Financial Services and Divisible Technology Dis-adoption among Farm Households:

Theory and Empirical Application Using Data from Ethiopia

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ABSTRACT

The adoption of improved varieties and technologies by rural agricultural households remains a major goal in development efforts. This is because researchers and development practitioners recognize it as a potential source of income growth for the poor. However, while studies on adoption of improved technologies abound, little evidence exist on the continued use of improved technologies. This study addresses this gap by focusing on divisible technologies which do not require significantly high investments or capital. A dynamic stochastic model is formulated which analyzes the mechanics of adoption and abandonment of improved technology among poor households. The model is solved using numerical approximation methods for different regimes of financial intermediation. The results show that increasing credit limits helps in sustained adoption and prevents abandonment of high-income crop. Using discrete choice panel data models, we test the implications of our theoretical results with data from rural Ethiopia. The estimation results confirm that for households already engaged in high income crops like maize, access to credit prevents abandonment of the maize crop.

1.0 Introduction

The adoption of improved varieties and technologies by rural agricultural households remains a major goal in development efforts. While adoption has been promoted with mixed successes in developing regions, a less researched question is on technology abandonment also known as disadoption in the development literature. The sustained use of improved varieties remains important given recent efforts to foster income growth for poor households through improved agriculture. A few studies have analyzed factors which lead to the abandonment of improved technologies after farmers have adopted. A study by Bravo-Ureta et al. (2006) examined the causes of technology abandonment among rural households in El Salvador. The authors find that farm sizes of the respondents act to prevent abandonment of the improved technology. Another study by Moser and Barrett (2003) analyzed the use of improved rice variety in Madagascar. Moser and Barrett (2003) found that while farmers readily adopted the high-yielding rice variety when introduced, there was significant abandonment of the variety in subsequent years. Though the study by Moser and Barrett(2003) indicate that uncertainty with the improved variety and production risk contributed to abandonment, liquidity constraints played a crucial role in the decision to abandon the technology.

These studies lay an essential foundation for the current study. This study examines the mechanics behind technology abandonment among poor rural households and outlines a theoretical framework for the household’s choices. Using the theoretical model, the study first examines the effect of financial intermediation in the form of deposits or credit facilities on the decision to abandon the use of improved technology.

In addition to the theoretical model, data is used from rural Ethiopia to test the implications of the theoretical model. The Ethiopian Rural Household Survey is a panel dataset covering over 1,477 households surveyed six times is ideal to test the implications of the theoretical model. Cereal production has gained importance among rural households in Ethiopia and fundamental questions remain on factors explaining the changes in agricultural crops. Discrete choice models are used in examining the effect of financial intermediation particularly the access to credit on abandonment of the high-income maize crop.

Our theoretical results first show that increasing credit limits helps to sustain adoption of high-income technologies. Additionally, this result is independent of the interest rate of the credit received. The empirical data generally support the predictions of the theoretical model. For households who are engaged in the high income crop, access to credit leads to higher rates of crop retention.

2.0 Theoretical Model

The theoretical model is structured to reveal post-adoption credit policies. In order to clearly identify the effect of the financial policies on the decision of sustaining the production of a superior crop, the model abstracts from crop portfolio choices in which one could expect a mixed of crops to smooth households' income and consumption, and focus only on choices of either sorghum or maize. Let *i=0* represent the production of sorghum and *i=1* the production of maize. The income, $\tilde{y}_i$ associated to each crop is lognormally distributed and serially independent, with mean μ_i and volatility $\sigma_i > 0$. As maize is more profitable and more risky that sorghum, $0 < \mu_0 < \mu_1$ and $\sigma_1 > \sigma_0$.

The farmer begins each period possessing a pre-determined wealth, s, and invested in the advanced technology, $i = 1$, which generates her production income for the current period. The next period the farmer must decide whether to remain in the production of maize or switch to the production of sorghum. Even though the models allow for re-adoption in any subsequent period, the effects of financial policies on preventing dis-adoption are clearer by measuring abandonment rates forever excluding the dis-adopters. For instance, a circumstance where adoption requires a lumpy investment that can only be afforded via directed, one-time, credit will match this situation.

