Working Paper Series

#2023-028

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Published 14 August 2023

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UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology
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Does Exposure to Markets Promote Investment Behavior? Evidence from Rural Ethiopia

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Abstract

This study investigates the effect of exposure to markets on farm households' agricultural investment decisions. We assess whether and how market experience affects farmers' adoption of risky but profitable technologies and explore the role of plausible demand-side barriers therein. Specifically, we hypothesize that risk preferences and locus of control change with market experience and as such may explain the relationship between market experience and investment decisions. We use surveys and incentivized experimental data, collected from the Tigray regional state of Ethiopia and use an Endogenous Switching Probit and IV-Probit models to attenuate endogeneity issues. Our findings suggest, first, that market exposure induces farmers to adopt agricultural technologies, such as chemical fertilizer, improved seeds, manure, and row planting and second, that market experience attenuates risk aversion and, although less robustly so, leads to a more internal locus of control. Policies to increase farmers' investments may thus not be confined to providing access to technologies and information but should perhaps be complemented with interventions that attend to lowering psychological barriers.

JEL Classification: C93, G22, H41, O17

Keywords: Agricultural investment, locus of control, markets, risk preference, Ethiopia

1. Introduction

Agriculture remains the cornerstone of several developing countries' economies and continues to serve as the principal source of income, employment, and foreign exchange. However, most existing studies unequivocally point out that the performance of agriculture did not live up to the expectations. In Sub-Saharan Africa and elsewhere in developing countries, the sector is still characterized by stagnant and volatile productivity (Evenson and Gollin, 2003; Pretty et al., 2011; Suri, 2011; Block, 2014; Barrett et al., 2017). The use of modern agricultural technologies has been considered as a pathway to boost productivity. However, despite concerted policy efforts to increase the use of modern agricultural technologies, the adoption rate has been far from complete (Zerfu and Larson, 2010; Sheahan and Barrett, 2017; Foster and Rosenzweig, 2010).

There is a plethora of explanations for the low take up of productivity enhancing agricultural technologies, including heterogeneous return to these technologies (Suri, 2011), weather risks (Alem et al., 2010; Dercon and Christiaensen, 2011; Holden and Quiggin, 2017), credit and insurance market imperfections (Duflo et al., 2011; Karlan et al., 2014), social network and learning (Oster and Thornton, 2012; Maertens and Barrett, 2012; Conley and Udry, 2010; Krishnan and Patnam, 2013), access to agricultural cooperatives and extension services (Abebaw and Haile, 2013; Krishnan and Patnam, 2013; Minten et al., 2013), quality of inputs (Bold et al., 2017), access to input and output markets (Zeller et al., 1998; Minten et al., 2013; Aggarwal, 2018; Aggarwal et al., 2018), knowledge and education (Asfaw and Admassie, 2004).[1] Following Abay et al. (2017), we label these factors as *external constraints*.

Recent behavioral insights provide a complementary perspective by demonstrating the role of psychological barriers in explaining low investments in remunerative agricultural technologies (Duflo et al., 2011; Liu, 2013; Brick and Visser, 2015; Holden and Quiggin, 2017; Bernard et al., 2014; Abay et al., 2017; Taffesse and Tadesse, 2017). Duflo et al. (2011) for example finds that farmers with time-inconsistent preferences are less likely to invest in inorganic fertilizer in Western Kenya. Related, since farmers in developing countries operate in inherently risk environments low uptake of agricultural technologies may be related to preferences for risk aversion. For instance, Liu (2013) finds that risk and loss averse Chinese farmers' exhibited substantial delays in the adoption of new technologies (Bt cotton). Similarly, Brick and Visser (2015) demonstrates that risk-aversion deters the use of modern farming inputs in framed field experiments in South Africa, even though index insurance for crop loss is readily available,

[1] see Foster and Rosenzweig (2010) for a review.

suggesting the presence of basis risk. The findings of a recent field experimental study from Central and Southern Malawi by Holden and Quiggin (2017) also lend support to these findings. The authors show that while risk-averse farmers are more likely to adopt and dis-adopt drought tolerant and traditional maize varieties, respectively, they are less likely to use improved maize varieties. Next to risk aversion, a person's locus of control is expected to matter in investment decisions. An internal locus of control, that is the extent to which people believe life's outcomes generally result from a person's own efforts rather than fate, luck, or powerful others, has been shown to affect savings **?** ; job search and labour supply **???**; educational decisions **?**; and technology adoption Bernard et al. (2014) Abay et al. (2017) Taffesse and Tadesse (2017). Following Abay et al. (2017), we label these factors as *internal constraints*.

This paper combines these two strands of literature and posits that *internal and external* factors may influence each other: exposure to markets (an external constraint) may affects farmers' investment behavior through its effects on internal constraints like risk preferences and locus of control. [2] For market experience to have a causal impact on investment decisions through changes in preferences and locus of control we require such preferences and personal traits to be malleable to some extent. Fortunately there is now a well-established theoretical and empirical literature that refutes the old idea of preferences and traits being exogenous and stable over the life-cycle (Becker and Mulligan, 1997; Bowles, 1998; Netzer, 2009) (Cobb-Clark and Schurer, 2013; Elkins et al., 2017).

New research documents that market experience significantly affect risk preferences (Melesse and Cecchi, 2017; Haile et al., 2020).[3][4]

We are not aware of previous studies on the effect of market experience on locus of control, but empirical studies provide indirect evidence to support to our premise. Elkins et al. (2017) for example reports that locus of control systematically varies with small but frequent life events - like market experience. Further, Bernard et al. (2014) shows that a person's locus of control can be changed through simple behavioral interventions.

In this paper, we hypothesize that farmers with high market exposure will exhibit less

[2] in this paper we try to identify a plausible causal link running from market exposure to changes in risk preferences and locus of control although we of course acknowledge that causality may go in both directions - that is, changes in preferences and locus of control through some sort of shock or experience may affect market access.

[3] Markets also significantly affect social (Henrich et al., 2001, 2010; Siziba and Bulte, 2012; Dietrich et al., 2018) and moral (Falk and Szech, 2013; Bartling et al., 2015; Nigus et al., 2020) preferences.

[4] The concept of endogeneity of preferences and the role of social, economic, and environmental factors in the formation of preferences has garnered the attention of researchers over the course of the last two decades. Existing empirical evidence show that environmental shocks and natural disasters (Page et al., 2014; Cameron and Shah, 2015; Hanaoka et al., 2018; Kahsay and Osberghaus, 2018; Di Falco et al., 2019; Sakha, 2019), macroeconomic and financial shocks (Malmendier and Nagel, 2011; Cohn et al., 2015; Guiso et al., 2018; Sakha, 2019), exposure to violence and crime (Voors et al., 2012; Callen et al., 2014; Jakiela and Ozier, 2019; Brown et al., 2019) shape preferences.

risk-aversion and high internal locus of control, and in turn, are more likely to use productivity-enhancing agricultural technologies. To test the tenability of this hypothesis, we take advantage of a unique, albeit cross-sectional survey and field experimental data collected from landed farm households in the Tigray regional state of Ethiopia. Ethiopia, especially, Tigray regional state, is an interesting testing ground to study the indirect effect of market exposure on farmers' investment behavior. This is because in rural Tigray and elsewhere in the country, modern agricultural inputs are primarily supplied through a parastatal agricultural cooperatives (Dercon and Christiaensen, 2011; Abebaw and Haile, 2013; Minten et al., 2013). Interestingly, these cooperatives are established in nearly all villages in the country, and farmers hardly have a significant difference in access to these inputs. Markets may thus promote the adoption of modern farming inputs through attenuating risk-aversion and enhancing internal locus of control.[5]

Identifying the causal effect of market exposure on farmers' investment behavior is, however, empirically challenging and poses a serious concern for at least two reasons. First, market experience and investment decisions may co-evolve - the causal effect may go from investment behavior to experience in trading. Second, there might be omitted variables, such as entrepreneurial ability, which drive both market experience and investment behavior simultaneously. To attenuate these concerns, we employ an endogenous switching probit (ESP) and instrumental variable (IV) approaches. Following previous studies, we instrument farmers' market exposure using household-level distance to the market (Melesse and Cecchi, 2017).[6] We find that market exposure significantly increases the adoption of risky but profitable agricultural technologies. We show that market exposure alters farmers' investment behavior by attenuating risk-aversion and improving internal locus of control.

Our findings contribute to two strands of literature. First, the findings extend the large literature on the drivers of farm households' investment behavior. To date, the existing literature treat *internal* and *external* constraints as independent. However, we argue that both constraints may not be independent, and *external* factors, such as markets, may predict the changes in the *internal* constraints, including preferences and personality traits. Second, it contributes to the thin literature on the effect of change in economic institutions on economic preferences and personality traits.[7] Our findings have important policy implications, especially in Sub-Saharan Africa, where concerted policy efforts are undertaking to spur the use of modern inputs and boost agricultural productivity. The results suggest that market exposure is an important mechanism

[5] Market exposure may affect investment behavior through a multitude of channels, among others, via increasing their income, social network, and access to information. Nevertheless, this is beyond the scope of this paper.

[6] Geographical distance has also been employed as an instrument to address the endogeneity concerns in previous studies (e.g., see Theil and Finke (1983); Hall and Jones (1999); Nigus et al. (2018))

[7] To our knowledge, the study by Melesse and Cecchi (2017) is a notable exception to establish a causal and rigorous effect of market exposure on risk preference.

to attenuate risk-aversion and improve locus of control, thereby increasing the adoption of productivity-enhancing agricultural technologies.

The remainder of the paper proceeds as follows. Section 2 provides details on the field setting, data type, and source. Section 3 presents the identification and estimation strategies. In section 4, we present the results of the study. Section 5 concludes.

