credit out to farmers	Credit taken in
	(1)	(2)	(3)	(4)
Any Conflict Indicator (CSI >=1)				
Any Conflict	0.014	-0.035	-0.003	-0.020
	(0.034)	(0.035)	(0.025)	(0.022)
Controls	Yes	Yes	Yes	Yes
Agro-ecological Zone Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
N	1,237	760	1,531	1,531
R2	0.057	0.055	0.038	0.062

Estimates from linear probability models (LPM). Dependent variables are binary indicators equal to one if the business provided credit to farmers (credit out) or borrowed credit for business operations (credit taken in) in the survey year. The conflict indicator equals one if CSI≥1. Input retailer estimations include data from 2020-25 for credit out and 2022-25 for credit in; rice mill estimations use data from 2021-24 survey rounds. Controls described in Section 4.3. Standard errors clustered at township level in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

6. CONCLUSION

Conflict has fundamentally altered agricultural credit markets in Myanmar. Using data from farm households and agribusinesses across the conflict period, we document large declines in overall farm credit receipt since the 2021 coup, estimate the relationships between conflict severity and credit receipt from formal and informal sources, and examine the supply side of informal credit provided by agribusinesses.

We find that conflict severity is strongly associated with reduced farm credit receipt, driven primarily by the collapse of formal credit markets. Government-provided credit – predominantly through MADB – shows the steepest declines in conflict-affected townships, consistent with state-administered credit programs being concentrated in areas under military control and withdrawn from contested areas. MFI credit receipt also declines in high-conflict areas, though less markedly than MADB credit, likely reflecting operational challenges faced by MFIs in conflict zones. The conflict timing decomposition to pre- and post-planting periods supports this interpretation as formal credit receipt shows similar relationships in both periods, consistent with institutional withdrawal from conflict areas as a whole rather than responses to conflict at specific points in the agricultural calendar.

In contrast, informal credit markets are more resilient to conflict. Credit receipt from family and friends and from agribusinesses holds steady or increases in conflict-affected areas. Conflict in the pre-planting window shows stronger relationships to informal credit receipt – particularly from family and friends – than post-planting conflict, consistent with farmers seeking informal credit from social networks when conflict disrupts the period of highest input demand.

Our credit constraint elicitation results – applied to both formal and informal sources of credit – show that most farmers are price-rationed and therefore not excluded from credit markets. The largest single category is price-rationed non-borrowers who finance their production without credit. Still meaningful shares of farmers are unable to obtain credit or find the risk or transaction costs to be too high. High conflict is associated with a lower probability of being price-rationed borrowers and a higher probability of price-rationed non-borrowing. This pattern suggests that farmers in conflict areas are more likely to voluntarily withdraw from credit markets, with some farmers shifting toward self-financing in the absence of accessible formal credit.

There are important differences in credit market responses to conflict across farm sizes. Larger farms have larger declines in formal credit receipt in conflict areas, predominantly from MADB loans, and are more likely to shift to self-financing as price-rationed nonborrowers. In contrast, smaller farms are more likely to receive informal credit – particularly from family and friends – in conflict-affected townships. Thus, conflict relates to the credit market positions of large and small farmers in distinct ways: larger farmers lose formal credit and turn to their own resources, while smaller farmers remain in credit markets but increasingly rely on informal credit.

Our supply side results confirm the resilience of agribusiness credit markets during conflict: both input retailers and rice mills in conflict-affected townships show no significant declines in credit provision to farmers or in credit uptake for their operations. Input retailers, who have stronger, more direct relationships with farmers, are particularly resilient, while rice mills, who have weaker direct linkages to farms, show a decline in credit provision over time.

