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Forced to Sell Early? Smallholder Farmers' Access to Credit and Commodity Marketing Behaviour in Rural Ethiopia

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ABSTRACT *Large and predictable seasonal crop price variations in local markets offer African farmers substantial intertemporal arbitrage opportunities. But smallholder farmers are not commonly observed taking advantage of these arbitrage opportunities. In this paper, we study the effect of rural credit on shaping farmers' commodity marketing behaviour as related to the timing of crop sales. Using a large dataset from Ethiopia and an instrumental variables (IV) approach, we find that households who accessed credit are more likely to sell their crops early at substantially depressed prices. Households pay a financial penalty for selling early, as they forego an expected 31% increase in crop revenues over three to six months. Our results highlight a hidden but potentially relevant cost of farmers' participation in credit markets. Overall, current designs of rural credit products exacerbate the negative impacts of binding liquidity constraints and seasonal crop price cycles on poor households.*

KEYWORDS: Commodity markets; seasonality; liquidity constraints; rural credit market; Ethiopia

JEL CLASSIFICATIONS: D21; D51; G21; O13; O12; O16; Q1; Q12; D91

1. Introduction

Crop prices in Sub-Saharan Africa are characterized by substantial seasonal fluctuations (Gilbert, Christiaensen, & Kaminski, 2017; Minot, 2014). Typically, crop prices are lowest right after harvest but steadily and predictably rally to their peak over the lean (planting) season, with nominal prices of some crops peaking as much as 50–100% higher than their levels in the harvest season (Burke, Bergquist, & Miguel, 2019; Kaminski, Christiaensen, & Gilbert, 2014). These predictable seasonal price variations offer farmers apparent arbitrage opportunities for returns higher than those available from local financial mechanisms. However, many farmers do not take advantage of these profitable opportunities (Stephens & Barrett, 2011). Instead, they are commonly observed selling their crops right after harvest when crop prices are at their

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lowest and buying back food grains during the lean season at higher prices (Burke et al., 2019; Stephens & Barrett, 2011).

The empirical literature has put forward several complementary reasons for why farmers fail to take advantage of profitable seasonal arbitrage opportunities. Common explanations include information asymmetry about price increases, limited storage facilities, high storage costs and losses, and high time discount rates and price risks (e.g., Benirschka & Binkley, 1995; Byerlee, Jayne, & Myers, 2006; Williams & Wright, 1991). Given the short and predictable agricultural cycles, these explanations do not fully account for why farmers do not take advantage of arbitrage opportunities (Stephens & Barrett, 2011). Seasonal cycles and associated price changes are well known to farmers. Storage losses for staple foods at farmer level are generally lower than what is commonly assumed in developing countries (Burke et al., 2019; Delgado, Schuster, & Torero, 2017). Considering the substantial price variations over a short period, extremely high discount rates would be needed to rationalize farmers' failure to take advantage of seasonal price variations (Kaminski et al., 2014). As smallholders are both producers and consumers of grain, price risk aversion should motivate more storage rather than less, as lean season repurchases are more costly (Burke et al., 2019).

A recent literature emphasizes the role of liquidity constraints in explaining why farmers do not take advantage of seasonal arbitrage opportunities (Burke et al., 2019; Dillon, 2021; Stephens & Barrett, 2011). When liquidity constraints are binding, expectations about future prices and incomes would no longer affect present consumption choices (Fafchamps & Minten, 2001). In such situations, farmers' decisions about whether to sell or store their produce are primarily driven by cash demands to meet urgent expenditures. In this study, we analyse how rural credit arrangements shape Ethiopian farmers' commodity marketing behaviour and cause them to sell their crops early and forgo profitable arbitrage opportunities. Credit services in Africa are often extended to farmers during the planting season to finance modern inputs, alleviate seasonal labour shortages, and smooth consumption shocks (Pitt & Khandker, 2002). To minimize risks of default, rural credit contracts in Ethiopia are routinely stipulated such that loans are congruent with crop cycles with repayments due at harvest season (Croppenstedt, Demeke, & Meschi, 2003; Tarozzi, Desai, & Johnson, 2015). With short payback periods, these loans have rigid repayment plans, and hardly any credit can be carried over from one season to the next (Amha & Peck, 2010). These rural credit arrangements essentially give rise to a disguised form of credit-output market interlinkages that govern the timing of household crop sales.

We use a rich dataset from more than 6,950 farm households in four major regions in Ethiopia –Tigray, Amhara, Oromia, and Southern Nations, Nationalities and Peoples (SNNP). Using an instrumental variables (IV) approach to control for endogeneity of credit use, we find that households who used rural credit are more likely to sell their crops at harvest or immediately after harvest at low prices. As expected, farm households pay a financial penalty for selling early, as they forego roughly 31% expected increases in crop revenues over three to six months. A counterfactual analysis indicates that households in the poorest quintile lost 3.38 Ethiopian Birr per one Birr credit used in foregone revenues. The total penalty paid by poor households who took large loans could have far reaching adverse welfare consequences. These findings suggest that current designs of rural credit exacerbate negative impacts of liquidity constraints and undermine farmers' ability to take advantage of seasonal price arbitrages. Overall, we highlight a hidden but potentially relevant cost of farmers' participation in credit markets. Our study casts some doubt on suggestions to sell agricultural inputs at harvest time to promote adoption of modern technologies (Casaburi & Willis, 2018; Duflo, Kremer, & Robinson, 2011), since such a suggestion ignores welfare impacts of seasonal price cycles.

The rest of the paper proceeds as follows. Section 2 presents the data and descriptive analyses. Section 3 discusses patterns of seasonality, crop price cycles, credit use and repayment, and

cost of early crop sales to farmers. Section 4 outlines the empirical strategy. Section 5 presents and discusses the results. Section 6 concludes with policy implications.

2. Data and descriptive analyses

2.1. Sampling design

We used pooled data collected in two waves by the Central Statistical Agency (CSA) of Ethiopia in collaboration with the International Food Policy Research Institute (IFPRI). The data were collected in 2013 and 2015 as part of the Feed the Future (FtF) program in Ethiopia, which aims to address hunger through improving productivity, access to markets and incomes of the poor. The strategy was to focus on defined area of coverage—Zone of influence (ZOI)—to measure impact. The ZOI covers 149 districts where the FtF projects implemented over the five year period of 2013–2017 (Bachewe et al., 2014).

The survey design followed stratified random sampling of districts, Enumeration Areas (EAs) and households from major regions of the country—Tigray, Amhara, Oromia, and SNNP. First, 56 districts from among the 149 FtF districts and 28 comparable non-FtF districts were randomly selected from these regions. Then, from each district, three EAs were randomly selected. Finally, 28 households were randomly selected from each EA. This procedure produced a total of 6,977 households for the first-wave in 2013 and 6,696 households for the second-wave in 2015. The survey included detailed modules on crop production and utilization, timing of crop sales, credit use and repayment, and relevant sociodemographic characteristics.

2.2. Rural credit market and household participation in Ethiopia

The survey elicited households' credit use over the 12 months prior to the survey. Both survey rounds were conducted at similar times of the year, and the 12-month recall period covers the recent main (meher) growing season (June to September). The survey question was posed as: "over the last 12 months, did you or anyone in this household borrow credit from someone outside the household or an institution?". Table 1 presents the description of the credit data.