2. Context and Data

2.1. Sample and Setting

The present study is part of a larger experiment that focuses on whether or not markets erode socially responsible behavior and the role of regulations and culture on social responsibility in competitive markets (Nigus et al., 2020). We collected both survey and monetary incentivized experimental data from a randomly selected 544 farm households belong to 32 tabias[8] located in five woredas (districts) in the Tigray regional state of Ethiopia. Farm households were invited to participate in some lab-in-the-field experiments, namely, risk, competition, market and joy of destruction, and a follow-up survey. Farmers first take part in the experimental games and then be involved in a household survey. The household survey extracts detailed information on farm households' demographic characteristics, wealth and assets, social capital, self-reported information on idiosyncratic and covariate shocks. The survey also contains information on farmers' locus of control, market exposure, adoption of agricultural technologies (chemical fertilizer, improved seed, organic fertilizer, and row planting), etc. Although we collected the data from 544 households, the analysis in this study is confined to 502 farm households who own agricultural land. This is mainly because farm households who do not own any agricultural land by default do not adopt any of the agricultural technologies. The description and descriptive statistics of the variables used in this study are presented in Table A1 in the appendix.

2.2. Outcome Variables

The key variable of interest is farmers' investment behavior, which is proxied by the adoption of agricultural technologies. This study focuses on four agricultural technologies, namely, chemical fertilizer, improved seed, organic fertilizer, and row planting. Following the standard practice in the literature, we measure technology adoption using survey data (Dercon and Christiaensen, 2011; Kebede and Zizzo, 2015; Abay et al., 2017). Agricultural technology adoption is a binary variable taking the value of 1 if the farmer adopted an agricultural technology, and 0 otherwise.

[8]Tabia, synonymous to a village, is the smallest administrative unit in Ethiopia.

2.3. Impact Pathways

2.3.1. Risk Preference

To elicit farmers' risk preference, we use an incentivized risk game with positive expected payoffs that follow Gneezy and Potters (1997) and Gneezy et al. (2009). This is one of the simplest risk elicitation methods one can use, especially in rural areas of developing countries where the majority of households cannot read and write. At the beginning of the experiment, subjects received an initial endowment of 30 Birr and subsequently asked to decide on how much of their initial endowment to keep on a risk-free account with a zero interest rate and how much to invest in a risky investment with a 50% probability of tripling and 50% probability of losing their entire investment. The precise form of the risk experiment is provided in appendix B.

The main interest in this study is to test whether market exposure affects investment behavior through attenuating risk-aversion. Hence, we measure households' risk-aversion as the proportion of the initial endowment, which is not invested in a risky investment relative to the total endowment of 30 Birr. Figure 1 displays the distribution of farmers' risk-aversion index. The figure shows the presence of considerable heterogeneity in the risk preference of the farmers in our sample. While a relatively large number of farmers (13%) decided not to invest in the risky investment at all, a non-trivial number of farmers (9%) chose to spend their entire endowment in the risky investment. Figure 1 also reveals that most of the farm households are risk-averse and decided to invest only about one-third of their entire endowment.

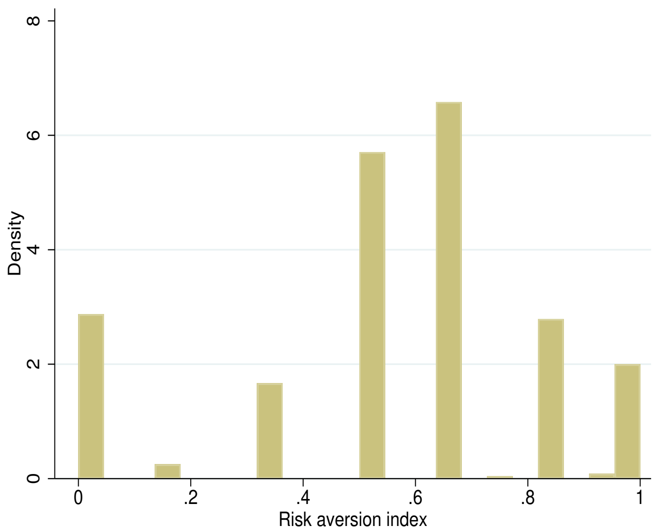

Figure 1: Distribution of Farmers' Risk-aversion

2.3.2. Locus of Control

We elicit farmers' locus of control using farmers' response to Rotter (1966) scale. Specifically, respondents were asked to indicate how much they agree with the statements presented in Table 1 using a five-point Likert scale ranging from "strongly disagree" to "strongly agree." We use factor analysis to construct a single index of the five items measuring locus of control. The use of factor analysis to create a single index of locus of control is not new. Such an approach has been commonly used in previous studies exploring the effect of locus of control on various economic outcomes (e.g., see Heckman et al. (2006); Caliendo et al. (2015); Cobb-Clark et al. (2016); Abay et al. (2017); Schurer (2017)). The factor analysis shows that all five items load unambiguously onto one factor, and we used the first predicted factor in our analysis. Larger values of the locus of control index correspond to an increasing internal locus of control. For ease of interpretation, we standardize this index to have zero mean and standard deviation of 1. Figure 2 offers the distribution of the locus of control index. The figure reveals substantial heterogeneity in farmers' internal locus of control, with most farmers' locus of control concentrated around the mean.

Table 1: Components of Internal Locus of Control

Item	Mean	Std. Dev
My life is determined by my own actions.	4.221	0.623
When I get what I want, it is usually because I worked hard for it.	4.070	0.68
I am usually able to protect my personal interests.	4.024	0.736
I can mostly determine what will happen in my life.	3.962	0.800
When I make plans, I am almost certain/guaranteed/sure to make them work.	4.046	0.718

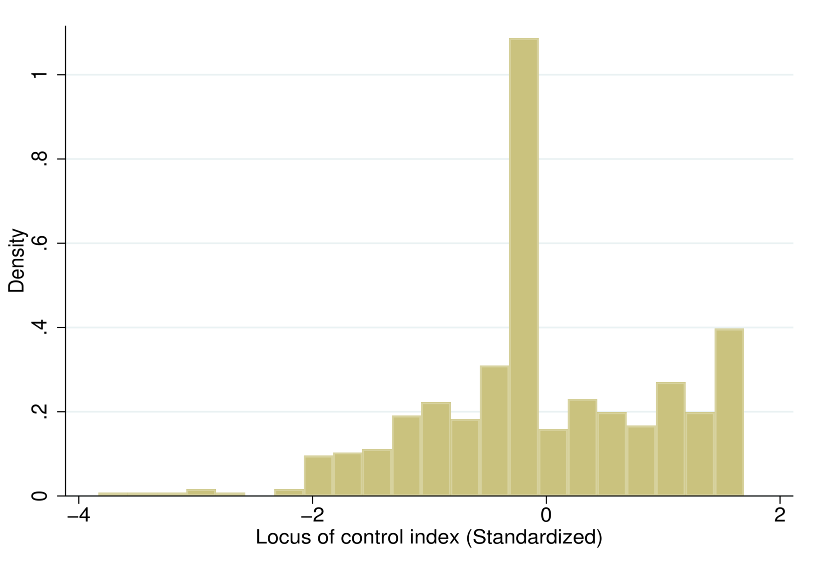

Figure 2: Distribution of Farmers' Internal Locus of Control (Standardized).

2.4. Market Exposure

In the economics literature, exposure to market[9] has been defined and measured in several ways. For instance, Henrich et al. (2001, 2010) and Dietrich et al. (2018) define exposure to market as the share of calories purchased from the market relative to the total calorie consumption. Market exposure has also been measured as income earned from different sources (wage labor, trades, and rent) other than home production. Furthermore, market exposure was also proxied by the frequency of wage labor and the frequency of purchasing goods for a future resale (Henrich et al., 2001, 2010). On the other hand, market exposure has been measured as the average number of actual transactions (both buying and selling) made in a typical month (Melesse and Cecchi, 2017). Further, market exposure is defined as the number of trips to markets regardless of whether or not farmers made transactions and the volumes of transactions (Melesse and Cecchi, 2017; Henrich et al., 2001, 2010).

We measure farmers' exposure to the market in terms of the average number of market transactions, instead of the share of consumption goods purchased from the market. This is because measuring market exposure using the former approach offers several advantages. First, the latter approach captures the buying, not the selling-side of the market. Second, in developing countries where Ethiopia is not an exception, the majority of farm households are male-headed households, which constitute more than 70% of our sample households. However, females are primarily responsible for the purchase of consumption goods. Hence, the latter approach may impede us from properly measuring male-headed households' market exposure. Further, the calorie-based approach is very susceptible to measurement errors and extreme values compared to the transaction-based measure of exposure to the market. We constructed two measures of exposure to the market. First is a continuous measure of exposure to market - market experience - the average number of market transactions made in a typical month. Second is a binary measure of market exposure - market exposure - taking a value of 1 if a farm household made greater than the median number of market transactions, 0 otherwise.

3. Estimation Strategy

This study aims to examine whether and how exposure to large output markets affects farmers' agricultural investment decisions. However, exposure to markets may be endogenous as farmers may self-select into making trades (buying and selling) or not. Perhaps, the endogeneity problem may also eventuate from the opposite direction due to reverse causality, that is, from farmers'

[9]We used market integration and market exposure interchangeably.

investment behavior to market participation. Additionally, there might be omitted variables, such as innate ability and entrepreneurship, that affect the decision to make trades and farmers' investment decisions. Hence, in the absence of randomization, failure to address the endogeneity concern may impair the causal impact of exposure to markets on investment decisions. We attempted to address the endogeneity concern by using two econometric models, which have received considerable attention in the recent econometrics literature - endogenous switching probit (ESP) and instrumental variable (IV) models.

As has already been mentioned, we constructed two proxies of exposure to the market: (i) "market experience" - a continuous variable capturing the number of actual market transactions made in a typical month, (ii) "market exposure" - a binary variable taking a value of 1 if a household made greater than the median number of market transactions. To estimate the impact of a continuous endogenous regressor - market experience – on binary outcomes (adoption of agricultural technologies), we use the IV-probit model. Similarly, we utilize the ESP model to estimate the impact of a binary endogenous regressor - market exposure – on binary outcomes.