While we document important patterns and robust associations between conflict and credit outcomes, there are several limitations to this study. First, our estimates do not establish causal relationships, and unobserved heterogeneity could affect both conflict incidence and credit markets. Second, we focus on the extensive margin – i.e., credit market participation – and do not analyze the intensive margins – i.e., credit amounts – which could, in theory, show different patterns. Third, our results reflect the specific context of the conflict in Myanmar – a military coup in a country with some sustained conflict for most of the past century, and with a large state-supported farm credit scheme – and other conflict settings may have different initial conditions and therefore different patterns and relationships. These limitations should be addressed in future research, which should also explore the relationships between agricultural credit receipt and household-level outcomes in conflict settings.

Taken together, our findings highlight that the informal segment of agricultural credit markets is an underappreciated source of resilience in fragile settings and should receive more attention and support. Governments and donors seeking to sustain or expand agricultural credit access in fragile countries should prioritize channels that can operate in conflict-affected areas where state-administered credit programs may decline. These could include MFI lending and support for agribusiness-led input credit or similar relationship-based schemes.

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APPENDIX 1. TABLES

Table A.1. Regression variable means by monsoon season

	2020	2021	2022	2023	2025
Asset index (PCA)	-0.174	-0.179	-0.140	-0.111	-0.094
Cultivated land (ln(acres))	1.4	1.3	1.2	1.2	1.2
Household members	4.9	4.9	4.5	4.4	3.2
Dependency ratio	0.204	0.206	0.203	0.194	0.049
Female manager	0.425	0.427	0.432	0.204	0.228
Manager age	41.7	41.7	47.4	47.9	48.6
Manager education: secondary	0.127	0.126	0.095	0.101	0.110
Manager education: above secondary	0.077	0.076	0.044	0.040	0.048
Travel time to input retailer (IHS)	0.581	0.581	0.542	0.562	0.532
Travel time to township center (IHS)	0.674	0.674	0.648	0.695	0.690
Crops grown					
Rice	0.658	0.654	0.643	0.666	0.647
Maize	0.101	0.100	0.107	0.094	0.096
Pulses/Oilseeds	0.272	0.272	0.240	0.225	0.253
Tree crops	0.135	0.134	0.147	0.115	0.131
Horticulture	0.275	0.279	0.230	0.200	0.214
States and regions					
Kachin	0.028	0.028	0.028	0.028	0.021
Kayah	0.007	0.007	0.006	0.007	0.004
Kayin	0.025	0.025	0.023	0.024	0.027
Chin	0.013	0.013	0.011	0.011	0.013
Sagaing	0.143	0.142	0.142	0.141	0.143
Tanintharyi	0.021	0.021	0.022	0.021	0.024
Bago	0.112	0.111	0.112	0.111	0.113
Magway	0.095	0.095	0.095	0.097	0.093
Mandalay	0.107	0.106	0.108	0.107	0.113
Mon	0.025	0.025	0.026	0.025	0.039
Rakhine	0.056	0.056	0.058	0.059	0.036
Yangon	0.031	0.031	0.027	0.030	0.030
Shan	0.183	0.185	0.189	0.187	0.190
Ayeyarwady	0.139	0.139	0.136	0.136	0.138
Naypyitaw	0.015	0.015	0.016	0.016	0.015
Conflict Severity Index					
CSI=0	0.914	0.467	0.373	0.427	0.427
CSI=1	0.043	0.206	0.224	0.247	0.191
CSI=2	0.043	0.194	0.133	0.095	0.144
CSI=3	0.000	0.069	0.060	0.061	0.092
CSI=4	0.000	0.064	0.210	0.170	0.145

Table A.2. Share of townships classified as any and high conflict by year, by state and region