Table 1. Description of credit data

Variables	Total	2013	2015
Proportion of HHs who took credit (% share)	12.0	8.1	15.2
Overall credit characteristics (sample: credit users)			
Average size of credit (ETB)	3,487	3,040	3,728
Source of credit –Formal (%)	67.5	74.7	63.2
Institutions (e.g. cooperatives)	13.27	13.38	13.34
Microfinance institutions	49.52	47.09	51.75
Others (Banks, NGO)	2.21	2.66	2.49
Source of credit –Informal (%)	35.2	26.7	40.2
Relatives, friends and neighbours	21.94	31.56	27.95
Others (local merchant, employer)	3.06	5.31	4.47
Reason for credit: purchase of agri-input (%)	70.1	80.1	64.57
Reason for credit: purchase of food crops (%)	15.3	9.44	18.56
Reason for credit: business start-up/expansion (%)	6.7	6.07	7.12
Reason for credit: Others (%)	7.8	4.38	9.75
Repaid their loans at least partially (%)	70.5	71.9	68.77
Reason for not repaying credit (sample: non-repaying households)			
Harvest failure (%)	6.1	5.5	6.4
Used for unintended purpose (%)	21.5	19.9	22.4
Other reasons (%)	72.5	74.6	71.2

Source: *Ethiopian FtF survey (2013, 2015)*.

Overall, about 12% of households took some form of credit. The average volume of credit among those who took credit was 3487 Ethiopian Birr (~$193; the official exchange rate was about 1 USD = 18 Ethiopian Birr during the survey periods). Looking at the two survey rounds, about 5% of the respondents took credit only in 2013 survey year and about 11% only in 2015 survey year, while about 3% took credit in both survey years, showing high imbalance and rendering the use of the panel data unattainable. There is an increase in credit use by households over time, with 8% of households taking credit in 2013 and 15% in 2015 (Table 1). While reasons were not specifically asked in the surveys, some external factors, such as expansion of microcredit institutions and the nation-wide drought in 2014, might explain part of the growth in credit.

Households in Ethiopia secure access to credit from both formal and informal channels. Formal credit sources include institutions, such as microfinance institutions, commercial banks, and member-owned financial cooperatives. On the other hand, informal sources include family and social networks, local merchants and grocery stores, moneylenders, and informal associations, like rotating savings groups (Eqqub) and social insurance groups (Iddir) (Regassa, Degnet, & Melesse, 2023). Most of the credit users (68%) accessed credit through formal sources, while 35% relied on informal sources, with about 3% credit users having a portfolio of formal and informal credit sources. Households reported to have obtained credit for different purposes. Most of them (70%) took credit for agricultural input. Other purposes included financing food expenditure (15.3), business start-up and expanding business (6.7), and other miscellaneous household expenses, such as wedding and funerals (7.8%).

Other key aspects of rural credit markets are interest rates, maturation period, and structure of credit. While the surveys did not collect information on interest rates on the loans, the interest rate structure in the rural credit market in Ethiopia is well characterized (Caudell, Rotolo, & Grima, 2015; Gashayie & Singh, 2016). Generally, interest rates imposed on loans vary depending on their sources. Compared to commercial banks, microfinance institutions (MFIs) and credit associations charge higher interest rates due to higher operation costs and credit risks. Majority of Ethiopian MFIs charge annual nominal rates of 15% to 24% (CGAP, 2008). Conversely, interest rates in the informal credit markets are less clear and greatly vary depending on sources. While loans from friends and families are interest free, village moneylenders typically charge exploitative interest rates (Caudell et al., 2015). Looking at the average credit, most of the loans were short-term and small in quantity. About 71% of credit user households reported paying their loans at least partially within the 12 months prior to the survey period. Using credit for unintended purpose (45%) and crop failure (19%) were notable reasons for not repaying credit. Most borrowers (92%) preferred to repay loans at harvest time when they had high income.

Finally, while our sample size is large, relatively small proportion of the sample used credit (12%), warranting a discussion on the distinction between credit demand and access. We closely looked at the reasons of non-credit users (the remaining 88%) for not participating in credit markets. About 13% among non-users mentioned availability of enough own capital as their reason for not using credit. The remaining credit non-user households (87%) were interested in using credit but were constrained by various reasons, including risk aversion (56%), transaction cost factors (24%) and price of credit (7%) due to high interest rates and associated costs of borrowing. Risk-related factors include dislike for being in debt, belief that they would be refused credit, and fear of not being able to repay loans. Transaction cost factors included perceived challenges of obtaining credit, inadequate collateral to secure loans, and lack of knowledge about available lenders. Generally, the demand-side of the credit market is potentially big regardless of the limited participation of households. But limited access to credit in rural Ethiopia continues to hamper credit market participation, constraining households' ability to generate income and smooth consumption (Mukasa, Simpasa, & Salami, 2017; Regassa et al., 2023).

Table 2. Descriptive statistics and simple mean difference tests of variables by credit use status

	Credit use			
	Overall sample	No	Yes	Mean difference test
Credit use	0.12	0.00	1	***
Early crop sale (yes = 1)	0.50	0.49	0.58	***
Female head (yes = 1)	0.29	0.29	0.24	***
Head age (in years)	43.8	44.0	42.1	***
Average education level of HH head	1.41	1.38	1.61	***
Household size (in numbers)	4.82	4.78	5.20	***
Religion of the Head (proportion)				
Muslim	0.24	0.26	0.12	***
Orthodox	0.50	0.49	0.64	***
Other Christian	0.23	0.23	0.23	
Others	0.02	0.03	0.01	***
Wealth indicators				
Land size (ha)	1.58	1.56	1.75	***
Livestock (in TLU)[a]	3.29	3.31	3.11	*
Durable asset index (PCA)[b]	0.00	−0.03	0.23	***
Off-farm activity (yes = 1)	0.08	0.07	0.17	***
Good floor (yes = 1)	0.09	0.09	0.09	
Good roof (yes = 1)	0.41	0.39	0.53	***
Plot and village characteristics				
Access to electricity (yes = 1)	0.06	0.06	0.08	***
Average plot distance from residence (in km.)	14.7	14.4	17.4	***
Proportion of fertile soil	0.71	0.72	0.66	***
Proportion of plain slopped plot	0.73	0.73	0.74	
Average size of credit in village	303.6	195.6	1171.5	***
Distance from formal credit source (in km)	13.18	13.74	8.76	***

Source: *Ethiopian FtF survey (2013, 2015)*.
Notes: [a]We measured livestock using tropical livestock units (TLU), which is a common metrics used to quantify a wide range of various livestock species to a single figure that captures the total amount of livestock owned by a household. We used a tropical livestock unit applicable for Sub-Saharan Africa. [b]We generated the durable assets index using principal component analysis (PCA) from individual asset items owned by households.

2.3. *Explanatory and outcome variables*

Table 2 presents descriptive statistics and mean difference tests by credit use status. The key explanatory variable is credit use. Credit use is defined as a dummy variable. This is informed by the fact that quantities of credit offered to rural households are categorical as they are predetermined (in packages) and thus not a continuous choice variable. However, we also report results using credit quantity and repayment variables in the robustness analyses.