We use both econometric models as each model has its own advantage over the other. Both estimation methods rely on the normality assumption. The IV-probit performs well when applied to the estimation of binary choice models with continuous endogenous regressors such as the market experience variable. On the other hand, the ESP method fits well when applied to a binary choice model with a binary endogenous regressor. Moreover, as the ESP model relaxes the assumption of the equality of coefficients of the outcome variable in two regimes, it is more efficient than the IV strategy. Further, while the ESP model enables to estimate the average treatment effect on the treated (ATT) and marginal treatment effect (MTE) (Lokshin and Glinskaya, 2009), the IV strategy measures only local average treatment effect (LATE) (Angrist, 1991). Next, we discuss the details of ESP and the IV-probit models.

3.1. Endogenous Switching Probit Model

Following Lokshin and Sajaia (2011), consider a farm household with two binary outcome equations (adoption of modern agricultural technologies) and the criterion function M_i (market exposure) that determines which regime the farm household faces.

$$\begin{aligned} M_i = 1 \quad if \;\; \Gamma Z_i + \mu_i > 0 \\ M_i = 0 \quad if \;\; \Gamma Z_i + \mu_i \leq 0 \end{aligned} \tag{1}$$

$$y_{1i}^* = \eta_1 X_{1i} + \epsilon_i \quad y_{1i} = I(y_{1i}^* > 0) \tag{2}$$

$$y^*_{0i} = \eta_0 X_{0i} + \epsilon_i \quad y_{0i} = I(y^*_{0i} > 0) \tag{3}$$

where y^*_{1i} and y^*_{0i} are the latent variables (use of modern agricultural technologies) that define the observed binary outcomes y_1 and y_0 (whether the farm household adopted improved agricultural technologies) for a household with high or less market exposure, respectively; X_i is a vector of exogenous variables determining adoption of agricultural technologies; Z_i is a vector of variables that determines market exposure; $\eta 1$, $\eta 0$, and Γ are vectors of unknown parameters to be estimated; and μ_i, ϵ_{1i}, and ϵ_{0i} are the error terms of the selection and outcome equations, respectively, which are assumed to be jointly normally distributed with a mean-zero vector and correlation matrix:

$$\Omega = \begin{pmatrix} 1 & \rho_0 & \rho_1 \\ & 1 & \rho_{10} \\ & & 1 \end{pmatrix} \tag{4}$$

while ρ_0 and ρ_1 are the correlations between μ_i, ϵ_{0i}, and μ_i, ϵ_{1i}, respectively, ρ_{10} is the correlation between ϵ_{0i} and ϵ_{1i}.The statistical significance of either ρ_0 or ρ_1 is an indication of the presence of self-selection bias in markets exposure. In addition, the likelihood ratio test, $\rho_0 = \rho_1$, is used to test the joint independence of equations [(1) - (3)]. Equations [(1) - (3)] can be estimated using the full information maximum likelihood (FIML) following the procedure of ESP model in previous studies (Lokshin and Glinskaya, 2009; Lokshin and Sajaia, 2011). However, since we do not observe y_{1i} and y_{0i} simultaneously, the joint distribution of (ϵ_0, ϵ_1) is not identified, and thus, ρ_{10} cannot be estimated. The model is identified by nonlinearities of its functional form of the bivariate normal distribution. Nevertheless, to improve identification, we employ a variable (household distance to a market) which is believed to affect household's market exposure but not to directly influence investment decisions (we will discuss this in detail later in this section).

The advantage of the ESP model is that it enables us to estimate a range of treatment effect measures. Following Aakvik et al. (2005) and Lokshin and Sajaia (2011), after estimating the ESP's parameters, we can calculate a variant of treatment effects - the effect of the treatment on the treated (TT), the effect of the treatment on the untreated (TU), the treatment effect (TE), and the marginal treatment effect (MTE) - using equations 5, 6, 7, and 8, respectively:

$$\begin{aligned} TT(x) = Pr(y_1 = 1|M = 1, X = x) - Pr(y_0 = 1|M = 1, X = x) = \\ \frac{\Phi_2(X_1\eta_1, Z\gamma, \rho_1) - \Phi_2(X_0\eta_0, Z\gamma, \rho_0)}{F(Z\gamma)} \end{aligned} \tag{5}$$

$$Tu(x) = Pr(y_1 = 1|M = 0, X = x) - Pr(y_0 = 1|M = 0, X = x) = \frac{\Phi_2(X_1\eta_1, -Z\gamma, -\rho_1) - \Phi_2(X_0\eta_0, -Z\gamma, -\rho_0)}{F(-Z\gamma)} \tag{6}$$

$$TE(x) = Pr(M = 1, X = x) - Pr(M = 0, X = x) = F(X_1\eta_1) - F(X_0\eta_0) \tag{7}$$

$$MTE(x, \bar{\upsilon}) = Pr(M = 1|X = x, \mu = \bar{\mu}) - Pr(M = 0|X = x, \mu = \bar{\mu}) = F(\frac{X_1\eta_1 + \rho_1\bar{\mu}}{\sqrt{1-\rho_1^2}}) - \frac{X_0\eta_0 + \rho_0\bar{\mu}}{\sqrt{1-\rho_0^2}}) \tag{8}$$

where F is the cumulative function of the univariate normal distribution, and $\Phi 2$ is the cumulative function of a bivariate normal distribution. TT is the difference between the predicted probability of adopting agricultural technologies for households with high market exposure and the probability of adopting agricultural technologies for households if they had no exposure to the market. TU is the expected effect on the adoption of agricultural technologies if households with less market exposure have had high exposure to the market. TE is the effect of market exposure for a farmer randomly drawn from the population, and MTE is the effect of the treatment for farmers with observed characteristics x and unobserved characteristics, $\bar{\mu}$. The average treatment effects (ATT, ATU, and ATE) for the corresponding subgroups of the population can be calculated by averaging 6 through 8 over the observations in the subgroups.

3.2. Instrumental Variable (IV) Approach

To account for the continuous nature of our key variable of interest (market experience), we employ the IV-probit model. The IV-probit fits models with a dichotomous dependent variable and a continuous endogenous regressor. Given the binary nature of the outcome variable (whether a farm household adopts modern agricultural technologies or not) and the continuous nature of the endogenous regressor (market experience), we utilize the IV-probit model.

The IV-probit model can be defined as:

$$A_i^* = M_i\beta + x_{1i}\gamma + \upsilon_i \tag{9a}$$

$$M_i = x_{1i}\pi_1 + x_{2i}\pi_2 + \epsilon_i \tag{9b}$$

where $i = 1, ..., N$, M_i stands for a $1 \times \rho$ vector of endogenous variables such as market experience, x_{1i} is a $\kappa_1 \times 1$ vector of exogenous variables, x_{2i} is a $\kappa_2 \times 1$ vector of additional instruments, and the equation for M_i is written in reduced form. By assumption, $(\epsilon_i; \upsilon_i) \sim$ N(0;Σ), where σ_{11} is normalized to one to identify the model. β and γ are vectors of structural parameters, and π_1

and π_2 are matrices of reduced-form parameters. This is a recursive model: M_i appears in the equation for A_i^*, but A_i^* does not appear in the equation for M_i. While we do not observe the latent variable A_i^*, we observe

$$A_i = \begin{cases} 1, & \text{if } A_i^* \geq 0 \\ 0, & \text{if } A_i^* < 0 \end{cases}$$

The necessary condition for identification of the structural parameters requires at least one instrumental variable for one endogenous variable. We use household-level distance to market as an instrument for farmers' market exposure.

4. Results and Discussions

In this section, we first present the estimation results of the endogenous switching probit followed by the results of the IV-probit model. Next, we discuss the causal mechanisms through which market exposure affects farmers' investment behavior.

4.1. Results of Endogenous Switching Probit Model

Tables 2, A2 and A3 present the estimation results of the full information maximum likelihood (FIML) of the ESP model. At the bottom of Tables A2 and A3, we report the correlation between the error terms in the selection (μ_i) and outcome equations for adopter's (ϵ_1) and non-adopters of (ϵ_0) of agricultural technologies which is used to test for the presence of self-selection in market exposure. The tables also report the wald $\chi 2$ test statistic to test the joint independence of the equations. The tables show that the correlation between the error terms in the selection (market exposure) and the technology adoption equations of farmers with high market exposure (ρ_1) are negative and statistically significant,[10] suggesting that self-selection exists for farmers with high market exposure. This implies that using the ESP model to account for the self-selection bias is necessary. The wald $\chi 2$ test is also significantly different from zero, indicating that the regimes of technology adoption for households with high and less market exposure are distinct, and the ESP model is preferred to probit and bivariate probit models.

Although the ESP model is identified by the non-linearities in the functional form of the bivariate normal distribution and does not require exclusion restrictions, for better identification, we used household-level distance to a weekly market as an exclusion restriction. We run several diagnostic tests to verify the validity of our exclusion restriction, and these tests are reported in Tables A2, A3, and A4. First, following Di Falco et al. (2011), we conducted the falsification

[10]Except for the adoption of chemical fertilizer.

test - whether the selected instrument (distance to market) affects farmers' market exposure but not the technology adoption decisions of farmers with less market exposure. The falsification test for the admissibility of the exclusion restriction shows that the selected instrument is valid as the distance to market is negatively and significantly correlated with market exposure ($p < 0.01$), but not correlated with the investment decisions of farm households who are less exposed to the market (Table A4). Second, in parsimonious and full specifications, we show that distance to the market negatively and significantly affects market exposure (not shown, but available upon request). Finally, we executed a series of tests to validate the admissibility of our results, including the test for the weak and under-identification of the selected instrument. The results reveal that our instruments are not weak and correctly identified.