	Any Conflict (CSI >=1)					High Conflict (CSI >=3)				
States and Regions	2020	2021	2022	2023	2025	2020	2021	2022	2023	2025
Kachin	0.00	0.85	0.77	0.54	0.71	0.38	0.38	0.15	0.00	0.18
Kayah	0.00	0.67	0.50	0.75	0.75	0.33	0.33	0.25	0.25	0.23
Kayin	0.17	0.50	0.57	0.75	0.83	0.17	0.14	0.38	0.33	0.20
Chin	0.11	0.56	0.86	0.75	0.60	0.22	0.43	0.12	0.20	0.20
Sagaing	0.03	0.67	0.88	0.89	0.68	0.33	0.79	0.60	0.45	0.44
Tanintharyi	0.08	0.58	0.82	0.73	0.90	0.00	0.64	0.55	0.60	0.36
Bago	0.00	0.39	0.43	0.57	0.75	0.04	0.11	0.21	0.36	0.14
Magway	0.00	0.64	0.76	0.54	0.68	0.16	0.32	0.29	0.40	0.23
Mandalay	0.04	0.56	0.81	0.71	0.56	0.04	0.07	0.18	0.24	0.11
Mon	0.00	0.90	0.80	0.70	0.50	0.10	0.40	0.50	0.10	0.22
Rakhine	0.76	0.47	0.41	0.21	0.50	0.00	0.12	0.00	0.10	0.04
Yangon	0.00	0.50	0.39	0.09	0.11	0.00	0.00	0.00	0.00	0.00
Shan	0.18	0.49	0.43	0.45	0.42	0.18	0.08	0.05	0.04	0.07
Ayeyarwady	0.04	0.23	0.18	0.23	0.35	0.00	0.00	0.00	0.00	0.00
Naypyitaw	0.00	0.25	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A.3. Conflict severity and farm credit receipt by source – full regression results

	Any Source	Formal Sources			Informal Sources		
		Any Formal	Gov't	MFI	Any Informal	Family/ Friend	Agribusi-ness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Conflict Severity Index							
CSI = 1	0.013	-0.004	-0.006	-0.011	0.020	0.008	0.024 **
	(0.018)	(0.017)	(0.017)	(0.008)	(0.015)	(0.007)	(0.010)
CSI = 2	-0.031	-0.054 **	-0.057 ***	-0.001	0.025 *	0.018 **	0.022 **
	(0.019)	(0.021)	(0.020)	(0.009)	(0.015)	(0.009)	(0.011)
CSI = 3	-0.117 ***	-0.131 ***	-0.123 ***	-0.016 **	0.008	0.009	0.008
	(0.027)	(0.023)	(0.022)	(0.008)	(0.022)	(0.014)	(0.010)
CSI = 4	-0.111 ***	-0.157 ***	-0.150 ***	-0.016 **	0.040 **	0.049 ***	0.018
	(0.023)	(0.019)	(0.019)	(0.008)	(0.017)	(0.013)	(0.011)
Asset index (PCA)	0.002	0.019 ***	0.021 ***	-0.002	-0.017 ***	-0.015 ***	-0.001
	(0.006)	(0.005)	(0.005)	(0.002)	(0.005)	(0.003)	(0.002)
Cultivated lands (ln(acres)	0.066 ***	0.055 ***	0.059 ***	0.000	0.026 ***	0.009 ***	0.016 ***
	(0.006)	(0.006)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)
Household members	0.002	-0.001	0.000	-0.001	0.004	0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Dependency ratio	0.045	-0.028	-0.070 **	0.034 **	0.081 ***	0.044 **	0.037 **
	(0.033)	(0.030)	(0.027)	(0.015)	(0.028)	(0.018)	(0.016)
Female manager	0.022 *	0.026 **	-0.001	0.033 ***	0.000	-0.001	-0.003
	(0.012)	(0.011)	(0.010)	(0.006)	(0.011)	(0.007)	(0.005)
Manager age	0.000	0.003 ***	0.003 ***	0.000	-0.003 ***	-0.002 ***	-0.001 ***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Manager education: secondary	-0.034 **	0.014	0.023 *	-0.006	-0.049 ***	-0.017 **	0.003
	(0.015)	(0.013)	(0.012)	(0.007)	(0.013)	(0.008)	(0.008)
Manager education: above secondary	-0.068 ***	-0.002	-0.001	-0.002	-0.085 ***	-0.037 ***	-0.002
	(0.018)	(0.015)	(0.015)	(0.008)	(0.014)	(0.008)	(0.008)
Travel time to input re-tailer (IHS)	-0.024 *	-0.017	-0.020	0.007	-0.005	0.000	-0.022 ***
	(0.013)	(0.013)	(0.013)	(0.005)	(0.013)	(0.009)	(0.008)