Our main outcome variable is early crop sale, which is defined as crop sale during or immediately after harvest or peak period of agricultural production (hereafter, harvest time sale). Farmers were asked about the months of their crop harvests and sales. The definition of early sale is based on the difference between harvest and sale times, where a crop sale by a household is an "early sale" if the difference between harvest and sell is one month or less. This definition provides a conservative measure of an early crop sale. However, this classification of crop sales as early sale does not precisely match with the agricultural harvest season. To allay this concern, we report results for early sale based on the Ethiopian agricultural calendar in the sensitivity analyses (Section 5.2). In addition, the surveys collected data on crop sales only about the largest three sales of each crop. As such, the sales data did not cover all crop sales. Using data from crop production and utilization modules, we estimated the share of the three largest sales

for the major crops from the total sales of the crops. Overall, the three largest sales accounted for about 95% of the total crop sales of households (Table A1 in the Appendix).

Generally, the descriptive results show that credit users are more likely to sell their crops early than non-credit users (Table 2). But these results are not definitive regarding the effect of credit on the timing of crop sell, since they do not account for potential confounding factors. Thus, we employ an instrumental variables (IV) approach for identification.

3. Seasonality, credit use and grain marketing in Ethiopia

3.1. Seasonality, crop price cycles, and credit use and repayment

Agriculture in Ethiopia is almost entirely rain-fed, where production of crops is characterized by significant seasonal cycles (Taffesse, Dorosh, & Gemessa, 2012). Production of many crops is limited to the main rainy season, which extends from June to September and accounts for more than 90% of total crop production in the country (Taffesse et al., 2012). Crops are mostly planted in June through August, while the harvest period is situated in October through December. The post-harvest season covers January to March, while the lean season runs from June to September. Seasonality of agricultural production results in recurring patterns of crop supply and prices, driving crop price cycles.

To get a glimpse of the seasonal patterns of prices, Figure 1 plots seasonal patterns of local producer prices of major crops (teff, maize, wheat, oilseeds and pulses) in Ethiopia over the period of 2001–2017. As spatially disaggregated time series price data are not available for most crops, we rely on producer price data collected by the Central Statistical Agency (CSA). Figure 1 shows that prices demonstrate clear seasonality. The lowest prices are observed in the post-harvest period (January–March). Prices rise steadily thereafter, with highest prices observed during

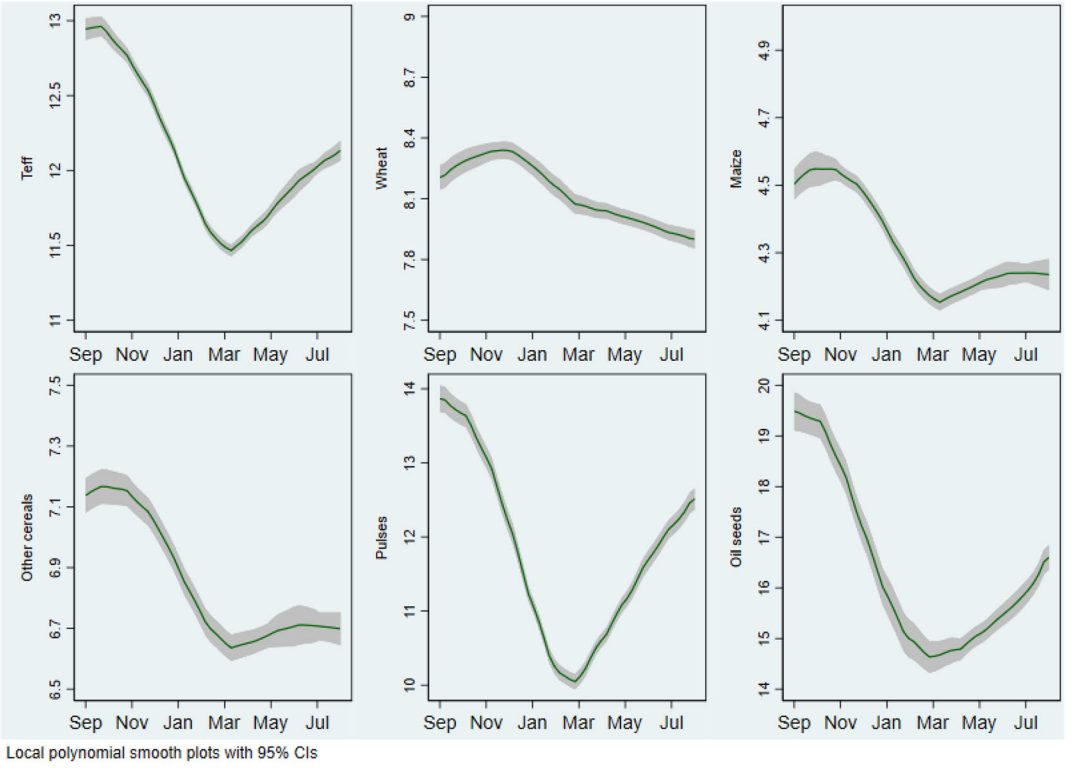

Figure 1. Monthly average producer nominal prices per kg across Ethiopian markets, for the period 2001–2017.
Source: Authors' calculations using CSA nominal price data.

the lean or hungry season (June– September). Seasonal price variability is relatively higher for pulses and oilseeds. This may be attributed to a relatively high supply of these crops immediately after harvest combined with relatively consistent demand for the crops across seasons. Conversely, wheat and maize prices show relatively low variability, perhaps because of relatively stable demand and better integration to the international market. These seasonal variations in prices for staple grains offer households substantial arbitrage opportunities.

Two further qualifications are in order. First, while the producer price remains important for smallholders, seasonality of prices would be much more pronounced in retail market prices. Figure A1 (in the Appendix) presents seasonality of retail market prices and indeed illustrates clear seasonality trends. Second, averaging prices across markets may limit spatial price variations. Figure A2 in the Appendix presents locally weighted regressions of average prices for main cereals for the period 2001–2017 across the major grain markets in the study regions. The graphs are fairly flat, indicating absence of significant spatial variations in retail prices.

Figure 2 displays patterns of credit use (borrowing) and repayment among sampled households along with the timing of their crop sales, where (a) presents for all credits accessed and (b) considers only credits taken for agricultural production purposes. The pattern of smallholders' credit market participation follows the agricultural cycle, where credits are taken out immediately before the cropping season and returned immediately after harvest, with slightly strong distinction of credits taken for agricultural purposes. The peak borrowing period occurs in April through June, which is near the start of the main planting period (June - September), and many loans are repaid during the harvest and the post-harvest periods (November–March). Related to the total credit accessed, about 45% of the loans were taken over the three months close to the main planting season (April–June), while 61% of the credit repayments were made during the harvest and the post-harvest seasons (November–March).

Mirroring the pattern of loan repayments, the bulk of crop sales occurs from November through March (Figure 2). This suggests that farmers store grains for only about two to three months, rather than the economically optimal three to six months. There is a clear correlation between the timings of loan repayments and major crop sales, suggesting that households sell crops early to settle credit repayments.