The effects of market exposure on farmers' agricultural investment decisions, which are estimated using equations 5 through 8, are presented in Table 2. The results of the average treatment effect on the treated (ATT) reveals that, on average, market exposure increases the probability of chemical fertilizer adoption by 16 percentage points for farmers with high market exposure than in the counterfactual scenario of less market exposure. In a similar vein, farmers with less than median exposure to the market would also have increased the adoption of chemical fertilizer by 13 percentage points if they have had high exposure to the market. Further, the results of the average treatment effect (ATE) indicate that if all farm households have had high access to the market, they would have increased the adoption of mineral fertilizer by about 15 percentage points. Since the treatment effects can be influenced not only by observed factors *per se* but also by unobserved factors, we compute the marginal treatment effect (MTE) to address this concern. Table 2 report that the MTE results are qualitatively the same with the average treatment effects, which vary only by observed characteristics.

Table 2: Impact of Market Exposure on Agricultural Investment decisions

	(1) ATT	(2) ATU	(3) ATE	(4) MTE
Chemical fertilizer adoption	0.160***	0.126***	0.147***	0.168***
	(0.014)	(0.014)	(0.008)	(0.005)
Improved seed adoption	0.493***	0.442***	0.477***	0.644***
	(0.013)	(0.015)	(0.007)	(0.010)
Organic fertilizer adoption	-0.071***	0.491***	0.154***	0.470***
	(0.015)	(0.014)	(0.005)	(0.005)
Row planting adoption	0.333***	0.623***	0.456***	0.936***
	(0.017)	(0.023)	(0.010)	(0.013)

Notes. ATT, ATU, ATE, and MTE stand for Average Treatment Effect on the Treated, Average Treatment Effect on the Untreated, Average Treatment Effect, and Marginal Treatment Effect, respectively; Bootstrapped standard errors; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2 also shows that exposure to the market increases the use of improved seeds by 49 percentage points compared to the counterfactual case. Likewise, exposure to markets would have led to about 44 percentage points increase in the use of improved seed among farmers with less than median market exposure. The estimation results from the ATE and MTE also report qualitatively similar results. As shown in Table 2, we also estimated the impact of market exposure on organic fertilizer use. Market exposure has a differential impact on organic fertilizer use among farmers with high and less market exposure. While the ATT shows that exposure to market decreases the use of organic fertilizer by 7 percentage points for households with high market exposure, market exposure would have increased organic fertilizer adoption by 49 percentage points if farmers with less market exposure have had high market exposure. Finally, we also find that market exposure has a large and significant effect on the probability of using row planting. It increases the use of row planting by 33 percentage points for farm households with high market exposure compared to the counterfactual scenario of less market exposure. Likewise, the adoption rate of row planting of farmers with less market exposure would have increased by 62 percentage points if they have had higher than median exposure to the market. Overall, the estimation results suggest that market exposure significantly affects farmers' agricultural investment decisions. Interestingly, the estimated coefficients are economically meaningful and indicate that markets are important institutions in influencing preferences and behavior besides their indispensable role in the efficient allocation of scarce resources.

4.2. Results of the IV-Probit Model

To probe the robustness of our results in section 4.1 and to account for the continuous nature of our key variable of interest (market experience), we use the IV-probit model. Table 3 presents IV-probit estimates, using a household-level distance to a weekly market as an instrument for the market experience. At the bottom of Table 3, the Wald test of exogeneity rejects the null hypothesis that market exposure is exogenous. This suggests that using a naïve probit model may not be appropriate, instead, the IV-probit model should be used to attenuate the endogeneity concern. Next, we verify the validity of our instrument – household distance to market. For an instrument to be valid, it should satisfy two conditions: (i) the instrument should be correlated with the endogenous variable, and (ii) it should not be correlated with the outcome variable. Based on previous studies (e.g., see Melesse and Cecchi (2017)), we believe that household distance to market meets these criteria.

First stage estimates of the IV-probit model are provided in Table A5 in the appendix and shows that distance to market is negatively and significantly associated with market exposure. On average, one hour increase in the distance to the nearest market leads to a 0.6 decrease in the number of market transactions. The result is robust across different specifications and with and without controls. Table 3 also reports the Kleibergen-Paap F statistic to test the relevance of the instrument. The F statistic exceeds the minimum 10 critical values, suggesting that the instrument is not weak (Stock et al., 2002). The Kleibergen-Paap rk LM statistic for the under-identification test is also significant, indicating that our model is correctly identified.[11]

Table 3 shows that market experience positively and significantly affects farmers' agricultural investment decisions. Column (1) reports that farmers with a greater market experience are more likely to adopt chemical fertilizer. Results are robust and stable even after controlling a battery of control variables (column 2). Columns (3) and (4) report that market experience has a positive and statistically significant effect on the adoption of improved seeds. However, although market experience has a positive effect on the adoption of organic fertilizer, the impact is not statistically significant. Interestingly, columns (7) and (8) show that market exposure positively and significantly affects the adoption of row planting. More precisely, the estimation result shows that a 1 percent increase in market experience leads to a 28, 28, and 34 percent increase in the adoption of chemical fertilizer, improved seed, and row planting, respectively. In a nutshell, the estimation results from the IV-probit model corroborates the results from the ESP model in section 4.1. We probe the robustness of the estimation results from the ESP and IV-probit models using the conditional mixed process estimator (CMP) (Roodman, 2011). We

[11]Since we have one instrument for one endogenous variable, we are unable to conduct the overidentification test.

find qualitatively similar results that market exposure promotes farm households' investment behavior (results are not shown, but available upon request).

Table 3: Effects of Market Experience on Agricultural Investment Decisions

	(1) Chemical fertilizer	(2) Chemical fertilizer	(3) Improved seed	(4) Improved seed	(5) Organic fertilizer	(6) Organic fertilizer	(7) Row planting	(8) Row planting
Market experience	0.309***	0.283***	0.297***	0.276***	0.135	0.064	0.315***	0.336***
	(0.065)	(0.088)	(0.053)	(0.068)	(0.084)	(0.110)	(0.046)	(0.048)
Age		-0.011		0.007		0.040		-0.043
		(0.032)		(0.027)		(0.032)		(0.027)
Age square		-0.000		-0.000		-0.000		0.000*
		(0.000)		(0.000)		(0.000)		(0.000)
Male		0.312*		0.079		0.235		0.240
		(0.184)		(0.157)		(0.167)		(0.157)
Household size		0.125***		0.044		0.022		0.020
		(0.045)		(0.033)		(0.035)		(0.033)
Education		0.056		0.119		0.092		-0.027
		(0.160)		(0.134)		(0.146)		(0.120)
Land size		-0.096**		0.019		-0.066		-0.015
		(0.046)		(0.036)		(0.040)		(0.035)
Livestock		0.024		0.045***		0.079***		0.038***
		(0.020)		(0.016)		(0.019)		(0.014)
Housing condition		0.049		-0.138		-0.489*		0.054
		(0.253)		(0.205)		(0.251)		(0.218)
Own phone		-0.406**		-0.337**		-0.445***		-0.314**
		(0.177)		(0.136)		(0.168)		(0.122)
Own radio		0.206		-0.167		-0.116		-0.150
		(0.162)		(0.110)		(0.137)		(0.112)
Iddir member		-0.233		0.276*		0.024		0.389**
		(0.185)		(0.146)		(0.147)		(0.163)
Eqqub member		-0.258*		0.313**		0.357***		0.262**
		(0.142)		(0.128)		(0.129)		(0.127)
Cooperative member		0.105		0.122		-0.013		-0.096
		(0.149)		(0.119)		(0.121)		(0.110)
Distance to FTC		-0.002		-0.002		0.002		-0.000
		(0.003)		(0.003)		(0.003)		(0.003)
Drought exposure		-0.063***		-0.025*		-0.027*		0.023
		(0.020)		(0.015)		(0.016)		(0.015)
Constant	-0.242	0.681	-1.002***	-1.502**	-0.430	-0.859	-1.388***	-1.283*
	(0.325)	(0.816)	(0.172)	(0.665)	(0.295)	(0.788)	(0.120)	(0.678)
Observations	502	502	502	502	502	502	502	502
Wald test of exogeneity $\chi2$	7.48***	3.28*	19.07***	8.75***	1.66	0.06	24.54***	22.55***
KP rk LM statistic	22.935***	18.607***	22.935***	18.607***	22.935***	18.607***	22.935***	18.607***
Weak iden test (KP F-Stat)	27.890	22.340	27.890	22.340	27.890	22.340	27.890	22.340

Notes. KP stands for Kleibergen-Paap. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

4.3. Impact Pathways

In this section, we elucidate some of the causal mechanisms through which market exposure affects agricultural investment decisions. As has already been mentioned, access to the market may affect farmers' investment behavior in multiple ways. However, in this paper, we emphasize only on the personality traits - risk preference and locus of control - that are largely acknowledged by the recent theoretical and empirical studies as key determinants of the adoption of risky but profitable technologies.

Before discussing our main results, we first probe the findings of earlier studies on whether the adoption of agricultural technology is correlated with risk preference and locus of control.[12] Table A6 shows that risk-aversion is negatively and significantly associated with the adoption of agricultural technologies. Similarly, a greater internal locus of control is positively and significantly associated with modern agricultural technologies use. Particularly, the internal locus of control is positively and significantly correlated with the adoption of chemical fertilizer and improved seed. These results reaffirm the role of personality traits on investment decisions, specifically, the role of risk-aversion (Liu, 2013; Brick and Visser, 2015; Holden and Quiggin, 2017) and internal locus of control (Abay et al., 2017; Taffesse and Tadesse, 2017; Bukchin and Kerret, 2020) on agricultural households' investment decisions. Next, we present whether market exposure is associated with causal mechanisms. We first present the results of a descriptive analysis followed by the results of the endogenous switching regression model and 2SLS.