Farmer's incentives to abandon arise from the higher-risk implicit in the production of maize. He might also abandon because the per-period operational cost, κ, associated with the production of maize is also higher, thus $\kappa_1 > \kappa_0$. These costs are incurred in the current period, i, for harvesting the crop in the next period, j. Therefore, when the farmer makes her crop choice in the current period, she allocates a portion of his current income to the purchase of some operational inputs. These inputs purchased in advance will then generate next period's income, thus each crop choice is also a savings decision, which is not financial but in kind.

Transfer of wealth across periods is captured by a continuous choice variable, x, which denotes the amount of deposits or credit. A negative value of x indicates the farmer carries debt and a positive value indicates a financial savings. The farmer may deposit an unlimited amount, but borrow up to a limit $\bar{b}$ at a per-period interest rate $r > 0$. We also assume that $\min\{\tilde{y}_j\} > r\,\bar{b}$, so that in every period the farmer is able to cover the minimum required interest payment the following period. As deposit facilities are scarce in rural Ethiopia and savings in cash are more frequent, the model penalizes the deposit with a negative interest rate of one percent.

We assume that the utility function u exhibits constant relative risk aversion, $(c) = \frac{c^{1-\alpha}}{1-\alpha}$, and is a twice, continuously differentiable function of current consumption, with $u'(c) > 0$, $u" < 0$, and $u'(0) = -\infty$, where α is the parameter of risk aversion. The farmer maximizes the present value of current and expected future utility of consumption over an indefinite time horizon, at a per-period discount factor $\delta \in (0,1)$. The optimization problem is summarized by the Bellman equation:

$$V_i(s) = \max_{\substack{j=\{0,1\} \\ x \geq -\bar{b}}} \{u\big(s - \kappa_j - x\big) + \delta E\ V_j\big(\tilde{y}_j + x(1+r)\big) \tag{1}$$

where the unknown value function, V_i, represents the maximum present value of the current and expected utility of a farmer currently engaged in technology i. Given his wealth at the beginning of the period, s, and her choice of technology for the following period j, the difference $(s - \kappa - x)$ represents the farmer's current consumption.

The solutions for this problem of the representative farmer are the optimal choices of credit and crop, under different credit limits and interest rates. These policies are then used to evaluate the financial polices in an economy inhabited by a larger number of farmers, who are heterogeneous with respect to wealth and crop choice throughout the period.

2.1 Numerical Approximations

The value functions described by equation (1) are approximated via the collocation method (Miranda and Fackler, 2002). This method converts the Bellman functional equation with no known analytical solution into a finite-dimensional nonlinear equation that can be solved using nonlinear equation methods such as Newton's or Broyden's method. Specifically, each value function *V(s)* is approximated using a linear combination of M basis functions ϕ defined on the state space S, whose coefficients c are set by requiring the value function approximant to satisfy the Bellman equation at M collocation nodes $s_1, s_2, \dots, s_M$. That is, $V(s) \approx \sum_{w=1}^{M} c_w \, \phi_w(s)$, where

$$\sum_{m=1}^{M} c_w \phi_w(s_m) = \max_{x \in (-\bar{b}_i, \infty)} \{u(s_m, x) + \delta \sum_{h=1}^{H} \sum_{w=1}^{M} q_h c_w \phi_w(x(1+r) + \tilde{y}_{j,h}))\} \tag{2}$$

where the continuous random income is replaced with a discrete approximation constructed by using Gaussian quadrature, such that H is the number of quadrature nodes and q_h is the probability of income $\tilde{y}_h$.