Travel time to township center (IHS)	0.012	-0.026 *	-0.019	-0.005	0.035 **	0.007	0.022 ***
	(0.015)	(0.014)	(0.014)	(0.006)	(0.015)	(0.010)	(0.008)
State/Region Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop Portfolio Indicators	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,745	20,745	20,745	20,745	20,745	20,745	20,745
R2	0.095	0.133	0.166	0.036	0.047	0.019	0.043

Notes: Estimates from linear probability models (LPM). Dependent variables are binary indicators equal to one if the household received credit from the indicated source in the survey year. Conflict severity index is defined at the township level and discussed in Section 3.3, and the control variables discussed in Section 4.1. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.4. Conflict and farm credit receipt by source – alternative conflict variable definitions

	Any Source	Formal Sources			Informal Sources		
		Any Formal	Gov't	MFI	Any Informal	Family/ Friend	Agribusiness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Estimation A: Any Conflict Indicator (CSI >=1)							
Any Conflict	-0.032 **	-0.054 ***	-0.055 ***	-0.009	0.023 **	0.018 ***	0.021 ***
	(0.015)	(0.015)	(0.014)	(0.006)	(0.012)	(0.007)	(0.007)
Estimation B: High Conflict Indicator (CSI >=3)							
High Conflict	-0.109 ***	-0.132 ***	-0.123 ***	-0.013 **	0.016	0.027 **	0.001
	(0.018)	(0.016)	(0.015)	(0.006)	(0.014)	(0.011)	(0.008)
Estimation C: Conflict Fatalities (IHS)							
Fatalities (IHS)	-0.023 ***	-0.029 ***	-0.028 ***	-0.003 *	0.005	0.006 ***	0.004 *
	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
All Estimations:							
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Region Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,745	20,745	20,745	20,745	20,745	20,745	20,745

Notes: Estimates from linear probability models (LPM). Dependent variables are binary indicators equal to one if the household received credit from the indicated source in the survey year. Conflict severity index is defined at the township level and discussed in section 3.3, and the control variables in Section 4.1. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A. 5. Conflict severity and farm credit receipt by source – Probit average partial effects

	Any Source	Formal Sources: Any Formal	Formal Sources: Gov't	Formal Sources: MFI	Informal Sources: Any Informal	Informal Sources: Family/ Friend	Informal Sources: Agribusi-ness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Conflict Severity Index							
Low (CSI = 1)	0.012	-0.006	-0.009	-0.010	0.019	0.007	0.022 ***
	(0.018)	(0.017)	(0.016)	(0.008)	(0.014)	(0.007)	(0.008)
Medium (CSI = 2)	-0.031	-0.054 **	-0.058 ***	-0.002	0.025 *	0.018 **	0.020 *
	(0.019)	(0.021)	(0.020)	(0.008)	(0.014)	(0.008)	(0.011)
High (CSI = 3)	-0.120 ***	-0.140 ***	-0.131 ***	-0.024 ***	0.009	0.009	0.009
	(0.029)	(0.024)	(0.023)	(0.008)	(0.023)	(0.014)	(0.010)
Highest (CSI = 4)	-0.113 ***	-0.169 ***	-0.159 ***	-0.022 ***	0.042 **	0.055 ***	0.016
	(0.023)	(0.018)	(0.017)	(0.008)	(0.018)	(0.015)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Region Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,745	20,745	20,745	20,745	20,745	20,745	20,745