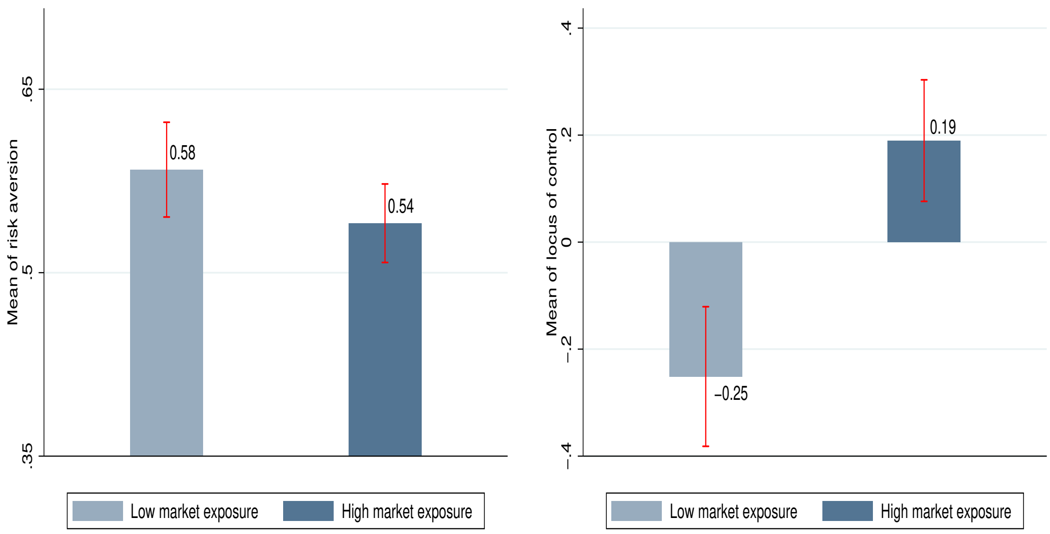

Figure 3: Market exposure, risk-aversion and locus of control, 95% CI

[12]Interestingly, we find no statistically significant correlation between risk-aversion and locus of control (-0.051, 0.252 (P-value)).

Figure 3 compares farmers' risk-aversion and locus of control across those with relatively high and less market exposure. The figure shows that farmers with high market exposure are less risk-averse compared to farmers with less market exposure ($P < 0.10$). Figure 3 also shows that farmers with high exposure to markets have a greater degree of internal locus of control ($P < 0.001$). In sum, we find that market exposure attenuates farmers' risk-aversion and boost their internal locus of control.

Figures A1 and A2 in the appendix provide the distribution of farmers' risk-aversion and internal locus of control across farm households' with high and less market exposure. The figures support the results from Figure 3 in the sense that market exposure attenuates risk-aversion and enhances internal locus of control. However, the results of the unconditional mean difference test do not provide causal effects due to the fact that market exposure may be endogenous and the difference in risk-aversion and locus of control may not be the result of the difference in market exposure *per se*, rather it might also be due to differences in observable and unobservable factors. To address this concern, we present the estimation results of the endogenous switching and instrumental variable (IV) regression models in sections 4.3.1 and 4.3.2, respectively.

4.3.1. Results of Endogenous Switching Regression model

Table 4 and Table A7 in the appendix present the FIML estimates of the endogenous switching regression (ESR) model. Before discussing the impact of market exposure on risk-aversion and locus of control, we first discuss the model diagnosis. The Wald $\chi 2$ test for joint independence of the outcome equations (risk-aversion and locus of control) and the selection equation (market exposure) presented in Table A7 in the appendix shows that the outcome and selection equations are not independent (Abdulai and Huffman, 2014). These suggest that OLS regression may yield biased estimates due to unobserved factors simultaneously affecting market exposure, and farmers' locus of control and risk-aversion.

Table 4 presents the estimates of the average treatment effect on the treated, on the untreated, and the transitional heterogeneous treatment effects under actual and counterfactual conditions.[13] The results show that market exposure significantly decreases risk-aversion. The expected proportion of the amount of money not invested in the risky investment by households with high and less market exposure is 0.541 and 0.582, respectively. In the counterfactual case, farmers with high market exposure would have invested 14 Birr less in the risky investment if they have had less exposure to the market. On the other hand, farmers with less market

[13]This study aims to investigate whether market exposure promotes farmers' investment behavior by attenuating risk-aversion and enhancing locus of control. Thus, to economize on space, the detailed ESR model estimates such as the drivers of market exposure and the determinants of risk-aversion and locus of control other than market exposure are not discussed, but the full estimation results are available in Table A7.

exposure would have invested 5 Birr more if they had high exposure to the market. The estimation results suggest that market exposure significantly attenuates risk-aversion. However, the heterogeneous treatment effect is negative, indicating that the impact of market exposure is significantly smaller for farmers with less market exposure compared to those with high market exposure. The estimation results are consistent with the findings of a recent study by Melesse and Cecchi (2017) who used similar risk preference elicitation experimental game in the Amhara regional state of Ethiopia and find that market exposure reduces risk-aversion.

Table 4: Impact of Market Exposure on Risk-Aversion and Locus of Control

		Exposure stage		
Outcomes	Household type	Exposed	Not exposed	Treatment effects
Risk-aversion	High exposure (ATT)	0.541	1.212	-0.672***
	Low exposure (ATU)	0.420	0.582	-0.162***
	Heterogeneous effects			-0.510***
Locus of control	High exposure (ATT)	0.198	-0.138	0.336***
	Low exposure (ATU)	1.694	-0.251	1.945***
	Heterogeneous effects			-1.609***

Notes. ATT and ATU stand for Average Treatment Effect on the Treated and Average Treatment Effect on the Untreated, respectively; Robust standard errors; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4 also presents the impact of market exposure on internal locus of control. The results show that market exposure increases the internal locus of control by 0.2 standard deviations. On the other hand, farmers with less market exposure would have increased their internal locus of control by 1.70 standard deviations if they have had high exposure to the market. However, the transitional heterogeneity effects for internal locus control is negative, suggesting that the impact is smaller for farmers with high market exposure compared to those with less market exposure. The results from the ESR model reaffirms that locus of control may not be truly time-invariant (Cobb-Clark and Schurer, 2013) and may systematically vary with small but frequent life events (Elkins et al., 2017). In a nutshell, the estimation results of the ESR model show that market exposure attenuates risk-aversion and enhances locus of control, and thus, promotes the adoption of high-risk-high-return technologies.

4.3.2. Results of the Instrumental Variable Estimation

To validate the results of the ESR model in section 4.3.1, we employ the instrumental variable (IV) method. The endogeneity test indicates that market exposure is indeed endogenous, and

OLS may provide biased estimates. Household-level distance to a large weekly market is used as an instrument for both the continuous and binary measures of market exposure. We used the Kleibergen-Paap F statistic to test for weak instruments. Table 5 shows that the F statistic is greater than the minimum 10 threshold values of Stock et al. (2002), suggesting that our -

Table 5: Impact of Market Exposure on Risk-Aversion and Locus of Control

	(1) Risk aversion	(2) Risk aversion	(3) Risk aversion	(4) Risk aversion	(5) Locus of control	(6) Locus of control	(7) Locus of control	(8) Locus of control
Market experience	-0.093***	-0.078***			0.153**	0.082		
	(0.026)	(0.026)			(0.076)	(0.076)		
Market exposure			-0.582***	-0.513***			0.957**	0.541
			(0.174)	(0.190)			(0.485)	(0.509)
Age		-0.001		-0.002		0.052**		0.053**
		(0.007)		(0.007)		(0.026)		(0.026)
Age square		0.000		0.000		-0.001**		-0.001**
		(0.000)		(0.000)		(0.000)		(0.000)
Male		-0.096**		-0.116**		0.146		0.166
		(0.041)		(0.047)		(0.112)		(0.115)
Household size		-0.012		0.006		0.041		0.023
		(0.009)		(0.011)		(0.025)		(0.029)
Education		0.027		0.027		0.215**		0.215**
		(0.032)		(0.038)		(0.096)		(0.097)
Land size		-0.001		0.003		0.001		-0.003
		(0.010)		(0.011)		(0.027)		(0.027)
Livestock		-0.005		-0.002		0.018		0.015
		(0.004)		(0.005)		(0.012)		(0.011)
Housing condition		-0.030		-0.057		0.430**		0.459**
		(0.048)		(0.064)		(0.201)		(0.198)
Own phone		-0.026		-0.042		-0.003		0.013
		(0.036)		(0.040)		(0.117)		(0.114)
Own radio		0.029		0.006		0.100		0.124
		(0.033)		(0.036)		(0.095)		(0.089)
Iddir member		-0.037		-0.052		0.162		0.177*
		(0.034)		(0.042)		(0.100)		(0.100)
Eqqub member		0.009		0.015		-0.101		-0.108
		(0.030)		(0.036)		(0.089)		(0.091)
Cooperative member		0.030		0.042		0.246***		0.233***
		(0.030)		(0.034)		(0.082)		(0.083)
Distance to FTC		0.000		-0.000		-0.000		-0.000
		(0.001)		(0.001)		(0.002)		(0.002)
Drought exposure		0.007*		0.006		0.016		0.017
		(0.004)		(0.004)		(0.011)		(0.011)
Constant	0.879***	0.912***	0.891***	0.957***	-0.526**	-2.570***	-0.545*	-2.618***
	(0.086)	(0.170)	(0.099)	(0.181)	(0.263)	(0.627)	(0.280)	(0.635)
KP F-Stat	27.89	22.34	20.86	14.34	27.89	22.34	20.86	14.34
KP rk LM statistic	22.935***	18.607***	22.935***	18.607***	22.935***	18.607***	22.935***	18.607***
Observations	502	502	502	502	502	502	502	502

Notes. KP stands for Kleibergen-Paap. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

instrument is not weak.[14] Table 5 also provides further support for the validity of our instruments in that the Kleibergen-Paap rk LM statistic which is used to test for the under-identification shows that the models are correctly identified. Table A8 in the appendix also reports that household distance to the market negatively and significantly affects farmers' market exposure. The results are robust to different specifications and even after controlling a large battery of controls.[15]

Table 5 shows that market exposure significantly affects risk-aversion and internal locus of control. The most parsimonious specifications in columns (1) and (3) indicate the prevalence of negative and significant association between market exposure and risk-aversion. Column (1) suggests that risk-aversion decreases as farmers' market experience increases. Similarly, column (3) shows that the binary market exposure is also negatively associated with risk-aversion. In columns (2) and (4), we added a battery of controls. However, adding the control variables does not attenuate the significant effect of both the continuous (column 2) and the binary (column 4) measures of market exposure. Results for the internal locus of control are provided in columns (5) through (8). In columns (5) and (7), we again present the parsimonious specifications. The estimation results show that higher market exposure is positively associated with the internal locus of control. However, including relevant controls into the analysis attenuates the effect of market exposure (columns 6 and 8). Nevertheless, in sum, our estimation results suggest that market exposure stimulates agricultural investment behavior through attenuating risk-aversion and improving non-cognitive skills such as locus of control.