Table 1. Baseline Parameter Values

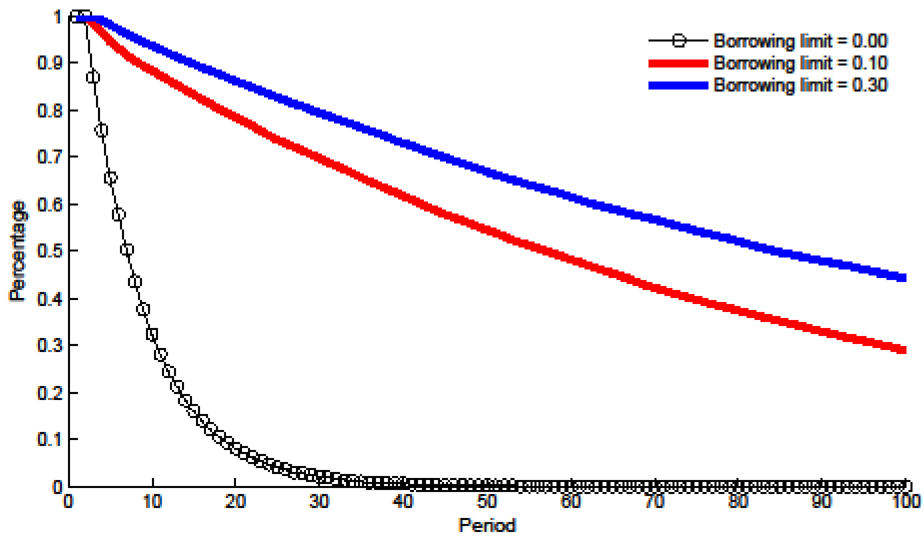
Parameter	Value	Description
δ	0.85	Per-period discount factor
α	2.09	Relative risk aversion
$[\bar{y}_0, \bar{y}_1]$	[0.80, 1.0]	Expected incomes
$[\sigma_0, \sigma_1]$	[0.25, 0.35]	Income volatility
$[\kappa_0, \kappa_1]$	[0.20 0.25]	Production costs
r	0.15	Per-period interest rate on loans
$\bar{b}$	0, 0.10, and 0.3	Borrowing Limits

The value functions and optimal policies are approximated using the parameters shown in Table 1. Parameters are chosen to reflect the economic environment of rural Ethiopia. The discount factor is reflective of impatience farmers and the risk parameter displays a high degree of risk aversion, both values are obtained from the prefer model of Fafchamps and Pender (1997). Income from maize production is normalized to unity using the gross income of maize producers in the final round of the survey. In order to better capture the Ethiopian credit environment, the interest rate on credit is set at an arbitrarily large value, 15 percent, compare to the literature (Dercon, 1998; Gomez-Soto, 2007; Miranda and Farrin, 2012).

Our parameter of interest is the credit limit, for which we simulate three different scenarios. In the first one, the credit limit is zero. This scenario portrays a situation where credit is conditioned on the adoption of an advanced technology, but once the adoption was achieved the farmer is excluded from the market. The second scenario represents a situation where there is continuous access to credit, but it is severely rationed (10 percent of the expected income). The third case represents an environment where the financial intermediary has found mechanisms to expand the credit limits to 30 percent without incurring in risk of default.

Figure 1 shows how the proportion of farmer engaged in the superior crop, i.e., maize evolves over hundred periods, given the distinctive policies of credit. It shows how in the absence of the financial mechanisms farmers tend to abandon the maize at a very rapid pace. For instance, in period 7 already 50% of the farmers dis-adopted.

Figure 1. Rates of Abandonment of Maize for Distinctive Credit Policies



The access to post-adoption credit might substantially mitigate the abandonment rates. The red line shows that, despite the credit limit being highly restrictive, the sole access to the financial service represents a risk coping mechanism that allows farmers to sustain the production of corn for prolonged periods, the 50% rate of abandonment is not reached until the period 57 when the limit is 10 percent the average income. Clearly, when the credit limits are extended, the ability of farmer to sustain the advanced technology is enhanced, which decreases the rates of abandonment.

It is worth nothing that the policy implication of the theoretical results is not simply an overflowing of credit in the rural sector, nor subsidized rates. Indeed, the relatively high interest rates seeks to portray the high cost of offering credit in rural areas. The results rather illustrate that sustain adoption of advanced production technologies require a continuous access to the financial mechanism.

3.0 Background and Data

Ethiopia's economy is mainly agrarian with agriculture contributing to about 80% of GDP. Similar to other regions in Sub-Saharan Africa, Ethiopia's agriculture is mainly small-scale, has low input and is characterized by traditional technology. Since 2005, several efforts have been made to spur agricultural production in the country by the government of Ethiopia and her development partners. Recent reports by Dorosh and Rashid (2013) indicate high levels of agricultural growth in the nation's economy. According to Dorosh and Rashid (2013) growth in the agricultural sector increased from 2.9% in the early 1990's to 6.2% in the 2000's. Despite these trends, Dorosh and Rashid (2013) indicate that gains in agricultural production have to be sustained and accelerated in order to ensure that poverty reduction goals for the country are met.