Notes: Estimates are average partial effects following probit regression using MAPS data 2020-23, and 2025. Dependent variables are binary indicators equal to one if the household received credit from the indicated source in the survey year. Controls include household asset index, cultivated land area (log), household size, dependency ratio, manager age, gender, and education, travel time to input retailer and township center, and crop portfolio indicators. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.6. Conflict severity and farm credit receipt by source – rice farmers only

	Any Source	Formal Sources			Informal Sources		
		Any Formal	Gov't	MFI	Any Informal	Family/ Friend	Agribusi-ness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Conflict Severity Index							
Low (CSI = 1)	0.019	0.013	0.013	-0.008	0.016	0.004	0.018
	(0.024)	(0.024)	(0.023)	(0.008)	(0.017)	(0.009)	(0.012)
Medium (CSI = 2)	-0.020	-0.061 **	-0.061 **	-0.003	0.042 **	0.026 **	0.030 **
	(0.024)	(0.026)	(0.026)	(0.009)	(0.020)	(0.011)	(0.014)
High (CSI = 3)	-0.152 ***	-0.146 ***	-0.143 ***	-0.013 *	-0.016	-0.004	0.005
	(0.031)	(0.027)	(0.027)	(0.007)	(0.024)	(0.014)	(0.014)
Highest (CSI = 4)	-0.120 ***	-0.170 ***	-0.169 ***	-0.008	0.042 *	0.043 ***	0.023 *
	(0.028)	(0.025)	(0.025)	(0.008)	(0.022)	(0.015)	(0.013)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Region Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,857	13,857	13,857	13,857	13,857	13,857	13,857
R2	0.083	0.129	0.146	0.031	0.044	0.022	0.039

Notes: Sample includes rice farmers only. Estimates from linear probability models (LPM) using MAPS data 2020-23, and 2025. Dependent variables are binary indicators equal to one if the household received credit from the indicated source in the survey year. Controls include household asset index, cultivated land area (log), household size, dependency ratio, manager age, gender, and education, travel time to input retailer and township center, and crop portfolio indicators. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.7. Conflict severity and farm credit receipt by source – sample excluding Sagaing

	Any Source	Formal Sources			Informal Sources		
		Any Formal	Gov't	MFI	Any Informal	Family/ Friend	Agribusi-ness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Conflict Severity Index							
Low (CSI = 1)	0.016	-0.001	-0.004	-0.011	0.021	0.008	0.025 **
	(0.018)	(0.018)	(0.017)	(0.008)	(0.016)	(0.008)	(0.010)
Medium (CSI = 2)	-0.032	-0.049 **	-0.053 ***	-0.001	0.022	0.015	0.025 **
	(0.020)	(0.022)	(0.020)	(0.009)	(0.016)	(0.009)	(0.012)
High (CSI = 3)	-0.077 **	-0.092 ***	-0.085 ***	-0.017 *	0.010	0.012	0.004
	(0.031)	(0.026)	(0.024)	(0.010)	(0.028)	(0.017)	(0.011)
Highest (CSI = 4)	-0.101 ***	-0.137 ***	-0.122 ***	-0.023 **	0.026	0.037 **	0.016
	(0.029)	(0.021)	(0.019)	(0.010)	(0.021)	(0.018)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Region Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	17,592	17,592	17,592	17,592	17,592	17,592	17,592
R2	0.087	0.119	0.160	0.035	0.047	0.019	0.042

Notes: Sample excludes Sagaing. Estimates from linear probability models (LPM) using MAPS data 2020-23, and 2025. Dependent variables are binary indicators equal to one if the household received credit from the indicated source in the survey year. Controls include household asset index, cultivated land area (log), household size, dependency ratio, manager age, gender, and education, travel time to input retailer and township center, and crop portfolio indicators. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.8. High conflict and farm credit receipt by source – timing decomposition of conflict, pre- and post-planting