Table 5 also shows that a range of variables affects farmers' risk-aversion and internal locus of control. Male-headed households are less risk-averse compared to female-headed farm households. Farmers who reside in villages exposed to frequent droughts are also more risk-averse than those who live in villages with less exposure to drought. On the other hand, internal locus of control non-linearly decreases with the age of the household head. Consistent with Abay et al. (2017) and Taffesse and Tadesse (2017), locus of control initially increases with the age of the household head but declines after a certain age limit. Literate farmers have a relatively higher internal locus of control compared to the illiterate farmers that is in line with the findings of previous studies (Heckman et al., 2006). Relatively wealthy households (farmers who own houses with at least average condition) have a higher internal locus of control. Furthermore, internal locus of control is positively associated with membership in social networks such as membership in funeral insurance and agricultural cooperatives.

[14] Since the threshold values for strong instruments do not exist for the Kleibergen-Paap statistic, following Baum et al. (2007), we apply the Stock and Yogo critical values in order to test for weak IV.

[15] However, as we have only one instrument for one endogenous variable, we could not conduct the over-identification test.

5. Conclusion

Understanding farmers' investment behavior is key to spur the adoption of modern farming inputs, thereby boost productivity and facilitate agricultural transformation in Sub-Saharan Africa. The existing literature, however, points out that the rate of investment in improved farming technologies in the region is rather slow, which resulted in low agricultural productivity. There is an extensive theoretical and empirical literature devoted to uncovering the constraining factors for the adoption of these technologies. A large body of literature demonstrates that *external factors*, including imperfect credit and insurance markets, transaction costs, quality of inputs, and heterogeneous returns to farming inputs (Duflo et al., 2011; Suri, 2011; Minten et al., 2013; Karlan et al., 2014; Bold et al., 2017) explain the low level of investments in profitable agricultural technologies. Recently, economists are increasingly pushing the frontiers of the economics of technology adoption literature to accommodate behavioral drivers (*internal constraints*) of high-risk-high-return technologies (Duflo et al., 2011; Bernard et al., 2014; Abay et al., 2017; Taffesse and Tadesse, 2017). However, to date, both strands of literature considered *internal* and *external constraints* as independent. This paper argue that *internal* and *external constraints* are interdependent, and *external* factors such as markets may predict the change in *internal* constraints, which in turn, influence the use of modern farming inputs.

Specifically, we investigate whether markets affect farmers' investment behavior by altering their preferences (risk-aversion) and personality traits (locus of control). To this end, we utilize survey and lab-in-the-field experimental data collected from 544 farm households in the Tigray regional state of Ethiopia. Ethiopia is an interesting context to test if this hypothesis indeed holds. This is because, in the country, agricultural inputs are supplied by the parastatal agricultural cooperatives, that are available in every village. However, in the absence of random or exogenous exposure to markets, identifying the causal effect of market exposure is challenging due to the potential endogeneity problem stemmed from simultaneity and omitted variable biases. To address these concerns, we employ the endogenous switching probit (ESP) and IV-probit models. The diagnosis tests in both models show that market experience is indeed endogenous, and the use of ESP and IV-probit is preferred than the naïve probit and bivariate probit models.

We find that greater market integration promotes farmers' investment behavior - use of productivity-enhancing inputs such as chemical fertilizer, improved seeds, organic fertilizer, and row planting. The findings show that farmers with higher market exposure tend to be less risk-averse and possess a high internal locus of control, and in turn, are more likely to adopt these farming inputs. Likewise, farm households with less market exposure would have substantially reduced their risk-aversion and increased their internal locus of control, and thereby would have used more improved agricultural technologies. The average treatment effects from the ESP model show that farmers would have increased the use of chemical fertilizer, improved seeds, organic fertilizer, and row planting by 15, 48, 15, and 46 percentage points, respectively. Our results are robust to alternative measures of market exposure and different specifications and estimation strategies.

Our study contributes to the extensive economics of technology adoption literature. We provide new evidence that *internal* and *external* factors which predict farmers' technology adoption decisions are interdependent, and *external* constraints such as markets may influence farm households investment behavior by modifying *internal* constraints (risk preference and locus of control). This paper, therefore, suggests alternative pathways through which the adoption of improved technologies could be increased in developing countries, especially in Sub-Saharan Africa. Further, our findings also contribute to the growing literature on whether preferences and personality traits are endogenous and malleable. Particularly, we add to the thin literature on the effect of market exposure on risk preference. Consistent with the findings by Melesse and Cecchi (2017), market exposure significantly, and robustly attenuates risk-aversion. Additionally, in line with Cobb-Clark and Schurer (2013) and Elkins et al. (2017), we show that locus of control may not be truly time-invariant and systematically respond to small but more frequent life events, such as market participation.

Finally, while our findings are informative and stimulate further research, we are constrained by a lack of experimental and longitudinal data. Since this paper is based on cross-sectional data, it warrants further investigation through exogenously varying farmers' exposure to markets. The Sub-Saharan African Challenge Program (SSA-CP) that involves penetration of markets in remote villages and linking farmers to regional and national markets is an interesting example (see Siziba and Bulte (2012) for details). Additionally, further research is needed to probe the robustness of our findings using longitudinal data to understand the dynamics of risk-aversion and locus of control, and thus, investment behavior.

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A. Additional Analyses

Table A1: Variable Definitions and Summary Statistics

Variables	Descriptions of variables	Mean	Standard Deviation
Outcome Variables			
Chemical fertilizer	Dummy: =1 if the respondent uses chemical fertilizer, =0 otherwise	0.843	0.365
Improved seed	Dummy: =1 if the respondent uses improved seed, =0 otherwise	0.51	0.5
Organic fertilizer	Dummy: =1 if the respondent uses organic fertilizer, =0 otherwise	0.514	0.5
Row planting	Dummy: =1 if the respondent uses row planting, =0 otherwise	0.323	0.468
Mechanisms			
Risk-aversion	Continuous: Risk-aversion index	0.558	0.281
Locus of control	Continuous: Locus of control index (standardized)	0	1
Treatments			
Market transactions	Continuous: Average number of market transactions (buying & selling) per month	3.436	2.586
Market exposure	Dummy: =1 if the respondent has high market exposure, =0 otherwise	0.591	0.492
Instrument			
Distance to market	Continuous: Respondent's distance to the nearest weekly market	1.806	0.886
Controls			
Age	Continuous: Age of the household head	43.972	11.84
Male	Dummy: =1 if the household head is Male, =0 Female	0.737	0.441
Household size	Continuous: number of persons in the household	5.787	2.073
Education	Dummy: =1 if the household head attend formal education, =0 otherwise	0.582	0.494
Tsimad	Continuous: Agricultural land size	3.044	1.942
Livestock	Continuous: total livestock holding (TLU)	4.350	3.819
House condition	Dummy: =1 if the housing condition is average and above, =0 otherwise	0.932	0.252
Own phone	Dummy: =1 if the respondent owns phone, =0 otherwise	0.723	0.448
Own radio	Dummy: =1 if the respondent owns radio, =0 otherwise	0.426	0.495
Iddir member	Dummy: =1 if the household head is member of funeral association, =0 otherwise	0.787	0.410
Eqqub member	Dummy: =1 if the household head is member of eqqub, =0 otherwise	0.476	0.500
Cooperative member	Dummy: =1 if the household head is member of agricultural cooperatives, =0 otherwise	0.556	0.497
Distance to FTC	Continuous: Distance to the farmer training center	25.863	24.75
Village exposure to drought	Continuous: Number of drought periods in 30 years	6.985	4.109