One feature of Ethiopia's agricultural growth in the crop production sector is the importance that cereal crops and other key staples have gained in the diet of rural and urban Ethiopians. Cereal production has grown from an average of 5.6 million metric tonnes during 1980-1990 to 10.7 million tonnes during the 2001 to 2008 period (Dorosh and Rashid, 2013). These agricultural changes have occurred with minimal infrastructural and technological advancement. Thus key questions remain concerning the factors determining the growth of cereal production in rural Ethiopia. In particular, policy-makers remain unclear on which drivers within the rural economy facilitate continued participation in profitable crops. This study aims to shed more light on how presence of deposit-saving mechanisms influences the household's ability to abandon or remain with a particular crop.

The role of financial development in economic development has been well established in the development literature. Access to financial services in the form credit and deposit services help households smooth consumption against shocks. However, financial development in Ethiopia and rural sector of the country has been limited and sparsely distributed throughout the country. Formal microfinance was introduced in Ethiopia in 1994 and the country currently has approximately 28 microfinance institutions. Furthermore, financial services are largely dominated by commercial banking institutions which typically have terms of services that are high for the rural small holder. According to Dorosh and Rashid (2013) the minimum requirement for opening an account for small-holders was 50birr ($1 = 10birr: 2008). This minimum balance is extremely high for rural households and largely excludes them from having access to financial services.

In place of formal options to access credit, informal credit and financial options have developed to fill the void in rural Ethiopia. Dercon and Krishnan (2003) report little formal financial activity in their review of 15 villages surveyed for the Ethiopian Rural Household Survey (ERHS). Though some households engaged in formal lending, the loans obtained formed a small proportion of the total consumption of the household.

The data for this study come from the Ethiopian Rural Household Survey (ERHS), a longitudinal household survey conducted in 15 peasant associations across rural households since 1994[1]. The survey was administered by the International Food Policy Research Institute (IFPRI) in collaboration with the Department of Economics at

[1] An earlier round of the survey exists (1989). However, according to the survey administrators, this cannot be easily merged with the remaining rounds and they suggest using rounds from 1994 onwards (Dercon and Krishnan, 2003).

Addis Ababa University (AAU) and the Center for the Study of African Economies (CSAE) at Oxford University. The ERHS interviewed 1,477 households six times between 1994 and 2004. The time between each of the first three rounds is approximately six months while the time between the third and fourth round and the fourth and fifth round is approximately two years. The time from the fifth round and the sixth round is four years. Hence the surveys capture agricultural activities for six growing seasons among the selected households, their livestock holdings, household characteristics and locational features. The current study uses data from the first four rounds of the survey and restricts the sample size to 478 households who cultivated maize in the first round.

Descriptive statistics for the sampled households are presented in Table 2. This study investigates whether having credit influence decisions to remain cultivating high-income food crops. The primary dependent variable of interest is maize which is the high-income crop cultivated by rural households. The percentage of households cultivating the different cereal crops are shown in Table 2. Barley is one of the most widely cultivated cereals in the study area. Maize and sorghum are also widely cultivated by the sampled households. This table reports only the percentage of households that are cultivating the crop for each round and masks possible transitions that might occur for each particular household.

Table 2. Percentage of Households Cultivating Cereal Crops per Round

Variable	Round 1	Round 2	Round 3	Round 4
Maize	43.3	43.4	46.4	36.2
Sorghum	39.8	31.2	40.0	31.1
Barley	54.7	53.6	42.9	46.5
Wheat	14.2	17.1	12.3	16.1

Source: Ethiopian Rural Household Survey.

4.0 Econometric Model

The decision on whether or not to grow a particular crop or remain growing that crop constitutes a discrete choice often made by the farmer. Econometric analyses of farmers' discrete decisions involve specifying an estimation equation where relevant factors affecting the probability of a choosing a particular crop are included. Depending on the nature of the dependent variables of interest, a discrete choice model can be formulated to analyze factors affecting a choice between two or more alternatives. A binary choice model is used in the current analyses[2].

Access to panel data permits unobserved effects in these models to be taken into account. For example, skill level or ability of the household head is unobserved and this would impact the binary decision of whether or not to cultivate a cereal crop.