3.2. *Economic cost of early crop sales*

We conduct a simple counterfactual analysis to get an insight into the economic costs of seasonality for farmers. We estimate the revenue loss due to early crop sale as a difference between the revenue that could have been generated from selling at the lean season and the actual revenue received from the harvest time sale. Data on the actual revenue from crop sales were collected

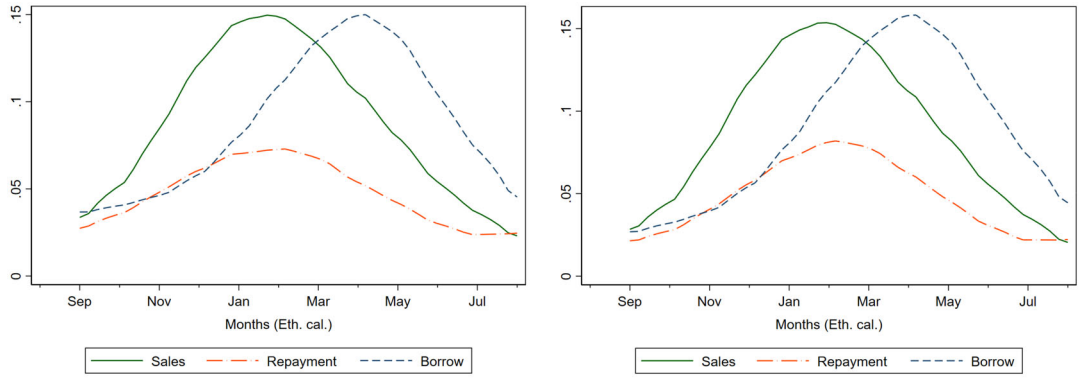

Figure 2. Timing of crop sales, borrowing and credit repayment by sampled households.

Table 3. Estimates of economic costs of early crop sale

Wealth Quintile	Revenue loss from early sale (birr)	Revenue loss as share of total revenue	Revenue loss per one birr of average credit taken
1	625.67	0.51	3.38
2	565.99	0.30	1.55
3	575.08	0.27	1.35
4	591.22	0.24	0.99
5	817.37	0.26	1.23
Total	632.67	0.31	1.44

Source: *Authors' calculation based on Ethiopian FtF survey (2013, 2015).*

in the surveys, reflecting crop prices at crop sales. The counterfactual revenue is determined using the average sales price of each crop during the lean or hunger season (i.e., June–September) of the same year. Some qualifications are relevant here. First, if many farmers could postpone their sales long after harvest, postponing sales might have depressing effects on grain prices across the seasons, making the current seasonal price variations unattainable. Second, storing crops to sell later may involve storage costs and losses, which have not been accounted for. This suggests that estimated economic costs provide an upper threshold of lost arbitrage gains. On the other hand, many farmers who sell crops at harvest time might rebuy grains at higher prices later, implying a potential understatement of economic costs. Thus, it is important to note that estimated economic costs may not reflect actual costs of early crop sales.

Table 3 presents revenue losses in terms of forgone revenue due to early sales disaggregated across wealth quintiles, both in absolute terms and relative to the total revenue. Households in higher quintiles are expected to be less financially constrained and may be able to settle credit repayments through other means, thus delaying their crop sales. Revenue losses due to early sale are substantial, compared to the average sales revenue per capita level of 1051 Birr for our sample. For example, households in the bottom wealth group forgo about 625 Ethiopian Birr (almost half of the average annual revenue from crop sales). For households in the upper groups, the revenue loss increases in absolute terms but decreases as a share of total revenue, indicating that early sale is more costly for poor households.

Table 3 also provides the revenue loss relative to the average credit taken by the various wealth quintiles. The revenue loss per unit of average credit taken is highest for households in the poorest wealth quintile, suggesting a credit poverty penalty where the poor are likely to have limited alternative options to meet immediate expenditure needs and incur more costs for accessing financial services. However, not all revenue from crop sales might have been used for credit repayment. Our data did not allow us to examine this issue as information on purposes of crop sales was not collected in the surveys.

4. Econometric approach

We model early sale decision (T_{it}) of household i at time t as a function of credit use (C_{it}) and specify the basic econometric model as:

$$T_{it} = \beta_0 + \beta_1 C_{it} + \beta_2 X_{it} + \alpha j + \mu t + \varepsilon_{it} \quad (1)$$

where X_{it} is a vector of household, plot and community level characteristics. Household characteristics cover household size, religion and education level, off-farm employment, wealth indicators, size of livestock owned in tropical livestock units (TLU), and land size. Plot level characteristics include slope, fertility and plot distance from residence. Regional dummies (αj)

are included to control for observed and unobserved policy and institutional differences across the regions. Administrative regions in Ethiopia are semi-autonomous, and policies and institutions have the potential to vary across the regions. For instance, each region has its own legislative and directive for establishing and regulating microcredit institutions and (financial) cooperatives. Wave dummies (μt) are included to control for time effects. The term, ε_{it}, is the random error. We report woreda (district) level fixed effects. When possible, we report standard errors clustered at the village level to account for remaining unobservable characteristics.

In equation 1, β_1 measures the effect of credit use on early crop sale. Households who took credit are more likely to sell their crops at harvest or immediately after harvest to finance credit repayments and, hence, β_1 is positive. However, credit use might be endogenous due to omitted variables and reverse causality. For instance, credit users might have distinct risk profile or entrepreneurship quality. To mitigate this concern, we use instrumental variables (IV) approach.

We rely on the literature and insights from recent efforts in Ethiopia to expand agricultural credit to find relevant instrumental variables. Over the last decades, Ethiopia has embarked on a more market-oriented financial system to expand agricultural credit (Amha & Peck, 2010). At the same time, many smallholders heavily depend on informal credit sources. Drawing on these insights, we use distance to the nearest formal source of credit and the average credit amount in the village excluding the household of interest as instruments. Distance to formal credit sources is an important determinant of transaction costs of accessing credit by the poor. The average credit amount in the village excluding the household of interest reflects community level differences in costs and norms related to accessing credit, reflecting the overall availability of credit from both formal and informal sources.

The validity of an IV strategy depends on the relevance and exclusion criteria (Melesse & Cecchi, 2017). The relevance criterion requires that instruments should be good predictors of credit use. To formally test for this criterion, we estimate credit use as a function of the instruments and other relevant variables using a linear probability model (LPM) that generates tests that help assessing the appropriateness of the IV approach (Table A2 in the appendix). The first-stage regression results are significant and appear with expected signs, indicating that they are good predictors of credit use.

The exclusion restriction requires that instruments should not be correlated with early sale decision, other than through the credit channel. It is difficult to satisfy this condition unreservedly. The average credit size is largely a result of a combination of policy, institutional and other community level factors and can reasonably be considered exogenous to sale choices of individuals. But a potential concern may be the low credit market participation of survey households, particularly concentration of credit users in a few districts. Figure A3 in the Appendix shows that the distribution (%) of credit users across all districts is not concentrated only in a few locations, suggesting that the average credit is not capturing location-specific fixed-effects. Regarding the distance to the nearest formal credit source, households have limited scope to influence distance to formal credit sources, except through migration decisions. But household-level mobility and migration would not be widespread in Ethiopia as the land proclamation requires permanent physical residence as a condition for enjoying secure and continuous land use rights.

More formally, we run a falsification test to indirectly assess the validity of the exclusion restriction for our instrument variables (Di Falco, Veronesi, & Yesuf, 2011). The idea is that instruments should not affect the outcome variable among non-credit user households. The results for the falsification tests show that the instruments are not correlated with early crop sale for non-credit users (Table A2, column c). Furthermore, Table A2 contains additional tests on the validity of the instrumental variables. The Cragg-Donald test statistic rejects the null hypothesis that the endogenous regressor (credit use) is weakly identified. The Kleibergen-Paap test also rejects the hypothesis of under-identification. The Hansen test statistics for over-identification fail

to reject the null hypothesis of zero correlation between the instruments and the error term. Further, the partial F-statistic ($F = 212.5$) of the first-stage regression with only the instruments as explanatory variables is higher than the minimum threshold value of 10, the "rule of thumb" for strong and valid instruments.