Table A2: Endogenous Switching Probit Estimation

	Chemical fertilizer			Improved seed		
	Market exposure	Adopters	Non-adopters	Market exposure	Adopters	Non-adopters
Age	0.014	-0.008	0.011	0.012	-0.003	0.062
	(0.030)	(0.062)	(0.044)	(0.032)	(0.048)	(0.052)
Age square	-0.000	-0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Male	-0.209	0.300	0.446*	-0.187	-0.069	0.282
	(0.162)	(0.243)	(0.270)	(0.162)	(0.195)	(0.226)
Household size	0.060*	0.144**	0.071	0.058*	0.067	-0.057
	(0.035)	(0.059)	(0.073)	(0.035)	(0.051)	(0.047)
Education	0.159	0.206	-0.160	0.144	0.168	0.156
	(0.136)	(0.211)	(0.234)	(0.141)	(0.171)	(0.270)
Land size	-0.003	-0.114**	-0.200***	-0.007	-0.026	0.009
	(0.035)	(0.055)	(0.076)	(0.040)	(0.049)	(0.054)
Livestock	-0.001	0.004	0.029	0.001	0.050**	0.029
	(0.018)	(0.031)	(0.032)	(0.018)	(0.025)	(0.024)
Housing condition	0.172	-0.173	0.477	0.157	-0.132	0.173
	(0.234)	(0.403)	(0.379)	(0.249)	(0.288)	(0.353)
Own phone	0.116	-0.527**	-0.050	0.095	-0.077	-0.366
	(0.147)	(0.268)	(0.303)	(0.151)	(0.188)	(0.227)
Own radio	0.073	0.548***	0.080	0.073	0.005	-0.162
	(0.126)	(0.199)	(0.242)	(0.126)	(0.147)	(0.198)
Iddir member	-0.073	-0.240	-0.211	-0.077	0.321*	0.383*
	(0.149)	(0.288)	(0.283)	(0.150)	(0.192)	(0.217)
Eqqub member	0.108	-0.319	-0.069	0.107	0.407***	0.197
	(0.125)	(0.210)	(0.215)	(0.124)	(0.157)	(0.263)
Cooperative member	0.092	0.009	0.382	0.082	-0.054	0.325
	(0.123)	(0.198)	(0.264)	(0.121)	(0.145)	(0.283)
Distance to FTC	0.001	0.003	-0.006	0.001	-0.002	0.001
	(0.002)	(0.004)	(0.004)	(0.002)	(0.003)	(0.004)
Drought exposure	0.014	-0.054*	-0.075**	0.016	-0.013	-0.029
	(0.016)	(0.028)	(0.029)	(0.016)	(0.020)	(0.025)
Distance to market	-0.261***			-0.278***		
	(0.067)			(0.060)		
Constant	-0.126	2.098	0.697	-0.020	-0.045	-2.844**
	(0.715)	(1.385)	(1.172)	(0.793)	(1.084)	(1.304)
Wald $\chi2$			3.13			6.26**
ρ_{ij}		-0.658	-0.367		-0.726**	-0.721
		(0.269)	(0.484)		(0.188)	(0.598)
Observations	502	502	502	502	502	502

Notes. Wald$\chi2$ tests the joint independence of the equations. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Endogenous Switching Probit Estimation

	Organic fertilizer			Row planting		
	Market exposure	Adopters	Non-adopters	Market exposure	Adopters	Non-adopters
Age	0.015	-0.019	0.072	0.025	-0.039	-0.027
	(0.033)	(0.039)	(0.044)	(0.031)	(0.043)	(0.037)
Age square	-0.000	0.000	-0.001	-0.000	0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.189	0.393**	-0.006	-0.191	-0.018	0.819***
	(0.156)	(0.169)	(0.276)	(0.161)	(0.182)	(0.291)
Household size	0.064*	-0.001	-0.027	0.045	0.006	-0.115**
	(0.035)	(0.040)	(0.072)	(0.034)	(0.042)	(0.050)
Education	0.154	-0.028	0.246	0.159	-0.040	0.224
	(0.134)	(0.143)	(0.224)	(0.136)	(0.157)	(0.203)
Land size	-0.009	-0.064*	-0.045	0.006	-0.065	-0.035
	(0.035)	(0.037)	(0.061)	(0.035)	(0.046)	(0.048)
Livestock	0.003	0.050**	0.097***	-0.003	0.055**	0.012
	(0.018)	(0.022)	(0.031)	(0.019)	(0.023)	(0.022)
Housing condition	0.201	-0.483*	-0.416	0.140	0.342	0.365
	(0.244)	(0.271)	(0.365)	(0.236)	(0.336)	(0.360)
Own phone	0.122	-0.458***	-0.305	0.064	-0.246	-0.104
	(0.146)	(0.165)	(0.305)	(0.148)	(0.174)	(0.241)
Own radio	0.030	-0.149	0.026	0.069	-0.108	0.038
	(0.124)	(0.135)	(0.205)	(0.125)	(0.139)	(0.190)
Iddir member	-0.043	0.141	-0.074	-0.107	0.325*	0.876***
	(0.142)	(0.149)	(0.218)	(0.151)	(0.191)	(0.271)
Eqqub member	0.104	0.313**	0.242	0.097	0.413**	0.188
	(0.124)	(0.137)	(0.210)	(0.123)	(0.162)	(0.167)
Cooperative member	0.093	0.044	-0.197	0.086	-0.281*	0.025
	(0.117)	(0.123)	(0.245)	(0.123)	(0.149)	(0.178)
Distance to FTC	0.001	0.000	0.004	0.001	0.000	0.003
	(0.002)	(0.002)	(0.004)	(0.002)	(0.003)	(0.004)
Drought exposure	0.015	-0.021	-0.023	0.015	0.026	0.061**
	(0.016)	(0.016)	(0.025)	(0.016)	(0.019)	(0.024)
Distance to market	-0.227***			-0.307***		
	(0.056)			(0.056)		
Constant	-0.240	1.259	-1.088	-0.098	0.268	-2.829***
	(0.803)	(0.932)	(1.290)	(0.739)	(0.985)	(1.060)
Wald $\chi2$			20.84***			6.95**
ρ_{ij}		-1.000***	0.223		-0.894***	-1.000
		(0.000)	(1.068)		(0.110)	(0.007)
Observations	502	502	502	502	502	502

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Test on the Validity of the Selection Instruments - Outcome Variables

	(1) Chemical fertilizer	(2) Improved seed	(3) Organic fertilizer	(4) Row planting
Age	0.002	0.033**	0.029	-0.006
	(0.009)	(0.014)	(0.019)	(0.015)
Age square	-0.000	-0.000**	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.098	0.097	0.002	0.205***
	(0.063)	(0.098)	(0.114)	(0.058)
Household size	0.017	-0.017	-0.014	-0.031*
	(0.014)	(0.021)	(0.021)	(0.016)
Education	-0.010	0.118	0.098	0.110
	(0.048)	(0.111)	(0.087)	(0.067)
Land size	-0.044**	0.003	-0.017	-0.017
	(0.022)	(0.022)	(0.027)	(0.017)
Livestock	0.005	0.015	0.040***	0.002
	(0.008)	(0.011)	(0.013)	(0.005)
Housing condition	0.147	0.099	-0.176	0.130***
	(0.120)	(0.118)	(0.137)	(0.046)
Own phone	-0.003	-0.166	-0.140	-0.018
	(0.066)	(0.105)	(0.091)	(0.104)
Own radio	0.028	-0.070	0.009	0.022
	(0.052)	(0.095)	(0.087)	(0.059)
Iddir member	-0.053	0.162*	-0.028	0.219***
	(0.066)	(0.090)	(0.105)	(0.052)
Eqqub member	-0.011	0.125	0.088	0.098
	(0.071)	(0.088)	(0.075)	(0.076)
Cooperative member	0.093*	0.173**	-0.092	0.037
	(0.048)	(0.073)	(0.094)	(0.080)
Distance FTC	-0.001	0.001	0.002	0.002
	(0.001)	(0.002)	(0.002)	(0.001)
Drought exposure	-0.016*	-0.010	-0.009	0.028***
	(0.008)	(0.010)	(0.012)	(0.010)
Distance to market	-0.018	-0.073	-0.008	-0.083*
	(0.036)	(0.049)	(0.033)	(0.043)
Observations	216	216	216	216

Notes. Robust standard errors (clustered by village) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A5: First Stage Estimation Results

	Chemical fertilizer		Improved seed		Organic fertilizer		Row planting	
	Market experience	Market experience	Market experience	Market experience	Market experience	Market experience	Market experience	Market experience
Distance to market	-0.663***	-0.614***	-0.663***	-0.614***	-0.663***	-0.614***	-0.663***	-0.614***
	(0.125)	(0.128)	(0.125)	(0.128)	(0.125)	(0.128)	(0.125)	(0.128)
Age		0.041		0.041		0.041		0.041
		(0.055)		(0.055)		(0.055)		(0.055)
Age square		-0.000		-0.000		-0.000		-0.000
		(0.001)		(0.001)		(0.001)		(0.001)
Male		-0.221		-0.221		-0.221		-0.221
		(0.356)		(0.356)		(0.356)		(0.356)
Household size		-0.077		-0.077		-0.077		-0.077
		(0.078)		(0.078)		(0.078)		(0.078)
Education		0.398*		0.398*		0.398*		0.398*
		(0.234)		(0.234)		(0.234)		(0.234)
Land size		-0.060		-0.060		-0.060		-0.060
		(0.066)		(0.066)		(0.066)		(0.066)
Livestock		-0.037		-0.037		-0.037		-0.037
		(0.023)		(0.023)		(0.023)		(0.023)
Housing condition		0.726**		0.726**		0.726**		0.726**
		(0.316)		(0.316)		(0.316)		(0.316)
Own phone		0.499**		0.499**		0.499**		0.499**
		(0.222)		(0.222)		(0.222)		(0.222)
Own radio		0.450*		0.450*		0.450*		0.450*
		(0.231)		(0.231)		(0.231)		(0.231)
Iddir member		0.004		0.004		0.004		0.004
		(0.241)		(0.241)		(0.241)		(0.241)
Eqqub member		0.182		0.182		0.182		0.182
		(0.206)		(0.206)		(0.206)		(0.206)
Cooperative member		0.043		0.043		0.043		0.043
		(0.242)		(0.242)		(0.242)		(0.242)
Distance to FTC		0.006		0.006		0.006		0.006
		(0.008)		(0.008)		(0.008)		(0.008)
Drought exposure		0.040		0.040		0.040		0.040
		(0.032)		(0.032)		(0.032)		(0.032)
Constant	4.633***	2.547*	4.633***	2.547*	4.633***	2.547*	4.633***	2.547*
	(0.301)	(1.439)	(0.301)	(1.439)	(0.301)	(1.439)	(0.301)	(1.439)
Observations	502	502	502	502	502	502	502	502

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Correlation Between Risk-aversion, Locus of Control and Investment Behavior