The binary choice panel data model is given as:

$$P(Y_{it} = 1 \,|X_{it}\beta + c_i + \epsilon_i) \quad for\ t = 1, \dots, T \tag{1}$$

[2] While several cross-sectional multinomial or multivariate models exist, these models cannot be used with panel datasets without highly restrictive distributional assumptions.

Estimating equation (1) involves specifying a parametric distribution which relates the probability of choosing a particular crop ($Y_{it} = 1$) to the covariates (X_{it}) and unobserved effects (c_i). Additionally, binary choice panel data models require distributional assumptions between the unobserved effects c_i and the covariates X_{it} in the estimation equation. One method for estimating partial effects of the covariates while sidestepping distributional assumptions between c_i and X_{it} is the linear probability model (LPM). While the LPM does not have probabilities falling between zero and one, this estimation method allows for consistent fixed effects estimates (Wooldridge, 2002).

A fixed effects model could be specified which assumes that the conditional distribution of the dependent variable follows a logit distribution. Maximum likelihood estimation routines are used in this framework and involve maximizing a likelihood function to obtain the desired parameters. The identification strategy in this model is dependent on the logit functional form. However, this estimator is appropriate only for individuals that change state. Time-invariant explanatory variables cannot be included in the model. The logit model also results in inconsistent estimates when the conditional independence assumption fails.

The methods previously discussed do not model the conditional distribution of the unobserved effects in the model. The random effects (RE) probit model assumes that, conditional on the observed covariates, the unobserved component is normally distributed with constant variance (Wooldridge, 2002). This is given as $c_i|x_i \sim N(0, \sigma_\mu^2)$. This specification allows the unobserved component to be integrated out of the likelihood function following a procedure by Buttler and Moffit (1980). This approach is referred to as the conditional maximum likelihood method for estimating the random effects probit model. One restriction of this procedure is the independence between the unobserved effects and the observed covariates. However, this can be relaxed following a specification proposed by Chamberlain (1982) and Mundlak (1978). Chamberlain (1982) and Mundlak (1978) indicate that the unobserved effect can be allowed to be correlated with the covariates following a linear specification ($c_i = \gamma + \beta_i \bar{x_i} + \mu$). The variable $\bar{x_i}$ is the time-average of the exogenous covariates, γ is the constant and μ is the idiosyncratic error term. Probit models estimated with the Chamberlain and Mundlak extension are referred to as the correlated random effects probit model (CRE Probit Model). In this study, the linear probability models and the correlated random effects probit model are used.

5.0 Results

Our results verify whether access to credit services in rural Ethiopia significantly affect the adoption. The dependent variable is a dummy variable which takes the value of one if the household cultivates maize. Table 3 presents results using maize as the dependent variable. Table 4 uses sorghum as the dependent variable. The first model presents the results from the linear probability model. The last two columns in Table 3 presents the estimation results using the correlated random with and without village effects. For the results using the correlated random effects probit models, the marginal effects are reported.

From the LPM results, the amount of loan that the household receives significantly affects remaining in the technology. Thus one birr increase in the amount of the loan increases the probability of remaining in maize crop by 0.0002. Livestock value and household size significantly affect the likelihood of remaining in the high-income crop. From the results, young household heads are less inclined to remain growing maize. On the other hand, older household heads are more likely to remain growing maize. Regressions of loan amounts on the age of the household head reveal a similar pattern. This suggests that younger household heads' are less likely to receive credit and hence would be unable to remain in the technology. Older household heads who are more experienced and would have stronger social ties can access credit and also remain cultivating maize. The results for household demographic variables on the likelihood of cultivating maize are robust for the different specifications in Table 3. The correlated random effects probit model allows the inclusion of time-invariant variables in the estimation. The robustness of the analysis to the inclusion of village controls and other time invariant variables indicates that the effect of credit on reducing dis-adoption remains significant after accounting for village specific and other fixed effects.

Table 4 presents results using sorghum as the dependent variable. This set of results comes from the sample of households who cultivated maize in the first period of the survey. Thus this estimation asks whether access to loan significantly affect a decision to cultivate the low-income crop (sorghum). Results from the linear probability model show that while loan amount positively and significantly affects sorghum growth, this effect becomes insignificant when other time-invariant factors are taken into account. Furthermore, other household demographics were insignificant for the decision to cultivate sorghum.