5. Results and discussion

5.1. Main result

We set out to assess the effect of credit use on farmers' propensity to sell crops during or immediately after harvest when crop prices are at their lowest levels. Early crop sale is defined as crop sale at harvest time based on data reported by farmers. In Table 4, we first estimate the association between credit use and the propensity to sell early through estimating simple linear probability models (LPM). Results show that credit use is positively correlated with early crop sale. The results from the elaborated model (column c) suggest that credit users are about 7.3 percentage points more likely to sell their produce when prices are depressed than those who did not take credit.

However, as discussed earlier, credit use may be endogenous to farmers' early sale decisions. To attenuate this concern, we employ an IV strategy using distance to the nearest formal source of credit and average credit in the community excluding the household of interest as instruments. We recognize that the use of LPM in the first-stage might lead to inconsistent standard error estimates in the second-stage as the fitted values may not always be bounded between 0 and 1. To address this, we report bootstrapped standard errors in our second-stage. Table 4 (column d) contains the IV results. Credit use is causally linked to higher propensity to sell early, suggesting that credit users are more likely to sell crops early than credit non-users. Specifically, credit use increases the likelihood of early sale by about 14 percentage points.

While the results of the OLS and IV models are largely consistent, the credit use coefficient is higher for the IV model as compared to the OLS regression. Such differences are consistent with measurement errors, as is common in retrospective rural household surveys. While measurement errors can lead to an attenuation bias towards zero in simple regressions (Theil, 1971), IV approaches mitigate such problems (Gujarati, 2003), because identification in the IV comes from households responding to changes triggered by the instruments *–á la* Local Average Treatment Effects (LATE).

Furthermore, Table 4 shows that farmers' early crop sale is correlated with many other covariates. Young farmers are more likely to sell late, perhaps due to their better capacity to get market information and delay the sale of their crops. As expected, ownership of livestock appears to buffer households from engaging in distress crop sale. But households engaged in off-farm activity are more likely to sell their produce early, which seems counterintuitive. Perhaps, this might be related to the fact that poorer households engage in off-farm activities primarily as adaptation and mitigation strategies against shocks and income shortfalls rather than strategic business considerations (Cunguara, Langyintuo, & Darnhofer, 2011). Similarly, Van den Broeck and Kilic (2019) documented the dynamic nature of participation in off-farm employment activities in Sub-Saharan Africa, including Ethiopia, where many individuals frequently entered and exited off-farm employment with occurrence of shocks being one of the important drivers of this dynamics. Further, many rural non-farm businesses are strongly linked with agriculture and follow similar seasonal patterns in terms of operation capital needs and other expenditures.

The survey round dummy for 2015 appears with positive and significant coefficient, suggesting that the propensity of early sale increased between 2013 and 2015, as did nominal credit. Results for regional dummies are interpreted relative to the reference region, Tigray. Results show that farm households in Amhara, Oromia and SNNP regions are less likely to sell their crops early as compared with those from Tigray region.

Table 4. Effect of credit use on households' propensity of early crop sale

	Dependent variable: Early crop sale			
	(a) LPM	(b) LPM	(c) LPM	(d) IV: 2SLS
Credit use, yes = 1	0.091***	0.095***	0.073***	0.139***
	(0.016)	(0.015)	(0.028)	(0.052)
Survey round, 2015			0.112***	0.108***
			(0.012)	(0.014)
Household head is female			0.001	0.001
			(0.027)	(0.016)
Log(age of household head)			0.042***	0.045**
			(0.014)	(0.018)
Household size			0.004	0.003
			(0.003)	(0.004)
Education level of the head			−0.001	−0.001
			(0.004)	(0.002)
Log(land size owned in hectares)			0.022	0.019
			(0.016)	(0.015)
Log(livestock owned, in TLU)[a]			−0.006*	−0.005***
			(0.003)	(0.002)
Log(Ownership of durable assets, PCA)[b]			−0.001	−0.001
			(0.003)	(0.005)
Off-farm activity			0.070***	0.064***
			(0.012)	(0.021)
Household has good floor			0.040	0.042**
			(0.051)	(0.020)
Household has good roof			0.005***	0.007
			(0.001)	(0.017)
Household access to electricity			−0.011	−0.012
			(0.015)	(0.027)
Religion (reference = Muslim)				
Religion-Orthodox			−0.024	−0.025
			(0.032)	(0.021)
Religion-other Christian			0.010	0.007
			(0.041)	(0.027)
Religion-others			0.008	0.010
			(0.048)	(0.056)
Log(distance of plot from residence)			−0.001	−0.000
			(0.007)	(0.005)
Proportion of plots with fertile soil			0.040***	0.042**
			(0.006)	(0.017)
Proportion of plots with plain slope			−0.008	−0.009
			(0.033)	(0.018)
Region (reference = Tigray)				
Region, Amhara			−0.230***	−0.214
			(0.010)	(0.201)
Region, Oromia			−0.392***	−0.374*
			(0.145)	(0.197)
Region, SNNP			−0.257*	−0.073
			(0.147)	(0.200)
Woreda fixed effects		Yes	Yes	Yes
Constant	0.488***	0.000*	0.387***	0.383**
	(0.007)	(0.000)	(0.060)	(0.193)
Number of observations	7,242	7,242	6,949	6,949
R2	0.004	0.089	0.109	0.107
Adjusted R2	0.004	0.079	0.096	0.094

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Bootstrapped standard errors in parentheses. [a]We measured livestock using tropical livestock units (TLU), which is a metric used to quantify a range of various livestock species to a single figure. We used a TLU applicable for Sub-Saharan Africa. [b]We generated the durable assets index using principal component analysis (PCA) from individual asset items owned by households. LPM = Linear probability model; 2SLS = Two-Stage least squares.

Why might farm households not use other means to finance credit repayments at harvest time and store their crops until prices reach their seasonal peak? Generally, farm households in sub-Saharan Africa have limited access to adequate savings, reasonably priced credit at harvest time, or other sources of regular income, leaving them with crop sales to secure cash. Households living in poverty have very little savings. All the more so, they are reluctant to part with their little savings. Once in debt, poor households have limited opportunity to get new loans. Particularly, loans are not extended to agricultural households at the harvest season (Burke et al., 2019). For example, Tarozzi et al. (2015) show that, of a total of 1,682 registered microloans, only 25 loans were initiated to repay other loans in rural Ethiopia.

Another possibility of financing credit repayment may be income from the sale of live animals and livestock products. Indeed, ownership of livestock appear buffer households from engaging in distress crop sale (Table 4). However, livestock production is not a regular source of employment, and farmers sell livestock for income only when in distress. In addition, like in much of sub-Saharan Africa, off-farm income in rural Ethiopia reflects a coping strategy for managing consumption shocks and liquidity constraints rather than an income maximization strategy (Dercon & Krishnan, 2000). Taken together, income from other sources is less likely to bail households out from harvest crop sales at low prices.

5.2. *Sensitivity analyses*

We assess the robustness of the main result in several ways. First, we use quantity of credit instead of the credit use dummy, as the quantity of credit may better capture the effect of credit repayment on timing of crop sales. Table 5 (column a) reports that the likelihood of selling crops early increases with the size of credit. Second, as crops are sold early to repay credit, credit repayment may be a better measure of effect of credit on early crop sales. Table 5 (column b) provides 2SLS results based on credit repayment, which are once again robust. Additionally, the coefficient on credit repayment is larger as compared to the standard model (Table 4).