	Chemical fertilizer	Improved seed	Organic fertilizer	Row planting
Risk-aversion	-0.097**	-0.121***	-0.082*	-0.150***
	(0.031)	(0.007)	(0.067)	(0.001)
Locus of control	0.144***	0.083*	0.005	0.064
	(0.001)	(0.062)	(0.904)	0.152

Notes. P-values in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

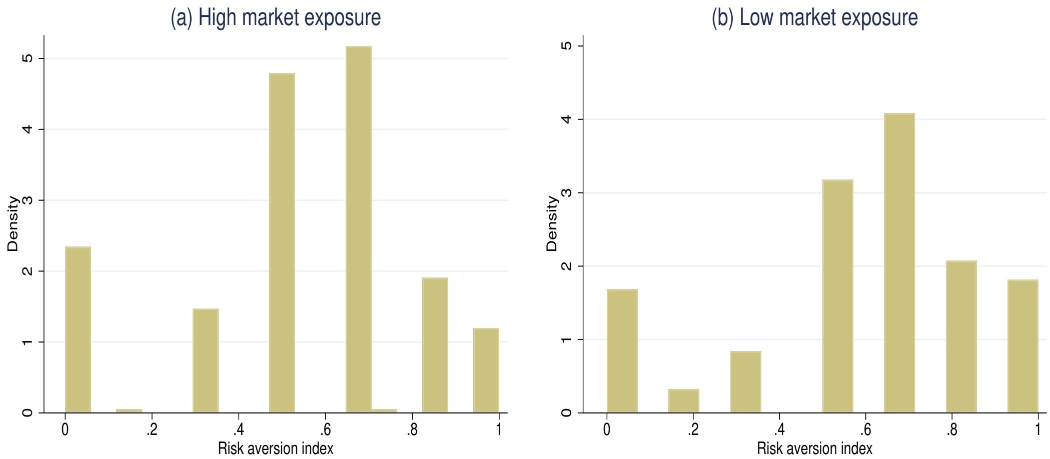

Figure A1: Distribution of Farmers' Risk-Aversion

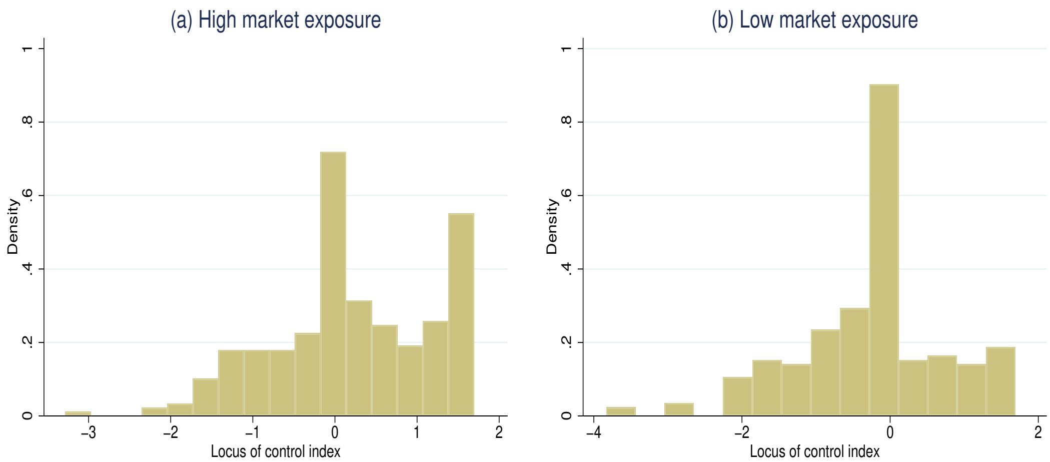

Figure A2: Distribution of Farmers' Internal Locus of Control (Standardized)

Table A7: Endogenous Switching Regression

	(1) Risk_1	(2) Risk_0	(3) market exposure	(4) Locus_of control_1	(5) Locus_of control_0	(6) market exposure
Age	0.002	-0.008	0.003	0.010	0.065*	0.011
	(0.010)	(0.015)	(0.078)	(0.049)	(0.036)	(0.038)
Age square	0.000	0.000	-0.000	-0.000	-0.001*	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Male	-0.074	-0.123	-0.197	0.282	0.225	-0.253
	(0.064)	(0.121)	(0.189)	(0.319)	(0.188)	(0.192)
Household size	-0.003	0.016	0.033	0.002	0.026	0.057
	(0.015)	(0.065)	(0.065)	(0.089)	(0.059)	(0.055)
Education	0.018	0.014	0.224	0.090	0.197	0.150
	(0.044)	(0.088)	(0.201)	(0.266)	(0.169)	(0.172)
Land size	0.007	-0.005	-0.006	-0.004	0.013	-0.011
	(0.011)	(0.025)	(0.053)	(0.050)	(0.053)	(0.043)
Livestock	-0.007	0.003	0.002	0.021	0.008	0.009
	(0.005)	(0.007)	(0.019)	(0.022)	(0.015)	(0.025)
Housing condition	-0.115*	0.008	0.064	0.277	0.507**	0.108
	(0.062)	(0.223)	(0.372)	(0.548)	(0.227)	(0.322)
Own phone	-0.026	-0.050	0.032	0.143	-0.294	0.154
	(0.045)	(0.128)	(0.139)	(0.265)	(0.209)	(0.150)
Own radio	-0.003	-0.002	0.063	0.058	0.205	0.012
	(0.030)	(0.103)	(0.226)	(0.149)	(0.159)	(0.165)
Iddir member	-0.035	-0.065	-0.029	0.250	0.041	-0.002
	(0.034)	(0.052)	(0.117)	(0.264)	(0.160)	(0.126)
Cooperative member	0.027	0.048	0.133	0.215	0.240	0.150
	(0.035)	(0.092)	(0.126)	(0.136)	(0.208)	(0.129)
Drought exposure	0.004	0.008	0.013	0.030	-0.004	0.011
	(0.006)	(0.007)	(0.032)	(0.020)	(0.019)	(0.016)
Distance to market			-0.250			-0.187
			(0.189)			(0.122)
Constant	0.558**	1.148**	0.315	-0.742	-2.386***	-0.018
	(0.269)	(0.507)	(1.690)	(2.162)	(0.915)	(0.833)
Model diagnosis						
σ	0.274***	0.421**		1.180**	0.875***	
	(0.089)	(0.507)		(0.674)	(0.054)	
ρ	0.328	0.969		-0.867	0.008	
	(0.779)	(0.406)		(0.584)	-1,240	
Wald $\chi 2$	30.49***			4.39**		
Observations	502	502	502	502	502	502

Notes. Robust standard errors (clustered by village) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table A8: First Stage Estimation Results - Mechanisms

	(1) Market experience	(2) Market experience	(3) Market exposure	(4) Market exposure
Distance to market	-0.663***	-0.614***	-0.106***	-0.093***
	(0.125)	(0.130)	(0.023)	(0.025)
Age		0.041		0.005
		(0.056)		(0.010)
Age square		-0.000		-0.000
		(0.001)		(0.000)
Male		-0.221		-0.071
		(0.362)		(0.060)
Household size		-0.077		0.023*
		(0.079)		(0.013)
Education		0.398*		0.060
		(0.238)		(0.052)
Land size		-0.060		-0.001
		(0.067)		(0.013)
Livestock		-0.037		0.000
		(0.023)		(0.007)
Housing condition		0.726**		0.057
		(0.321)		(0.090)
Own phone		0.499**		0.045
		(0.226)		(0.056)
Own radio		0.450*		0.024
		(0.235)		(0.047)
Iddir member		0.004		-0.029
		(0.245)		(0.056)
Eqqub member		0.182		0.039
		(0.209)		(0.047)
Cooperative member		0.043		0.031
		(0.246)		(0.046)
Distance to FTC		0.006		0.000
		(0.008)		(0.001)
Drought exposure		0.040		0.005
		(0.033)		(0.006)
Constant	4.633***	2.547*	0.761***	0.474*
	(0.302)	(1.463)	(0.047)	(0.247)
Observations	502	502	502	502
R-squared	0.052	0.105	0.036	0.079

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

B. Experimental Instructions - Risk Game

At the beginning of this activity you will receive 30 Birr. You are asked to choose the portion of this amount (between 0 and 30) that you wish to invest in a risky option. The rest of the money will be accumulated in your total balance.

The risky investment: there is an equal chance that the investment will fail or succeed. If the investment fails, you lose the amount you invested. If the investment succeeds, you receive 3 times the amount invested.

How do we determine if you win? After you have chosen how much you wish to invest, you toss a coin to determine whether you win or lose. If you choose heads and heads shows up, you win 3 times the amount you chose to invest. If you choose heads and tails shows up, you lose the amount invested.

Examples

1. If you choose to invest nothing, you will get the 30 Birr for sure. That is, the coin flip would not affect your profits.

2. If you choose to invest 15 Birr, then you choose heads or tails, and afterward you throw the coin. If you choose heads and heads shows up, you win 60 Birr (15+3*15), and if the coin lands on tails, you win 15 Birr.

3. If you choose to invest all of the 30 Birr, then you choose heads or tails, and afterward you throw the coin. If you choose heads and heads shows up, you win 90 Birr, and if the coin comes up tails, you win nothing and end up with 0.

Do you have any questions?

Now you may start.

Record Sheet – Activity Two

Respondent Name: ____________________	Household Code: I___I___I___I___I___I___I
Village Name: ________________________	Village Code: I___I___I___I___I
District Name: _______________________	District Code: I___I___I
Interviewer Name: ____________________	Interviewer Code: I___I___I___I___I

Initial endowment	Amount kept [1]	Amount invested [2]	Participant's choice 0. Head 1. Tail [3]	Result of the draw 0. Head 1. Tail [4]	Amount earned [1+3(2)] if 3=4 [1] if 3≠4
30					

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