	Any Source	Formal Sources			Informal Sources		
		Any Formal	Gov't	MFI	Any Informal	Family/ Friend	Agribusi-ness
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High Conflict Indicator (CSI>=3) at different timings:							
Pre-planting (60 days)	-0.032 **	-0.053 ***	-0.053 ***	-0.005	0.022 *	0.017 ***	0.010
	(0.015)	(0.014)	(0.013)	(0.006)	(0.012)	(0.006)	(0.009)
Post-planting (30 days)	-0.040 ***	-0.040 ***	-0.041 ***	-0.005	-0.001	0.004	0.008
	(0.015)	(0.014)	(0.014)	(0.006)	(0.012)	(0.007)	(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Region Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20,745	20,745	20,745	20,745	20,745	20,745	20,745
R2	0.093	0.128	0.162	0.036	0.047	0.018	0.042

Notes: High conflict indicators calculated in pre- and post- planting date windows at the township level. Estimates from linear probability models (LPM) using MAPS data 2020-23, and 2025. Dependent variables are binary indicators equal to one if the household received credit from the indicated source in the survey year. Controls include household asset index, cultivated land area (log), household size, dependency ratio, manager age, gender, and education, travel time to input retailer and township center, and crop portfolio indicators. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table A.9. Credit related challenges reported by agribusinesses (%), by year

	Input Retailers				Rice Mills			
Year	Increased farmer demand for credit	Collecting repayment from farmers	Obtaining new credit/loans	Paying off credit/loans	Increased farmer demand for credit	Collecting repayment from farmers	Obtaining new credit/loans	Paying off credit/loans
2020	.	.	.	.	.	.	.	.
2021	.	.	.	.	19	16	12	15
2022	41	51	22	12	11	10	6	7
2023	32	42	30	31	6	6	3	5
2024	51	47	50	31	15	8	12	9
2025	50	31	21	12	.	.	.	.

Note: Share of businesses reporting credit-related challenges by year. Missing values (.) indicate survey round not conducted for that business type

Table A.10. Conflict and credit provided to farmers and borrowed in by agribusinesses - alternative conflict variable definitions

	Input Retailers		Rice Mills	
	Credit out to farmers	Credit taken in	Credit out to farmers	Credit taken in
	(1)	(2)	(3)	(4)
Estimation A: High Conflict Indicator (CSI>=3)				
High Conflict	-0.073	-0.008	0.022	-0.025
	(0.044)	(0.041)	(0.044)	(0.021)
Estimation B: Conflict Severity Index (CSI)				
Low (CSI = 1)	0.040	-0.060	0.015	-0.015
	(0.046)	(0.046)	(0.032)	(0.029)
Medium (CSI = 2)	0.047	-0.009	-0.068 **	-0.025
	(0.046)	(0.049)	(0.032)	(0.032)
High (CSI = 3)	-0.040	-0.038	-0.053	-0.052
	(0.057)	(0.067)	(0.037)	(0.033)
Highest (CSI = 4)	-0.061	-0.024	0.108	-0.010
	(0.055)	(0.052)	(0.070)	(0.029)
Estimation C: Conflict Fatalities (IHS)				
Fatalities (IHS)	-0.005	-0.001	0.002	-0.007
	(0.011)	(0.008)	(0.010)	(0.005)
All Estimations:				
Controls	Yes	Yes	Yes	Yes
State/Region Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
N	1,237	760	1,531	1,531

Estimates from linear probability models (LPM). Dependent variables are binary indicators equal to one if the business provided credit to farmers (credit out) or borrowed credit for business operations (credit taken in) in the survey year. Each panel presents a separate set of regressions using an alternative conflict measure defined at the township level. Estimation A uses a binary high conflict indicator equal to one if CSI≥3 (high conflict). Estimation B uses each CSI category. Estimation C uses the inverse hyperbolic sine (IHS) transformation of total conflict fatalities over the period. Input retailer estimations include data from 2020-25 for credit out and 2022-25 for credit in; rice mill estimations use data from 2021-24 survey rounds. Controls described in Section 4.1. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A.11. Conflict and credit-related challenges reported by agribusinesses