Third, seasonal intertemporal arbitrages are potentially possible for non-perishable and storable crops. We differentiate between perishable and non-perishable crops and limit our analysis only to grains (i.e., non-perishable crops) that can be stored and sold later when prices are high. The results in Table 5 (column c) show that credit use has significant effect on early crop sales, confirming that the results are not driven by the sale of perishable products.

Fourth, the indicator for early crop sale was based on the difference between crop harvest and crop sale times. However, this assessment of the timing of crop sales does not precisely match the agricultural calendar of the seasons. Here, we use the time when farmers sold their crops and calibrated it with the Ethiopian agricultural calendar to generate an early sale indicator. Since the main rainy (meher) season covers the period June to September, we consider an early sale if the sale happens during the harvest or the immediate post-harvest period (November to March) (Taffesse et al., 2012). The results (Table 5, column d) remain significant and consistent with the results reported in Table 4.

Fifth, another concern with our results might be the use of the LPM in the first-stage, and the associated IV estimation based on this model. The use of LPM is preferred for its simplicity, ease of interpretability, computational efficiency, and generation of tests for assessing the appropriateness of the IV approach. But the model may lead to inconsistent standard error estimates as the fitted values may not always be bounded between 0 and 1. To address this, we run an ivprobit estimator that uses a maximum likelihood method to account for the binary nature of the endogenous variable (Wooldridge, 2002). The results are again significant (Table 5, column e), suggesting that the non-linearity of the outcome variable does not drive the result.

Finally, if we remain skeptical about whether our instruments fully satisfy the exclusion restriction, then the main concern is unobserved heterogeneity. We formally examine this threat

Table 5. Robustness analysis: Quantity and repayment of credit, alternative definitions of early sales, and alternative model specifications, IV-regressions

	Dependent variable: Early crop sales					
Explanatory variables	(a) quantity of credit (2SLS)	(b) credit repayment (2SLS)	(c) non-perishable crops (2SLS)	(d) agricultural calendar (2SLS)	(e) ivprobit model	(f) heteroscedasticity-based identification (2SLS)
Log (amount of credit used)	0.019**					
	(0.008)					
Credit repayment (yes = 1)		0.356**				
		(0.147)				
Credit use			0.142***	0.119**	0.142***	0.074***
			(0.053)	(0.054)	(0.053)	(0.026)
Plot, household and community characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Woreda fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.386***	0.376***	0.202**	0.483***	0.202**	0.387***
	(0.09)	(0.093)	(0.085)	(0.151)	(0.085)	(0.090)
Adjusted R^2	0.108	0.072	0.085	0.074	0.085	0.096
IV Diagnostics:						
Kleibergen-Paap LM statistic:	59.48	41.27	59.75	60.38		64.83
Kleibergen-Paap p-value:	0.00	0.00	0.00	0.00		0.00
Cragg-Donald test:	447.2	123.36	419.02	437.10		1901.53
Hansen-J test:	1.85	1.585	0.015	0.444		7.088
Hansen-J p-value:	0.174	0.208	0.904	0.505		0.131
Wald test of exogeneity						
$\chi 2(1)$					1.56	
Prob > $\chi 2$					0.21	
Number of observations	6,951	6,951	6,382	6,947		6.949

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Standard errors clustered at the village level in parentheses. Coefficients on plot, household and community characteristics omitted to save space.

in two ways. First, we use a heteroscedasticity-based identification strategy that does not depend on whether the exclusion restriction is adequately satisfied (Lewbel, 2012). The approach works in two steps. Let us suppose that Z_{it} represents the vector of exogenous variables. First, the endogenous variable (i.e. credit use) is regressed on the exogenous variables (Z_{it}), and the residual $\hat{\varepsilon}$ is retrieved. Next, the instruments are obtained as $(Z - E(Z))\,\hat{\varepsilon}$, where E(Z) is the expected value of Z. The basic requirement of the model is that there is heteroscedasticity in $\hat{\varepsilon}$ (i.e., $cov(\hat{\varepsilon}^2, Z_{it}) \neq 0$). Then, internally generated instruments are used without imposing any exclusion restriction (Lewbel, 2012). We selected the exogenous variables, including plot level characteristics (share of plots with fertile soil, share of plots with plain slope, and average distance of plots from residence), and community level infrastructure (distances of the village from the nearest credit sources and availability of credit in the village). The Breusch–Pagan test rejects the null of homoscedasticity at the 1% level. The results based on this procedure are robust once again (Table 5, column f).

Second, we test the robustness of our results to unobserved heterogeneity using the sensitivity analysis proposed by Imbens (2003). This test assesses whether reported results are appreciably affected by omitted variable bias. To implement this procedure, we take the IV results in Table 5 and consider the correlation between credit use and unobserved covariates that are also potentially correlated with early crop sale. By generating pseudo-observables over 200 iterations, Figure 3 shows a series of points representing the combination of R-squared values that would lead to a reduction of the size of the effect coefficient by half. On the vertical axis, we plot the marginal increase in R-squared that results when an unobserved covariate is added to a regression of the outcome variable on the full set of significant controls. The horizontal axis plots the marginal increase in R-squared from adding the covariate to a regression of credit access on the full set of controls.

Figure 3 shows that a low correlation between credit access and an omitted variable would only be problematic if the correlation between the same omitted variable and the outcome variable was very high. To illustrate this finding, we also plot the partial correlation between credit access and the outcome variable for three significant control variables (household size, off-farm employment, and farm size). None of the three covariates approaches the threshold that reduces the effect of credit on the outcome variables by half. An omitted variable would have to be much more important than included covariates to undermine our results, which is unlikely.

6. Conclusion and policy implications

Large and predictable seasonal price variations in local grain markets offer smallholder farmers substantial intertemporal arbitrage opportunities. Yet, farmers are often observed not taking advantage of these arbitrage opportunities. In this paper, we study the effect of rural credit use and its repayment on shaping crop selling behaviour of farm households. Rural credit schemes are arranged in such a way that loans are extended to farmers at planting (lean) season to finance agricultural inputs and smooth consumption, while repayments are due at or immediately after harvest. Using an IV approach to address endogeneity of credit use, we find that credit user households are more likely to sell their produce at or immediately after harvest. Our results remain robust to alternative definitions of early crop sales and a battery of sensitivity analyses, including heteroscedasticity-based identification and alternative model specifications. Nevertheless, we realize that claiming neat causality remains challenging with cross-section data. Thus, we could not rule out the possibility that other factors beyond credit repayments might partly explain why households sell early.