Table 3. Effect of Loan amount on Maize Cultivation

	LPM Model	CRE Probit 1	CRE Probit 2
Loan (birr)	0.0002***	0.0003***	0.0002***
	(0.000)	(0.000)	(0.000)
Age of head (years)	-0.0280**	-0.0102**	-0.0088**
	(0.013)	(0.005)	(0.004)
Age of head (squared)	0.0003**	0.0001*	0.0001*
	(0.000)	(0.000)	(0.000)
Sex (=1 if male)	0.0448	-0.0186	-0.0030
	(0.123)	(0.034)	(0.032)
Education (=1, if head has completed primary education)	-0.1648	-0.0714**	-0.0036
	(0.139)	(0.031)	(0.030)
Land (acres)	0.0897*	0.0637	0.0835*
	(0.051)	(0.048)	(0.047)
Land (squared)	-0.0157**	-0.0161**	-0.0152**
	(0.006)	(0.007)	(0.007)
Household size	0.0259***	0.0168*	0.0198**
	(0.010)	(0.009)	(0.009)
Ln Livestock value	0.0175*	0.0133	0.0141*
	(0.009)	(0.008)	(0.008)
Rainfall index	0.0932*	0.0948**	0.1700***
	(0.053)	(0.042)	(0.040)
Time Controls	Yes	Yes	Yes
Village Controls		No	Yes
Constant	0.4980		
	(0.344)		
R^2	0.1643	-	-
R^2 within	0.1643	-	-
R^2 between	0.0269	-	-
R^2 overall	0.0953	-	-
Log likelihood	-7.6e+02	-9.6e+02	-8.9e+02
N	1.6e+03	1.6e+03	1.6e+03
Number of groups	478	478	478

***,**,* refer to significance at 1%, 5% and 10%, respectively. Standard errors are in parentheses.

Table 4. Effect of Loan amount on Sorghum Cultivation

	LPM Model	CRE Probit 1	CRE Probit 2
Loan (birr)	0.0001**	-0.0000	-0.0000
	(0.000)	(0.000)	(0.000)
Age of head (years)	-0.0184**	-0.0004	-0.0003
	(0.008)	(0.001)	(0.001)
Age of head (squared)	0.0002**	0.0000	0.0000
	(0.000)	(0.000)	(0.000)
Sex (=1 if male)	-0.0571	0.0163	0.0138
	(0.048)	(0.015)	(0.009)
Education (=1, if head has completed primary education)	-0.0822	-0.0510**	-0.0109
	(0.055)	(0.026)	(0.007)
Land (acres)	0.0149	0.0038	0.0072
	(0.036)	(0.017)	(0.008)
Land (squared)	-0.0029	-0.0005	-0.0010
	(0.005)	(0.003)	(0.002)
Household size	0.0116**	-0.0000	0.0003
	(0.006)	(0.002)	(0.001)
Ln Livestock value	-0.0022	-0.0034	-0.0015
	(0.005)	(0.002)	(0.001)
Rainfall index	-0.0230	-0.0146	0.0033
	(0.024)	(0.013)	(0.004)
Time Controls	Yes	Yes	Yes
Village Controls		No	Yes
Constant	0.5126***		
	(0.179)		
R^2	0.0789	-	-
R^2 within	0.0789	-	-
R^2 between	0.0000	-	-
R^2 overall	0.0237	-	-
Log likelihood	76.4069	-3.2e+02	-1.8e+02
N	1.6e+03	1.6e+03	1.6e+03
Number of groups	478	478	478

***,**,* refer to significance at 1%, 5% and 10%, respectively. Standard errors are in parentheses.

6.0 Conclusions and Recommendations

This study investigates the ability of financial services (particularly credit) to encourage dis-adoption of high-income crops. The theoretical model showed that higher levels of credit for low income households would enable these households sustain the production of risky but high income crops.

The empirical results using data from rural Ethiopia generally support the theoretical results. Estimation results from the linear probability model and the correlated random effects probit models, indicate that real loan amount have a positive and significant effect on decision to remain in the high-income crop (maize). On the other hand, loan amount did not have a significant effect on the low-income crop (sorghum). Furthermore, land holdings per households, livestock holdings and the household size significantly affect the decision to remain in the high-income crop.

At a minimum, these results suggest that increasing access to financial services and particularly to loans in rural Ethiopia would facilitate continued adoption of high-income crops and create pathways out of rural poverty.

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