	Input Retailers				Rice Mills			
	Increased farmer demand for credit	Collecting repayment from farmers	Obtaining new credit/loans	Paying off credit/loans	Increased farmer demand for credit	Collecting repayment from farmers	Obtaining new credit/loans	Paying off credit/loans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any Conflict Indicator (CSI >=1)								
Any Conflict	0.020	-0.020	-0.035	-0.048 *	-0.018	-0.006	-0.029 *	0.010
	(0.031)	(0.039)	(0.031)	(0.027)	(0.022)	(0.019)	(0.016)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Agro-ecological Zone Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	765	765	765	765	1,531	1,531	1,531	1,531
R2	0.049	0.032	0.071	0.074	0.039	0.034	0.033	0.044

Estimates from linear probability models (LPM). Dependent variables are binary indicators equal to one if the business reported disruptions in the survey year. The conflict indicator equals one if CSI≥1 over the growing season. Input retailer estimations use data from 2022-25; miller data are from 2021-2024. Controls described in Section 4.3. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A.12. Conflict and credit-related challenges reported by agribusinesses - alternative conflict variable definitions

	Input Retailers				Rice Mills			
	Increased farmer demand for credit	Collecting repayment from farmers	Obtaining new credit/loans	Paying off credit/loans	Increased farmer demand for credit	Collecting repayment from farmers	Obtaining new credit/loans	Paying off credit/loans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High Conflict	-0.031	0.002	-0.086 **	-0.076 **	0.019	-0.005	0.025	0.029
	(0.037)	(0.054)	(0.037)	(0.038)	(0.030)	(0.031)	(0.033)	(0.034)
Low (CSI = 1)	0.023	-0.008	0.008	-0.021	-0.013	-0.004	-0.015	0.015
	(0.046)	(0.046)	(0.038)	(0.033)	(0.027)	(0.029)	(0.022)	(0.023)
Medium (CSI = 2)	0.051	-0.050	-0.053	-0.048	-0.035	-0.007	-0.060 ***	-0.005
	(0.048)	(0.057)	(0.057)	(0.039)	(0.025)	(0.024)	(0.018)	(0.020)
High (CSI = 3)	0.028	0.137	-0.082	-0.088	0.011	0.014	0.027	0.010
	(0.088)	(0.093)	(0.065)	(0.058)	(0.047)	(0.042)	(0.038)	(0.032)
Highest (CSI = 4)	-0.027	-0.063	-0.089 *	-0.091 *	0.006	-0.029	-0.010	0.052
	(0.045)	(0.064)	(0.045)	(0.050)	(0.041)	(0.038)	(0.040)	(0.048)
Fatalities (IHS)	0.005	0.006	-0.015	-0.011	0.003	-0.002	-0.003	0.007
	(0.009)	(0.012)	(0.010)	(0.008)	(0.007)	(0.007)	(0.006)	(0.008)
All Estimations:								
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State/Region Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N								

Estimates from linear probability models (LPM). Dependent variables are binary indicators equal to one if the business reported disruptions in the survey year. Each panel presents a separate set of regressions using an alternative conflict measure defined at the township level. Estimation A uses a binary indicator equal to one if CSI≥3 (high conflict). Estimation B uses each CSI category. Estimation C uses the inverse hyperbolic sine (IHS) transformation of total conflict fatalities over the period. Input retailer estimations use data from 2022-25; miller data are from 2021-2024. Controls described in Section 4.3. Standard errors clustered at township level in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table A.13. Input retailer regression variable means by year