Households pay a financial penalty for selling early at harvest time, as they missed out on substantial expected price increments over three to six months. A counterfactual analysis indicates that the revenue loss is highest for the poorest quintile (as much as 51% of total revenue), suggesting a credit poverty penalty for poor households. Overall, the results indicate that

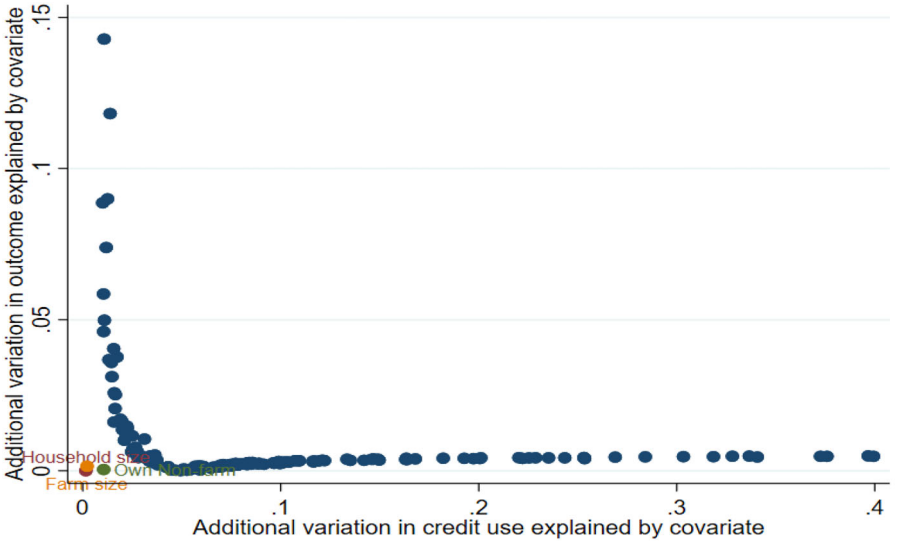

Figure 3. Sensitivity of estimated effect to omitted variable bias.

current rural credit arrangements tend to exacerbate the negative impacts of liquidity constraints and seasonal crop price cycles on poor households.

Our study provides insights into several empirical observations in the rural credit literature in the global south, reflecting on interesting interfaces between constraints, rationality, and preferences of poor rural households. The evidence presented cautiously speaks to the widely observed low demand for agricultural credit and mixed evidence on welfare impacts of rural (micro) credit (Banerjee, Chandrasekhar, Duflo, & Jackson, 2013; Tarozzi et al., 2015). Previous explanations for low demand for rural credit are founded on the notion that credit use is profitable. Our study highlights substantial (but often unaccounted) economic costs of early crop sales for credit repayments that could potentially dampen demand for credit.

Another important finding is about 92% of the borrowers sought to pay back credit at the harvest time. Given selling crops early is costly for farmers, this preference appears consistent with time-inconsistent behavior among poor farmers. However, several observations appear to discredit this interpretation. First, most of the loans were short-term loans, where farmers have limited option on the flexibility of repayments. Second, paying credit at harvest time may not be entirely against the interest of borrowers. We focus on the costs of paying credit at harvest time, but there could dynamic incentives to loan repayment—the prospect that borrowers could access to larger future loans upon repaying current loans. Third, defaulting on loans can be costly for borrowers, as it could tarnish their reputation and curtail their access to future loans. Fourth, losing collateral can be deleterious to household livelihoods, with many households withdrawing voluntarily from participating in rural credit markets.

Our results provide evidence against a recent literature that advocates for tailoring rural credit to the agricultural cycle, where repayments are typically due at harvest time (Casaburi & Willis, 2018; Duflo et al., 2011), ignoring seasonal price cycles. Specifically, our study casts some doubt on Duflo et al. (2011) that suggested for selling agricultural inputs at harvest time in Kenya. In contrast to this suggestion, Duflo et al. (2011) found that farmers did not seek to buy fertilizer immediately after harvest for later use at the planting season, a result which they interpreted as irrational time-inconsistent behaviour. But such behaviour could equally be explained by farmers' rational response to hard constraints.

Finally, our findings have important implications for policy. Notably, considerable welfare gains can be achieved by mitigating binding liquidity constraints and highly seasonal crop

prices that interact to be detrimental for poor households. From a rural credit policy perspective, flexible credit repayment schedules could be beneficial for poor households. But there is a need to move away from current thinking on designing flexible rural credit products where payments are due at harvest time. Instead, flexible credit products should allow farmers to repay credit later in the year when prices are generally higher. Innovative commitment schemes, such as warehouse receipt systems and secure community storage schemes, are likely to be needed to complement flexible credit repayment schedules.

A more broader policy lesson is the importance of addressing weak financial markets that are doubly costly for poor rural households. Facing weak financial markets, poor households are likely to be compelled to use much more expensive crop markets as a substitute for financial markets to meet their predictable and unpredictable expenditures. Improving access to inexpensive bridging credit at harvest can allow poor households to finance their expenditures at lower rates than those afforded by crop markets. Similarly, better development of crop markets and their regional integration could dampen the severity of seasonal price cycles.

We conclude by noting that costs and risks of poor farmers' participation in credit markets warrant more scrutiny. Profitability of credit has never been debated. Perhaps, a more direct way to assess whether rural credit markets are underutilized by farmers is to examine their profitability. While a full profitability analysis is beyond the scope of this paper, the material presented here hopefully highlights a potentially relevant hidden cost of rural credit market participation. Any future analysis of this topic must address purposes of early crop sales and account for the roles of various factors driving farmers to sell their crops early. Future studies may also investigate impacts of innovations and schemes (e.g., warehouse receipt systems) on farmers' ability to take advantage of price arbitrages and smoothing seasonal price dispersions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. Share of the three major crop sales in total sales

Crop	Share in total sales (%)
Teff	93.9
Wheat	94.0
Maize	94.3
Other cereals	94.6
Pulses	96.7
Oilseeds	96.8
Total	94.8

Source: *Ethiopian FtF survey (2013, 2015)*.

Table A2. First stage regression results and instrument falsification tests

Explanatory variables	(a) Credit use (LPM)	(b) Credit use (LPM)	(c) Early crop sale for non-credit users (LPM)
Log (credit size in village)	0.043***	0.052***	0.001
	(0.001)	(0.002)	(0.004)
Log (distance to credit source in km)	−0.002	−0.004*	−0.014
	(0.002)	(0.003)	(0.011)
Plot and household characteristics	No	Yes	Yes
Woreda fixed effects	No	Yes	Yes
Constant	0.037**	0.093**	0.455***
	(0.004)	(0.038)	(0.099)
Adjusted R2	0.163	0.210	0.094
F test of Excluded Instruments			
F(2, 251)	812.78	69.210	
Prob > F	0.000	0.000	
Weak-identification tests			
Cragg-Donald f-statistic		443.02	
Kleibergen-Paap rk Wald f-statistic		66.33	
Kleibergen-Paap p-value		0.000***	
Hansen J statistic		1.976	
Hansen J p-val		0.160	
Number of observations	11,912	11,921	5,929

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; LPM = Linear probability model; Standard errors clustered at the village level in parentheses. Coefficients on plot and household characteristics omitted to preserve space.