	2020	2021	2022	2023	2024	2025
Urban	0.67	0.67	0.68	0.72	0.62	0.58
Experience (IHS)	2.61	2.79	2.94	2.97	2.86	2.89
Permanent employees (IHS)	0.86	0.86	0.87	1.08	0.94	0.98
Manager female	0.29	0.29	0.29	0.30	0.26	0.26
Manager age	41.38	42.24	43.23	44.56	44.08	44.59
Manager education: secondary	0.11	0.10	0.10	0.15	0.16	0.16
Manager education: more than secondary	0.70	0.70	0.70	0.71	0.65	0.73
Agro-ecological Zones						
Hills	0.24	0.24	0.24	0.24	0.10	0.18
Dry Zone	0.36	0.37	0.37	0.35	0.40	0.28
Delta	0.36	0.36	0.35	0.38	0.49	0.52
Coastal	0.04	0.04	0.04	0.03	0.01	0.02
Conflict						
High conflict indicator (CSI>=3)	0.00	0.08	0.23	0.23	0.25	0.14

Table A.14. Rice mill regression variable means by year

	2021	2022	2023	2024
Urban	0.47	0.45	0.44	0.37
Experience (IHS)	3.11	3.11	3.13	3.31
Permanent employees (IHS)	2.13	1.98	1.89	1.79
Manager female	0.17	0.04	0.16	0.19
Manager age	48.77	48.56	49.05	48.93
Manager education: secondary	0.23	0.26	0.23	0.24
Manager education: more than secondary	0.52	0.49	0.52	0.51
Agro-ecological Zones				
Hills	0.17	0.18	0.19	0.17
Dry Zone	0.26	0.22	0.26	0.31
Delta	0.54	0.56	0.52	0.49
Coastal	0.03	0.04	0.03	0.03
Conflict				
High conflict indicator (CSI>=3)	0.06	0.11	0.09	0.16

APPENDIX 2. CREDIT CONSTRAINT CLASSIFICATION QUESTIONS AND MAPPING TO CATEGORIES

<table>
<tr><th colspan="5">Survey responses</th><th>Classification</th></tr>
<tr><td rowspan="2">Farmer received farm credit</td><td colspan="4">Did not want more credit</td><td>Price-rationed borrower</td></tr>
<tr><td colspan="4">Sought more credit, but did not receive</td><td>Quantity rationed</td></tr>
<tr><td rowspan="14">Farmer did not receive farm credit</td><td colspan="4">Sought credit</td><td>Quantity rationed</td></tr>
<tr><td rowspan="13">Did not seek credit</td><td rowspan="6">Could receive credit if wanted</td><td colspan="2">Did not want credit</td><td>Price-rationed nonborrower</td></tr>
<tr><td colspan="2">Interest rate too high</td><td>Price-rationed nonborrower</td></tr>
<tr><td colspan="2">Farming not profitable enough to repay</td><td>Price-rationed nonborrower</td></tr>
<tr><td colspan="2">Did not want risk of repayment</td><td>Risk and transaction cost rationed</td></tr>
<tr><td colspan="2">Do not have relationships to lenders</td><td>Risk and transaction cost rationed</td></tr>
<tr><td colspan="2">Too difficult or costly to find credit</td><td>Risk and transaction cost rationed</td></tr>
<tr><td rowspan="7">Could not receive credit if wanted</td><td colspan="2">Would apply if certain to receive</td><td>Quantity rationed</td></tr>
<tr><td rowspan="6">Wouldn't apply even if certain</td><td>Did not want credit</td><td>Price-rationed nonborrower</td></tr>
<tr><td>Interest rate too high</td><td>Price-rationed nonborrower</td></tr>
<tr><td>Farming not profitable enough to repay</td><td>Price-rationed nonborrower</td></tr>
<tr><td>Did not want risk of repayment</td><td>Risk and transaction cost rationed</td></tr>
<tr><td>Do not have relationships to lenders</td><td>Risk and transaction cost rationed</td></tr>
<tr><td>Too difficult or costly to find credit</td><td>Risk and transaction cost rationed</td></tr>
</table>

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