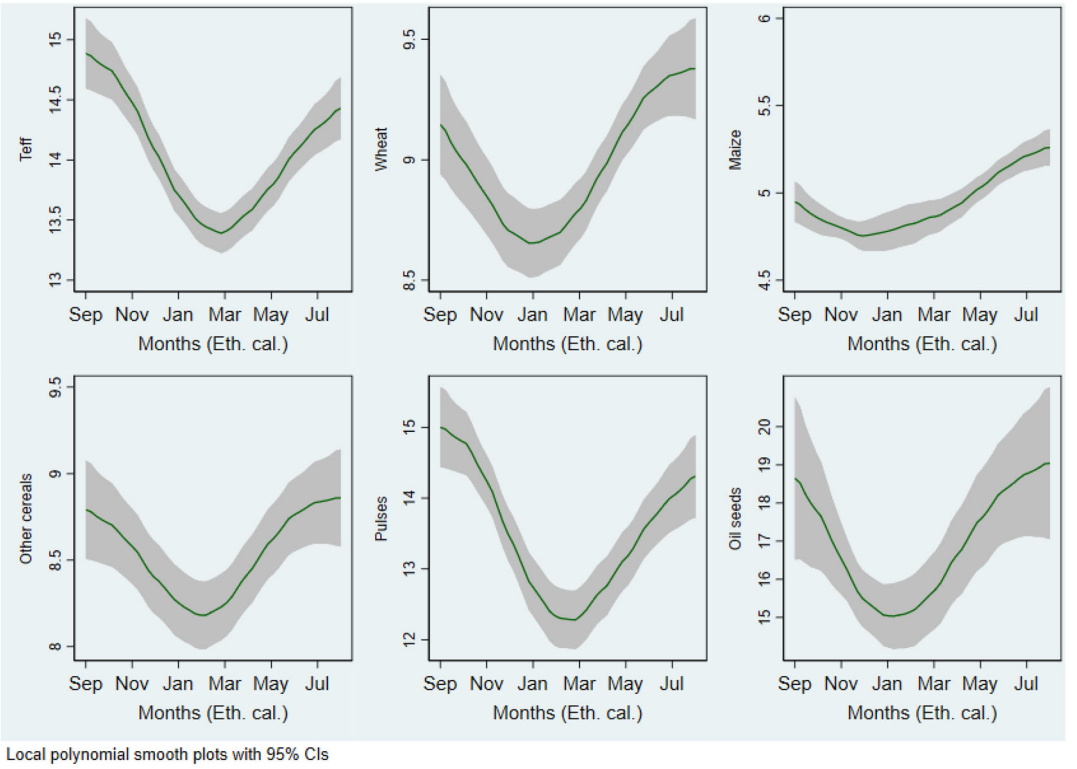

Figure A1. Monthly average retail nominal prices per kg across Ethiopian markets, for the period 2001–2017. *Source*: Authors' calculations using CSA nominal price data.

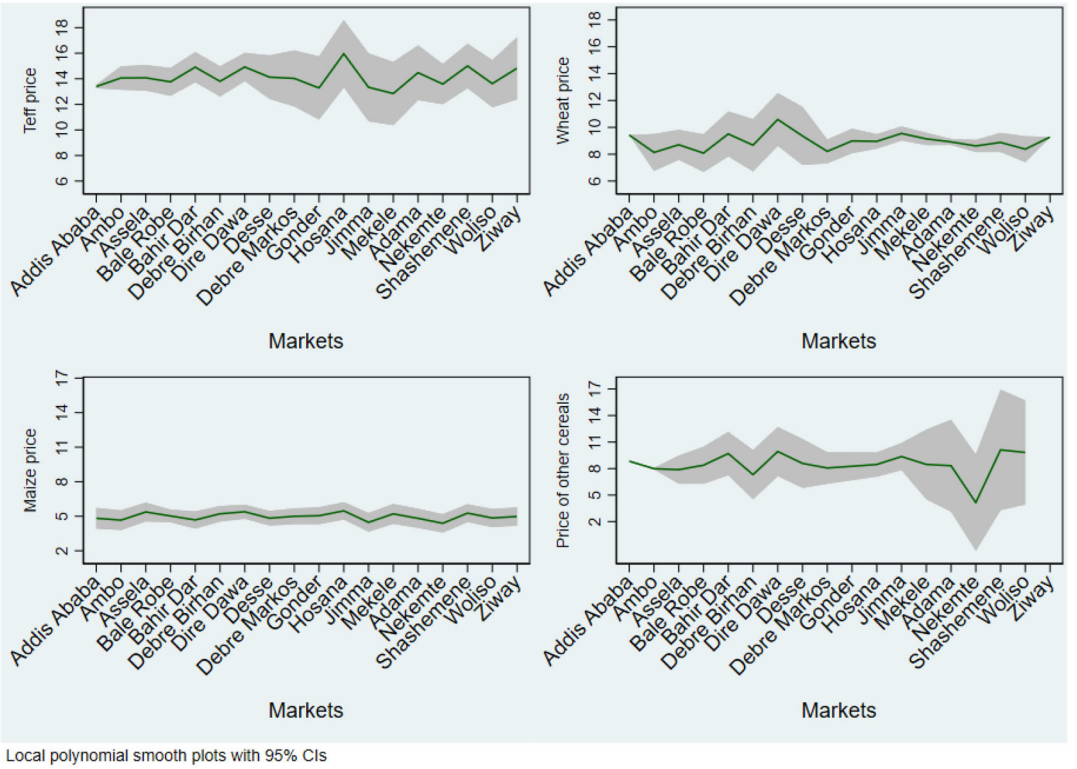

Figure A2. Average retail nominal prices per kg over the 12 months across major grain markets in Ethiopia, for the period 2001–2017. Local polynomial regressions; shaded areas refer to 95% confidence intervals. *Source*: Authors' calculations using CSA nominal price data.

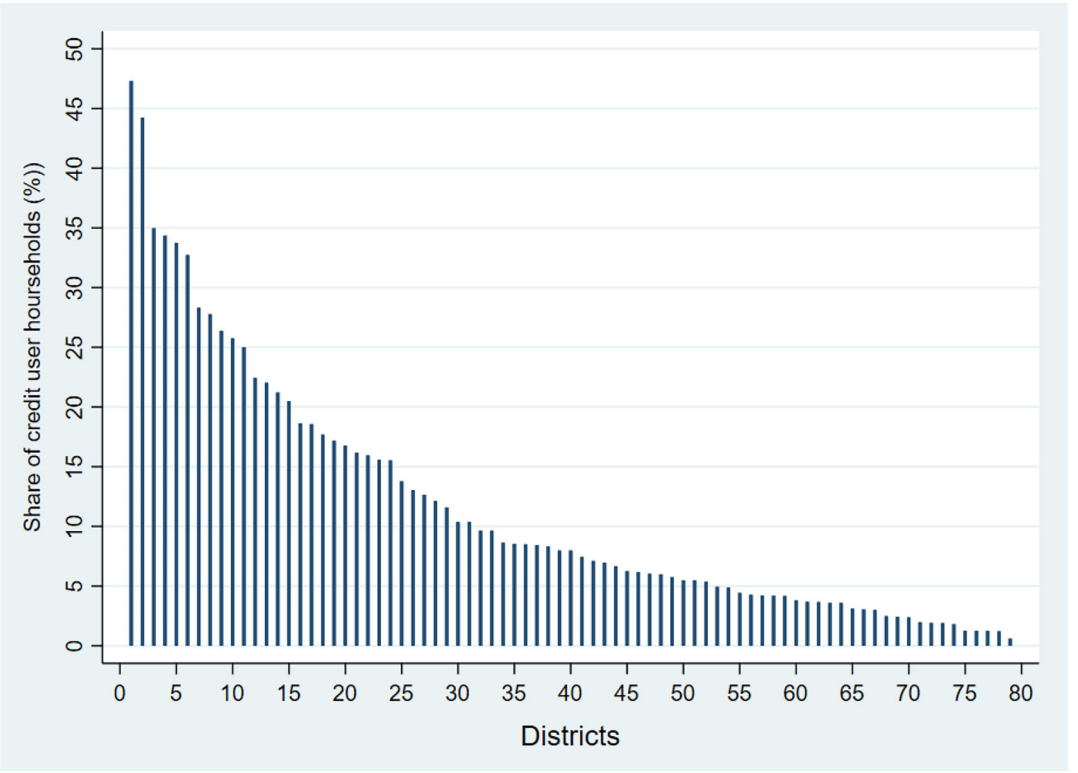

Figure A3. Percentage share of credit user households by district.